Illinois Institute of Technology
CS484 Introduction to Machine Learning

ML ALGORITHM FOR CREDIT CARD FRAUD DETECTION

Group 9
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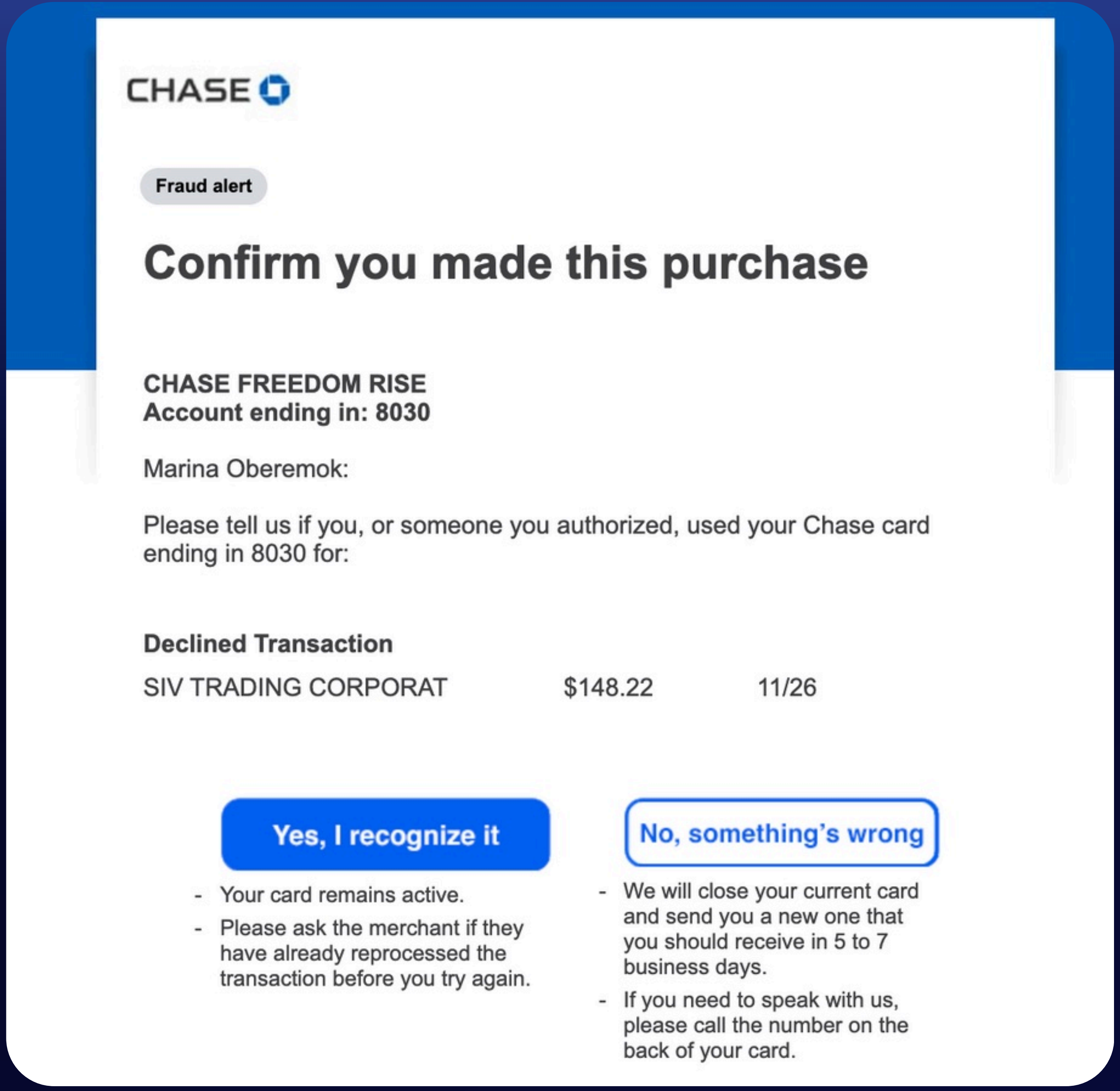
2024



CHASE

Fraud alert

Confirm you made this purchase

CHASE FREEDOM RISE
Account ending in: 8030

Marina Oberemok:

Please tell us if you, or someone you authorized, used your Chase card ending in 8030 for:

Declined Transaction

SIV TRADING CORPORAT	$148.22	11/26

Yes, I recognize it

- Your card remains active.
- Please ask the merchant if they have already reprocessed the transaction before you try again.

No, something's wrong

- We will close your current card and send you a new one that you should receive in 5 to 7 business days.
- If you need to speak with us, please call the number on the back of your card.

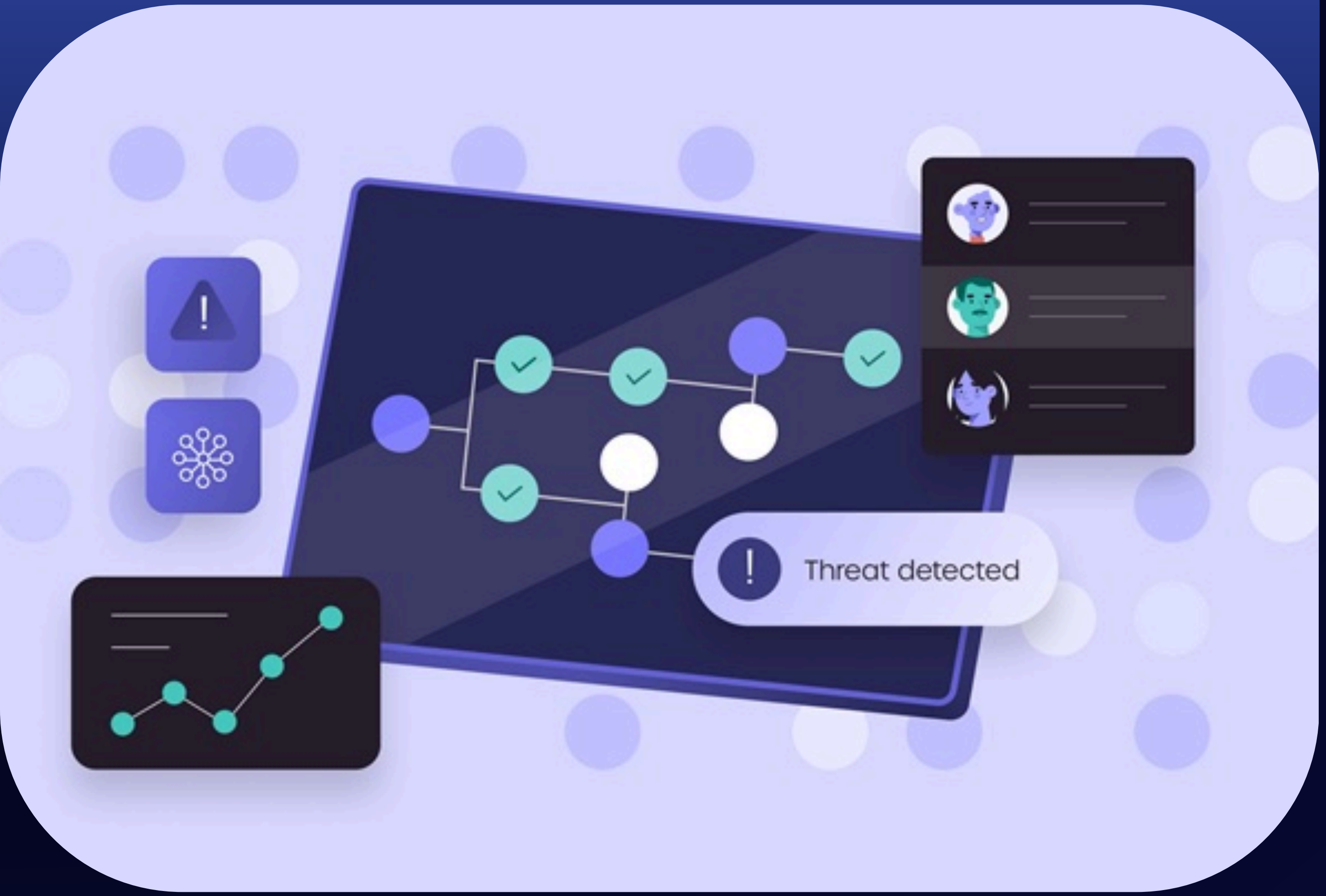
INTRODUCTION

Effective fraud detection is crucial to reduce financial losses and maintain customer trust.

In 2023, 60% of cardholders faced attempted fraud. Global fraud losses reached $33 billion in 2022 (Nilson Report).

ML enables learning patterns from large datasets and predicting fraudulent activities.

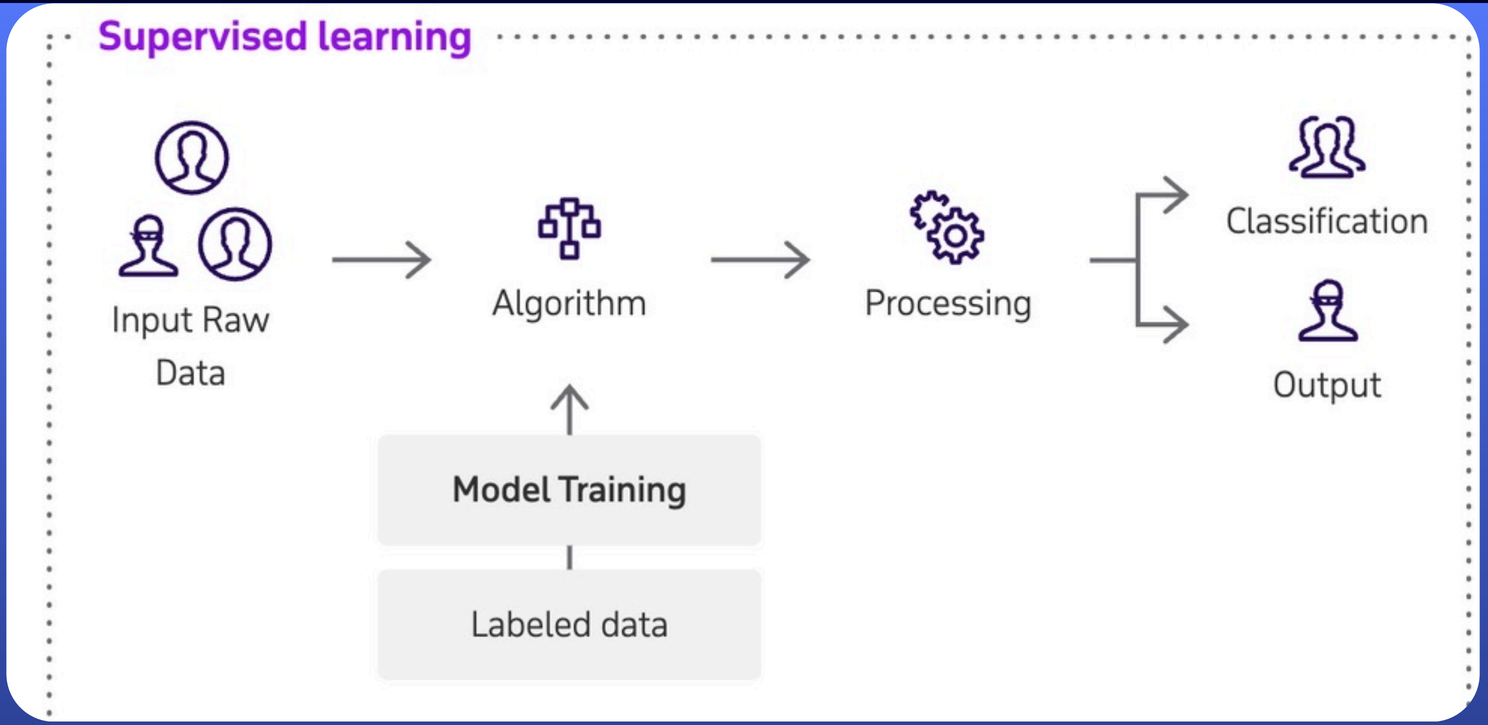
Current key challenges include class imbalance, evolving fraud tactics, and high false alarm rates.

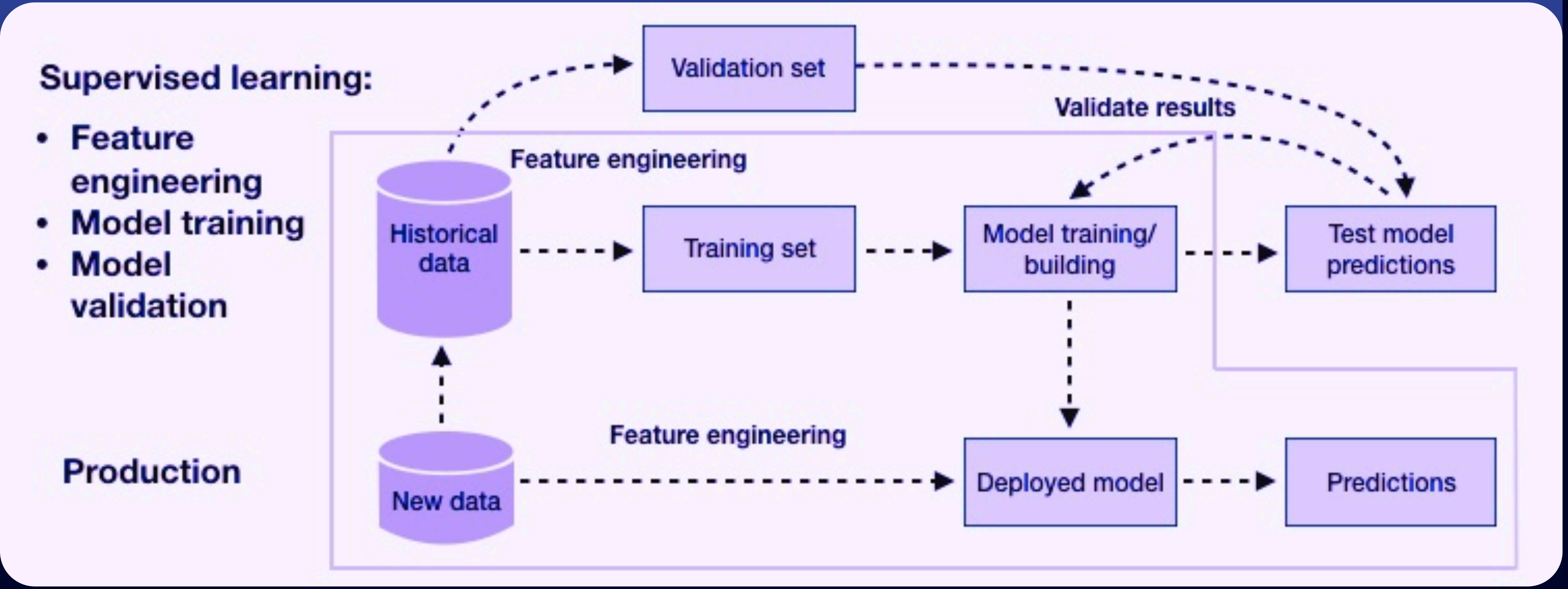


OBJECTIVES

- To apply machine learning techniques to detect fraudulent credit card transactions
- To compare the performance of algorithms such as *logistic regression, K-Nearest Neighbors (KNN), decision trees, and naïve Bayes*
- *To* determine the most effective algorithm for improving detection accuracy, reducing false positives, and enhancing the robustness of fraud detection systems

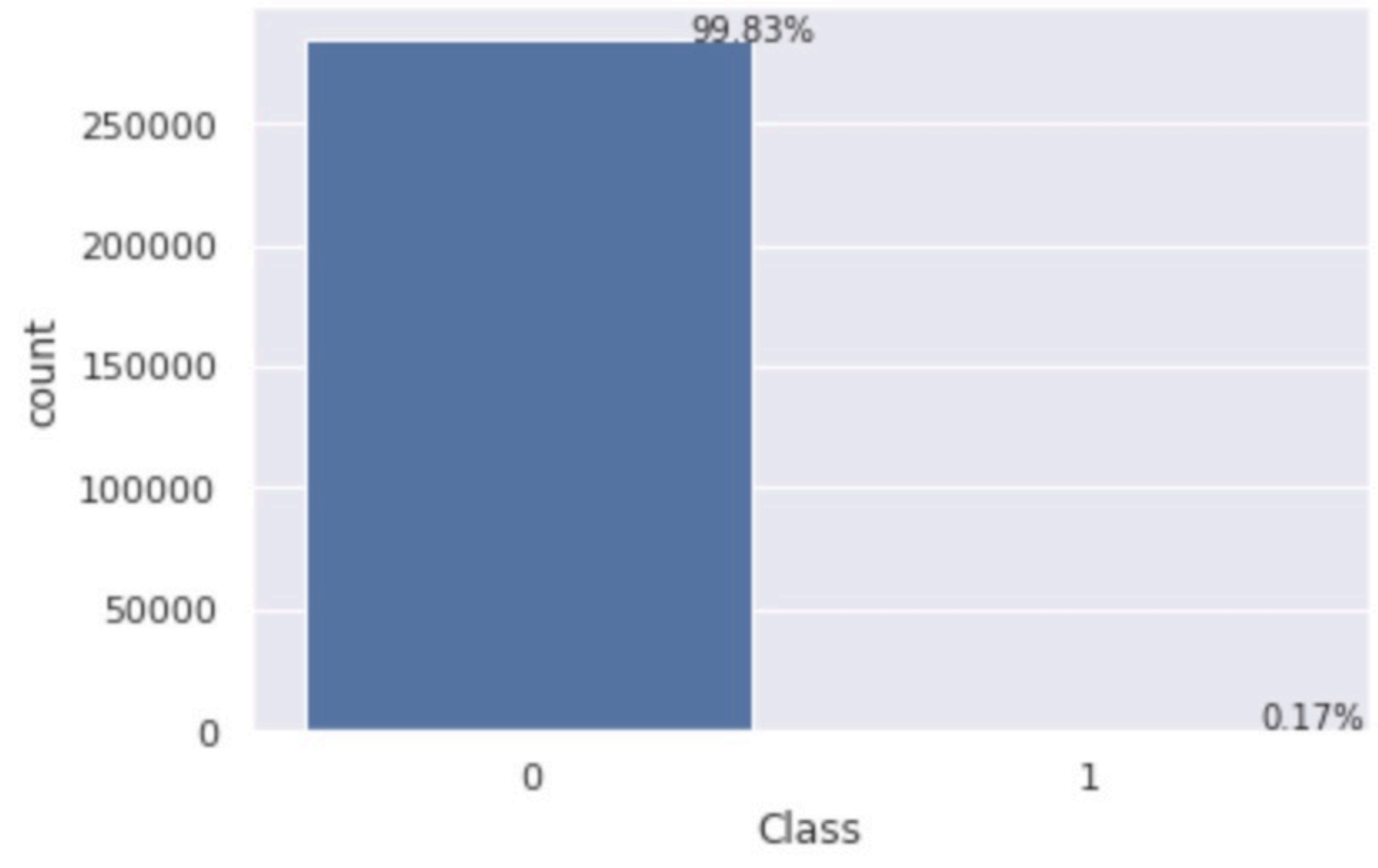
ALGORITHMS IN MACHINE LEARNING FOR FRAUD DETECTION





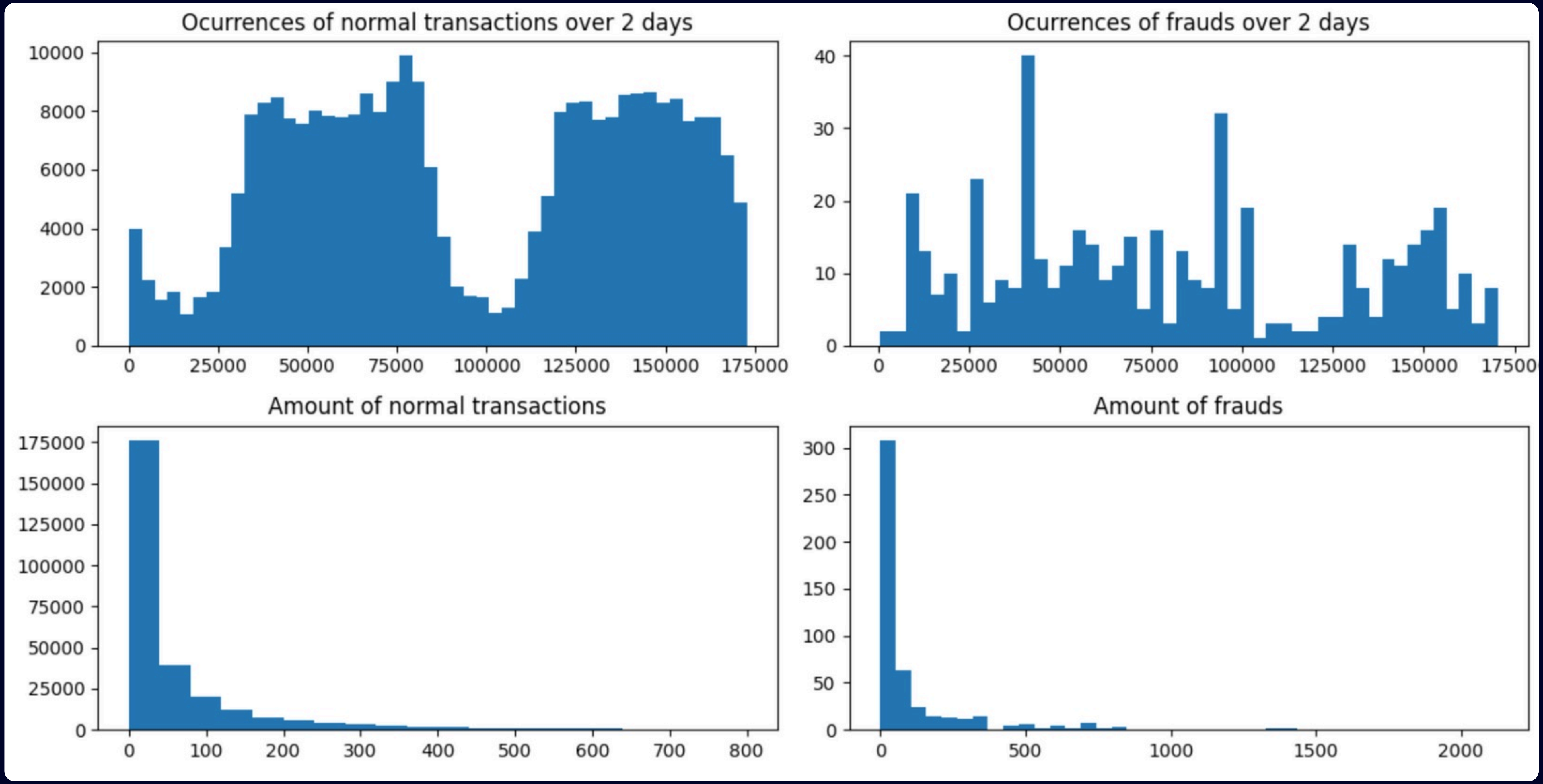
1. Linear Regression
2. Logistic Regression
3. Decision Tree
4. SVM
5. Naïve Bayes
6. CNN
7. K-Means
8. Random Forest
9. Dimensionality Reduction Algorithms
10. Gradient Boosting Algorithms

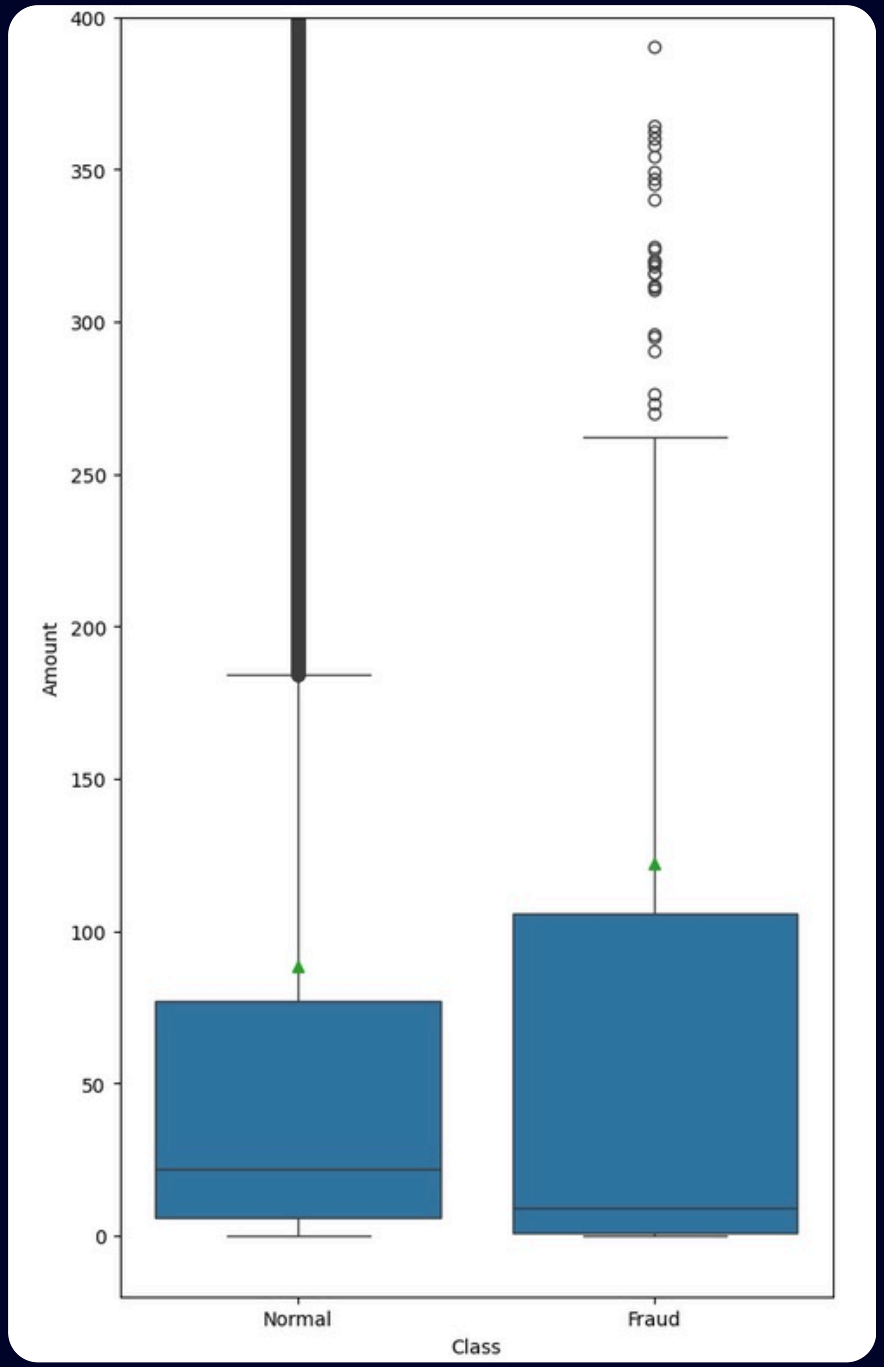
THE DATASET

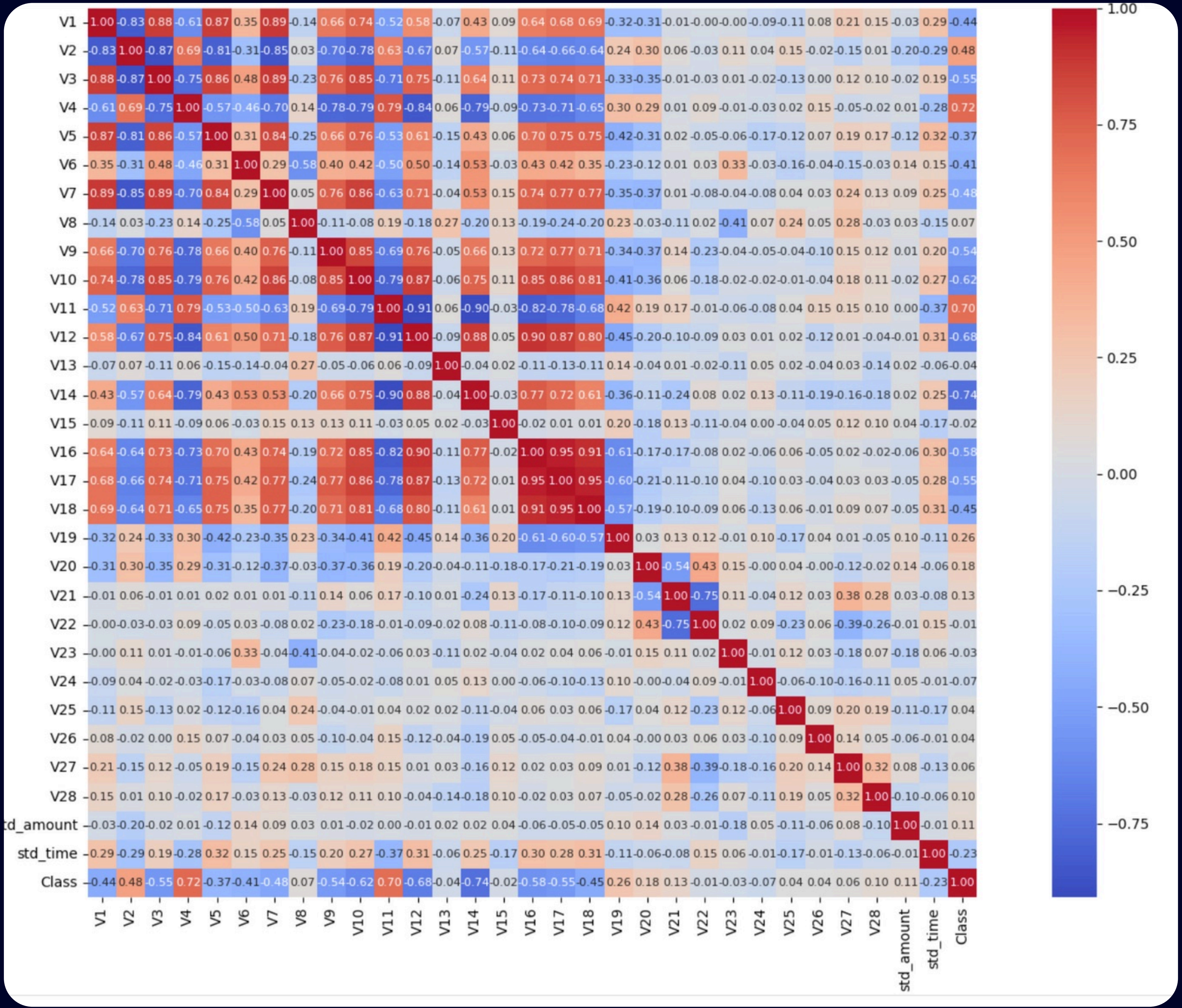


- The dataset contains credit card transactions made by European cardholders in September 2013.
- Transactions span over two days, with 492 fraudulent transactions out of 284,807 total transactions.
- The dataset is highly unbalanced, with fraud accounting for only 0.172% of transactions.
- Due to confidentiality, original features and background information are not provided.

Investigating normal and fraudulent transaction patterns







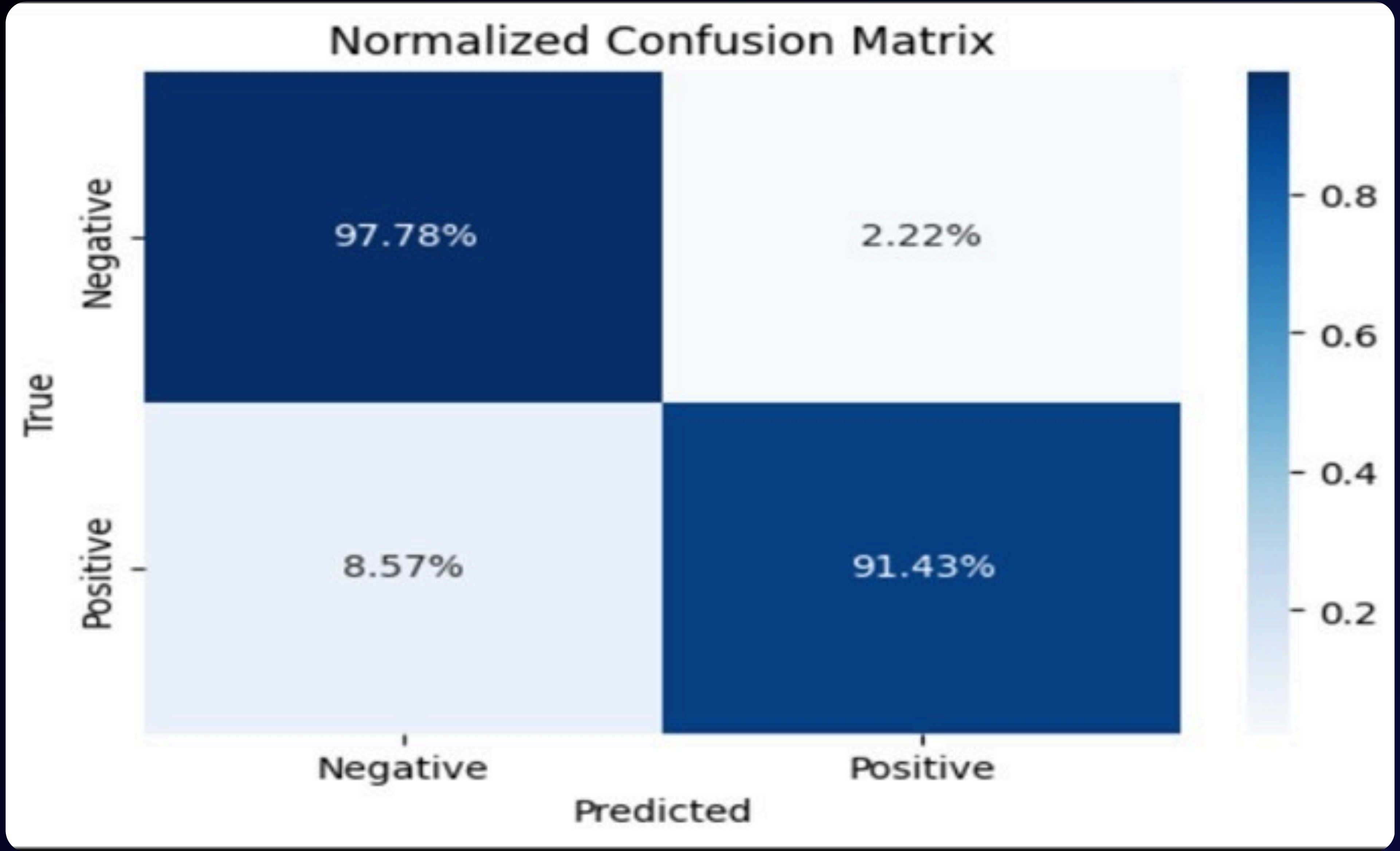
PREPROCESSING

1. **Standardization**
- Adjusting the values in each column to have a mean of 0 and a standard deviation of 1.

2. **Splitting into training and validation set**

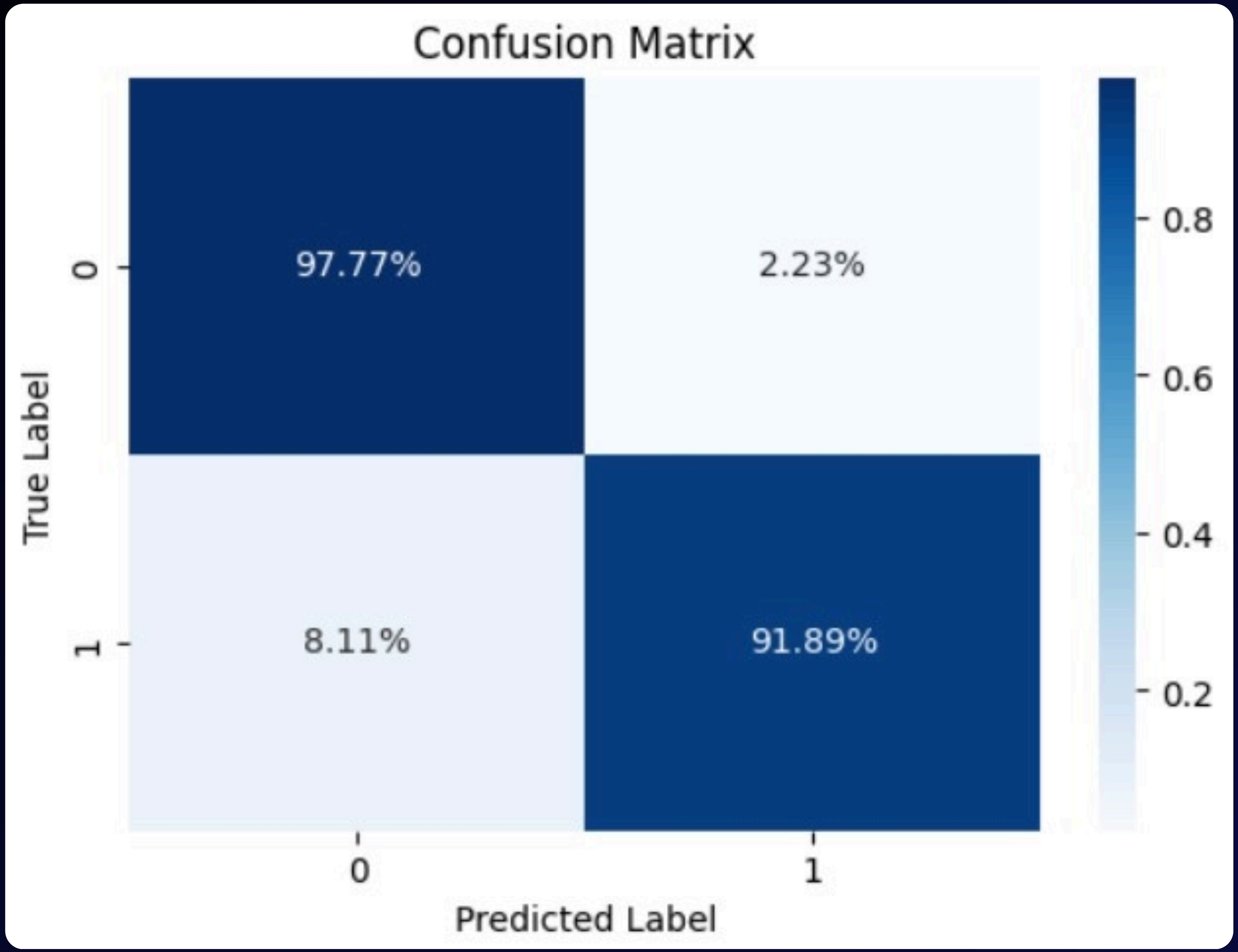
3. **Balancing**
- Undersampling involves extracting a random subset of the majority class while retaining all instances of the minority class.

Logistic Regression
(undersampling - validation)



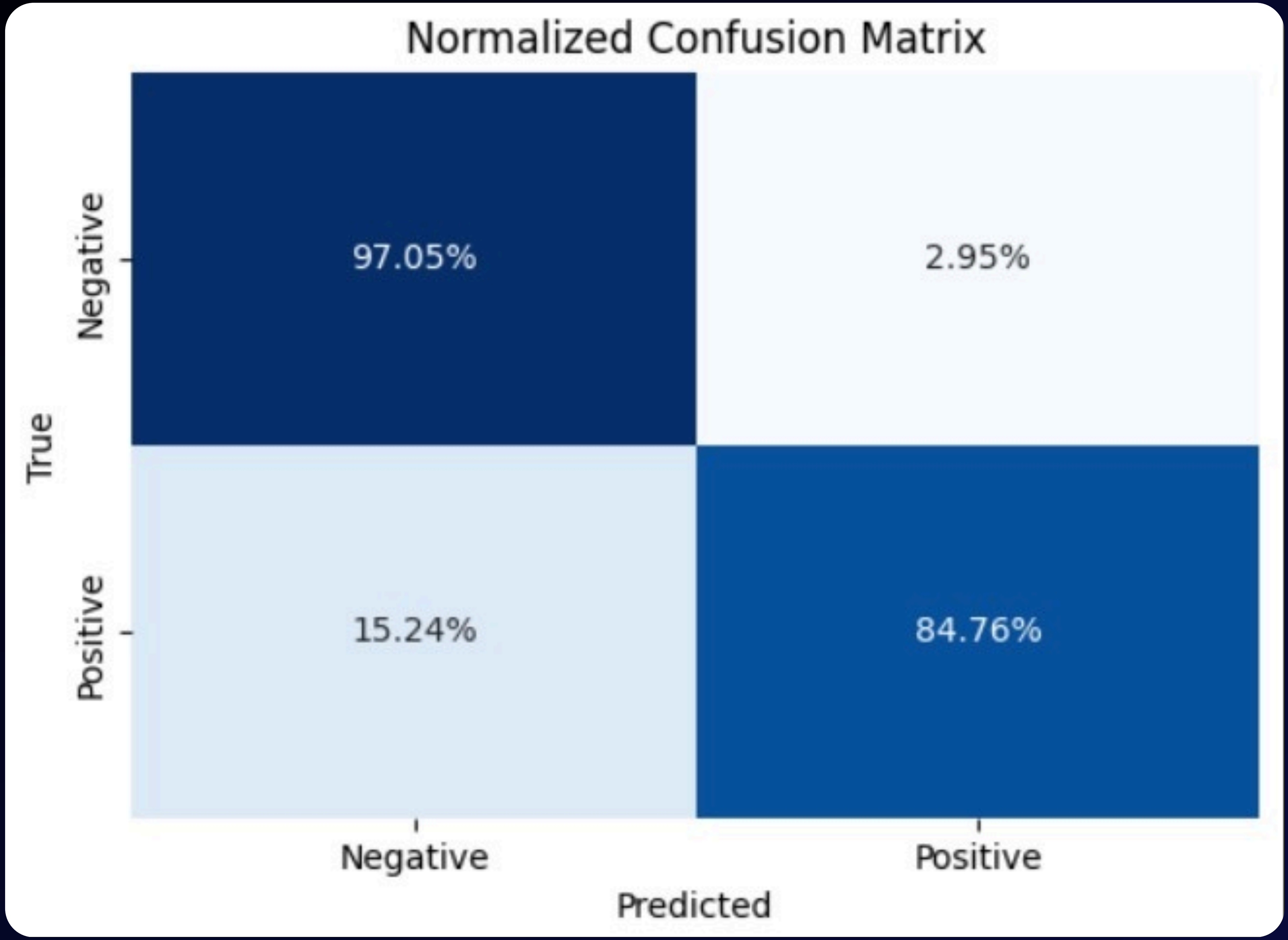

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9998    0.9778    0.9887     60417
           1     0.0667    0.9143    0.1244       105

    accuracy                         0.9777     60522
   macro avg     0.5333    0.9460    0.5565     60522
weighted avg     0.9982    0.9777    0.9872     60522

Accuracy: 0.9777
AUC: 0.9460
Accuracy          Precision         Recall  F1-score          AUC
0.9777            0.0667            0.9143  0.1244            0.9460

Total of positive records: 105
Total of negative records: 60417
Execution no. 10
```

Logistic Regression (undersampling - testing)



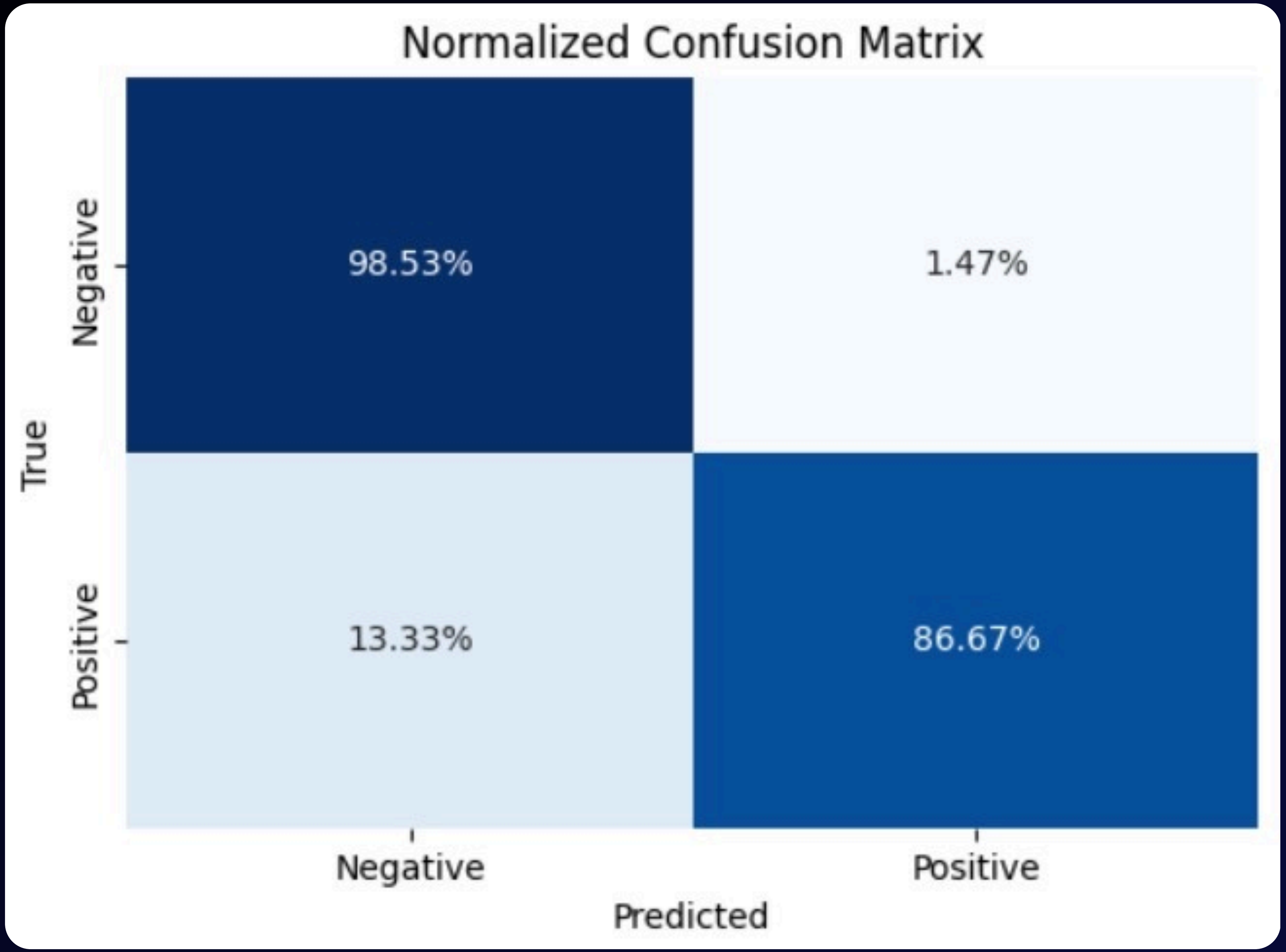

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9999    0.9777    0.9887     42647
           1     0.0668    0.9189    0.1245        74

    accuracy                         0.9776     42721
   macro avg     0.5333    0.9483    0.5566     42721
weighted avg     0.9982    0.9776    0.9872     42721

Accuracy: 0.9776
AUC: 0.9483
Accuracy        Precision       Recall  F1-score        AUC
0.9776          0.0668          0.9189  0.1245          0.9483

Total of positive records: 74
Total of negative records: 42647
Execution no. 10
```

Naïve Bayes



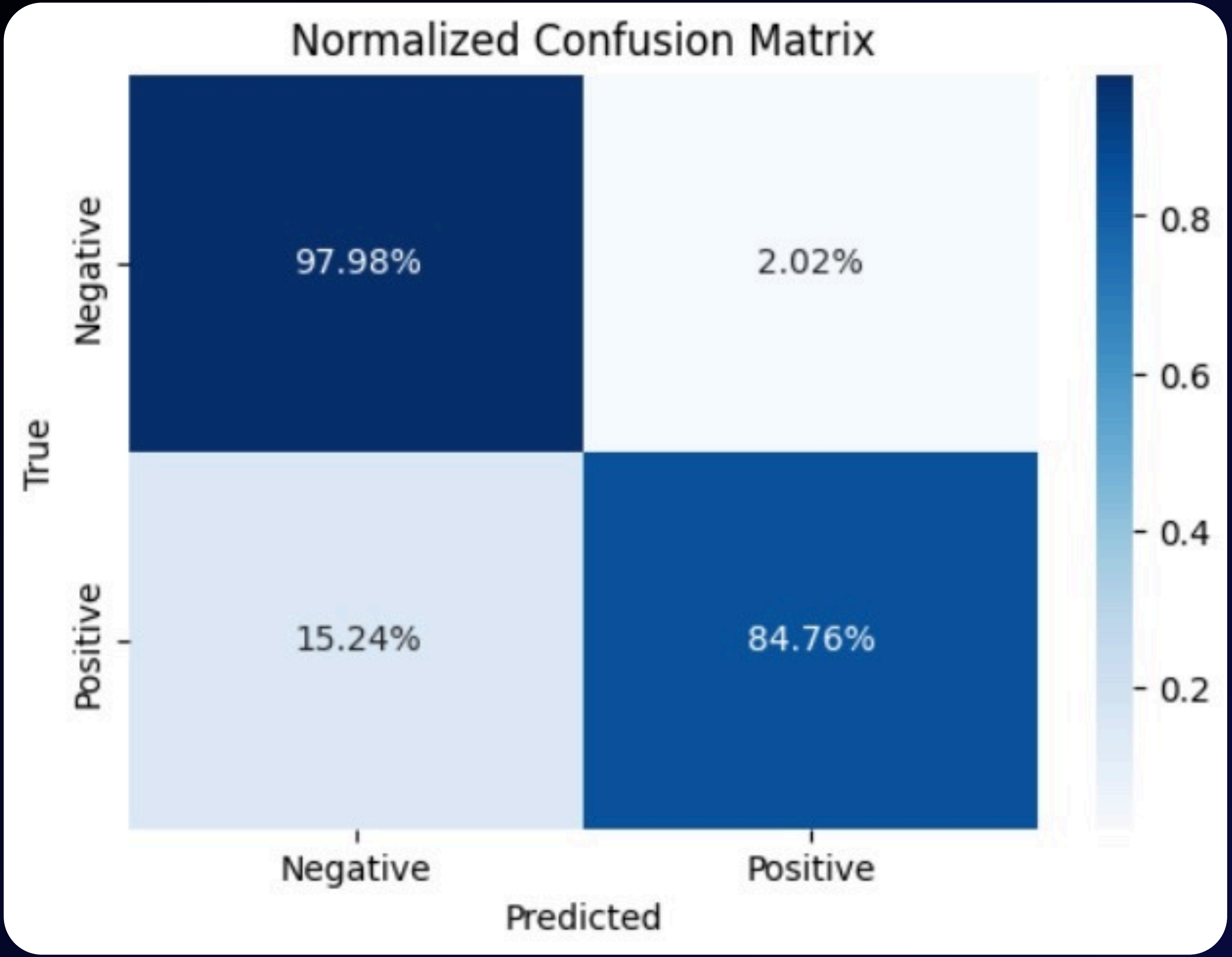

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9997    0.9705    0.9849     60417
           1     0.0475    0.8476    0.0900       105

    accuracy                         0.9703     60522
   macro avg     0.5236    0.9090    0.5374     60522
weighted avg     0.9981    0.9703    0.9833     60522

Accuracy: 0.9703
AUC: 0.9090
Accuracy        Precision       Recall  F1-score        AUC
0.9703          0.0668          0.8476  0.0900          0.9090

Total of positive records: 105
Total of negative records: 60417
Execution no. 10
```

K-Nearest Neighbor Classifier



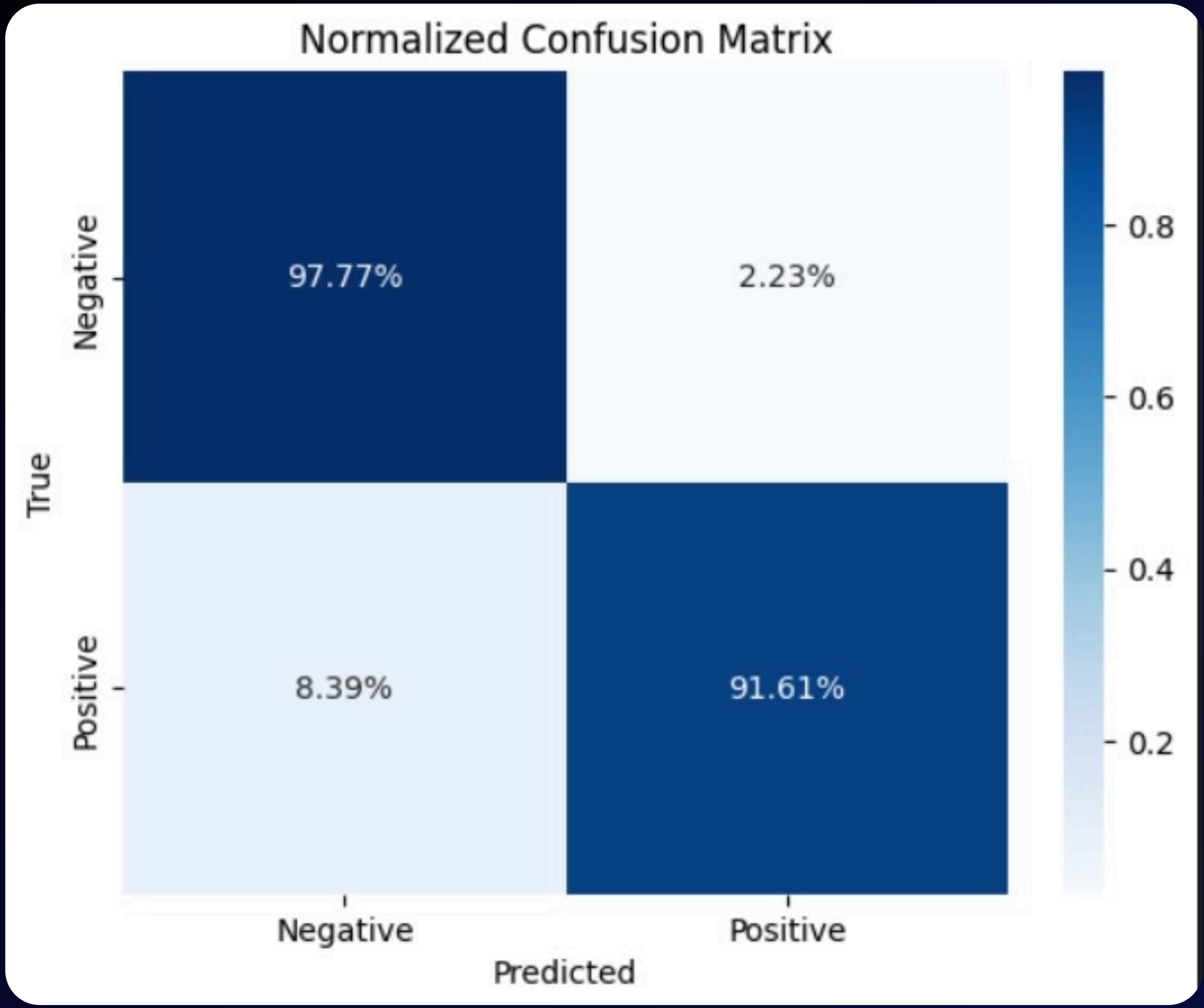

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9998    0.9853    0.9925     60417
           1     0.0930    0.8667    0.1679       105

    accuracy                         0.9851     60522
   macro avg     0.5464    0.9260    0.5802     60522
weighted avg     0.9982    0.9851    0.9911     60522

Accuracy: 0.9851
AUC: 0.9260

Accuracy        Precision       Recall   F1-score       AUC
0.9851          0.0930          0.8667   0.1679         0.9260

Total of positive records: 105
Total of negative records: 60417
Execution no. 10
```

Decision Tree



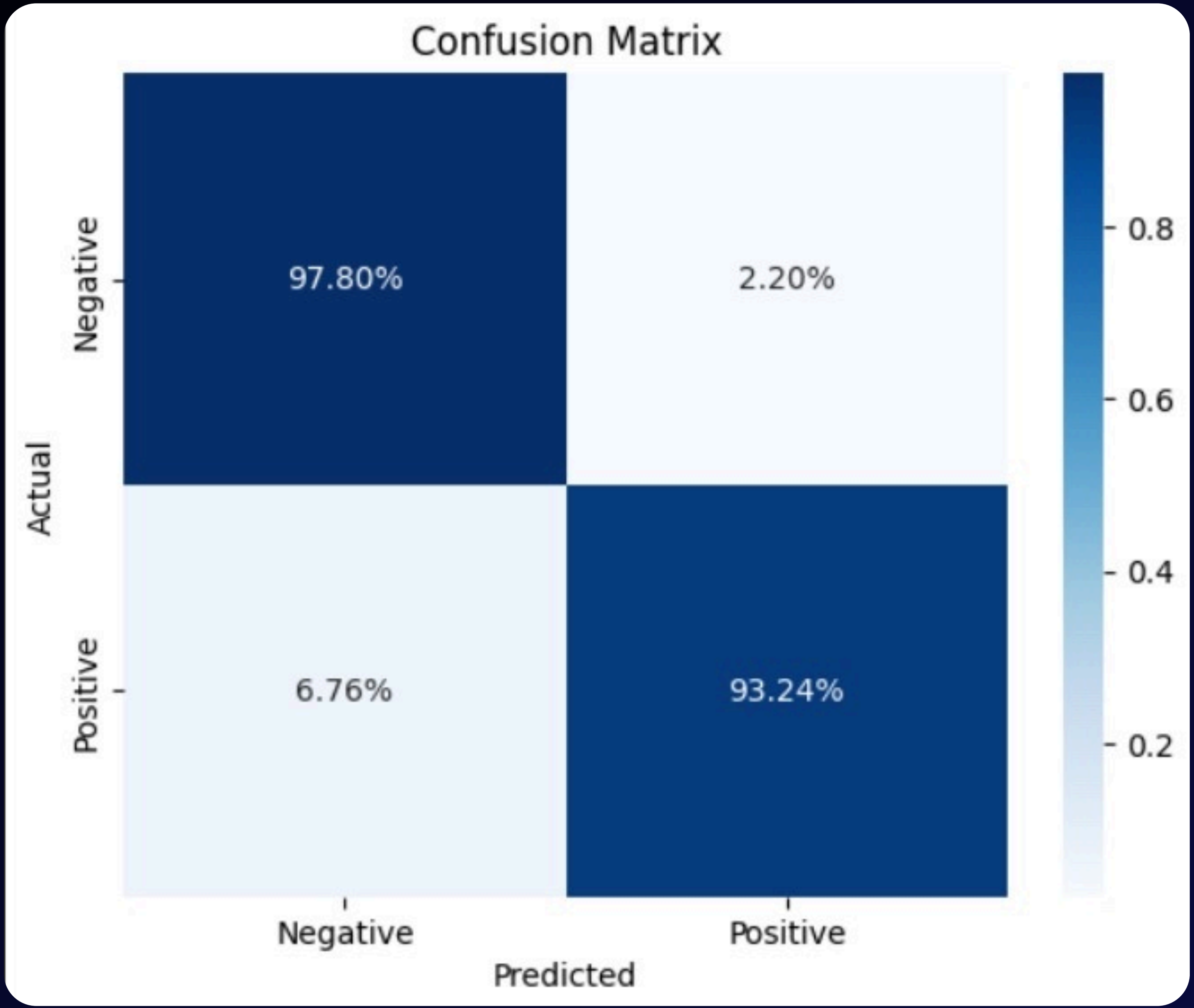

```
Classification Report:
              precision    recall  f1-score   support

           0     0.9997    0.9798    0.9897     60417
           1     0.0679    0.8476    0.1258       105

    accuracy                         0.9796     60522
   macro avg     0.5338    0.9137    0.5577     60522
weighted avg     0.9981    0.9796    0.9882     60522

Accuracy: 0.9796
AUC: 0.9137
Accuracy        Precision       Recall  F1-score        AUC
0.9796          0.0679          0.8476  0.1258          0.9137
Total of positive records: 105
Total of negative records: 60417
Execution no. 10
```

Logistic Regression (oversampling - validation)




```
              precision    recall  f1-score   support

           0     0.9210    0.9777    0.9485     54376
           1     0.9762    0.9161    0.9452     54375

    accuracy                         0.9469    108751
   macro avg     0.9486    0.9469    0.9469    108751
weighted avg     0.9486    0.9469    0.9469    108751

Accuracy: 0.9469
AUC: 0.9469
Accuracy        Precision       Recall  F1-score        AUC
0.9469          0.9762          0.9161  0.9452          0.9469
Positive records: 54375
Negative records: 54376
Execution no. 10
```

Logistic Regression
(oversampling - testing)




```
Classification Report:
              precision    recall  f1-score   support

           0     0.9999    0.9780    0.9888     42647
           1     0.0685    0.9324    0.1275        74

    accuracy                         0.9779     42721
   macro avg     0.5342    0.9552    0.5582     42721
weighted avg     0.9983    0.9779    0.9873     42721

Accuracy: 0.9779
AUC: 0.9552
Accuracy         Precision        Recall           F1-score         AUC
0.9779  0.0685  0.9324  0.1275  0.9552
Positive records: 74
Negative records: 42647
```

PERFORMANCE EVALUATION AND CONCLUSIONS

ML model	Balancing method	Prediction data	Accuracy	Precision	Recall	F1-score	AUC	Positives	Negatives
Logistic Regression	under-sampling	Validation	0.9777	0.0667	0.9143	0.1244	0.946	105	60417
Naïve Bayes	under-sampling	Validation	0.9703	0.0668	0.8477	0.09	0.909	105	60417
K-Nearest Neighbours	under-sampling	Validation	0.9851	0.093	0.8667	0.1679	0.926	105	60417
Decision tree	under-sampling	Validation	0.9796	0.0679	0.8476	0.1258	0.9137	105	60417
Logistic Regression	over-sampling	Validation	0.9469	0.9762	0.9161	0.9452	0.9469	54375	54376
Logistic Regression	under-sampling	Test	0.9776	0.0668	0.9189	0.1245	0.9483	74	42647
Logistic Regression	over-sampling	Test	0.9779	0.0685	0.9324	0.1275	0.9552	74	42647

- Logistic Regression with SMOTE (over-sampling) provided the best precision-recall and overall AUC, with precision improving significantly over the under-sampling approach.

- K-Nearest Neighbors (KNN) achieved high recall but had limited precision, resulting in a lower F1 score due to false positives.

- Decision Tree and Naive Bayes struggled with low precision, even though they detected most fraud cases (high recall).

- Addressing this issue will likely require the utilization of more advanced ML models to reduce the occurrence of false positives.

CONTRIBUTIONS

- **Sri Samhitha Bobba**: data preprocessing, analyzing the results, and reporting the outcomes.
- **Lokareddy Prishitha Reddy:** coding ML algorithms for fraud detection, and reporting the results.
- **Marina Oberemok:** the literature review, research on the implementation of ML algorithms for fraud detection, comparison of the algorithms' outcomes, and the presentation and the final report.

References

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QUESTIONS?