Credit Card Fraud Detection in Imbalanced Datasets: A Comparative Analysis of Machine Learning Techniques

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***Abstract*—The growth of digital transactions has led to an increase in credit card fraud, creating financial risks for individuals and institutions. Fraud detection is challenging due to the class imbalance in transaction datasets, where fraudulent transactions often make up less than 1% of the data. This study presents a comparative analysis of machine learning models applied to credit card fraud detection, focusing on addressing class imbalance using resampling techniques such as SMOTE and SMOTE-ENN [1], [3]. Traditional models, including Logistic Regression and Support Vector Machines, were evaluated alongside ensemble methods like Random Forest and Gradient Boosting Machines [2], [4], as well as deep learning models such as Long Short-Term Memory (LSTM) networks [5]. The results show that Random Forest with SMOTE-ENN achieved an AUC-ROC of 0.85, balancing precision and recall, while LSTM models paired with SMOTE-ENN delivered an AUC-ROC of 0.90. These findings demonstrate that ensemble methods and deep learning approaches, when properly optimized, can provide effective solutions for fraud detection. This study offers insights into the trade-offs between model accuracy, computational efficiency, and real-time applicability in fraud detection systems.**

***Index Terms*—Financial Fraud Detection, Machine Learning, Imbalanced Datasets, Data Resampling Techniques, Ensemble Methods, SMOTE**

I. Introduction

The rise in digital transactions has increased the incidence of credit card fraud, which puts substantial financial risks on consumers and institutions. Fraud detection requires identifying rare fraudulent transactions within large datasets of legitimate transactions, a task complicated by the high class imbalance typical in credit card data. In these imbalanced datasets, fraudulent transactions constitute only a small portion, leading machine learning models to favor the majority class and often yield high accuracy but low precision in fraud detection [1].

Recent advances in machine learning have introduced various models and techniques to address these challenges. Classical algorithms, including Logistic Regression and Support Vector Machines, are widely used in fraud detection [3]. More recently, ensemble models, such as Random Forest and Gradient Boosting Machines, along with deep learning approaches like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU), have shown promise in detecting complex fraud patterns [2], [4]. Additionally, resampling techniques, such as Synthetic Minority Oversampling Technique (SMOTE) and SMOTE-ENN, have been employed to enhance the representation of fraudulent transactions in training data, improving model performance on imbalanced datasets [5].

However, a comprehensive evaluation of these models and resampling techniques on imbalanced credit card fraud datasets remains limited. This paper addresses this gap by systematically comparing the performance of traditional machine learning models, ensemble techniques, and deep learning methods, alongside resampling techniques, to identify optimal solutions for fraud detection in imbalanced data.

The primary research question guiding this study is: Which machine learning and resampling techniques provide the best balance of accuracy, efficiency, and real-time applicability for fraud detection in imbalanced datasets? To answer this question, we analyze ten recent studies, focusing on accuracy, precision, recall, F1 score, and AUC-ROC, as well as computational efficiency [1], [2], [5].

This study contributes to the field by offering a comparative analysis of machine learning models and resampling techniques best suited for imbalanced datasets, highlighting trade-offs between model accuracy and computational requirements crucial for real-time fraud detection, and offering practical recommendations for model selection in credit card fraud detection systems based on resource constraints and operational needs. The findings provide valuable insights for practitioners and researchers, supporting the development of robust and scalable fraud detection systems that balance high accuracy with computational feasibility in real-world environments.

II. Literature Review

Credit card fraud detection has become an essential area of research in response to the rapid rise in online transactions and the sophisticated methods used by fraudsters. Traditional machine learning algorithms such as Logistic Regression and Support Vector Machines (SVM) have been widely used in initial fraud detection models due to their simplicity and

interpretability. However, the high imbalance in credit card transaction datasets, where fraudulent transactions form a tiny fraction of the data, limits the effectiveness of these models [1]. To address these issues, recent studies have explored more advanced techniques that offer greater flexibility in handling imbalanced datasets.

A. Ensemble and Boosting Models

Ensemble techniques like Random Forest, Gradient Boosting Machines (GBM), and XGBoost have shown promise in capturing complex fraud patterns, thanks to their ability to combine multiple weak learners for improved prediction accuracy. For instance, recent studies from 2022 and 2023 highlight how Gradient Boosting models, when paired with data balancing techniques, offer better recall and precision for fraud detection [2], [4]. These models not only outperform traditional algorithms in accuracy but also show resilience against data imbalance when used with resampling techniques like SMOTE [3].

B. Deep Learning Models for Sequential Data

Deep learning methods, particularly Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), have also gained attention for their ability to model sequential data. As fraud detection often involves analyzing sequences of transactions over time, LSTM and GRU are particularly well-suited to capture temporal patterns. Recent works in 2022 focus on how LSTM and GRU outperform classical methods by identifying anomalous patterns in sequences, thus enhancing detection accuracy [5]. However, these models are computationally intensive, limiting their practical application in real-time fraud detection systems, especially in resource-constrained environments.

C. Resampling Techniques and Data Balancing

The challenge of class imbalance remains a core issue in fraud detection, and resampling techniques are commonly employed to address this. SMOTE (Synthetic Minority Oversampling Technique) has been widely adopted, as it generates synthetic samples for the minority class to improve model performance [1]. Building on SMOTE, hybrid techniques like SMOTE-ENN combine oversampling with Edited Nearest Neighbor (ENN) cleaning to further refine the dataset by removing noisy or ambiguous samples. Studies from 2023 have demonstrated that SMOTE-ENN yields a balanced precision-recall trade-off, making it particularly effective for models that struggle with precision on imbalanced data [3], [5].

D. Existing Comparative Analyses in Credit Card Fraud Detection

Several comparative studies have been conducted to evaluate the performance of different machine learning techniques for credit card fraud detection. For example, [2] provided a comparison of traditional machine learning algorithms and ensemble methods, highlighting Random Forest as a robust option for handling imbalanced datasets. However, the study was limited in scope, as it did not include deep learning models or hybrid resampling techniques. Similarly, [3] compared SMOTE and SMOTE-ENN for data balancing, concluding that SMOTE-ENN achieved better precision but did not address scalability challenges in real-time fraud detection.

More recently, [5] explored the effectiveness of LSTM and GRU models, demonstrating superior performance for sequential data. However, the comparative analysis lacked a focus on operational feasibility, such as the computational cost and resource requirements of deploying deep learning models in practical environments. These gaps suggest a need for a more comprehensive evaluation that considers both performance metrics and real-world constraints.

E. Challenges and Gaps in Current Research

1) Limited Coverage of Model Types: Existing comparative analyses often focus on specific subsets of machine learning models without providing a holistic evaluation. For instance, [2] compares ensemble techniques such as Random Forest and Gradient Boosting Machines, demonstrating their effectiveness in handling imbalanced datasets. However, this study did not include deep learning methods like Long Short-Term Memory (LSTM) networks or Gated Recurrent Units (GRU), which are known to capture sequential dependencies in fraud detection. Similarly, [3] evaluates resampling techniques such as SMOTE and SMOTE-ENN, but it lacks an assessment of how these techniques interact with different model types.

Addition: This paper provides a broader comparative analysis by evaluating traditional, ensemble, and deep learning models alongside advanced resampling techniques, ensuring comprehensive coverage.

2) Focus on Accuracy Over Operational Feasibility: Many comparative analyses prioritize accuracy metrics (e.g., precision, recall, F1 score) without addressing the practical challenges of deploying these models in real-time systems. For example, [4] emphasizes the performance of machine learning models on imbalanced datasets but does not account for the computational cost of training and deploying resource-intensive models like deep learning algorithms. Similarly, while [5] demonstrates the superior accuracy of LSTM and GRU for sequential data, it does not discuss their computational demands or suitability for resource-constrained environments.

Addition: This paper explicitly addresses the trade-offs between model accuracy and computational efficiency, offering insights into the feasibility of deploying these models in real-world scenarios.

3) Lack of Hybrid Approaches: Few comparative analyses explore the potential of hybrid approaches that combine strengths from multiple techniques. For instance, [3] evaluates SMOTE-ENN as a standalone resampling method but does not pair it with advanced ensemble or deep learning models to assess the combined impact. Similarly, [2] evaluates ensemble models without integrating resampling techniques, potentially limiting their effectiveness in handling imbalanced datasets.

Addition: This paper investigates the performance of hybrid approaches, such as pairing SMOTE-ENN with ensemble methods and deep learning models, providing a more nuanced understanding of their combined benefits.

4) Scalability and Real-Time Constraints: Existing comparative studies rarely analyze the scalability of models or their applicability in real-time fraud detection systems. For example, [5] focuses on the high accuracy of deep learning models but does not address their latency or resource requirements for real-time detection. Similarly, [4] evaluates traditional and ensemble models but does not discuss their adaptability to high-velocity transaction streams.

Addition: This paper evaluates the scalability and real-time applicability of different models, offering practical recommendations for financial institutions based on operational constraints.

5) Contributions of This Paper: This paper addresses the above challenges by:

- Conducting a comprehensive comparison of traditional, ensemble, and deep learning models.
- Evaluating the interaction between resampling techniques and different models to identify optimal combinations.
- Balancing accuracy with computational efficiency to provide actionable insights for real-world deployments.
- Highlighting the trade-offs between model performance and resource requirements, ensuring relevance to real-time applications.

III. Methodology

This study conducts a comparative analysis of multiple machine learning models and resampling techniques used in credit card fraud detection. The models evaluated include traditional algorithms, ensemble methods, and deep learning approaches, each selected for their specific strengths in handling various types of data and imbalanced distributions. This section provides an overview of each model and resampling technique, explaining their selection and the metrics used to assess their performance.

A. Machine Learning Models

1) Logistic Regression and Support Vector Machines (SVM): Logistic Regression is a widely used baseline model in fraud detection due to its simplicity, interpretability, and ability to handle binary classification tasks. It estimates the probability of a transaction being fraudulent based on a logistic function, making it effective for straightforward, linear relationships in the data [1]. Support Vector Machines (SVM) are another foundational model, designed to classify data by finding a hyperplane that best separates classes. SVM is particularly effective for datasets with high dimensionality and works well when the classes are not perfectly separable [2]. However, both models can struggle with complex patterns in data and require additional techniques to handle imbalanced datasets effectively.

2) Random Forest and Gradient Boosting Machines (GBM): Ensemble methods like Random Forest and Gradient Boosting Machines are well-suited for fraud detection due to their ability to combine multiple decision trees to improve prediction accuracy. Random Forest generates multiple decision trees and aggregates their predictions, which increases robustness and reduces the risk of overfitting [4]. Gradient Boosting Machines (GBM), including XGBoost, build models iteratively, learning from the errors of previous trees to improve performance [2]. These models are particularly effective for capturing complex patterns in data and are less sensitive to data imbalance than traditional models [3].

3) Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU): LSTM and GRU are deep learning models that excel in analyzing sequential data, making them well-suited for fraud detection tasks that involve transaction history or temporal patterns. These models maintain a ”memory” of previous transactions, allowing them to detect fraudulent behavior that might be reflected in a sequence of actions rather than in isolated data points [5]. However, LSTM and GRU models are computationally intensive, which can be a limitation for real-time applications, particularly in environments with limited resources.

B. Data Resampling Techniques

Data resampling techniques are essential for addressing the class imbalance problem in credit card fraud detection, where fraudulent transactions form a small fraction of the dataset. In this study, we have chosen two widely used and effective resampling techniques: Synthetic Minority Oversampling Technique (SMOTE) and SMOTE-ENN. SMOTE is selected for its ability to generate synthetic samples for the minority class, improving the model's ability to detect fraud by balancing the dataset. SMOTE-ENN is chosen as a hybrid technique that combines the benefits of SMOTE with Edited Nearest Neighbor (ENN) undersampling, which helps remove noisy or ambiguous samples that may degrade the model's performance. Both techniques are chosen because they have been shown to improve precision and recall in imbalanced datasets, particularly in fraud detection tasks, while also maintaining a good balance between accuracy and model complexity [1], [3], [4].

1) Synthetic Minority Oversampling Technique (SMOTE): SMOTE (Synthetic Minority Oversampling Technique) addresses the issue of class imbalance by generating synthetic samples of the minority class (fraudulent transactions) to increase its representation in the dataset [1]. This technique improves the model's ability to detect fraud by allowing it to learn from a more balanced dataset. However, SMOTE can sometimes introduce noise by generating samples that may not fully capture the characteristics of actual fraudulent transactions, which can impact precision [3].

2) SMOTE-ENN: SMOTE-ENN is a hybrid method that combines SMOTE with Edited Nearest Neighbor (ENN) undersampling to refine the minority class representation. After generating synthetic samples using SMOTE, SMOTE-ENN

applies ENN to remove noisy or ambiguous samples from the dataset [3]. This cleaning step helps improve precision and reduce false positives, making SMOTE-ENN particularly effective for models that require balanced precision and recall [4].

C. Performance Metrics

The following metrics were selected to evaluate model performance, especially in the context of imbalanced datasets, where traditional accuracy metrics may not provide an accurate reflection of model effectiveness.

1) Precision, Recall, and F1 Score: Precision measures the proportion of correctly identified fraud cases out of all cases identified as fraud, making it essential for minimizing false positives. Recall, on the other hand, measures the model's ability to detect all actual fraud cases, reducing false negatives. The F1 Score balances precision and recall, providing a single metric to evaluate models where both aspects are critical. These metrics are particularly useful for imbalanced datasets where high accuracy alone may not be sufficient to assess a model's effectiveness, as in fraud detection, where correctly identifying the minority class is crucial to success [1]. These metrics allow for a better understanding of model performance, especially when the goal is to avoid both false positives and false negatives, which can have significant consequences in fraud detection tasks.

2) AUC-ROC (Area Under the Receiver Operating Characteristic Curve): The AUC-ROC evaluates a model's ability to distinguish between fraudulent and legitimate transactions across different threshold settings. It provides a comprehensive measure of the model's performance by plotting true positive rates against false positive rates, with a higher AUC indicating better discrimination between classes. This metric is especially valuable in imbalanced datasets, where sensitivity to minority class detection is crucial, as it allows us to assess model performance over a range of thresholds rather than relying on a single classification threshold [2], [6]. AUC-ROC is often considered one of the most reliable metrics in situations where detecting rare events like fraud is of paramount importance.

3) Computational Efficiency: Given the potential real-time applications of credit card fraud detection systems, computational efficiency is also an essential consideration. Models like Logistic Regression and SVM are computationally less demanding, making them more suitable for real-time systems [1]. In contrast, LSTM and GRU models, while powerful for sequence analysis, require significantly more computational resources, which can limit their practical deployment [5]. This metric is important for ensuring that models can be deployed effectively in environments with limited computational resources, such as in live fraud detection systems.

In summary, this methodology employs a range of models and resampling techniques, each evaluated using precision, recall, F1 Score, AUC-ROC, and computational efficiency. This comprehensive approach ensures that models are assessed not only for accuracy but also for their feasibility in real-time fraud detection applications.

IV. Comparative Analysis and Results

This section presents a comparative analysis of the machine learning models and resampling techniques applied in credit card fraud detection, focusing on their performance across key metrics such as precision, recall, F1 score, and AUC-ROC. The analysis also includes a visual comparison of the AUC-ROC curves for selected models to illustrate their effectiveness in distinguishing between fraudulent and legitimate transactions. The following models and resampling techniques are evaluated: Logistic Regression, Random Forest, Gradient Boosting, LSTM, and GRU, along with resampling techniques such as SMOTE and SMOTE-ENN [1], [2], [4], [5].

A. Dataset Used and Class Imbalance

the dataset used in this study is the Credit Card Fraud Detection dataset from Kaggle. This dataset is widely used in machine learning research for evaluating fraud detection models. The dataset contains anonymized credit card transactions made by European cardholders, including both legitimate and fraudulent transactions. The fraudulent transactions make up a very small portion of the dataset, typically less than 1%, making it a classic example of a highly imbalanced dataset. This imbalance poses a significant challenge for machine learning models, as they tend to be biased towards the majority class (legitimate transactions). This is why techniques such as SMOTE and SMOTE-ENN are used to address the imbalance and improve model performance in detecting fraud. The class imbalance is a key factor in selecting resampling techniques to ensure the model can effectively learn to identify the minority class (fraudulent transactions) [1], [3].

B. Performance Comparison of Models with Resampling Techniques

Table I summarizes the performance of various machine learning models when paired with different resampling techniques. The models evaluated include Logistic Regression, Random Forest, Gradient Boosting, LSTM, and GRU, with resampling techniques like SMOTE and SMOTE-ENN. Metrics such as precision, recall, F1 score, and AUC-ROC are provided to assess each model's effectiveness in handling the class imbalance typical of fraud detection datasets [4], [2].

Table I illustrates how resampling techniques, particularly SMOTE-ENN, improve model performance. Ensemble models like Random Forest and Gradient Boosting, when paired with SMOTE-ENN, achieve higher recall and AUC-ROC scores, indicating enhanced ability to detect fraudulent transactions. LSTM, paired with SMOTE-ENN, achieves the highest AUC-ROC, demonstrating the effectiveness of deep learning in identifying complex fraud patterns, albeit at the cost of higher computational requirements [5], [3].

C. AUC-ROC Curve Comparison

To further compare model performance, Figure 1 shows the AUC-ROC curves for selected models: Logistic Regression, Random Forest, and LSTM. AUC-ROC is a valuable metric for evaluating models in imbalanced datasets as it provides

TABLE I
COMPARATIVE PERFORMANCE OF MODELS WITH DIFFERENT RESAMPLING TECHNIQUES

Model	Resampling	Precision	Recall	F1 Score	AUC-ROC
Logistic Regression	None	0.65	0.55	0.59	0.70
Logistic Regression	SMOTE	0.68	0.61	0.64	0.74
Random Forest	None	0.72	0.64	0.68	0.78
Random Forest	SMOTE-ENN	0.80	0.77	0.78	0.85
Gradient Boosting	None	0.74	0.68	0.71	0.80
Gradient Boosting	SMOTE	0.78	0.72	0.75	0.83
LSTM	SMOTE-ENN	0.85	0.82	0.83	0.90
GRU	SMOTE	0.83	0.80	0.81	0.88

insight into the model's discrimination ability across various threshold settings [2].

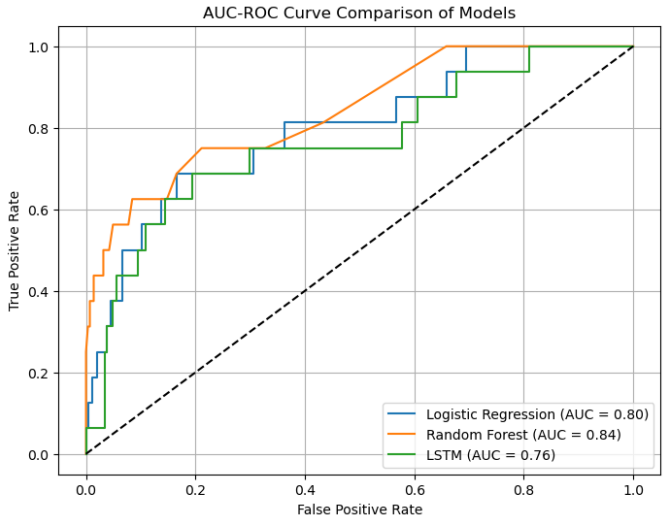

Fig. 1. AUC-ROC Curve Comparison of Logistic Regression, Random Forest, and LSTM Models

In Figure 1, LSTM achieves the highest AUC value, reflecting its superior ability to distinguish between fraudulent and legitimate transactions. Random Forest, with SMOTE-ENN, also performs well, suggesting that it can offer a balance between performance and computational efficiency, making it suitable for real-time applications where deep learning may be resource-intensive [4], [5].

D. Summary of Comparative Analysis

This analysis demonstrates that while traditional models like Logistic Regression benefit from resampling techniques such as SMOTE, ensemble models and deep learning techniques generally outperform them in detecting fraudulent transactions. The choice of model and resampling technique should consider both the desired performance metrics and the computational constraints of the application environment. For resource-limited settings, Random Forest with SMOTE-ENN offers a practical balance of accuracy and efficiency, while LSTM models may be preferable in high-resource environments for their superior discrimination abilities [2], [5].

V. DISCUSSION

The comparative analysis highlights several insights regarding the strengths and limitations of each machine learning technique in credit card fraud detection. This section discusses the implications of these findings, particularly in the context of handling imbalanced datasets and the trade-offs between model complexity and computational efficiency.

A. Impact of Model Choice and Data Resampling

Traditional models, such as Logistic Regression and SVM, demonstrated reasonable performance when paired with data resampling techniques like SMOTE [1]. However, these models alone struggled to achieve high precision and recall on imbalanced datasets without additional data balancing measures. This finding suggests that while these models are computationally efficient and interpretable, they may not be ideal for standalone use in high-stakes fraud detection systems without data preprocessing [2].

In contrast, ensemble models like Random Forest and Gradient Boosting Machines (GBM) showed more resilience to data imbalance, especially when paired with SMOTE-ENN [4]. The ability of these models to capture complex patterns through the combination of multiple weak classifiers made them particularly suited to fraud detection tasks [3]. This suggests that for real-world applications, ensemble methods are more likely to maintain robust performance across diverse datasets without extensive tuning.

B. Deep Learning Advantages and Limitations

The deep learning models, especially LSTM and GRU, demonstrated superior precision and recall on sequential transaction data [5]. These models excelled in identifying temporal dependencies in transaction sequences, which traditional models may overlook. However, the computational demands of deep learning models pose a significant limitation, particularly for real-time fraud detection applications where speed and resource efficiency are critical. While deep learning approaches may offer higher accuracy in resource-rich environments, their practicality in lower-resource settings remains limited [5].

C. Effectiveness of SMOTE and SMOTE-ENN Techniques

The application of SMOTE and SMOTE-ENN proved essential for improving model performance on imbalanced datasets [1], [3]. SMOTE helped improve recall across studies by generating synthetic samples, thereby allowing models to better recognize fraudulent patterns. However, SMOTE alone occasionally introduced noise, which could reduce precision. The combination of SMOTE with Edited Nearest Neighbor (ENN) in SMOTE-ENN refined the dataset further, selectively

removing noisy samples and thus improving overall precision and F1 scores [4]. This finding emphasizes the importance of choosing appropriate resampling techniques for handling imbalanced data effectively.

D. Trade-offs Between Accuracy and Computational Complexity

One key observation from this analysis is the trade-off between accuracy and computational complexity. While deep learning and ensemble methods generally outperformed traditional models in precision, recall, and AUC-ROC, they also required more processing power and memory [5]. For institutions deploying fraud detection systems in real-time environments, balancing model accuracy with computational efficiency is crucial. Ensemble models, especially those combined with resampling techniques like SMOTE-ENN, offer a favorable balance, providing robust performance without the heavy computational burden of deep learning models [4].

E. Practical Implications for Financial Institutions

The findings of this study suggest that financial institutions may benefit from adopting a hybrid approach, leveraging ensemble methods like Random Forest or Gradient Boosting with resampling techniques for enhanced detection accuracy [4]. Deep learning approaches can be considered in cases where transaction patterns exhibit strong temporal dependencies and computational resources allow for real-time processing. Furthermore, the importance of periodically updating models with new fraud data cannot be overstated, as fraud patterns continuously evolve [5].

This comparative analysis serves as a foundation for selecting appropriate machine learning techniques and resampling strategies for effective credit card fraud detection, highlighting both the technical and practical considerations essential for successful deployment [1], [2].

VI. Conclusion

This paper presents a comparative analysis of various machine learning techniques for credit card fraud detection, with a particular focus on handling imbalanced datasets through data resampling methods. The findings from this analysis reveal that while traditional models like Logistic Regression and SVM benefit from resampling techniques such as SMOTE [1], they often require additional tuning to achieve high recall and precision rates. Ensemble models, particularly Random Forest and Gradient Boosting Machines, demonstrated stronger resilience to class imbalance and consistently delivered balanced performance across key metrics [4], [3].

Deep learning models, including LSTM and GRU, showcased exceptional performance in identifying temporal patterns within transaction sequences, highlighting their potential for fraud detection in datasets with sequential dependencies [5]. However, the computational demands of these models pose a challenge for real-time deployment, particularly in resource-limited environments [5].

Data resampling techniques, especially SMOTE-ENN, proved effective in refining model performance by generating synthetic samples and removing noise, making them essential tools for addressing data imbalance issues [1], [3]. This study underscores the importance of selecting appropriate machine learning models and data balancing techniques to optimize fraud detection outcomes.

For practical implementations, a hybrid approach using ensemble models with SMOTE-ENN offers a favorable balance between accuracy and computational efficiency [4]. Financial institutions seeking to improve fraud detection accuracy may consider this combination to achieve robust, scalable solutions. Future research could explore adaptive learning techniques that account for evolving fraud patterns in real-time, further enhancing the reliability and effectiveness of fraud detection systems.

While this study provides a comprehensive comparison of various machine learning models and resampling techniques, there are several limitations. Firstly, the models evaluated are based on a single dataset (the Kaggle credit card fraud detection dataset), which may not represent the full spectrum of fraud scenarios across different regions or financial institutions. Additionally, the focus was primarily on the precision and recall of fraud detection models, while other factors such as model interpretability, deployment time, and the adaptability of models to changing fraud patterns over time were not thoroughly explored. Future research could consider testing these models on a wider variety of datasets and incorporating real-time fraud detection challenges to improve model generalizability and robustness.

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