Assessment Report

on

"Credit Card Fraud Detection Using Machine Learning"

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BACHELOR OF TECHNOLOGY DEGREE

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By

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Introduction

Credit card fraud is one of the most common types of financial frauds in the world today. With the rapid growth of online shopping, mobile payments, and electronic banking, fraudulent activities have become more sophisticated and harder to detect using traditional rule-based systems. These systems often fail to capture new fraud patterns and generate a high number of false positives, leading to poor customer experience and increased operational costs for banks and financial institutions.

To address these limitations, this project focuses on using **machine learning techniques** for fraud detection. Machine learning models can learn complex patterns from historical transaction data and make accurate predictions about whether a transaction is genuine or fraudulent. Unlike rule-based methods, machine learning models continuously improve with more data, adapt to new fraud strategies, and help reduce manual investigation efforts.

This report demonstrates the development of a credit card fraud detection system using a supervised classification approach. The dataset used contains anonymized features of transactions and a binary class label indicating whether a transaction is fraudulent. Special attention is given to the **class imbalance problem**, which is common in fraud datasets, where fraudulent transactions are extremely rare compared to legitimate ones. We tackle this problem using **SMOTE (Synthetic Minority Over-sampling Technique)**, which synthetically generates more samples of the minority class.

By the end of this project, the objective is to build a model with high precision and recall for the fraudulent class, ensuring minimal false negatives (i.e., actual frauds going undetected) while keeping false positives reasonably low.

Methodology

1. Data Loading and Exploration:
The dataset was uploaded and explored to understand the structure, null values, and class distribution. It consists of anonymized features (V1 to V28), along with 'Time', 'Amount', and the target variable 'Class'.

2. Data Preprocessing:

- The feature matrix X was separated from the target y.
- All features were scaled using StandardScaler to bring them to a uniform range.
- The dataset had a significant class imbalance, so SMOTE (Synthetic Minority Over-sampling Technique) was applied to oversample the minority class.

3. Train-Test Split:
The dataset was split into training and testing sets using an 80-20 ratio.

4. Model Training:
A Random Forest Classifier was chosen for its robustness and accuracy on classification problems. The model was trained using the resampled data.

5. Evaluation:
The model's performance was evaluated using:

- Accuracy
- Confusion Matrix
- Classification Report (Precision, Recall, F1-score)

Code

```
# 1. Import necessary libraries
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import accuracy_score, classification_report,
confusion_matrix

from imblearn.over_sampling import SMOTE
import warnings
warnings.filterwarnings("ignore")

# 2. Load the dataset
df = pd.read_csv('/content/7. Predict Credit Card Fraud.csv')

# 3. Display basic dataset info
```

```
print(f"Dataset shape: {df.shape}\n")
print("Sample data:")
print(df.head())

# 4. Check for missing values
print("\nMissing values in dataset:")
print(df.isnull().sum())

# 5. Check class imbalance
print("\nClass distribution before balancing:")
print(df['Class'].value_counts())

# 6. Split features and target
X = df.drop('Class', axis=1)
y = df['Class']

# 7. Apply SMOTE to balance the dataset
smote = SMOTE(random_state=42)
X_resampled, y_resampled = smote.fit_resample(X, y)
```

```
print("\nClass distribution after SMOTE:")

print(pd.Series(y_resampled).value_counts())


# 8. Split the resampled data into train and test sets

X_train, X_test, y_train, y_test = train_test_split(X_resampled,
y_resampled, test_size=0.2, random_state=42)


# 9. Train a simplified Random Forest model for faster execution

model = RandomForestClassifier(n_estimators=10, max_depth=10,
random_state=42)

model.fit(X_train, y_train)


# 10. Make predictions

y_pred = model.predict(X_test)


# 11. Evaluate model performance

acc = accuracy_score(y_test, y_pred)

print(f"\nAccuracy: {acc:.4f}")


print("\nClassification Report:")
```

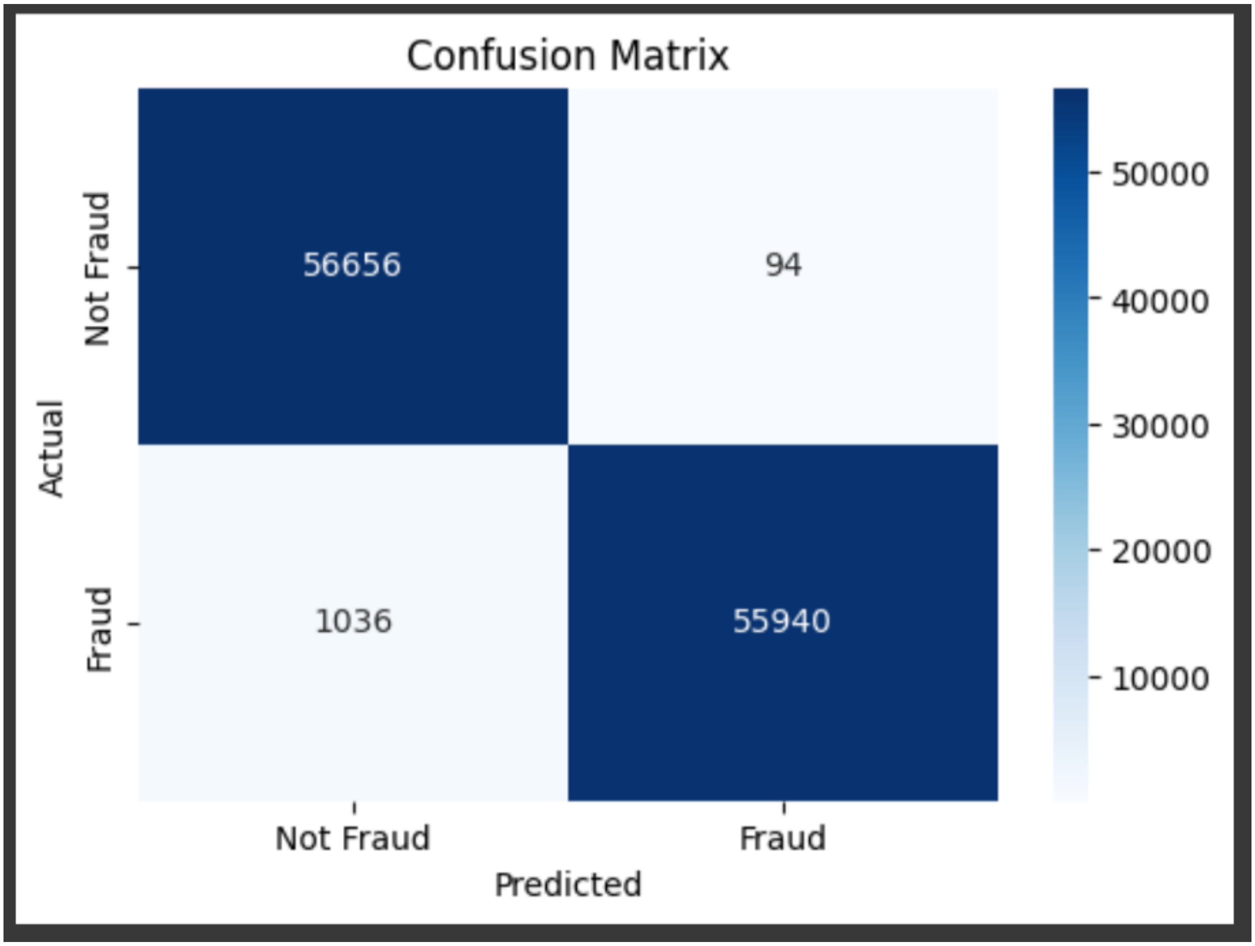
```python
print(classification_report(y_test, y_pred))


# 12. Plot confusion matrix
conf_mat = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(6, 4))
sns.heatmap(conf_mat, annot=True, fmt='d', cmap='Blues', xticklabels=["Not Fraud", "Fraud"], yticklabels=["Not Fraud", "Fraud"])
plt.xlabel('Predicted')
plt.ylabel('Actual')
plt.title('Confusion Matrix')
plt.show()
```

Output

```
Dataset shape: (284807, 31)

Sample data:
   Time        V1        V2        V3        V4        V5        V6        V7  \
0   0.0 -1.359807 -0.072781  2.536347  1.378155 -0.338321  0.462388  0.239599
1   0.0  1.191857  0.266151  0.166480  0.448154  0.060018 -0.082361 -0.078803
2   1.0 -1.358354 -1.340163  1.773209  0.379780 -0.503198  1.800499  0.791461
3   1.0 -0.966272 -0.185226  1.792993 -0.863291 -0.010309  1.247203  0.237609
4   2.0 -1.158233  0.877737  1.548718  0.403034 -0.407193  0.095921  0.592941

         V8        V9  ...       V21       V22       V23       V24       V25  \
0  0.098698  0.363787  ... -0.018307  0.277838 -0.110474  0.066928  0.128539
1  0.085102 -0.255425  ... -0.225775 -0.638672  0.101288 -0.339846  0.167170
2  0.247676 -1.514654  ...  0.247998  0.771679  0.909412 -0.689281 -0.327642
3  0.377436 -1.387024  ... -0.108300  0.005274 -0.190321 -1.175575  0.647376
4 -0.270533  0.817739  ... -0.009431  0.798278 -0.137458  0.141267 -0.206010

        V26       V27       V28  Amount  Class
0 -0.189115  0.133558 -0.021053  149.62      0
1  0.125895 -0.008983  0.014724    2.69      0
2 -0.139097 -0.055353 -0.059752  378.66      0
3 -0.221929  0.062723  0.061458  123.50      0
4  0.502292  0.219422  0.215153   69.99      0

[5 rows x 31 columns]

Missing values in dataset:
Time      0
V1        0
V2        0
```

```
V2        0
V3        0
V4        0
V5        0
V6        0
V7        0
V8        0
V9        0
V10       0
V11       0
V12       0
V13       0
V14       0
V15       0
V16       0
V17       0
V18       0
V19       0
V20       0
V21       0
V22       0
V23       0
V24       0
V25       0
V26       0
V27       0
V28       0
Amount    0
Class     0
dtype: int64
```

```
Class     0
dtype: int64

Class distribution before balancing:
Class
0    284315
1       492
Name: count, dtype: int64

Class distribution after SMOTE:
Class
0    284315
1    284315
Name: count, dtype: int64

Accuracy: 0.9901

Classification Report:
              precision    recall  f1-score   support

           0       0.98      1.00      0.99     56750
           1       1.00      0.98      0.99     56976

    accuracy                           0.99    113726
   macro avg       0.99      0.99      0.99    113726
weighted avg       0.99      0.99      0.99    113726
```


Confusion Matrix
Not Fraud
Fraud
Actual
56656
94
1036
55940
Not Fraud
Fraud
Predicted
50000
40000
30000
20000
10000

References

Dataset: Kaggle Credit Card Fraud Detection Dataset

SMOTE Documentation: https://imbalanced-learn.org/stable/references/generated/imblearn.over_sampling.SMOTE.html

Random Forest (Scikit-learn): https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html

Google Colab: For cloud-based Python environment