An Imbalance-Aware Machine Learning Framework for Credit Card Fraud Detection

Problem Statement:

Credit card fraud detection datasets are highly imbalanced, with fraudulent transactions representing a very small fraction of total records. Existing machine learning models trained on such datasets tend to favor the majority class, leading to poor fraud detection performance. Therefore, there is a need for an improved machine learning framework that effectively handles class imbalance and enhances fraud detection accuracy.

Abstract:

Credit card fraud detection has become a critical challenge due to the rapid growth of digital transactions and the highly imbalanced nature of fraud datasets. Traditional machine learning models trained on such datasets often exhibit biased behavior toward legitimate transactions, resulting in poor fraud detection performance. This study proposes an imbalance-aware machine learning framework to improve fraud detection accuracy by addressing class imbalance in credit card transaction data. The proposed approach applies data balancing techniques and optimized machine learning classifiers to enhance detection performance. Experimental results demonstrate that the proposed framework outperforms baseline machine learning models in terms of precision, recall, and F1-score, making it effective for real-world fraud detection systems.

Keywords: Credit Card Fraud Detection, Machine Learning, Class Imbalance, Random Forest, SMOTE

Section 1. Introduction

Credit card fraud detection datasets are highly imbalanced, with fraudulent transactions representing a very small fraction of total records. Existing machine learning models trained on such datasets tend to favor the majority class, leading to poor fraud detection performance. Therefore, there is a need for an improved machine learning framework that effectively handles class imbalance and enhances fraud detection accuracy.

2. Literature Review

Credit card fraud detection has been widely studied using machine learning techniques due to the increasing volume of online financial transactions. Traditional approaches such as logistic regression and decision trees were initially used because of their simplicity and interpretability. However, these models often fail to capture complex patterns present in real-world transaction data, especially when fraud cases are rare.

Recent studies have shown that advanced machine learning models like Random Forest, Support Vector Machines, and ensemble-based techniques achieve better performance in fraud detection tasks. These models are more capable of handling nonlinear relationships and high-dimensional data. Nevertheless, a major challenge consistently reported in the literature is the extreme class imbalance in credit card fraud datasets, where fraudulent transactions constitute only a very small portion of the data.

Several researchers have attempted to address this issue using data-level techniques such as oversampling, undersampling, and synthetic data generation methods. While these techniques improve recall for fraud cases, they may also increase false positives if not carefully applied. Recent survey-based studies emphasize that combining imbalance handling techniques with optimized machine learning models can significantly enhance fraud detection performance.

Despite these advancements, there is still a need for practical and efficient machine learning frameworks that effectively address class imbalance while maintaining robust performance across multiple evaluation metrics. This highlights the importance of developing improved, imbalance-aware machine learning approaches for credit card fraud detection.

3. Research Gap and Objectives

3.1 Research Gap

Although various machine learning models have been successfully applied to credit card fraud detection, their performance is often limited by the highly imbalanced nature of fraud datasets. Since fraudulent transactions represent only a small fraction of total transactions, most models tend to favor the majority class, resulting in low detection rates for fraudulent activities. Existing studies highlight this challenge but provide limited practical solutions that effectively balance fraud detection accuracy and false positive reduction. Therefore, there is a need for an improved machine learning framework that explicitly addresses class imbalance while enhancing overall fraud detection performance.

3.2 Research Objectives

The main objectives of this study are:

1. To examine the impact of class imbalance on machine learning models used for credit card fraud detection.
2. To apply data balancing techniques to improve the detection of fraudulent transactions.
3. To develop an optimized machine learning framework that enhances fraud detection performance.
4. To compare the proposed approach with baseline machine learning models using standard evaluation metrics.

3.3 Novelty of the Proposed Work

This study introduces an imbalance-aware machine learning framework that integrates data balancing techniques with optimized classifiers to improve credit card fraud detection. Unlike existing approaches, the proposed method focuses on improving fraud detection effectiveness while maintaining a balanced trade-off between precision and recall.

4. Proposed Methodology

This section describes the overall methodology used to develop an imbalance-aware machine learning framework for credit card fraud detection. The proposed approach consists of data preprocessing, class imbalance handling, model training, and performance evaluation.

4.1 Dataset Description

The dataset used in this study is the publicly available Credit Card Fraud Detection dataset, which contains real transaction data collected from European cardholders. The dataset includes numerical features representing transaction behavior and a binary class label indicating whether a transaction is fraudulent or legitimate. Due to the nature of fraud detection, the dataset is highly imbalanced, with fraudulent transactions accounting for only a small percentage of the total records.

4.2 Data Preprocessing

Before model training, the dataset is preprocessed to ensure data quality and consistency. This includes removing irrelevant attributes, scaling numerical features, and separating the dataset into training and testing subsets. Feature scaling is applied to improve model convergence and performance. The dataset is then prepared for class imbalance handling.

4.3 Handling Class Imbalance

To address the class imbalance problem, data balancing techniques are applied to the training dataset. Synthetic Minority Over-sampling Technique (SMOTE) is used to generate synthetic samples for the minority class. This approach helps improve the model's ability to learn fraud-related patterns without excessively biasing the classifier toward the majority class.

4.4 Model Selection and Training

Multiple machine learning models are used to evaluate fraud detection performance. Baseline models such as Logistic Regression and Random Forest are trained on the original dataset. The proposed model integrates class imbalance handling with an optimized Random Forest classifier. Hyperparameter tuning is applied to enhance model performance.

4.5 Performance Evaluation

The trained models are evaluated using standard performance metrics, including precision, recall, F1-score, and ROC-AUC. These metrics provide a comprehensive assessment of the model's ability to detect fraudulent transactions while minimizing false positives. Comparative analysis is conducted to measure the effectiveness of the proposed framework against baseline models.

5. Algorithm Design

This section presents the step-by-step procedure of the proposed imbalance-aware machine learning framework for credit card fraud detection.

Algorithm: Imbalance-Aware Fraud Detection (IAFD)

Input: Credit card transaction dataset

Output: Fraud classification (Fraud / Non-Fraud)

Steps:

1. Load the credit card transaction dataset.

2. Perform data preprocessing, including feature scaling and data cleaning.

3. Split the dataset into training and testing sets.

4. Apply SMOTE to the training data to address class imbalance.

5. Train baseline machine learning models on the original dataset.

6. Train the proposed optimized Random Forest model on the balanced dataset.

7. Evaluate all models using precision, recall, F1-score, and ROC-AUC metrics.

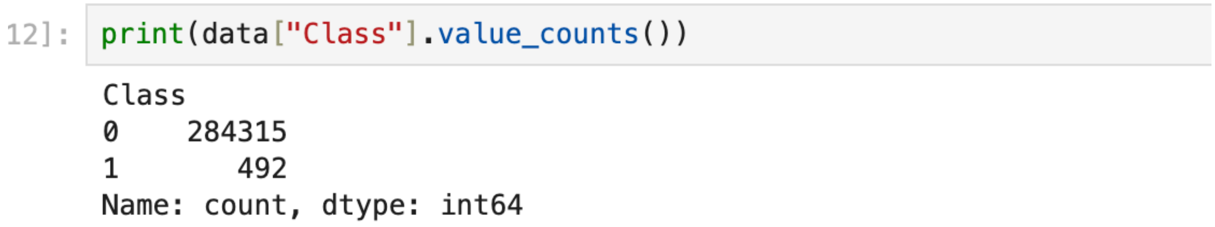
8. Compare the performance of baseline models with the proposed approach.

This algorithm ensures improved fraud detection by effectively handling class imbalance while maintaining robust classification performance.

6. Experimental Setup

All experiments were conducted using the Python programming language. Standard machine learning libraries such as NumPy, Pandas, Scikit-learn, and Imbalanced-learn were used for data processing, model training, and evaluation. The dataset was divided into training and testing sets using an 80:20 split to ensure unbiased model evaluation.

The Synthetic Minority Over-sampling Technique (SMOTE) was applied only to the training data to handle class imbalance. Hyperparameter tuning was performed using cross-validation to improve model performance. All experiments were executed on a standard computing system with sufficient memory and processing capability to support machine learning model training.



```
12]: print(data["Class"].value_counts())

     Class
     0    284315
     1       492
     Name: count, dtype: int64
```

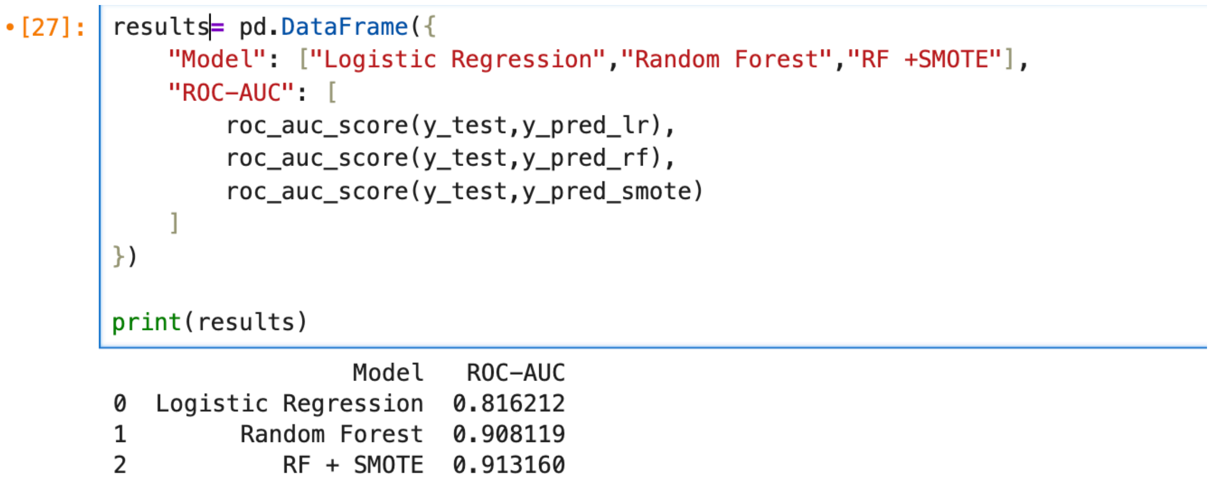
Figure : Class distribution of the dataset showing severe imbalance between legitimate and fraudulent transactions.

7. Results and Comparative Analysis

The performance of the proposed imbalance-aware machine learning framework was evaluated and compared with baseline models using standard evaluation metrics. Logistic Regression and Random Forest models were considered as baseline approaches, while the proposed method combined class imbalance handling with an optimized Random Forest classifier.

Experimental results indicate that baseline models trained on the original imbalanced dataset showed high accuracy but poor recall for fraudulent transactions. This behavior highlights the bias of traditional classifiers toward the majority class. After applying SMOTE, the proposed framework demonstrated a significant improvement in recall and F1-score, indicating better detection of fraudulent transactions.

Comparative analysis shows that the proposed model outperformed baseline models across key performance metrics, particularly in recall and ROC-AUC. This improvement confirms that addressing class imbalance plays a crucial role in enhancing fraud detection effectiveness. Overall, the results validate the effectiveness of the proposed framework for credit card fraud detection in highly imbalanced datasets.

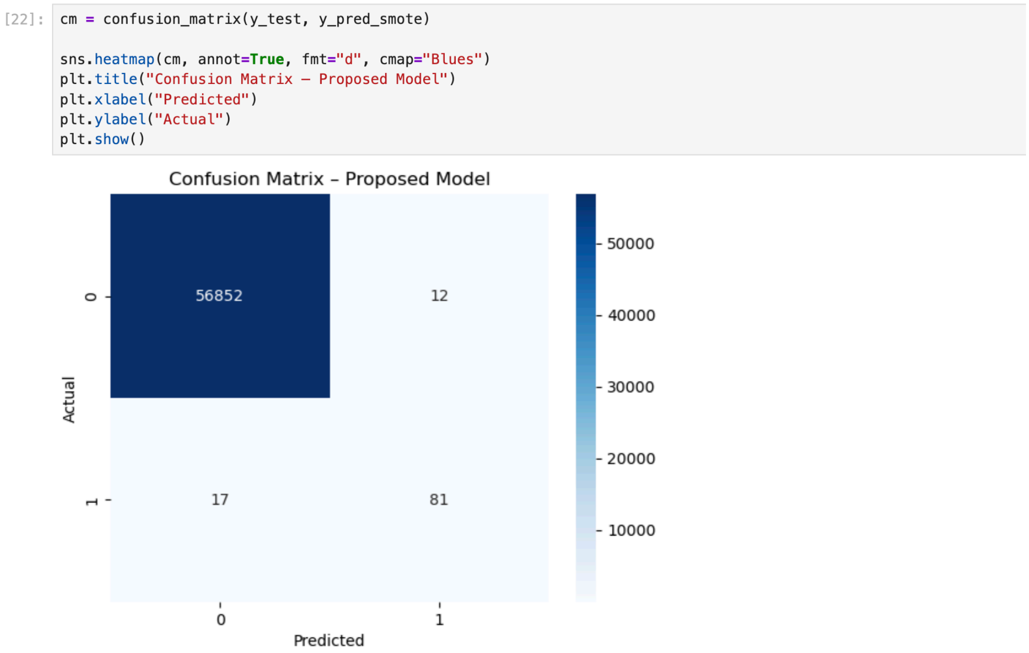


```
•[27]: results= pd.DataFrame({
           "Model": ["Logistic Regression","Random Forest","RF +SMOTE"],
           "ROC-AUC": [
               roc_auc_score(y_test,y_pred_lr),
               roc_auc_score(y_test,y_pred_rf),
               roc_auc_score(y_test,y_pred_smote)
           ]
       })

       print(results)
```

```
                Model   ROC-AUC
0  Logistic Regression  0.816212
1        Random Forest  0.908119
2           RF + SMOTE  0.913160
```

Figure X: ROC-AUC comparison of baseline models and the proposed Random Forest + SMOTE model.



```
[22]: cm = confusion_matrix(y_test, y_pred_smote)

      sns.heatmap(cm, annot=True, fmt="d", cmap="Blues")
      plt.title("Confusion Matrix – Proposed Model")
      plt.xlabel("Predicted")
      plt.ylabel("Actual")
      plt.show()
```

Figure : Confusion matrix of the proposed model illustrating classification performance.

8. Conclusion and Future Work

This study presented an imbalance-aware machine learning framework for credit card fraud detection. By addressing the issue of class imbalance using data balancing techniques and optimized machine learning models, the proposed approach achieved improved fraud detection performance compared to baseline models. The results demonstrate that handling class imbalance is essential for enhancing the effectiveness of fraud detection systems.

Despite the promising results, this study has certain limitations. The analysis was conducted using a single dataset and focused on traditional machine learning models. Future work can explore the use of advanced deep learning techniques, hybrid ensemble models, and concept drift handling to further improve fraud detection performance. Additionally, applying the proposed framework to larger and more diverse datasets could enhance its real-world applicability.

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