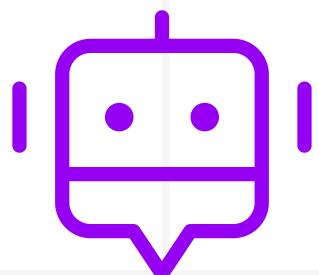


Detection of
Payment Fraud

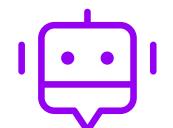
A Machine Learning Model



PROJECT SOPHIA



Identify and prevent payment fraud.



Model

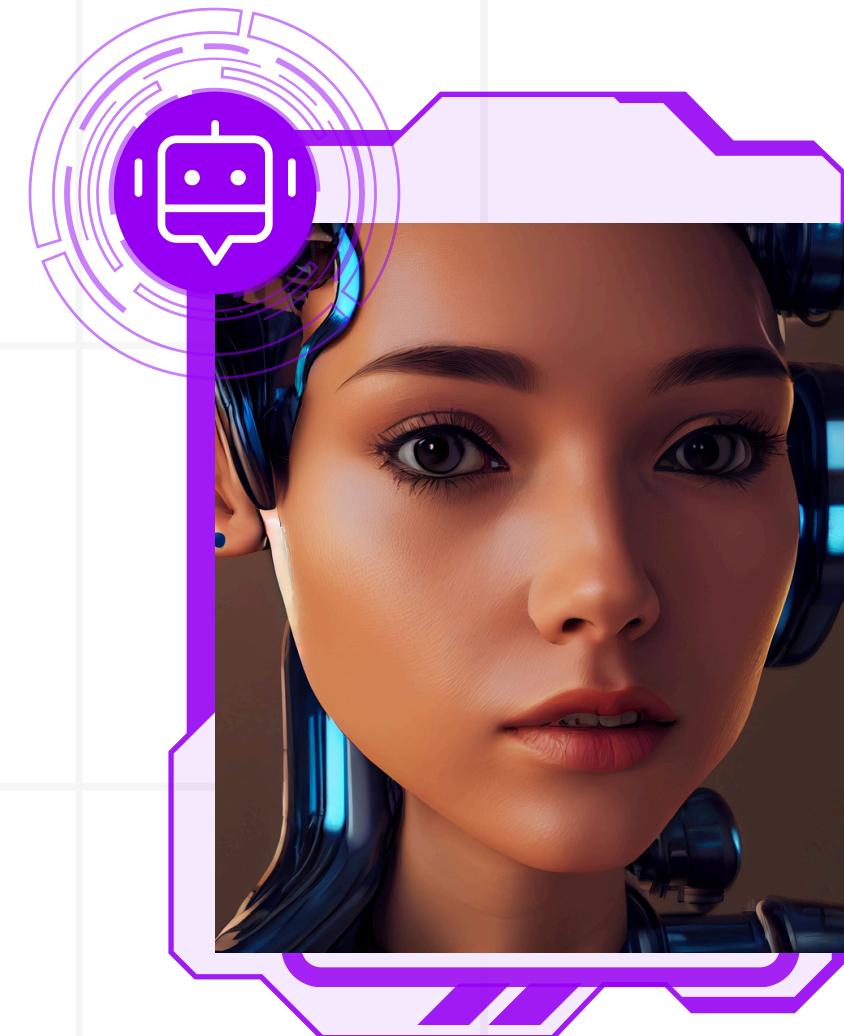
Introduction

As **New Bank**, we aim to provide secure payment systems to protect our clients from fraud that can lead to significant financial loss and erode customer trust. Online payment fraud is a significant issue in the banking industry, causing financial losses and reduced customer trust.

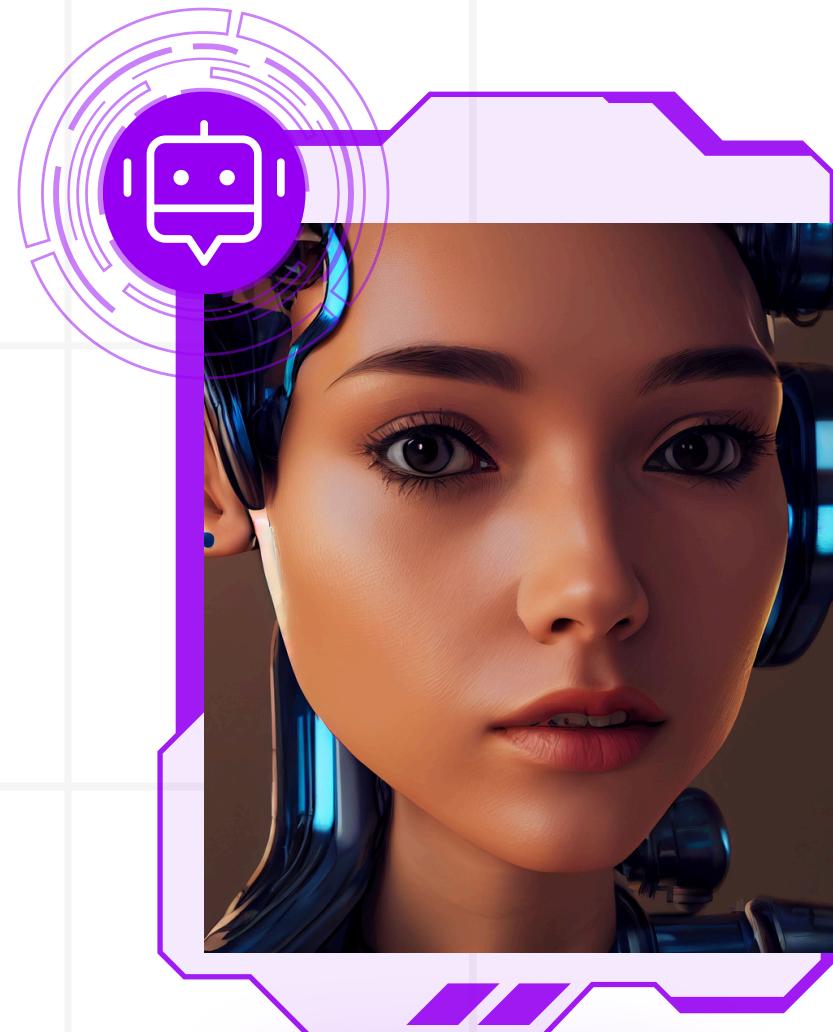
Our goal is to **detect** fraud early and **accurately** to improve transaction safety for our customers.

How can we efficiently identify fraudulent transactions while minimizing false alarms?

Security Operations for Payment Handling & Intelligent Analysis

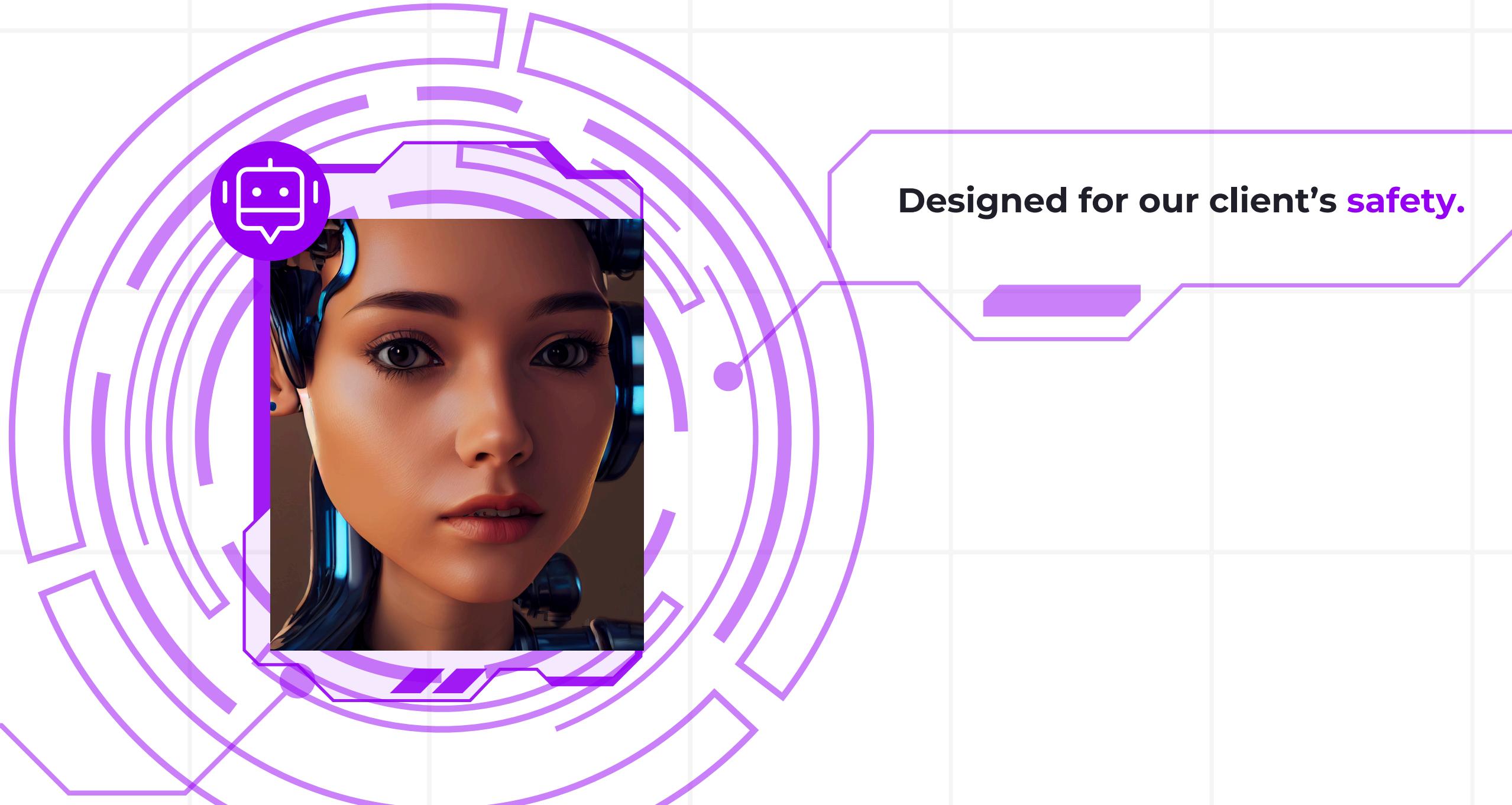


Security Operations for Payment Handling & Intelligent Analysis



SOPHIA v1

Security Operations for Payment Handling & Intelligent Analysis



Accurate & Optimised to flag Fraudulent payment transaction as they appear.

Designed for our client's safety.

SOPHIA VI

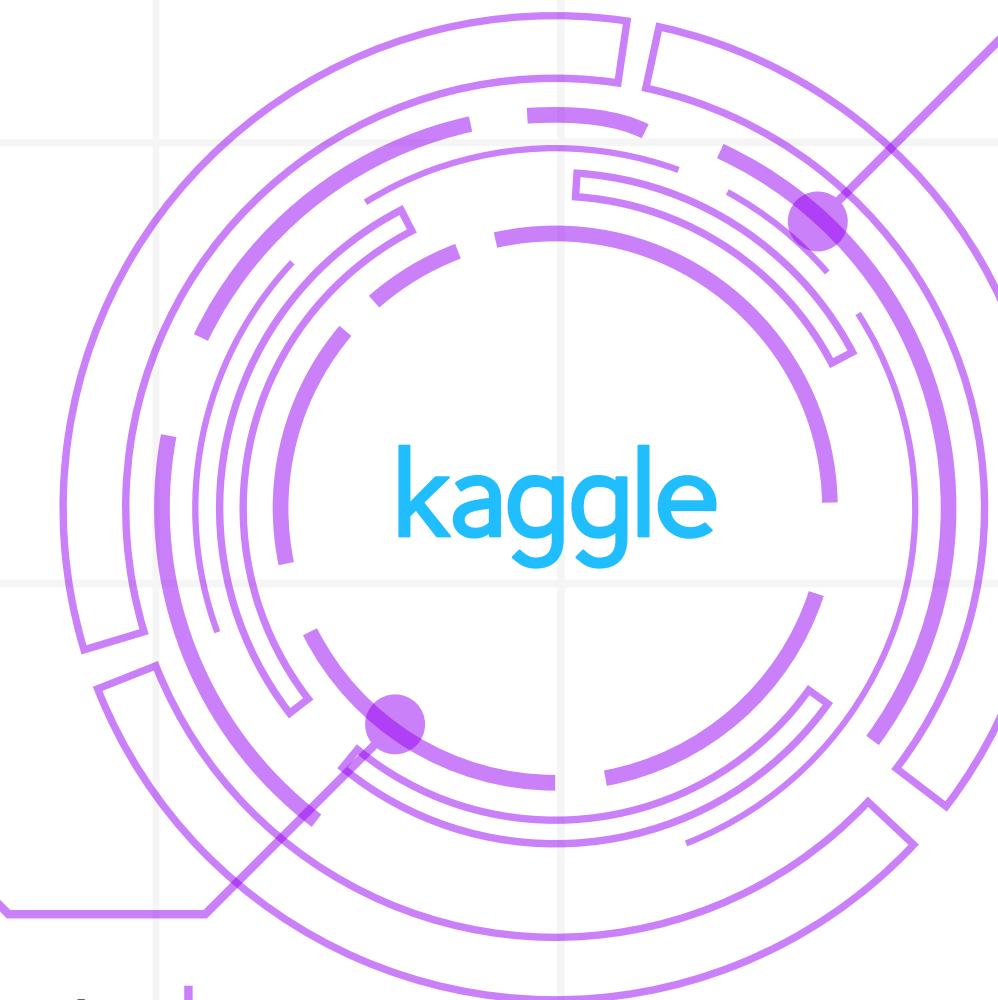


SOPHIA v1

my MISSION

- 1** My mission will consist of analysing New bank's daily payment transactions and identify fraudulent activities for safer banking transactions.

- 2** Improve New bank's internal processes and security protocols regarding online payment.



The dataset contains information about **online payment fraud**, to understand what type of transactions lead to fraud.

List of data points included:

- step**: unit of time (1 hour)
- type**: type of online transaction
- amount**: the amount
- nameOrig**: customer
- oldbalanceOrg**: customer balance before transaction
- newbalanceOrig**: customer balance after transaction
- nameDest**: recipient
- oldbalanceDest**: recipient balance before transaction
- newbalanceDest**: recipient balance after the transaction
- isFraud**: fraud marker

# step	=	Δ type	=	# amount	=	Δ nameOrig	=	# oldbalanc...	=	# newbalan...	=	Δ nameDest	=	# oldbalanc...	=	# newbalan...	=	# isFraud	=
1		PAYMENT		9839.64		C1231006815		170136.0		160296.36		M1979787155		0.0		0.0		0	
1		PAYMENT		1864.28		C1666544295		21249.0		19384.72		M2044282225		0.0		0.0		0	
1		TRANSFER		181.0		C1305486145		181.0		0.0		C553264065		0.0		0.0		1	
1		CASH_OUT		181.0		C840083671		181.0		0.0		C38997010		21182.0		0.0		1	
1		PAYMENT		11668.14		C2048537720		41554.0		29885.86		M1230701703		0.0		0.0		0	

Payment type

# type	
PAYMENT	
PAYMENT	
TRANSFER	
CASH_OUT	
PAYMENT	

Sender's Account Balance

# amount	# nameOrig	# oldbalance... =	# newbalan... =
21182.0		0.0	0.0
0.0		0.0	0.0
0.0		0.0	0.0
170136.0		160296.36	
21249.0		19384.72	
181.0		0.0	
181.0		0.0	
41554.0		29885.86	

# oldbalance... =	# newbalan... =
0.0	0.0
0.0	0.0
0.0	0.0
21182.0	0.0
0.0	0.0
0.0	0.0

Receiver's Account Balance

isFraud
0
0
1
1
0
0

is Fraud?

Data Imbalance

NON FRAUD PAYMENT

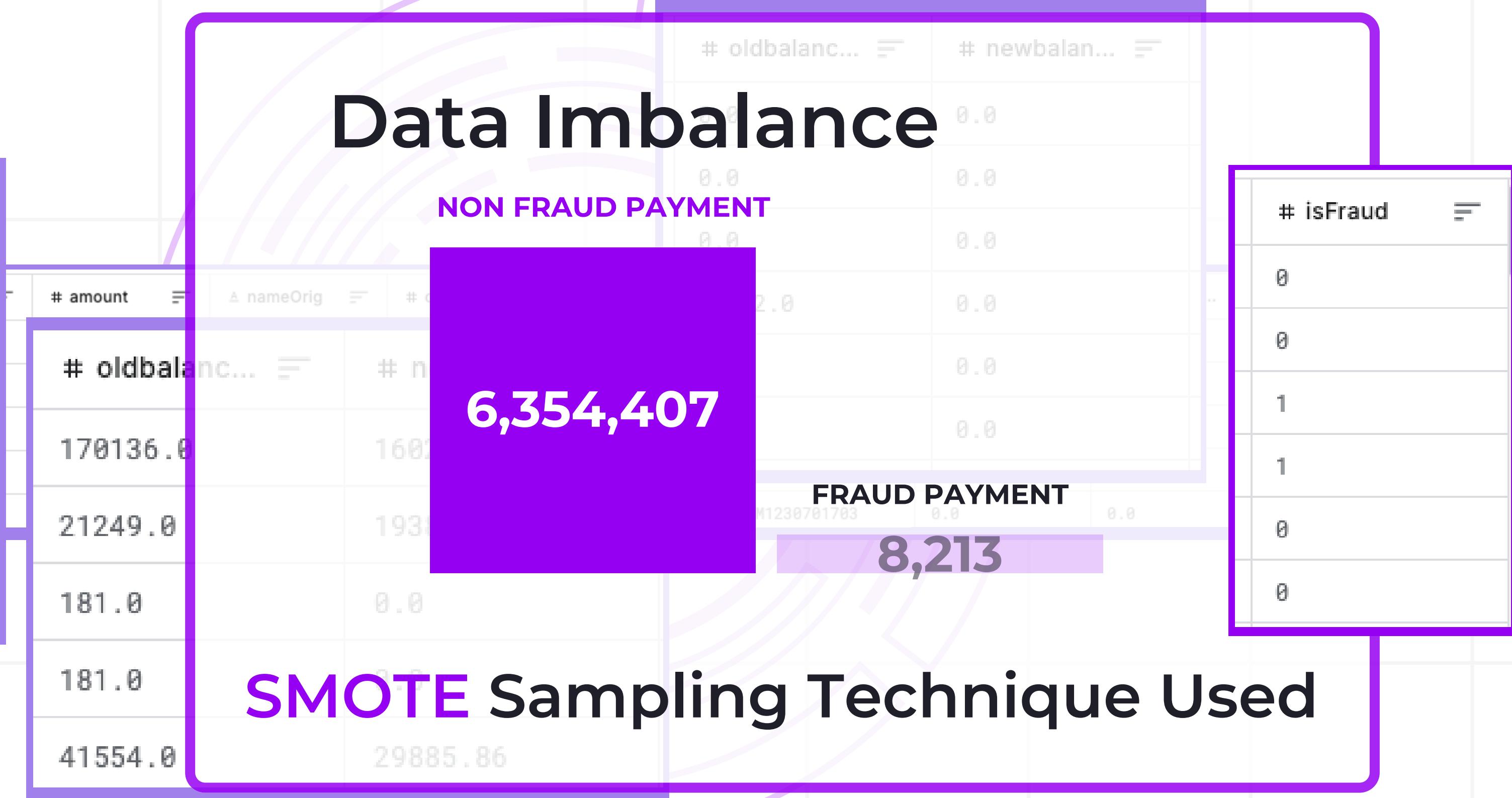
6,354,407

FRAUD PAYMENT

8,213

SMOTE Sampling Technique Used

type
PAYMENT
PAYMENT
TRANSFER
CASH_OUT
PAYMENT

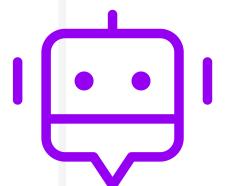


Our Method



Data Collection

Gather relevant data from diverse sources.



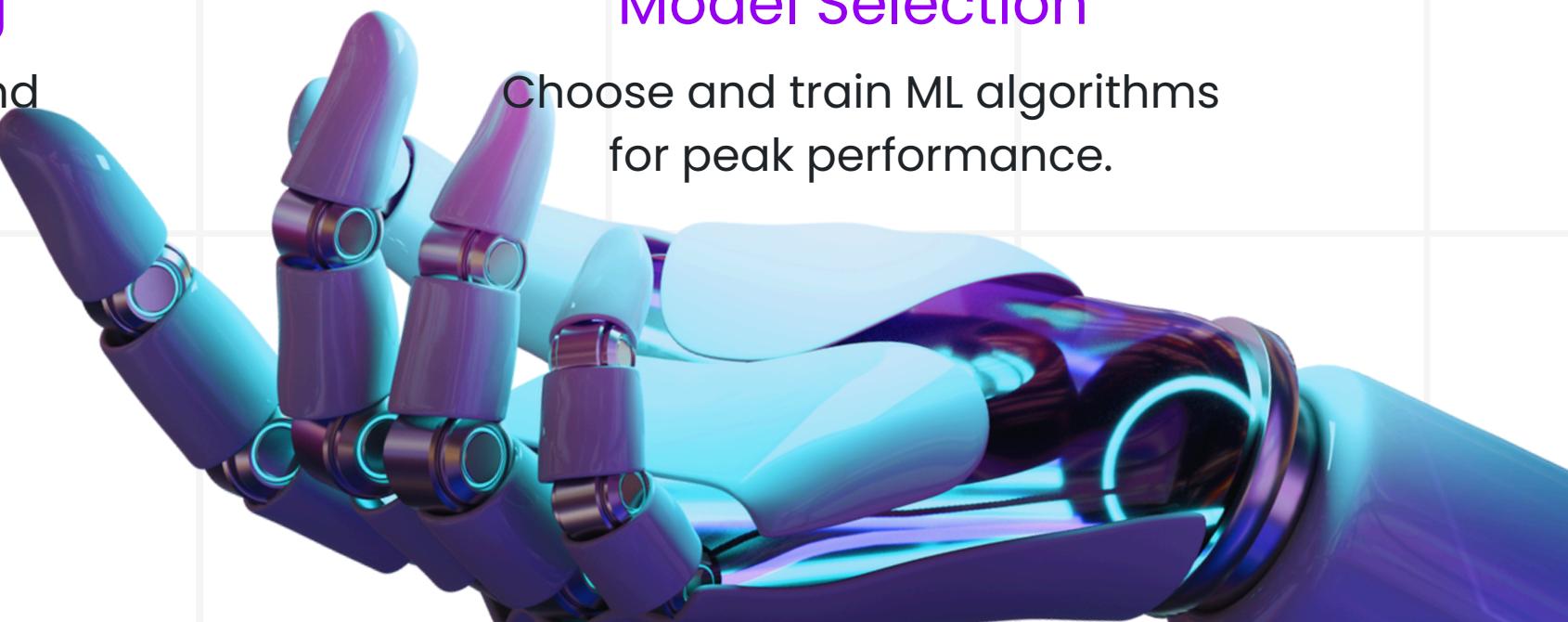
Preprocessing

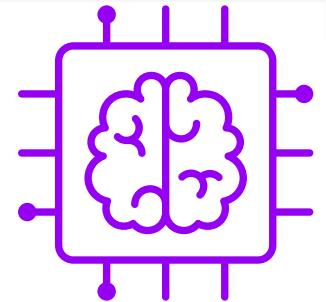
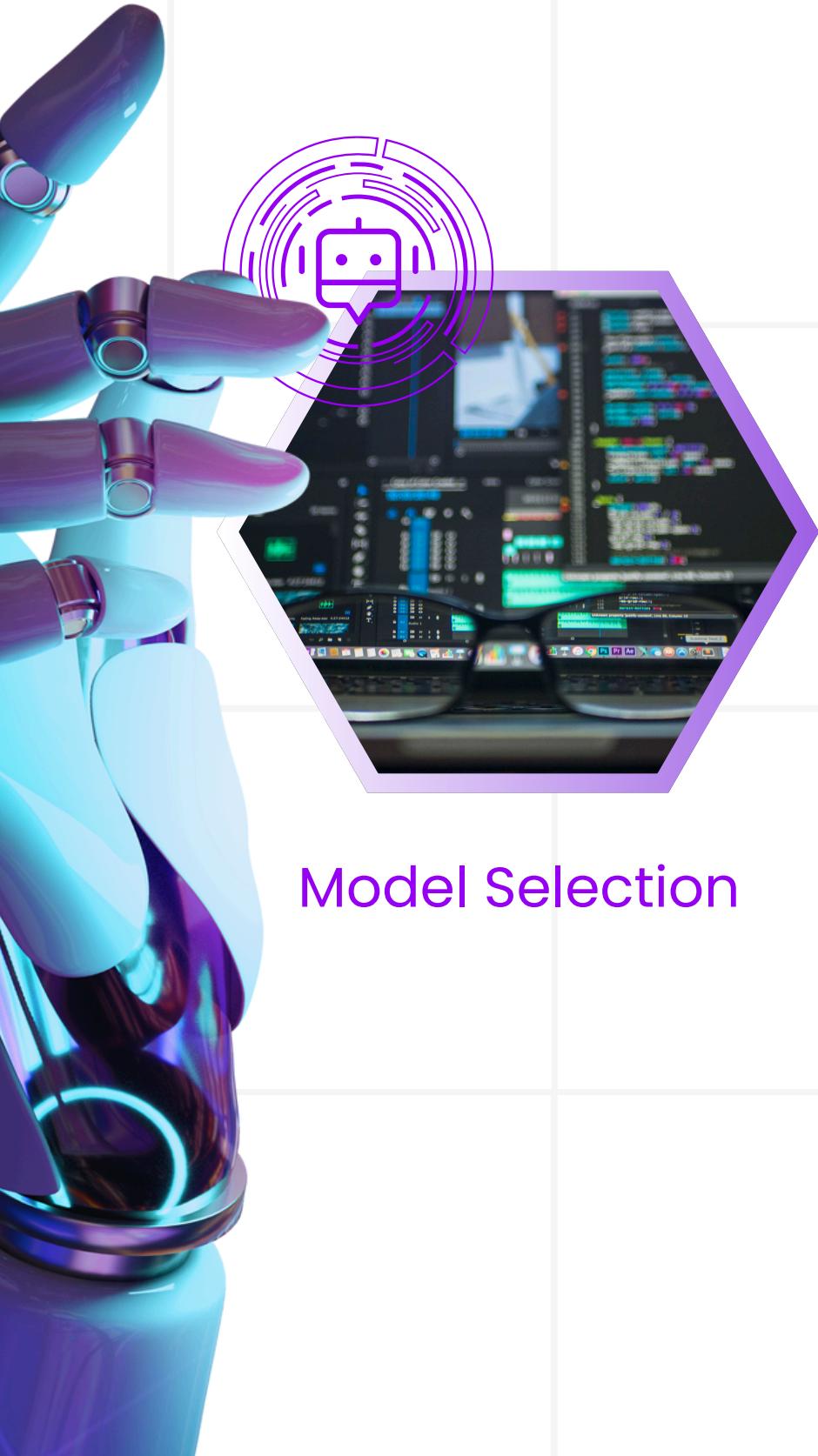
Clean, normalize, and engineer data.



Model Selection

Choose and train ML algorithms for peak performance.

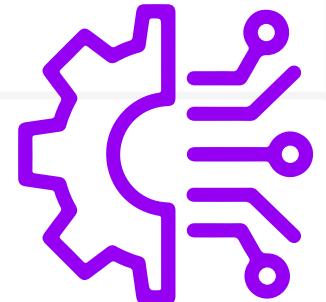




KNN Model

Simple & Effective: KNN is intuitive, making predictions based on the proximity of similar data points without needing complex training.

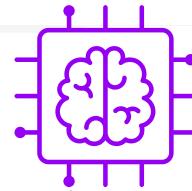
Pattern Adaptation: Works well in scenarios where fraudulent patterns change, as it relies on real-time similarities in the data.



Decision Tree Model

High Accuracy & Interpretability: Achieved 100% accuracy and is easy to interpret, with clear, step-by-step decision paths.

Handles Imbalanced Data: Decision Trees manage large, skewed datasets like fraud detection efficiently, making them robust for financial use cases.



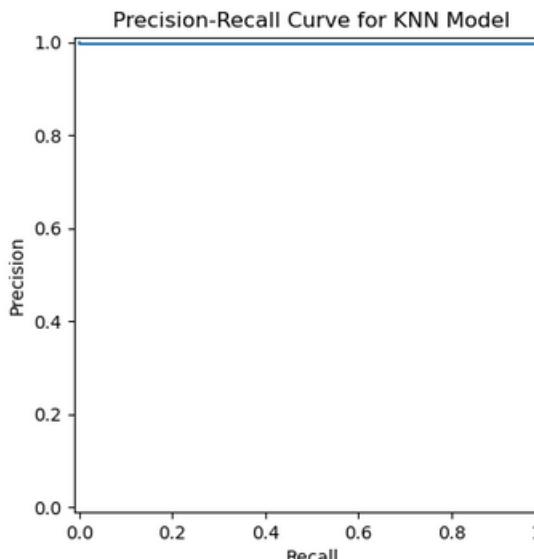
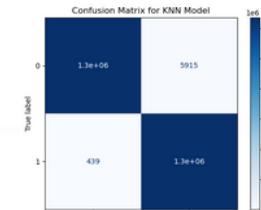
KNN Model

Accuracy Test: 1

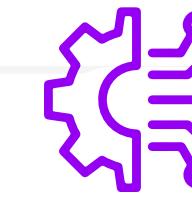
	precision	recall	f1-score	support
0	1.00	1.00	1.00	1269605
1	1.00	1.00	1.00	1272158
accuracy			1.00	2541763
macro avg	1.00	1.00	1.00	2541763
weighted avg	1.00	1.00	1.00	2541763

KNN Confusion Matrix:

```
[[1263598  6007]
 [ 401 1271757]]
```



MAE: 0.00
RMSE: 0.02
R2 score: 0.62



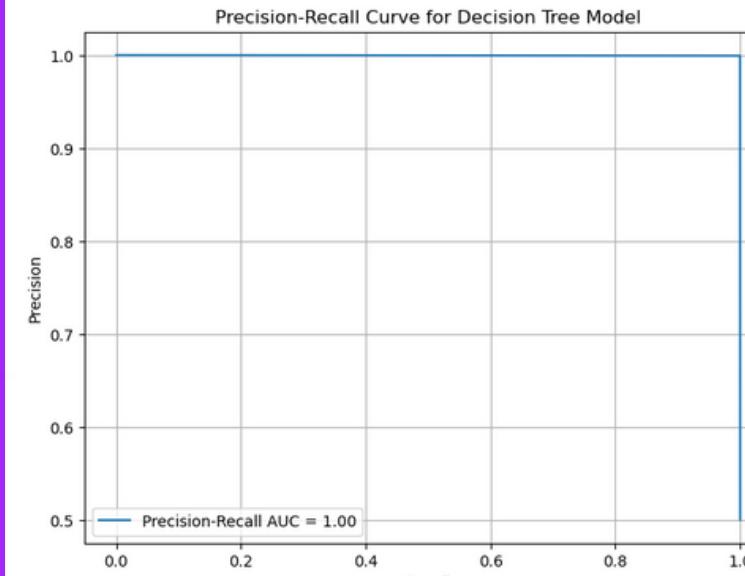
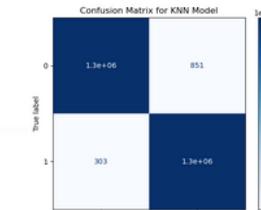
Decision Tree Model

Accuracy Test: 1

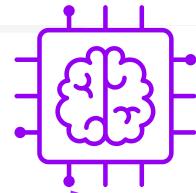
	precision	recall	f1-score	support
0	1.00	1.00	1.00	1269605
1	1.00	1.00	1.00	1272158
accuracy			1.00	2541763
macro avg	1.00	1.00	1.00	2541763
weighted avg	1.00	1.00	1.00	2541763

Decision Tree Confusion Matrix:

```
[[1268754  851]
 [ 303 1271855]]
```



MAE: 0.02
RMSE: 0.10
R2 score: 0.96

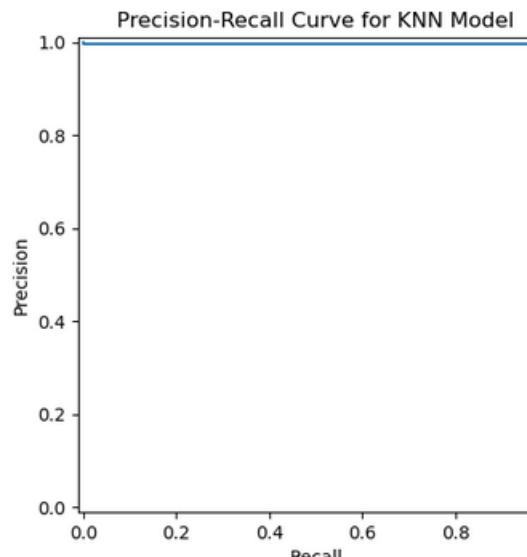


KNN Model

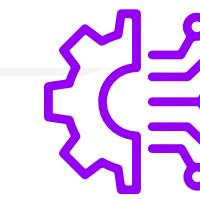
Accuracy Test: 1

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1269605
1	1.00	1.00	1.00	1272158
accuracy			1.00	2541763
macro avg	1.00	1.00	1.00	2541763
weighted avg	1.00	1.00	1.00	2541763

```
[[1263598  6007]
 [ 401 1271757]]
```



MAE: 0.00
RMSE: 0.02
R2 score: 0.62

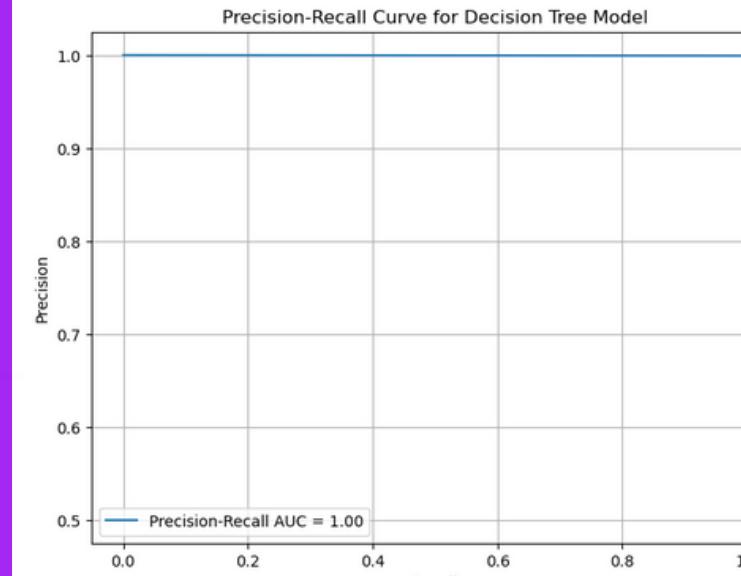


Decision Tree Model

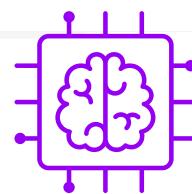
Accuracy Test: 1

	precision	recall	f1-score	support
0	1.00	1.00	1.00	1269605
1	1.00	1.00	1.00	1272158
accuracy			1.00	2541763
macro avg	1.00	1.00	1.00	2541763
weighted avg	1.00	1.00	1.00	2541763

```
[[1268754  851]
 [ 303 1271855]]
```



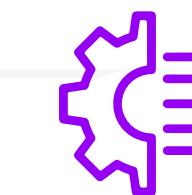
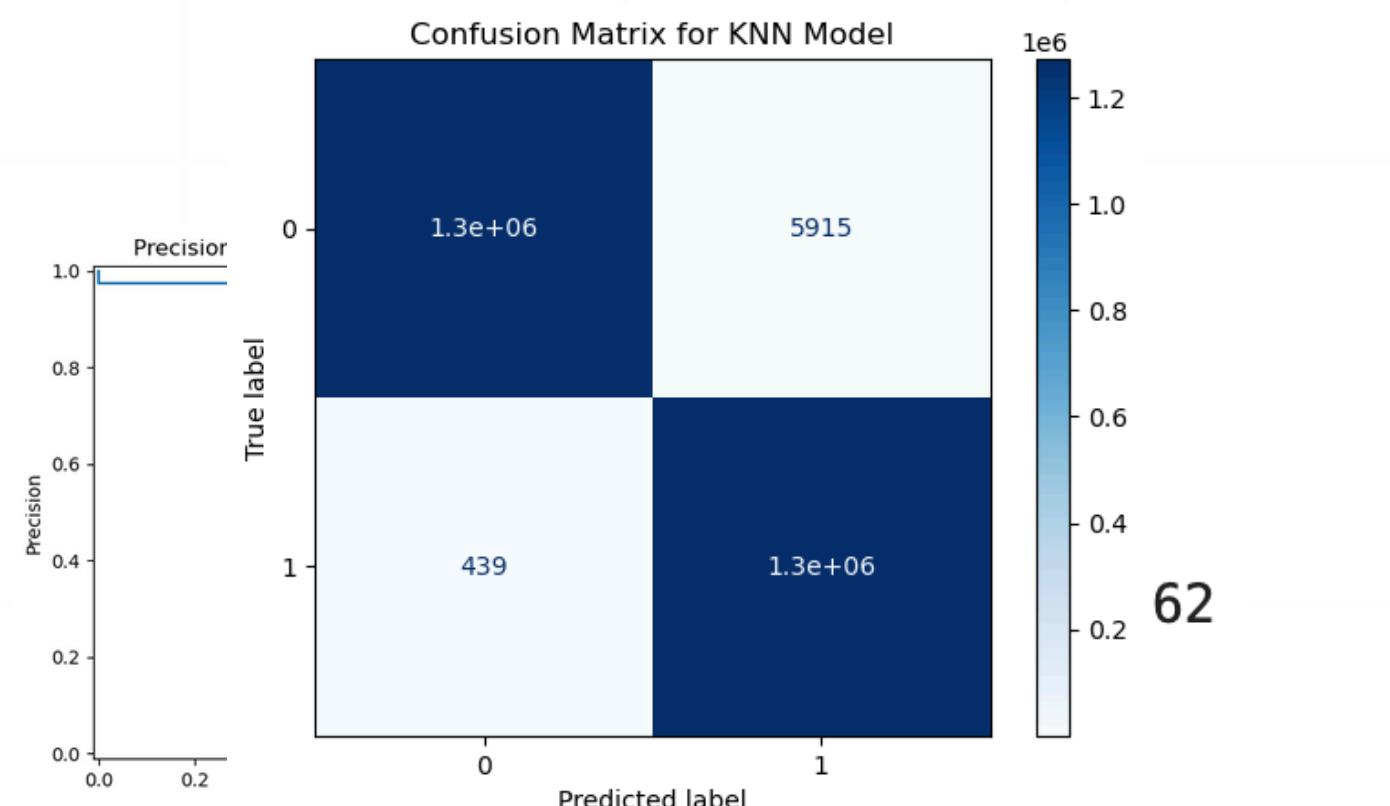
MAE: 0.02
RMSE: 0.10
R2 score: 0.96



KNN Model

Accuracy Test: 1

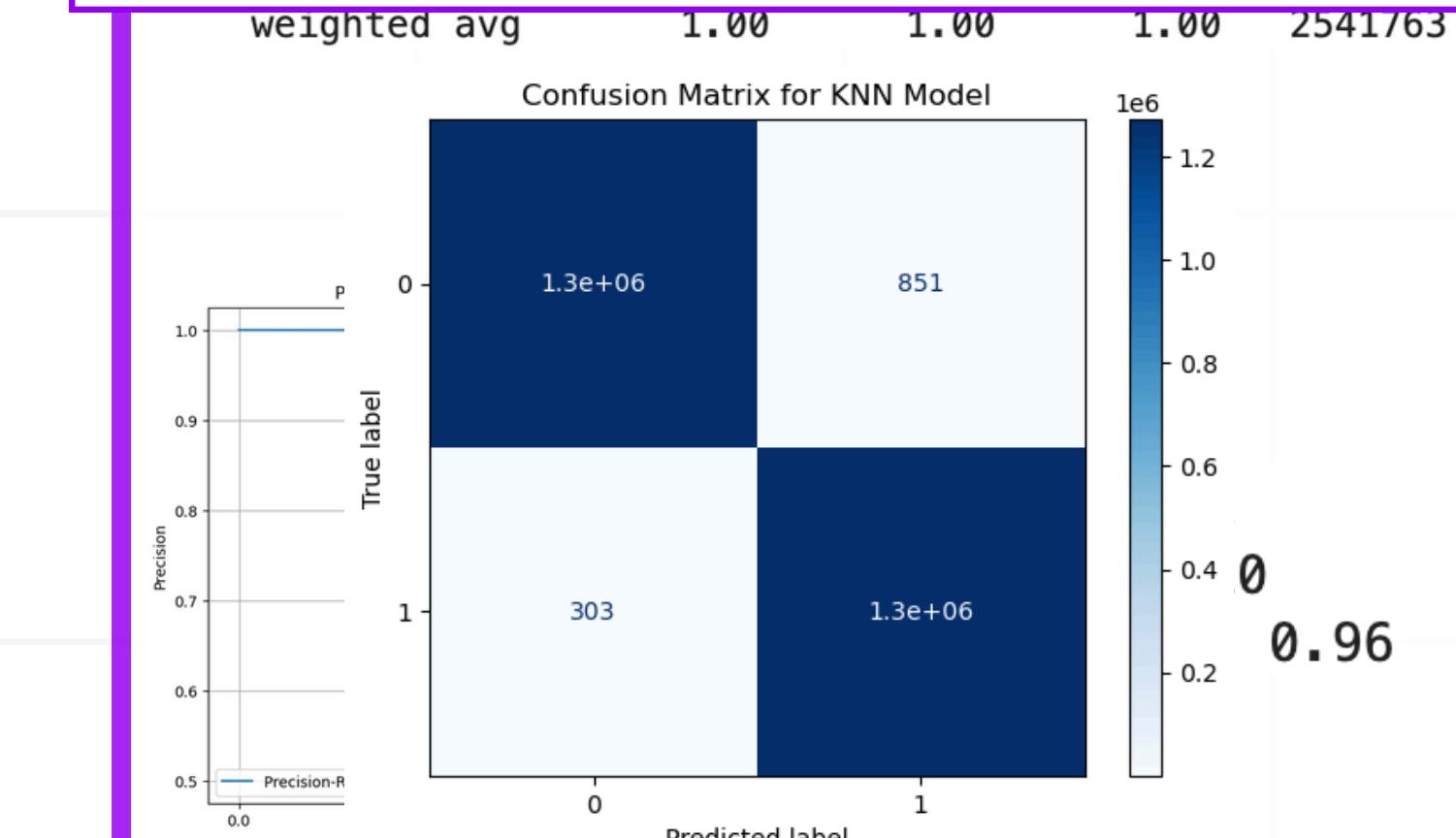
KNN Confusion Matrix:
[[1263598 6007]
 [401 1271757]]



Decision Tree Model

Accuracy Test: 1

Decision Tree Confusion Matrix:
[[1268754 851]
 [303 1271855]]





NEW BANK

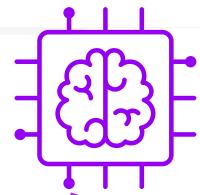
Bana

Marco

Amir

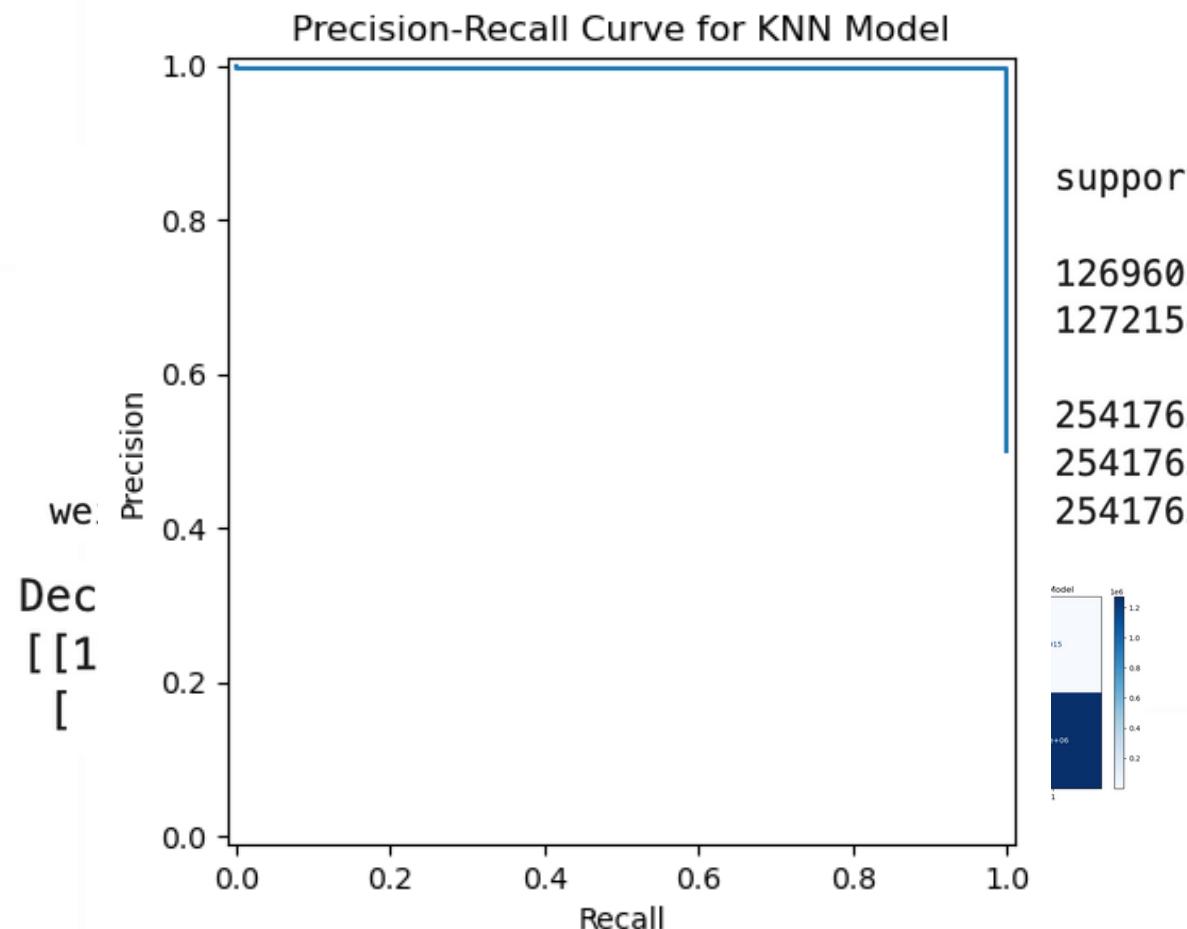
Jean Philippe

=



KNN Model

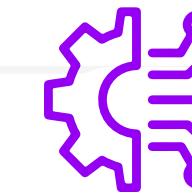
Accuracy Test: 1



MAE: 0.00

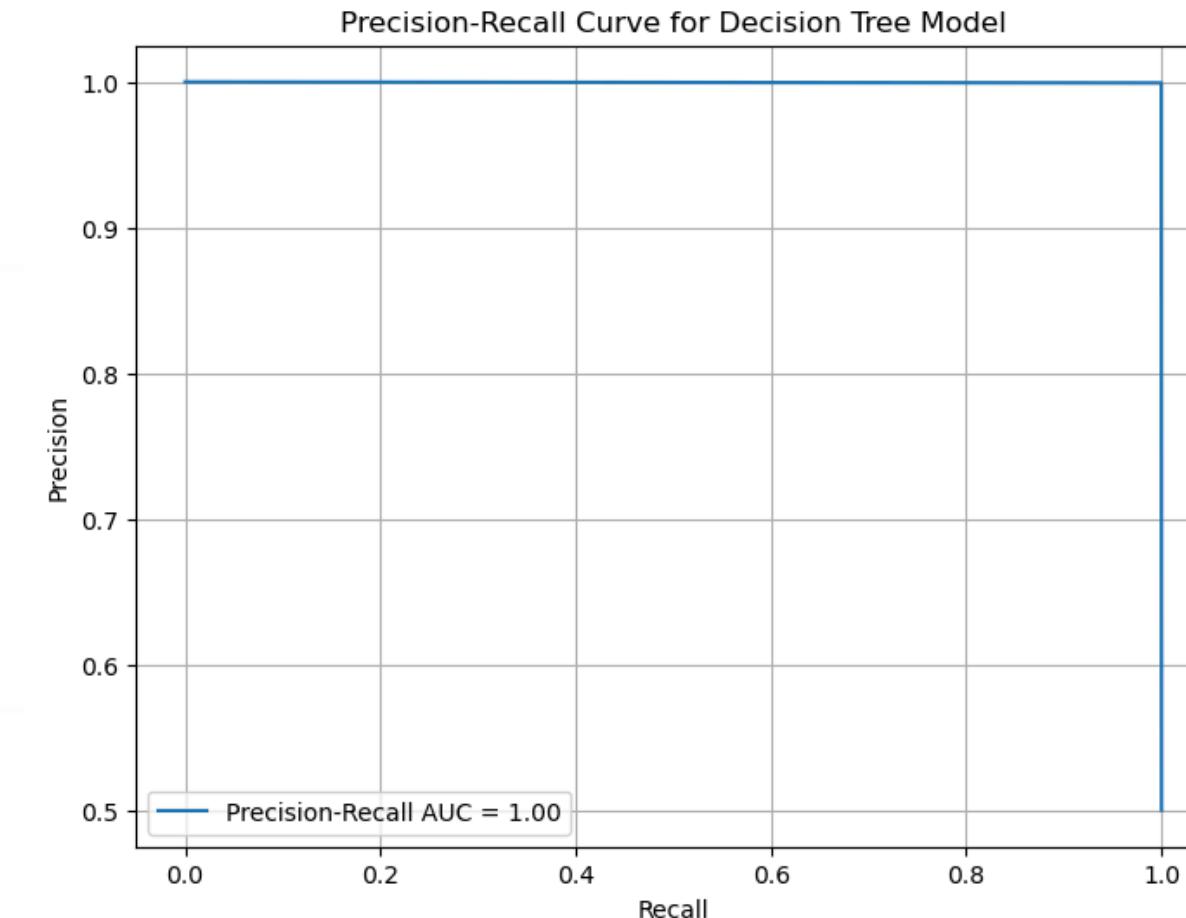
RMSE: 0.02

R2 score: 0.62



Decision Tree Model

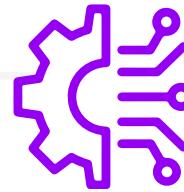
Accuracy Test: 1



MAE: 0.02

RMSE: 0.10

R2 score: 0.96



Decision Tree Model

From the Classification Report:

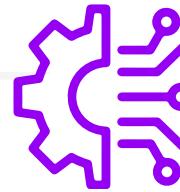
the performance across classes is balanced, and class imbalance (if present) is well handled. Precision, Recall and F1-Score all equals to 1.00

From the confusion matrix: => high precision and recall

The model predicts almost all instances correctly, but there are a small number of misclassifications (851 false positives and 303 false negatives). However, given the scale of the dataset, these numbers are relatively small.

From the MAE, RMSE, and R² Score:

on average error prediction is quite small (0.02) and difference between real and actual values are also small (0.10) indicating high accuracy with very good predictions.



Descision Tree Model

*We then decided to test those numbers:
Cross validation of the Training Set vs Test Set*

MAE: 0.23

RMSE: 0.42

R² score: 0.08

Test set MAE: 0.02

Test set RMSE: 0.10

Test set R² score: 0.94

Training set MAE: 0.00

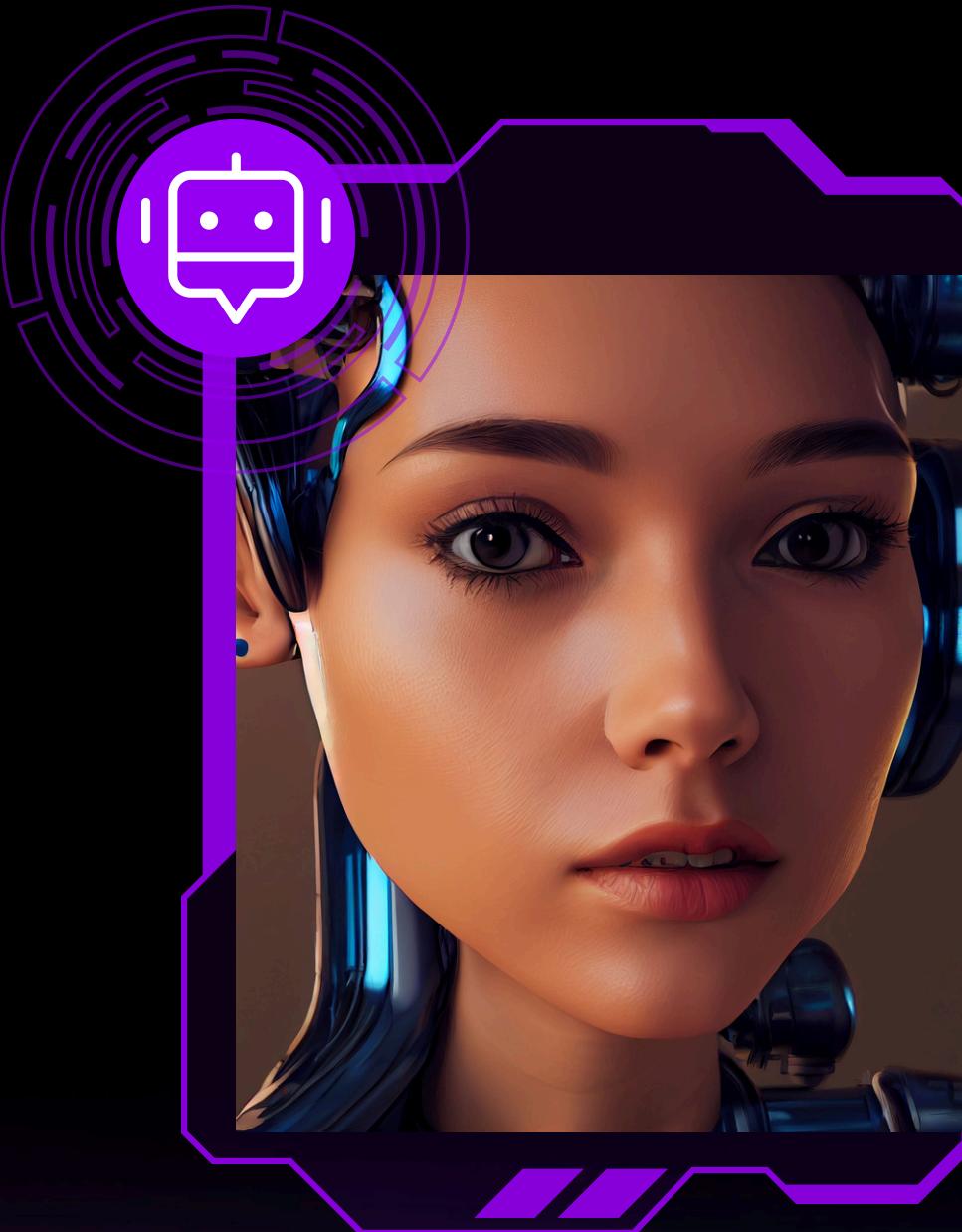
Training set RMSE: 0.00

Training set R² score: 1.00

Conclusion

The **SOPHIA v1 model**, powered by a **decision tree algorithm**, is highly effective in identifying both fraudulent and non-fraudulent transactions with minimal errors on its **trained data**. However, to enhance its practical application, further refinement is needed to make it as efficient on new **test data**.

Overall, SOPHIA proves to be a robust solution for payment fraud detection in the bank's operations.





SOPHIA

THANK YOU

I will be happy to answer all your questions and
hope this presentation on my machine learning
model was insightful and up to your
expectations.