Credit Card Fraud Detection Report

Introduction

This report evaluates machine learning approaches for credit card fraud detection, focusing on handling class imbalance using:

- **Balancing Techniques:** SMOTE, Random Oversampling, Random Undersampling
- **Models:** Neural Network (MLP)

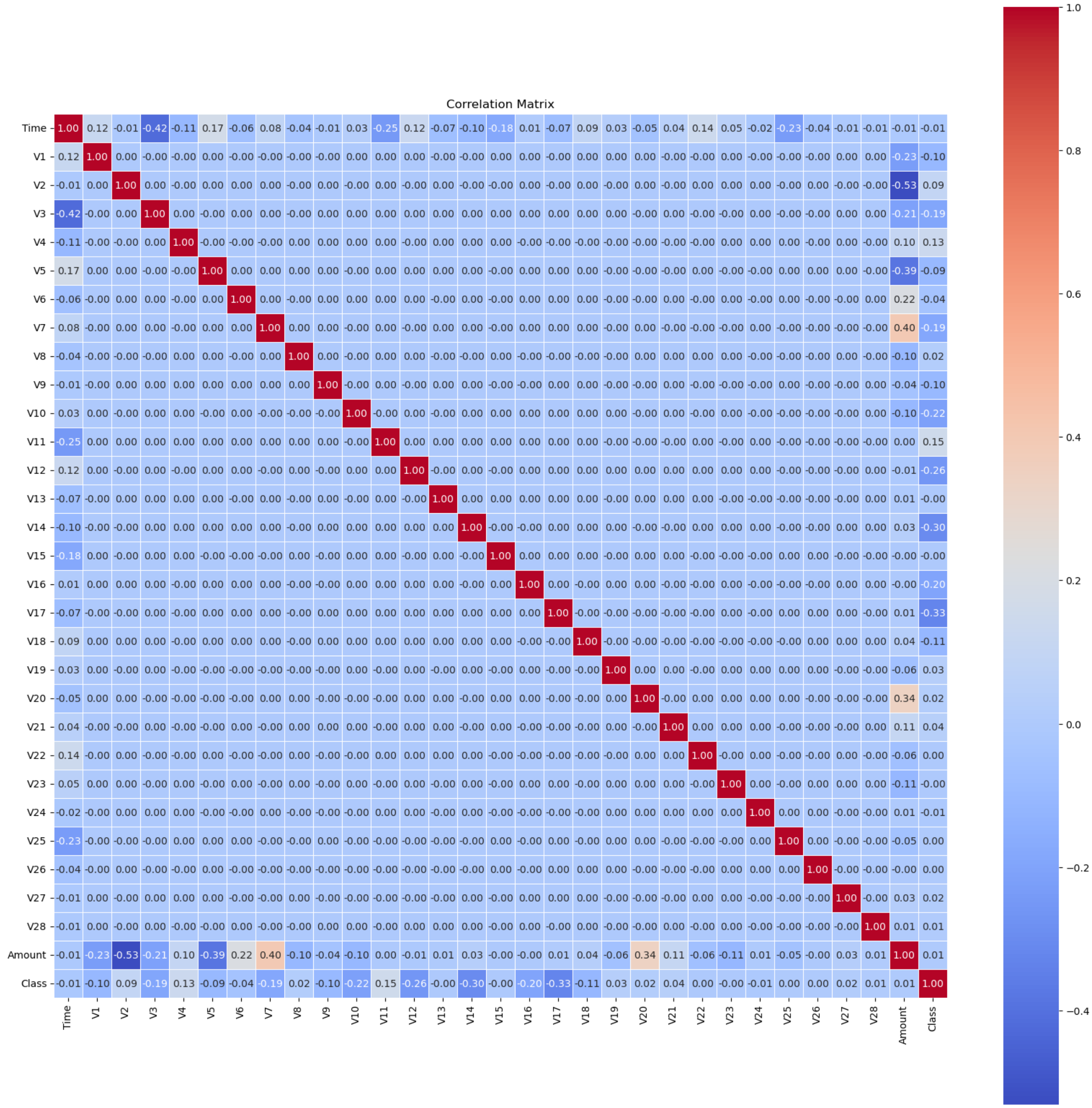
Methodology

Data Preparation

- **Dataset:** 284,807 transactions (492 frauds).
- **Preprocessing:**

  scaler = StandardScaler()
  No null/missing values in any columns
- **Correlation:**

  Below is the correlation between columns



Correlation Matrix
Time
V1
V2
V3
V4
V5
V6
V7
V8
V9
V10
V11
V12
V13
V14
V15
V16
V17
V18
V19
V20
V21
V22
V23
V24
V25
V26
V27
V28
Amount
Class
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

Balancing Techniques

Technique	Description	Pros/Cons
SMOTE	Generates synthetic fraud cases using k-NN.	+ Avoids overfitting; - May create noise.
Random Oversampling	Duplicates fraud records.	+ Simple; - Risk of overfitting.
Random Undersampling	Reduces non-fraud records randomly.	+ Faster training; - Loss of information.

Model

- **Neural Network (MLP):**

Evaluation

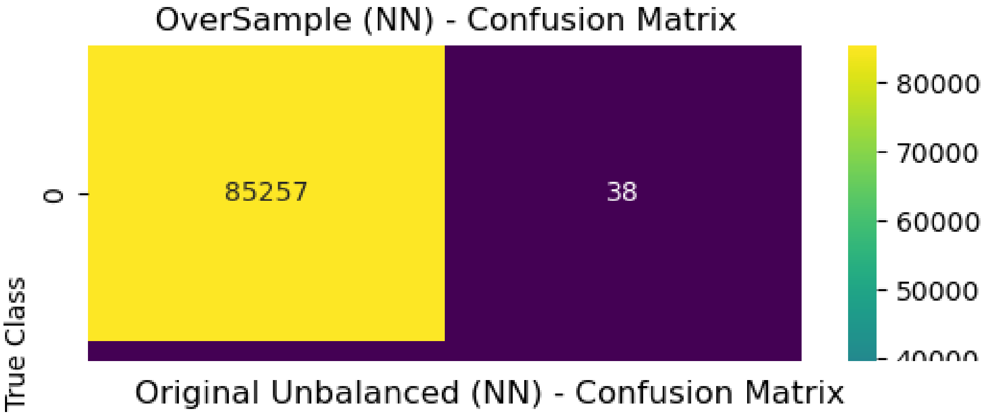
- **Focused on Class=1 (Fraud):**
    - Precision: Avoid false alarms.
    - Recall: Capture most frauds.
    - F1-Score: Balance of both.
- **Confusion Matrices: Visualized for each technique.**

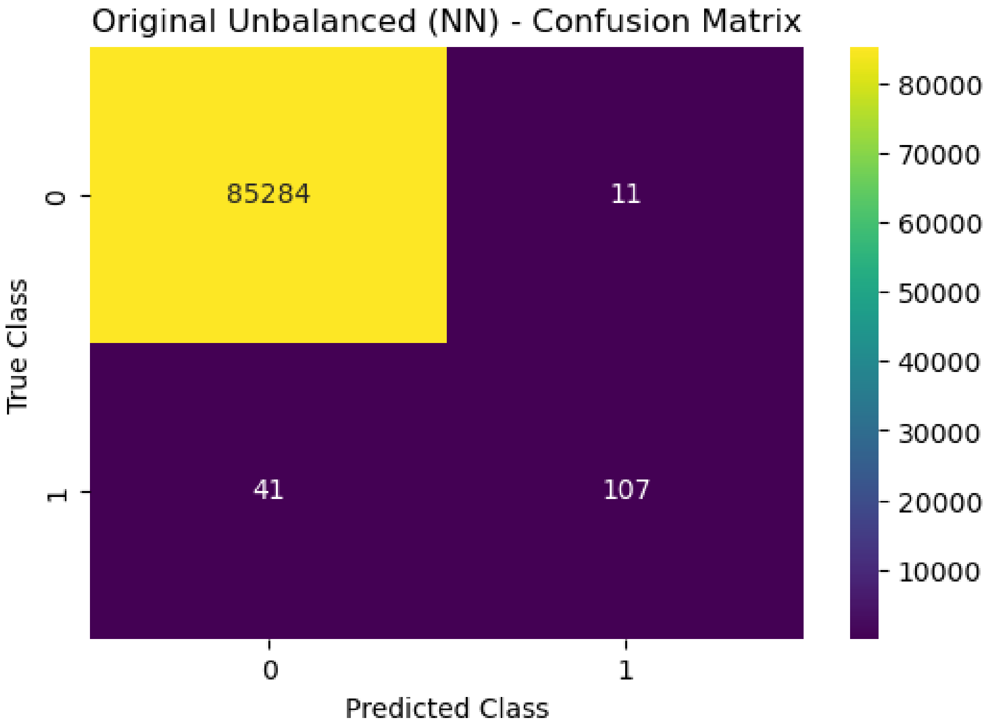
Results

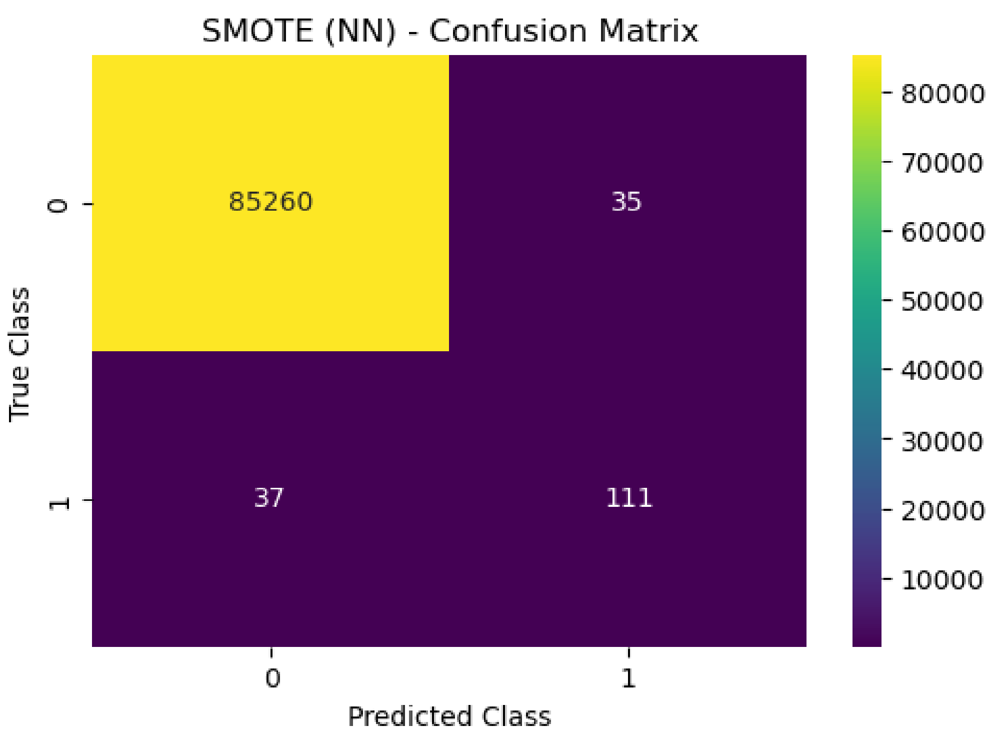
Neural Network (MLP)

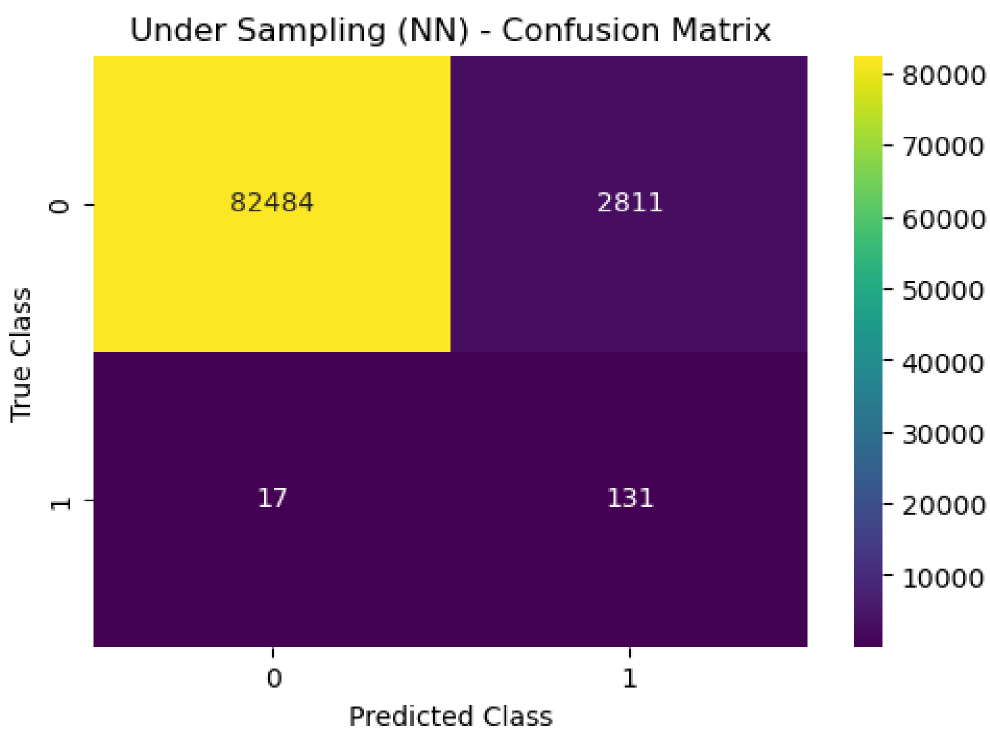
Technique	Precision	Recall	F1-Score
Original	0.90	0.72	0.80
SMOTE	0.76	0.75	0.75
Random Oversampling	0.73	0.72	0.73
Random Undersampling	0.04	0.88	0.08

Confusion Matrices:


OverSample (NN) - Confusion Matrix
True Class
0
85257
38
80000
70000
60000
50000


Original Unbalanced (NN) - Confusion Matrix
True Class
0
1
85284
11
41
107
0
1
Predicted Class
80000
70000
60000
50000
40000
30000
20000
10000


SMOTE (NN) - Confusion Matrix
True Class
0
1
85260
35
37
111
0
1
Predicted Class
80000
70000
60000
50000
40000
30000
20000
10000



Key Insights

1. **Original Data:**
    - Highest F1-score (0.80) but misses 28% frauds**.**
2. **SMOTE:**
    - Best balance (Precision=0.76, Recall=0.75)**.**
3. **Undersampling:**
    - Recall=0.88 (best fraud detection) but precision=0.04 (too many false positives).
4. **Random oversampling:**

   Moderate performance (Precision=0.73, Recall=0.72, F1=0.73) but can lead to overfitting on duplicated samples

Conclusion

- The MLP on original data achieved the highest F1-score (0.80) but missed 28% of frauds.
- SMOTE provided the best balance between precision and recall.
- Random Oversampling offers a simpler alternative with slightly lower performance