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A Comprehensive Analysis of Credit Card Fraud Detection Using Hybrid Oversampling and Machine Learning Models

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ABSTRACT

Detecting credit card fraud is a challenging problem due to heavy class imbalance inherent in real world transaction which only a small fraction of observation is classed as fraudulent. This imbalanced dataset greatly reduces the power of classical machine learning and deep learning models, as the performance accuracy of these models will be high but their fraud detection ability will be very low. This paper gives a systematic review on imbalance handling methods utilized in the credit card fraud detection with an emphasis on confusion-matrix–based performance evaluation. All the data-level techniques like SMOTE and its varieties, hybrid resampling techniques like SMOTE-ENN, SMOTE-Tomek and algorithm level techniques have been reviewed systematically. The literature shows performance trends that can be analyzed in terms of recall, precision, F measure, and false positive behavior. As suggested by the review, regularly, hybrid resampling approaches achieve a more balanced detection performance by improving fraud recall while managing false alarms. The findings offer actionable insights for selecting effective imbalance reduction plans in fraud detection systems.

1. Introduction

The quick expansion of electronic payment systems has severely increased the risk of credit card fraud, leading to substantial financial losses and decrease user trust. As a result, fraud detection has become a major research focus in financial analytics. A conventional rule-based fraud detection systems depend on predefined features derived from known fraud patterns; however, these systems struggle to adapt to evolving and previously hidden fraudulent behaviour's[1].

Machine learning and deep learning techniques have been widely adopted due to their capability to model complex transaction patterns and automatically identify irregular behavior[2][3]. Despite their advantages, the performance of these models is highly affected by the severe class imbalance exists in fraud datasets, where fraudulent transactions typically represent about 1% or less of whole dataset[4]. Under such conditions, classifiers resort to favor the majority class, leading in high accuracy but low fraud detection performance[5][6].

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This challenge has prompted increasing focusing on confusion-matrix–based evaluation metrics, such as recall, precision, and F1-score, which provides a more accurate assessment of minority-class detection. To handle class imbalance, many data-level and algorithm-level reduction methods have been proposed, including oversampling, hybrid resampling, cost-sensitive learning, and loss-based optimization[7] [8].

Although comprehensive research conducted, a unified synthesis focusing on how variety imbalance handling methods impact confusion-matrix results in credit card fraud detection remains limited[9][10]. This review addresses this gap by methodically analyzing existing studies with an assertion on imbalance reduction methods and their reported performance trade-offs. The main contributions of this paper are summarized as follows:

- A structured categorization of imbalance handling techniques used in credit card fraud detection.
- A confusion-matrix–oriented analysis of reported performance trends.
- Identification of practical challenges and future research directions.

2. Review methodology

This review was conducted following a structured literature screening process. Relevant studies were collected from major scientific databases, including Scopus, IEEE Xplore, Web of Science, and Google Scholar. The search keywords included "credit card fraud detection," "class imbalance," "SMOTE," "hybrid resampling," and "fraud detection machine learning."

Publications from 2015–2025 were considered to ensure coverage of recent developments. Only peer-reviewed journal articles and conference papers focusing on credit card or financial fraud detection with explicit imbalance handling techniques were included. Survey papers without experimental analysis and non-financial fraud studies were excluded unless used for methodological background.

After removing duplicates and screening abstracts, 56 studies were selected for detailed analysis. These papers were categorized according to imbalance strategy, models used, and reported performance metrics, which are summarized in Table 1.

3. Background on Class Imbalance

In the detection of credit card frauds, a critical challenge is class imbalance, where actual credit card transactions exceed frauds significantly [11]. Due to the scrambled class distribution, learning algorithms tend to favor the majority class resulting in biased decision boundaries and poor minority-class generalization[12]. Hence, the classifiers might achieve high overall accuracy while missing out on fraudulent transactions and generating an excessive number of false negatives[13].

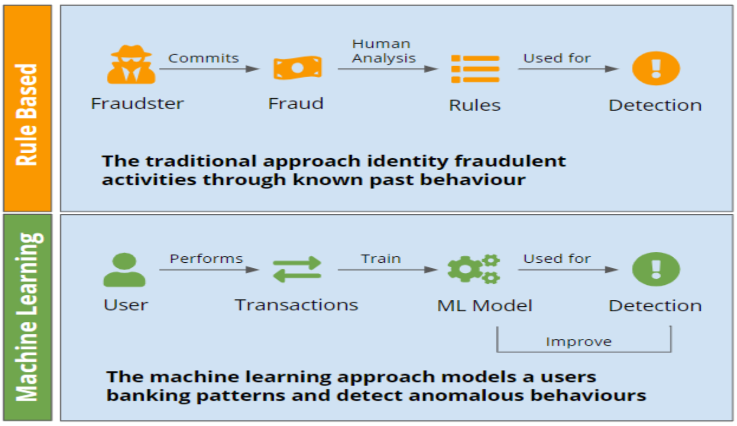

Figure 1. Comparison of rule-based and machine learning–based fraud detection approaches.

A variety of much more serious issues, such as class overlap, noisy labels, and concept drift, are largely present in fraud datasets. These traits make minority-class learning even more difficult and require an imbalance reduction technique [14].

3.1 Data-Level Imbalance Handling

Data-level techniques decrease the class skew or non-uniformity of the training data and unclear expression. Oversampling techniques, especially the Synthetic Minority Over-sampling Technique (SMOTE), are mostly being used to create synthetic minority-class samples [15]. Similar methods include Borderline-SMOTE. These methods focus on "hard"/borderline instances to generate new samples. These methods will always improve recall on fraud but may add artificial noise which may blow up false positives [16] [17][5] [18].

3.2 Algorithm-Level and Loss-Based Approaches

Algorithm-level tactics refer to the adjustments made to the learning process versus the data distribution in order to address class imbalance. Cost-sensitive learning assigns a higher penalty to fraud samples that are misclassified. As a result, the models become bolder in recognizing minority classes. Loss-based methods (e.g., focal loss) put even greater emphasis on difficult instances.

In many cases, focal loss had impacted fraud detection based on deep learning. Although these methods do not generate synthetic data, they are mostly sensitive to parameter tuning[19].

3.3 Evaluation Metrics for Imbalanced Detection

Precise evaluation is critical in imbalanced classification. Metrics such as accuracy and ROC-AUC may present misleading assessments under intense imbalance. Consequently, fraud detection studies increasingly depend on confusion-matrix–based metrics, such as recall, precision, F1-score, and false positive rate. Precision–recall analysis is particularly informational, as it directly shows the trade-off between fraud detection sensitivity and false alarms[20][21].

4. Balancing Techniques in Fraud Detection

Balancing techniques are central to reduce class imbalance in credit card fraud detection. Existing studies use a range of strategies to enhance minority-class representation and enhance fraud detection performance. These techniques can be generally grouped into oversampling-based methods, hybrid resampling technique, feature-selection–guided strategies, and algorithm-level solutions[9], [22]. A taxonomy of imbalance handling techniques is illustrated in Fig. 2.

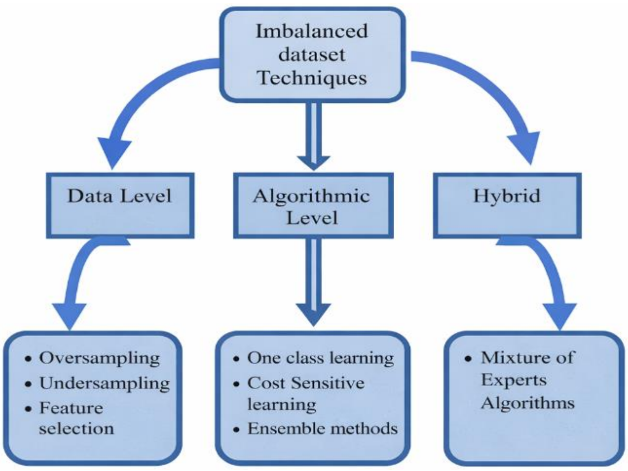

Figure 2. Taxonomy of class imbalance handling techniques

4.1. Oversampling-Based Approaches

Oversampling approaches are widely applied for imbalance reduction strategies in fraud detection research[23]. Methods like SMOTE produce synthetic fraudulent transactions to rise minority-class representation at training. Many studies report that SMOTE-based oversampling substantially enhances fraud recall and F1-score by decreasing false negatives by a wide range of classifiers[24] [25].

Adaptive oversampling approaches, including ADASYN and Borderline-SMOTE, aim to concentrate synthetic sample generation on hard or boundary instances These methods can improve minority-class detection in complex datasets, particularly when combined with nonlinear classifiers. However, their effectiveness depends on dataset characteristics and classifier sensitivity to noise.[26][16] [27].

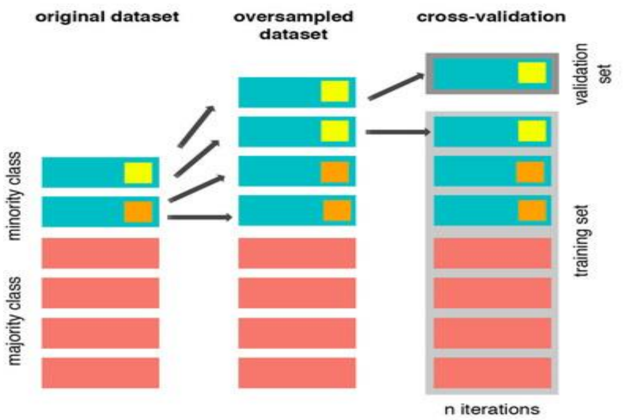

Figure 3. Oversampling of the minority class within cross-validation to balance training data while preserving validation data distribution.

4.2. Hybrid Resampling Techniques

Hybrid resampling techniques address the limitations of standalone oversampling by combining synthetic sample generation with noise removal or undersampling. Methods such as SMOTE-ENN and SMOTE-Tomek eliminate ambiguous or overlapping samples after oversampling, resulting in cleaner decision boundaries.

Across the reviewed literature, hybrid approaches consistently demonstrate more balanced confusion-matrix outcomes than standalone oversampling. By improving recall while controlling false positives, these methods are particularly suitable for operational fraud detection systems. Ensemble classifiers, including Random Forest and gradient-boosting models, are frequently reported to benefit most from hybrid resampling due to their robustness to residual noise.[28].

4.3 Feature-Selection–Guided and Algorithm-Level Strategies

To improve the identification of between fraudulent and legitimate transactions, feature selection is combined with resampling methods. Balancing methods guided by feature selection enhance accuracy and stabilize performance under imbalance by focusing on informative features[29].

Strategies that modify the algorithm level like cost-sensitive learning or loss-based optimization methods do not change the data distributions but modify the focus on certain data. Such algorithms push the model to conduct more fraud predictions during training, which has delivered promising results especially in deep-learning frameworks[30]. However, their performance is often sensitive to parameter adjustments. Several studies recommend getting these values from data-level balancing for improving robustness[31].

5. Analysis of Reported Performance

This section synthesizes performance trends reported across credit card fraud detection studies, with emphasis on confusion-matrix–based metrics. Instead of comparing absolute numerical results—which vary across datasets and evaluation protocols—the analysis focuses on consistent patterns in recall, precision, F1-score, and false positive behavior under different imbalance mitigation strategies.[32].

5.1 Performance on Raw Imbalanced Data

Across nearly all reviewed studies, models trained on unbalanced datasets exhibit a common limitation: high overall accuracy combined with poor fraud detection capability. Because fraudulent transactions represent a small minority, classifiers tend to predict the majority class, producing large numbers of false negatives. This behavior is reported for both classical machine learning and deep learning models and demonstrates that accuracy alone is not an appropriate performance metric in fraud detection.

Studies that evaluate models using recall and F1-score consistently show that minority-class performance is severely underestimated when imbalance is not addressed. These findings justify the widespread adoption of resampling and cost-sensitive techniques in fraud detection research.[33].

5.2 Impact of Oversampling Techniques

SMOTE-based oversampling improves fraud recall but may increase false positives due to synthetic noise. But many papers mention that false positives are increased, especially when the synthetic samples are created in overlapping or noisy regions. If improperly handled, this trade-off compromises precision and might limit practical usage[20], [34].

5.3 Effectiveness of Hybrid Resampling

When it comes to the confusion-matrix outcomes, using hybrid resampling methods brings us better results than using only oversampling methods. The techniques such as SMOTE-ENN and SMOTE-Tomek avoid false negatives or false positives through noise removal techniques. According to the literature, the approaches yield more stable decision boundaries and enhance generalization, particularly with ensemble classifiers[5], [17], [28].

5.4 Classifier-Specific Trends

The effectiveness of imbalance mitigation heavily relies on the classifier choice. Ensemble-based models like Random Forest and the gradient-boosting method are robust to noisy synthetic samples and exhibit good precision–recall trade-offs.

Balanced techniques help linear and distance-based classifiers but are more sensitive to noise; thus, hybrid resampling is important in such cases.[35] [36].

5.5 Evaluation Practices

The evaluation protocols of the studies that we reviewed are quite different. Nonetheless, confusion-matrix metrics and precision-recall analysis has become a popular choice. Compared with accuracy or the ROC-AUC, these metrics give a better idea of performance for fraud detection, especially with severe class imbalance[37].

5.6 Synthesis of Performance Trends

The literature evaluated had found results that are similar. To efficiently identify fraud, numerous balancing approaches, such as oversampling, informal[38]. But in all circumstances, we see hybrid resampling methods outperforming their standalone counterparts. They have more control over false positives. Ensemble classifiers are shown to produce the most stable performance under balancing; loss-based ones have a lot of potential [9]. The different trends viz. model characteristics and the application requirement together highlights the significance of choosing a wrong handling strategy. [39]

The reviewed literature indicates that hybrid resampling methods outperform standalone oversampling primarily because they reduce class overlap and synthetic noise while preserving minority-class representation. Their effectiveness is most pronounced when used with ensemble classifiers that are less sensitive to residual noise. However, hybrid methods may increase computational cost and require parameter tuning, particularly in large-scale or real-time fraud detection systems.

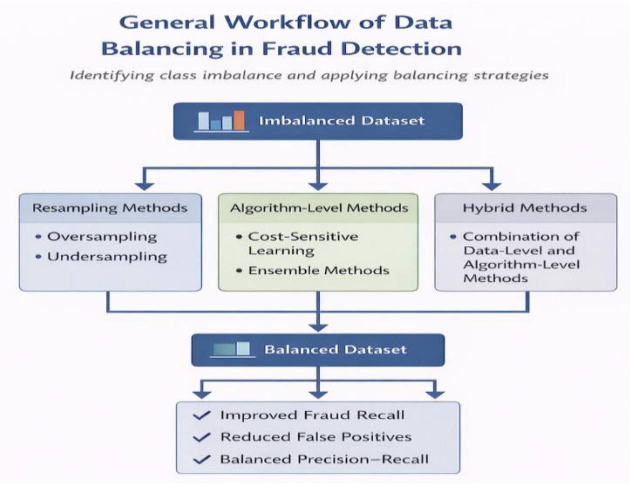

Figure 4. General workflow of data balancing in fraud detection

6. Advanced and Emerging Directions Recent studies in fraud detection have investigated advanced techniques to overcome the drawbacks of traditional resampling methods [40][41], particularly in the context of a highly skewed and complex transaction context. The new techniques aim to enhance the detection of minority classes while alleviating noise amplification and improving model robustness [42].

6.1 Generative Models for Imbalanced Fraud Data

Generative models, in particular GANs, have been suggested as alternatives to traditional oversampling techniques [43]. Generative Adversarial Networks (GANs) can enhance the performance of fraudulent transaction detection systems by generating synthetic samples. Many studies report reduced number of false negatives when you apply gan-based augmentation but these methods are very complicated and require careful tuning making it hard to use [44].

6.2 Graph-Based and Structural Approaches

Graph-based fraud detection techniques utilize relationships among entities such as cards, merchants, and users to identify and represent structural fraud patterns. The most recent works that integrated imbalance handling with graph learning (GL) reported better detection of minority classes due to preserving the relational information unlike existing literature and baselines. Graph-based techniques, despite their powerful efficacy, typically incur high computational costs. They also necessitate complex data preparation, which are limitations in the applicability of these methods to large-scale systems characterized by rich relational data[45].

6.3 Loss-Based and Hybrid Learning

The focus of loss-based approaches like the focal loss and cost-sensitive optimization is to tackle imbalance algorithmically rather than adjusting data distributions. The methods have achieved good results in the furtherance of deep learning-based fraud detection by focusing on hard to detect minority class instances. Hybrid techniques that embrace loss-based learning and data-level balancing are now more commonly reported to deliver more stable performances[19].

6.4 Explainability and Emerging Paradigms

Because of the importance of transparency and regulations, explainable AI techniques are getting popular in fraud detection. Although explainability doesn’t fix class imbalance directly, it helps us understand how the imbalance mitigation strategy affects model behaviour. New concepts including hybrid artificial–quantum intelligence are still in the experimental phase and need to be verified[19].

6.5 Practical Deployment Challenges

Despite promising research results, several challenges remain for real-world fraud detection deployment. Real-time processing requirements limit the use of computationally intensive resampling methods. Concept drift in transaction behavior reduces model accuracy over time, requiring adaptive retraining. Data privacy regulations restrict data sharing for model training, while high false positive rates may increase operational costs and customer dissatisfaction. Additionally, interpretability requirements in financial systems demand explainable fraud detection models. Addressing these issues is essential for translating imbalance-aware models into operational systems.

7. Open Challenges and Research Gaps

Imbalance-aware fraud detection has made great strides but is still under-developed. A big issue is the absence of official assessment evaluation protocols. Different datasets, resampling ratios, validation strategies, performance metrics make it difficult to make direct comparisons. Even though accuracy and ROC-AUC are being used in some papers, we believe some works may be masking the minority class performance [46].

Another limitation is that not all parts of the confusion matrix are reported. Numerous studies present derived metrics without sharing counts of true positive, false positive, false negative, and true negative, which limits reproducibility and further performance analysis. There is a need for more transparent reporting practices to enable trustworthy comparative research [47].

A constant trade-off will be fraud recall and false positive rates. When techniques to mitigate imbalances do help in detecting the minority classes but may raise the falsity alarms that would lead to higher operational costs and worse user experience. A study showed that it remains an open issue in research to determine trade-offs across applications [48]. Moreover, balancing techniques greatly depend on the dataset (the degree of imbalance, the number of attributes, noise, overlap and others). Existing works have limited cross-dataset validation and robustness analysis. Most research also focusses on off-line analysis while little attention to real-time deployment, concept drift, and scalability. Despite the growing interest in explainable artificial intelligence (AI), few studies have examined its interaction with imbalance handling strategies [19], [28].

8. Conclusion

The comparison shown in Table.1 indicates that dealing with class imbalance is vital for effective credit card fraud detection. Most studies make use of data level oversampling techniques like SMOTE and its variants. These have been proven to be useful in improving the detection of the minority class as exhibited by the reduced false negatives. Several works indicate that using oversampling methods on their own can lead to more false positives, which suggests that this calibration is trade-offed. Methods that combine oversampling and undersampling strategies such as SMOTE-ENN and those that rely on clustering for resampling often reduce noise and overlap and thus produce a more balanced confusion-matrix outcome. Furthermore, it has been shown that ensemble-based classifiers like Random Forest and gradient-boosting benefit from imbalance mitigation methods more than others. Based on the results presented in Table 1, we can say that hybrid resampling techniques with ensemble learning offer a more stable and generalizable solution for credit card fraud detection with severe class imbalance. It also reiterates the importance of confusion-matrix-based evaluation metrics over accuracy-based evaluation.

Table 2 summarises the main patterns observed across the reviewed credit card fraud detection studies. The comparison shows that SMOTE-based oversampling remains the most commonly used imbalance-handling technique, due to its simplicity and consistent improvements in fraud recall. However, hybrid resampling methods, particularly SMOTE-ENN and SMOTE-Tomek, generally achieve more balanced precision–recall performance by reducing synthetic noise and class overlap. The table also indicates that ensemble classifiers such as Random Forest and gradient-boosting models provide the most stable results when combined with imbalance mitigation strategies. Finally, the variation in evaluation metrics across studies highlights the need for standardised confusion-matrix reporting in fraud detection research.

To provide a visual summary of the performance trends reported in the reviewed studies, Fig.5 illustrates the comparative impact of common balancing techniques on confusion-matrix metrics, including recall, precision, and F1-score.

9. Future Work

Future study should focus on consistent evaluation methods with cross-dataset validation and comprehensive confusion-matrix reporting to improve comparability between investigations. Adaptive imbalance handling strategies that consider concept drift and evolving fraud behavior are necessary for real-time deployment. The computational cost and parameter sensitivity of hybrid resampling algorithms necessitate additional optimization for large-scale systems, notwithstanding their outstanding performance. Explainable AI and privacy-preserving learning must be combined with imbalance mitigation for widespread use and legal compliance. Finally, examining how to combine graph-based models and generative data augmentation with imbalance handling could enhance the detection of complex and novel fraud behaviours.

Table 1: Class imbalance strategies and corresponding findings in financial fraud detection literature

Author(s) / Year	Imbalance Strategy	Models Used	Key Findings
Zhu *et al.* (2024) [49]	SMOTE	Neural Network	SMOTE significantly improved fraud recall and F1-score while maintaining stable precision in neural network models.
Samant *et al.* (2024) [50]	SMOTE	RF, SVM, LR	Oversampling reduced false negatives substantially; RF achieved the most stable precision–recall balance.
Patel & Panday (2023) [29]	Feature Selection + Imbalance handling	GA-based ML models	Genetic algorithm–based feature selection improved minority-class detection under imbalance.
Albalawi & Dardouri (2025) [40]	SMOTE, loss-aware training	RF, DL models	Hybrid imbalance mitigation improved recall across both ML and DL models.
Salem *et al.* (2025) [51]	SMOTE	ML & DL models	SMOTE preprocessing consistently improved fraud recall and F1-score across classifiers.
Wang (2024) [52]	FS-SMOTE	ML classifiers	Feature-selected SMOTE reduced class overlap and improved precision.
Sakpal & Sinha (2024) [27]	SMOTE, ADASYN	ML models	SMOTE achieved better precision–recall trade-off than ADASYN.
Mustafa *et al.* (2025) [17]	SMOTE-ENN + ADASYN	RF, XGBoost, KNN	Hybrid oversampling achieved the lowest false negatives with controlled false positives.
Hidayat *et al.* (2024) [53]	Hybrid sampling	SVM	Hybrid sampling improved decision boundaries and fraud recall.
Al Dulaimi & Nnamoko (2025) [39]	Data-level + algorithm-level	ML classifiers	Combined imbalance strategies improved fraud detection robustness.
Damanik & Liu (2025) [46]	K-SMOTEENN	Stacking ensemble	Clustering-based hybrid oversampling produced the best F1-score and recall.
Patel *et al.* (2025) [28]	SMOTE-ENN	XGBoost	Hybrid resampling significantly improved real-time fraud detection performance.
Yu *et al.* (2016) [11]	SMOTE-based balancing	Ensemble ML	Ensemble classifiers demonstrated resilience to imbalance with improved recall.
Huang *et al.* (2024) [54]	Clustering-based undersampling	Hybrid NN	Noise removal reduced false positives while maintaining high recall.

Wen *et al.* (2024) [45]	Graph Trans-SMOTE	ML models	Graph-aware oversampling improved minority detection in transaction networks.
Bounab *et al.* (2024) [18]	SMOTE-ENN	ML classifiers	Hybrid resampling improved both recall and precision in healthcare-style fraud data.
Sundaravadivel *et al.* (2025) [47]	SMOTE	Random Forest	SMOTE improved recall, though results must be interpreted cautiously due to retraction.
Wang (2025) [9]	Data balancing + ensemble	Ensemble ML	Combined balancing and ensemble learning achieved strong recall gains.
Darwish *et al.* (2025) [55]	Imbalance-aware learning	ML models	Improved fraud detection across multiple transaction categories.
Rinku *et al.* (2021) [56]	Oversampling	ML classifiers	Oversampling reduced false negatives in imbalanced credit card data.
Purohit & Vishwakarma (2021) [1]	Imbalance-aware preprocessing	ML models	Class imbalance handling improved fraud classification reliability.

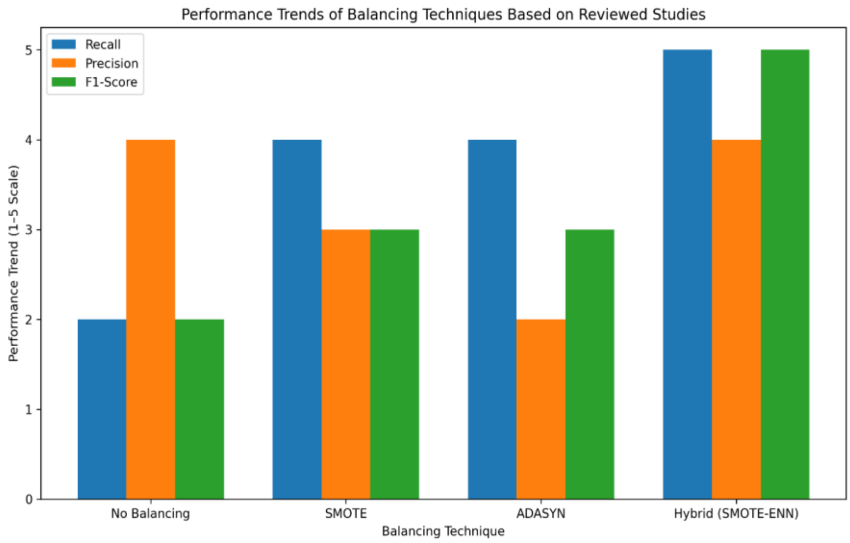

Figure 5. Summary of performance trends of imbalance handling techniques based on confusion-matrix metrics reported in credit card fraud detection studies. Values represent qualitative trends synthesized from Table 1.

Table 2. Key insights derived from the comparison of credit card fraud detection studies using imbalance handling techniques.

Observation	Evidence from Table 1	Implication
SMOTE widely used	Majority of studies use SMOTE-based balancing	Simple and effective baseline method
Hybrid resampling performs better	SMOTE-ENN / SMOTE-Tomek show balanced recall & precision	Noise removal is critical in fraud datasets
Ensemble models most robust	Random Forest, XGBoost common in high-performing studies	Ensemble learning handles imbalance better
Evaluation methods inconsistent	Different metrics and validation protocols	Need standardised confusion-matrix reporting

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