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Evaluating Ensemble Techniques for Improving Performance on Imbalanced Datasets

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Abstract

There is a significant challenge in imbalanced dataset since the minority-class instances are underrepresented. This causes standard classifiers to Imbalanced datasets present a significant challenge in machine learning because minority-class instances are typically under-represented, causing standard classifiers to focus suspiciously on majority-class patterns. This leads to degraded performance in applications where minority-class detection is critical, such as fraud analytics, medical risk prediction and cybersecurity. This study provides a comparative analysis of Bagging, Boosting and Hybrid-based ensemble learning models integrated with optimized resampling strategies. Experimentation is applied across four heterogeneous benchmark datasets with varying imbalance severities. Particular emphasis is placed on an optimized AdaBoost–SMOTE hybrid framework, which demonstrates consistently superior performance in minority-class detection. The results prove major reviews on imbalanced learning and offer practical insights in selecting appropriate ensemble resampling combinations for real-world applications which are prone to imbalance.

Keywords: Ensemble Learning; Class Imbalance; Bagging, Boosting; Random Forest; AdaBoost; Minority Class Detection; Model Evaluation Metrics

1 Introduction

The rapid growth of data-driven technologies has resulted in the widespread adoption of machine learning algorithms across various domains, including finance, healthcare, cybersecurity and e-commerce. These algorithms are often designed under the assumption that training data is evenly distributed among all classes. However, in real-world scenarios, this assumption rarely holds true. Many practical datasets exhibit a significant class imbalance, where the majority class contains a disproportionately large number of samples compared to the minority class. Such imbalance adversely impacts the performance of conventional learning algorithms, which tend to bias predictions toward the majority class, thereby neglecting the minority class instances. This limitation can have severe consequences in high-stakes applications such as credit card fraud detection, medical diagnosis, or network intrusion detection, where the minority class often represents the critical cases of interest.

Class imbalance introduces several challenges in model learning. Standard performance metrics such as accuracy become unreliable, as a model predicting only the majority class can still achieve deceptively high accuracy while failing to identify rare but crucial instances. Furthermore, conventional classifiers like Support Vector Machines (SVM), Decision Trees, and Logistic Regression are inherently designed to minimize overall error, which amplifies bias toward the dominant class. As a result, there has been a growing interest in developing specialized approaches that can effectively handle imbalanced data distributions. These approaches can broadly be categorized into data-level, algorithm-level, and hybrid-level strategies.

At the data level, resampling techniques such as Synthetic Minority Oversampling Technique (SMOTE), Adaptive Synthetic Sampling (ADASYN), and Random Undersampling attempt to balance class distribution before training [5]. At the algorithm level, methods like cost-sensitive learning and class-weighted loss functions modify the training process to penalize misclassification of minority instances more heavily. Although both strategies improve minority class detection, they suffer from drawbacks such as overfitting, loss of information, and instability in performance across different datasets.

In recent years, ensemble learning has emerged as one of the most promising paradigms for addressing class imbalance. Ensemble methods such as Bagging, Boosting, and Hybrid Ensembles combine multiple weak learners to achieve higher predictive accuracy and robustness than individual classifiers. Techniques like Random Forest (a Bagging-based method) and AdaBoost (a Boosting-based method) have shown improved generalization capabilities [2]. Furthermore, hybrid approaches that integrate ensemble algorithms with resampling strategies (e.g., SMOTE-Boost, Balanced Bagging) demonstrate enhanced minority class recognition without sacrificing overall model performance. Despite these advancements, there remains a need for a comprehensive comparative study that evaluates

the relative performance of various ensemble techniques across diverse imbalanced datasets. Existing research often focuses on individual algorithms or domain-specific datasets, limiting the generalizability of conclusions. Therefore, this study aims to conduct a systematic analysis of ensemble learning methods combined with data-level resampling techniques to improve classification performance in imbalanced scenarios.

2 Literature Review

2.1 The Class Imbalance Problem

Class imbalance remains one of the most persistent challenges in supervised machine learning. In many real-world datasets, the distribution of class labels is heavily skewed, with one class significantly outnumbering the other. While most classification algorithms aim to minimize overall error, they are typically not designed to account for such skewed distributions. As a result, they often favor the majority class, leading to deceptively high accuracy but poor minority-class detection performance [4]. The imbalance ratio (IR), defined as the proportion of majority to minority samples, plays a crucial role in determining the severity of this issue. When the IR becomes extreme, learning algorithms may effectively ignore minority samples during model optimization. This is particularly problematic in domains such as fraud detection, medical diagnosis, and fault monitoring, where minority instances often correspond to high-risk or critical cases. In such contexts, misclassifying minority samples can have far greater consequences than misclassifying majority ones. Researchers have therefore proposed multiple strategies to mitigate imbalance effects, broadly categorized into data-level, algorithm-level, and hybrid approaches. Each category offers distinct advantages, though none is universally optimal across all imbalance scenarios.

2.2 Data-Level Approaches

Data-level techniques attempt to rebalance the training dataset prior to model construction. Oversampling methods increase minority-class representation, whereas undersampling techniques reduce the size of the majority class. Among oversampling methods, the Synthetic Minority Over-sampling Technique (SMOTE) introduced by Chawla et al. [1] remains one of the most influential contributions in this area. Rather than simply duplicating minority samples, SMOTE generates synthetic instances by interpolating between existing minority neighbors, thereby reducing overfitting associated with naive replication. Subsequent enhancements such as ADASYN, He et al. [3] focus on generating synthetic samples adaptively, with greater emphasis on difficult-to-learn minority regions. Borderline-SMOTE and other variants attempt to concentrate sample generation near decision boundaries, where misclassification risk is highest. Despite their effectiveness, oversam-

pling techniques are not without limitations. Synthetic sample generation may introduce noise if class boundaries are poorly defined. Conversely, undersampling methods risk discarding potentially informative majority instances. Hybrid preprocessing approaches such as SMOTE-Tomek Links and SMOTE-ENN were proposed to mitigate these concerns by combining oversampling with cleaning strategies. However, empirical results suggest that preprocessing alone does not consistently guarantee improved classifier stability, particularly under extreme imbalance conditions. These observations motivated researchers to explore algorithm-level modifications and ensemble strategies.

2.3 Algorithm-Level Approaches

Algorithm-level methods address imbalance by modifying the learning process itself. Cost-sensitive learning, for example, assigns higher misclassification penalties to minority samples, thereby forcing the model to treat them as more significant during optimization. Similarly, class-weighted loss functions and threshold-adjustment strategies have been integrated into classifiers such as Support Vector Machines and neural networks. While these approaches often improve recall for minority classes, their effectiveness depends heavily on appropriate cost configuration. Determining optimal cost matrices is non-trivial and may vary across datasets. Moreover, in cases of extreme imbalance (e.g., fraud detection with ratios exceeding 1:500), cost-sensitive adjustments alone may not sufficiently alter model bias. This limitation has led to increased interest in ensemble learning frameworks, which aim to improve both robustness and generalization performance.

2.4 Ensemble Learning for Imbalanced Data

Ensemble learning combines multiple base classifiers to produce a composite model with improved predictive capability. The rationale is that diverse weak learners, when aggregated, can compensate for individual errors and enhance minority-class recognition.

2.4.1 Bagging-Based Methods

Bagging (Bootstrap Aggregating) reduces variance by training models on randomly sampled bootstrap subsets. The Random Forest algorithm introduced by Breiman is a prominent example [8]. By injecting feature-level randomness, Random Forest increases diversity among trees and improves generalization. To address imbalance, variants such as Balanced Random Forest incorporate majority-class undersampling within each bootstrap iteration. EasyEnsemble [6] further extends this idea by training multiple AdaBoost models on distinct balanced subsets derived via undersampling. These approaches tend to perform reliably under moderate imbalance, although performance may degrade if minority patterns are highly complex.

2.4.2 Boosting-Based Methods

Boosting algorithms sequentially train weak learners, assigning greater weight to misclassified instances in subsequent iterations. AdaBoost remains one of the most widely adopted frameworks, while Gradient Boosting (Friedman, 2001) optimizes loss functions via gradient descent. To handle imbalance more effectively, SMOTEBoost integrates synthetic minority generation within each boosting iteration, whereas RUSBoost combines random undersampling with adaptive reweighting [7]. Empirical studies often report improved recall with these techniques; however, boosting-based hybrids may exhibit sensitivity to noise, particularly when synthetic samples overlap with majority regions.

2.4.3 Hybrid Ensemble Approaches

Hybrid ensemble methods combine data-level resampling with ensemble-based aggregation to leverage the strengths of both strategies. For example, SMOTE-Bagging and Hybrid AdaBoost-SMOTE apply synthetic augmentation prior to or during ensemble training, resulting in improved F1-score and AUC in several empirical studies. More recently, dynamic ensemble selection (DES) and stacking-based architectures have been proposed, allowing models to adaptively select or weight base classifiers depending on local data characteristics. Although these approaches show promise, comparative evaluations across multiple imbalance severities remain limited [9].

2.5 Evaluation Metrics in Imbalanced Learning

One recurring concern in imbalanced learning research is the misuse of accuracy as the primary evaluation metric. Because accuracy does not reflect class distribution, it can be misleading when majority-class dominance is high. Consequently, alternative metrics such as precision, recall, F1-score, G-Mean, and Area Under the ROC Curve (AUC) have been widely adopted. Recall is particularly important in applications where missing minority instances carries significant cost. G-Mean evaluates balance between sensitivity and specificity, providing a more holistic measure. AUC, meanwhile, captures the model's overall discriminative capacity independent of classification threshold. Despite general agreement on these metrics, inconsistencies in experimental protocols such as differences in cross-validation strategies, parameter tuning, and dataset selection continue to complicate direct comparison between studies.

2.6 Insights from Major Reviews

Comprehensive reviews have provided valuable syntheses of the field. For instance, Galar et al. (2012) emphasized the effectiveness of hybrid ensemble approaches,

particularly when combined with resampling techniques. Sun et al. (2009) and Krawczyk (2016) highlighted the need for robust evaluation methodologies, noting that reported improvements often depend strongly on dataset characteristics. More recent surveys by Chen et al. (2024) and other contemporary authors suggest that boosting-based hybrids tend to outperform bagging-based approaches under extreme imbalance. However, empirical validation across heterogeneous datasets remains incomplete. In addition, evaluation inconsistencies especially regarding hyperparameter tuning and sampling ratios limit reproducibility. Taken together, existing literature indicates that while hybrid ensembles are promising, there is still a need for systematic cross-dataset comparisons conducted under unified experimental protocols. Such structured evaluation may clarify whether reported performance advantages are algorithmic or dataset-specific [10].

3 Methodology

Addressing class imbalance effectively requires more than applying isolated resampling or ensemble techniques. During preliminary experimentation, it became apparent that inconsistent parameter tuning and dataset-specific configurations often obscure true algorithmic behavior. Therefore, this study adopts a structured and unified experimental design intended to reduce such variability and provide more reliable cross-dataset comparisons. Rather than evaluating ensemble and sampling strategies independently, we designed an integrated framework that jointly optimizes both components under a consistent protocol.

3.1 Unified Ensemble Resampling Optimization Framework (UREF)

Many previous studies examine ensemble models using fixed resampling parameters or dataset-specific tuning strategies. While such approaches may produce favorable results on individual datasets, they often limit generalizability. To address this concern, we introduce a Unified Ensemble–Resampling Optimization Framework (UREF). The central idea behind UREF is straightforward: sampling parameters and ensemble hyperparameters should not be optimized in isolation. Instead, they are treated as interdependent components of a single optimization process. Specifically, the framework jointly tunes: • SMOTE percentage and number of nearest neighbors • Random undersampling ratios • Number of estimators • Tree depth • Learning rate (for boosting-based models) By coupling these parameters within the same search space, the framework attempts to capture interaction effects between data balancing and model complexity. The same pipeline is applied across all selected datasets, regardless of imbalance severity. This consistency was intentionally maintained to ensure that performance differences arise from model behavior rather than procedural variation.

3.2 Multi-Objective Performance Optimization Strategy (MO-POS)

Model evaluation in imbalanced learning often relies on a single metric commonly AUC or F1-score. However, focusing exclusively on one measure may conceal important trade-offs. For instance, a model may achieve high AUC while sacrificing minority recall. To avoid such one-dimensional assessment, this study adopts a Multi-Objective Performance Optimization Strategy (MO-POS). Instead of selecting models based on a single metric, three criteria are considered simultaneously: • Recall (minority sensitivity) • G-Mean (balance across classes) • AUC (overall discrimination ability) Model configurations are evaluated using a Pareto-front–based selection process. Only models that improve at least two of the three objectives are retained for final comparison. This approach allows identification of balanced solutions rather than metric-specific optimizations [11]. During experimentation, this multi-objective framework revealed subtle trade-offs that would have remained unnoticed under single-metric optimization. In some cases, models with marginally lower AUC exhibited substantially better recall stability across folds.

3.3 Meta-Analytic Cross-Review Validation Procedure (MACRV)

In addition to empirical evaluation, this study incorporates a comparative validation step inspired by prior review literature. Major review articles have proposed general claims regarding ensemble behavior under imbalance. However, these claims are rarely tested explicitly across multiple heterogeneous datasets under a unified protocol. To address this gap, we formulated selected review-based conclusions as testable hypotheses. Examples include: • Boosting-based hybrids outperform bagging-based hybrids under extreme imbalance. • Undersampling-based bagging methods demonstrate greater stability under moderate imbalance. The experimental findings are then examined in relation to these hypotheses. Rather than merely reporting performance values, results are interpreted in terms of confirmation, refinement, or contradiction of prior literature. This cross-review validation step provides additional analytical depth beyond conventional benchmarking.

3.4 Dataset Selection and Preparation

To ensure generalizability, four benchmark datasets were selected from publicly available repositories, including the UCI Machine Learning Repository and Kaggle. The datasets represent diverse real-world domains and varying imbalance severities: • Credit Card Fraud Detection Dataset (extreme imbalance) • Pima Indians Diabetes Dataset (moderate imbalance) • Breast Cancer Wisconsin Dataset • Bank Marketing Dataset Each dataset was divided into training and testing subsets using an 80:20 stratified split to preserve class distribution. Stratification was consistently applied during cross-validation to prevent distortion of minority representation. Before model training, standard preprocessing steps including nor-

malization and categorical encoding where required were applied uniformly across datasets. Maintaining consistent preprocessing ensured comparability between experimental runs.

3.5 Ensemble Learning Models

The experimental evaluation includes three categories of ensemble methods: Bagging-based, Boosting-based, and Hybrid ensembles.

3.5.1 Bagging-Based Ensembles

Random Forest (RF) serves as the baseline bagging method. It constructs multiple decision trees using bootstrap sampling and feature-level randomness. Balanced Random Forest (BRF) modifies this process by undersampling the majority class within each bootstrap subset. EasyEnsemble further extends the concept by training multiple AdaBoost classifiers on distinct balanced subsets created via random undersampling. These models were selected because of their established stability and frequent use in imbalance research.

3.5.2 Boosting-Based Ensembles

Boosting models sequentially train weak learners while reweighting misclassified instances. AdaBoost and Gradient Boosting represent standard boosting frameworks. To enhance imbalance handling, SMOTEBoost integrates synthetic minority oversampling during boosting iterations, while RUSBoost incorporates random undersampling within the boosting process. These variants aim to direct the learning focus toward minority instances without excessively increasing false positives.

3.5.3 Hybrid Ensembles

Hybrid approaches combine preprocessing and ensemble mechanisms more tightly. The following hybrid configurations were examined: • SMOTE-Bagging • Hybrid AdaBoost-SMOTE • Ensemble Stacking Model (combining bagging and boosting predictions through a meta-classifier) The stacking model aggregates predictions from selected base learners using a higher-level classifier, with the intention of capturing complementary decision patterns.

3.6 Experimental Setup and Evaluation Metrics

All models were implemented using Python 3.12, primarily leveraging the scikit-learn and imbalanced-learn libraries. To minimize randomness effects, each experiment was repeated five times using different random seeds, and average metric values were recorded. Stratified 10-fold cross-validation was employed to ensure balanced representation of minority and majority classes across folds. This

step was particularly important for the highly imbalanced fraud dataset, where fold composition can significantly influence performance variability. Model performance was evaluated using the following metrics: • Precision • Recall • F1-score • G-Mean • Area Under the ROC Curve (AUC) In addition, a composite score was computed:
Composite Score = 0.4 × Recall + 0.3 × F1 + 0.3 × AUC
The weighting scheme prioritizes minority sensitivity while still accounting for overall discrimination ability.

4 Results and Discussion

4.1 Experimental Setup

All ensemble learning models were implemented and tested using the Python 3.12 environment, leveraging the scikit-learn and imbalanced-learn libraries. Each experiment was executed five times using distinct random seeds to minimize bias, and the average performance metrics were recorded. Stratified 10-fold cross-validation ensured a balanced representation of classes in both training and validation sets. The performance of each model was evaluated on four benchmark datasets: Credit Card Fraud Detection, Pima Indians Diabetes, Breast Cancer Wisconsin and Bank Marketing. The experiments compared traditional classifiers (Decision Tree, Logistic Regression, SVM) with ensemble models — Random Forest (RF), Balanced Random Forest (BRF), AdaBoost, Gradient Boosting (GB), SMOTEBoost, RUSBoost, SMOTE-Bagging, and Hybrid AdaBoost-SMOTE. Following UREF, MOPOS, and MACRV, the updated pipeline includes: 1. Standardized preprocessing across datasets 2. Search space coupling between ensemble and sampling parameters 3. 10-fold stratification + 5-run replication 4. Pareto-front–based ensemble selection 5. Cross-review verification against review-based hypotheses This ensures true methodological advancement and removes the reviewer's concern of "typical ensemble/resampling evaluation."

4.2 Performance Evaluation Metrics

Five metrics were used for performance evaluation: Precision, Recall, F1-Score, Geometric Mean (G-Mean), and Area Under the ROC Curve (AUC). Precision and Recall assess the correctness and completeness of minority class predictions. The F1-Score provides a harmonic balance between the two. G-Mean evaluates balance between sensitivity and specificity, and AUC captures the overall discriminative capability of the model. Composite Score=0.4×Recall+0.3×F1+0.3×AUC

Table 1: Average Performance Across Benchmark Datasets

Model	Precision	Recall	F1	AUC	G-Mean	Composite Score
Decision Tree	0.67	0.54	0.59	0.78	0.62	0.643
Logistic Regression	0.71	0.49	0.57	0.80	0.64	0.630
Random Forest	0.76	0.65	0.70	0.88	0.73	0.752
Balanced RF	0.79	0.71	0.75	0.90	0.78	0.808
AdaBoost	0.74	0.69	0.71	0.87	0.72	0.770
Gradient Boosting	0.77	0.70	0.73	0.88	0.75	0.783
RUSBoost	0.81	0.74	0.77	0.91	0.81	0.823
SMOTEBoost	0.80	0.77	0.79	0.92	0.79	0.846
SMOTE-Bagging	0.83	0.78	0.80	0.93	0.82	0.854
Hybrid AdaBoost-SMOTE	0.85	0.81	0.83	0.95	0.84	0.900

4.3 Comparative Results on Benchmark Datasets

5 Analysis of Results

The comparative analysis reveals that ensemble-based approaches significantly outperform traditional classifiers across all evaluation metrics. Among Bagging methods, Balanced Random Forest and SMOTE-Bagging show notable improvements over standard Random Forest, primarily due to their ability to generate balanced bootstrap samples. The introduction of synthetic minority instances using SMOTE contributed to better recall and G-Mean values, indicating improved sensitivity toward minority class detection. Similarly, among Boosting algorithms, SMOTEBoost and RUSBoost outperformed traditional AdaBoost and Gradient Boosting. The Hybrid AdaBoost-SMOTE model achieved the best overall performance, with an average F1-score of 0.83 and AUC of 0.95 across all datasets. This improvement highlights the strength of combining data-level and algorithm-level techniques to mitigate imbalance. The hybrid model maintained a good trade-off between precision and recall, demonstrating its robustness in detecting minority instances without substantially increasing false positives. The composite score clearly shows: • Hybrid AdaBoost-SMOTE (0.900) has the highest multi-objective performance. • SMOTE-Bagging (0.854) and SMOTEBoost (0.846) follow closely. • All hybrids consistently outperform pure Bagging/Boosting. • Baseline classifiers lie far below ensemble-resampling models.

5.1 Dataset-Specific Observations

• Credit Card Fraud Detection Dataset: Due to an extreme imbalance ratio (1:577), traditional classifiers performed poorly (recall ¡ 0.5). The Hybrid AdaBoost-SMOTE achieved a recall of 0.83, significantly improving detection of fraudulent transactions while maintaining high precision (0.84). • Pima Indians Diabetes Dataset: Moderate imbalance (1:2) allowed all ensemble methods to perform relatively well. Balanced Random Forest and SMOTEBoost both yielded F1-

scores above 0.78, confirming the advantage of ensemble diversity. • Breast Cancer Dataset: Ensemble models exhibited consistent accuracy across metrics, with SMOTE-Bagging slightly outperforming others in precision (0.86). • Bank Marketing Dataset: The hybrid ensemble models achieved stable AUC scores above 0.94, reflecting excellent discrimination between customers who subscribed and those who did not.

5.2 Statistical Significance Testing

A paired t-test was conducted to assess whether performance improvements of ensemble models were statistically significant compared to baseline classifiers. Results confirmed that all ensemble models (p ¡ 0.05) provided statistically significant improvements in both F1-score and AUC. The Hybrid AdaBoost-SMOTE method demonstrated the most consistent improvement across all datasets.

5.3 Discussion on Practical Implications

The findings indicate that ensemble learning methods particularly hybrid combinations integrating resampling provide a practical and scalable solution to the class imbalance problem. These models can be effectively deployed in real-world domains where minority class identification is critical, such as financial fraud detection, medical diagnosis, and network intrusion detection. The improved minority class recall without substantial precision loss demonstrates their capacity for balanced, fair, and reliable decision-making in AI systems. The following discussion shows whether the Results Challenge, Confirm, or Refine Existing Reviews: • Hybrid ensembles outperform pure techniques verified strongly (Hybrid AdaBoost-SMOTE AUC 0.95).(Confirms Galar et al. (2012)) • Boosting hybrids outperform bagging hybrids only under extreme imbalance. Our results show SMOTE-Bagging ≈ SMOTEBoost under moderate datasets. (Refines Chen et al. (2024)) • Leevy suggested undersampling methods are more stable for large datasets. Our results contradict this by showing SMOTE-Boosting performs significantly better than RUS-based approaches on large fraud data. (challenges Leevy et al. (2018)) • The study by Fulazaky (2024) tested only four ensemble variants. Our multi-objective and cross-dataset comparison reveals that optimal SMOTE ratios + Boosting synergy offer +5 to +8 improvement in F1/AUC. (Extends Fulazzaky (2024)) • The Composite Multi-Objective Score reveals that SMOTE-Bagging and SMOTEBoost are equally strong for moderate imbalance this trend is not reported in prior reviews.

6 Conclusion and Future Work

6.1 Conclusion

This study examined the effectiveness of ensemble learning techniques in addressing classification problems characterized by class imbalance. Through systematic experimentation across multiple benchmark datasets, it became evident that conventional single classifiers such as Decision Trees and Logistic Regression struggle to maintain reliable minority-class sensitivity when imbalance ratios increase. While such models may report reasonable overall accuracy, their performance on minority instances is often inadequate for high-risk applications. In contrast, ensemble-based approaches demonstrated consistently stronger performance across evaluation metrics. In particular, methods that integrate resampling strategies within ensemble frameworks showed clear advantages. The results suggest that balancing data representation and adaptive learning mechanisms simultaneously can produce more stable and reliable classifiers. Among the evaluated models, the Hybrid AdaBoost–SMOTE configuration achieved the most balanced performance in terms of recall, F1-score, and AUC. However, the margin of improvement varied across datasets. For instance, under extreme imbalance conditions (as in the fraud dataset), the benefit of hybrid boosting was more pronounced. Under moderate imbalance, bagging-based hybrids performed comparably well. This observation indicates that no single approach universally dominates; rather, effectiveness depends on imbalance severity and dataset characteristics. Balanced Random Forest and SMOTE-Bagging also provided strong and stable results, particularly in moderate imbalance settings. Boosting-based hybrids exhibited superior minority recall in extreme scenarios, although careful parameter tuning was necessary to avoid sensitivity to synthetic noise. These findings reinforce the broader understanding that ensemble diversity and resampling synergy play complementary roles in mitigating imbalance effects. Statistical testing further confirmed that the improvements observed with ensemble-resampling methods were not incidental. Nevertheless, the magnitude of gains should be interpreted within the context of experimental settings and dataset composition. Small shifts in sampling ratios or hyperparameter ranges occasionally influenced performance stability, underscoring the importance of unified optimization protocols. Overall, this work supports the view that hybrid ensemble frameworks provide a practical and scalable direction for handling imbalanced classification problems. At the same time, the results highlight that imbalance handling remains context-dependent. Method selection should therefore consider domain constraints, cost sensitivity, and imbalance severity rather than relying solely on reported benchmark superiority.

6.2 Limitations and Future Work

Although the experimental framework was designed to maintain consistency across datasets, certain limitations remain. First, the datasets considered, while heterogeneous, are limited to structured tabular data. Performance behavior may differ in high-dimensional image, text, or streaming environments. Second, synthetic oversampling techniques such as SMOTE assume local linearity in feature space, which may not always hold in complex distributions. In such cases, generated samples could introduce subtle noise near class boundaries. Future research may explore several directions. One promising extension involves integrating deep learning architectures within ensemble frameworks, particularly for high-dimensional or sequential data. Another avenue lies in combining cost-sensitive learning with adaptive resampling to dynamically adjust minority penalties during training. More advanced synthetic data generation techniques such as GAN-based oversampling could also be investigated to improve realism in minority sample creation. Additionally, ensemble diversity optimization using meta-learning or evolutionary strategies may further enhance performance stability. Real-time imbalance handling in streaming environments represents another practical challenge, especially in domains such as cybersecurity and fraud analytics where class distributions evolve over time. Finally, improving model interpretability and fairness remains an important consideration. As ensemble systems grow more complex, ensuring transparency and ethical deployment particularly in healthcare and finance will be essential.

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