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COMPARATIVE EVALUATION OF MACHINE LEARNING ALGORITHMS AND CLASS IMBALANCE HANDLING STRATEGIES FOR CREDIT CARD FRAUD DETECTION

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ABSTRACT: Severe class imbalance complicates the evaluation of credit card fraud detection models. This study compares six classifiers under no balancing, class weighting, SMOTE, and random undersampling, yielding 24 configurations. Experiments used approximately 1.85 million synthetic Sparkov transactions with a temporal train-test split. Average Precision (AP) was the primary metric, complemented by classification and alert-budget measures.

Keywords: credit card fraud detection; machine learning; class imbalance; SMOTE; XGBoost; Average Precision; SHAP.

ANNOTATSIYA: Kredit karta firibgarligini aniqlash modellarini baholashda sinflar o'rtasidagi keskin nomutanosiblik murakkablik tug'diradi. Ushbu tadqiqotda balanslashsiz yondashuv, sinf vaznlarini qo'llash, SMOTE va tasodifiy kam tanlash sharoitlarida oltita klassifikator taqqoslanib, jami 24 ta konfiguratsiya shakllantirildi. Tajribalar vaqt bo'yicha o'qitish-test ajratish usuli asosida taxminan 1,85 millionta sintetik Sparkov tranzaksiyalaridan foydalangan holda amalga oshirildi. Asosiy baholash mezonini sifatida Average Precision (AP) qo'llanildi, u klassifikatsiya va ogohlantirishlar byudjeti ko'rsatkichlari bilan to'ldirildi.

Kalit so'zlar: kredit karta firibgarligini aniqlash; mashinaviy o'rganish; sinflar nomutanosibligi; SMOTE; XGBoost; Average Precision; SHAP.

АННОТАЦИЯ: Значительный дисбаланс классов усложняет оценку моделей выявления мошенничества с кредитными картами. В данном исследовании сравниваются шесть классификаторов при отсутствии балансировки, использовании весов классов, SMOTE и случайной недовыборке, что в совокупности формирует 24 конфигурации. Эксперименты проводились на основе примерно 1,85 млн синтетических транзакций Sparkov с временным разделением данных на обучающую и тестовую выборки. В качестве основного показателя использовалась средняя точность Average Precision (AP), дополненная показателями классификации и бюджета предупреждений.

Ключевые слова: выявление мошенничества с кредитными картами; машинное обучение; дисбаланс классов; SMOTE; XGBoost; Average Precision; SHAP.

INTRODUCTION

Automated fraud detection must identify rare suspicious transactions within large, evolving payment streams. Machine learning supports this task [1–3], but severe class imbalance makes overall accuracy an inadequate measure of fraud detection performance [4]. The relevant question is whether balancing improves the particular model and evaluation objective.

Balancing strategies can alter ranking quality, detection sensitivity, and false-positive burden differently [5–9]. Temporal evaluation is also necessary because models encounter transactions occurring after their training data [10]. Limited investigation capacity motivates the assessment of fraud capture within a defined alert budget [12]. This study compares six algorithms under four imbalance treatments using a common temporal holdout, with AP as the primary metric. It evaluates existing approaches rather than proposing a new balancing algorithm.

LITERATURE REVIEW

Research on financial fraud detection has focused on classifier selection and methods for handling rare fraudulent transactions. Preciado Martínez et al. [1] compared several algorithms on real bank-transfer data and identified Random Forest as the strongest model in their experiment. Chen and Guestrin [14] introduced

XGBoost as a scalable tree-boosting system, supporting the use of ensemble methods for large transaction datasets.

Two common approaches to class imbalance are resampling and cost-sensitive learning. Chawla et al. [5] introduced SMOTE, which generates synthetic minority observations and can be combined with majority undersampling. Singh and Jain [6] proposed a cost-sensitive ensemble that assigns greater importance to fraudulent transactions. Their effectiveness, however, depends on the classifier and evaluation metric.

Wijaya et al. [7] compared Logistic Regression, Decision Tree, Random Forest, and XGBoost under several balancing strategies and reported the highest F1-score for XGBoost with random oversampling. However, this result reflects a specific dataset, model, and metric. Therefore, a baseline without balancing is necessary to assess the actual contribution of each imbalance treatment.

RESEARCH METHODOLOGY

1. Related work

Preciado Martínez et al. reported strong Random Forest performance on bank-transfer data [1], while Dichev et al. demonstrated the effectiveness of XGBoost [2]. Naqvi's review of 77 studies identified ensemble and gradient-boosting methods among common fraud detection approaches [3], while Konsta et al. [16] also examined machine learning applications in banking fraud.

SMOTE [5] and cost-sensitive learning [6] address class imbalance through different mechanisms. Comparative studies [7–9] show that balancing effects depend on the classifier and dataset. Precision–Recall evaluation is particularly informative for rare positive cases [4], while temporal drift [10] and preprocessing choices [11] support the use of chronological validation.

2. Dataset and temporal split

The synthetic Sparkov dataset [13] contains approximately 1.85 million transactions. The *fraudTrain.csv* and *fraudTest.csv* files were combined, chronologically sorted, and repartitioned. The first 75% formed the training set and the remaining 25% the test set, with identical timestamps kept together. The training set contained 1,389,295 transactions, including 7,891 fraud cases (0.568%).

3. Feature engineering and preprocessing

Ten features were constructed: *haversine_distance_km*, *age*, *hour*, *day_of_week*, *amt_to_city_pop_ratio*, *num_txn_last_1h*, *num_txn_last_24h*, *avg_amt_last_7d*, *amt_ratio_to_avg7d*, and *merchant_risk_score*.

The *haversine_distance_km* feature measures customer–merchant distance using the Haversine formula with an Earth radius of 6,371.0088 km. Temporal and transaction-history features were calculated using only preceding observations. The *merchant_risk_score* estimates historical merchant fraud risk using smoothing strength $\alpha = 20$ and excludes current, same-timestamp, and future labels.

Test risk scores were derived only from training data. Although transaction-level leakage was prevented, operational implementation should account for possible delays in fraud-label availability.

The *cc_num*, *first*, *last*, *street*, and *trans_num* columns were excluded. Scaling, encoding, and resampling were fitted only on training data. SMOTE and random undersampling were applied only to the training set.

Artificial intelligence tools were used to a limited extent of approximately 10% in preparing and editing the methodological description, while methodological decisions, data processing, model construction, evaluation, and interpretation remained based on the authors' analytical procedures.

4. Algorithms and imbalance treatments

KNN, Gaussian Naive Bayes, SVM, Logistic Regression, Random Forest, and XGBoost [14] were evaluated under baseline, class-weighting, SMOTE, and random-undersampling conditions. KNN used $k = 5$, Random Forest 100 trees, XGBoost 200 trees, and SVM an RBF kernel. SVM used a stratified sample of 20,000 training observations because of computational constraints.

SVM, Logistic Regression, and Random Forest used *class_weight='balanced'*; Gaussian Naive Bayes used balanced sample weights. XGBoost used *scale_pos_weight = 175.06*. KNN probabilities were adjusted after fitting using the same imbalance ratio. Overall, 24 model-strategy combinations were evaluated.

5. Evaluation and explainability

AP was the primary metric. Additional measures included ROC-AUC, F1-score, MCC, Precision, Recall, and Recall@5% [12]. Threshold-dependent metrics used a fixed threshold of 0.5.

For the highest-AP model, SHAP [15] TreeExplainer was applied to 1,000 randomly selected test observations. SHAP values for *avg_amt_last_7d* were compared between the lower and upper quartiles.

Permutation evaluation used 50,000 stratified test observations with three repeats per feature. The features *amt_to_city_pop_ratio*, *amt_ratio_to_avg7d*, and *haversine_distance_km* were permuted separately. Positive AP decreases indicate predictive information used by the fitted model.

ANALYSIS AND RESULTS

1. Average Precision comparison

Table 1 presents the AP results for all 24 model-strategy combinations. Class-weighted XGBoost achieved the highest AP (0.9334), followed by baseline XGBoost (0.9299) and baseline Random Forest (0.9126). Figure 1 presents the same comparison.

Table 1. Average Precision for all model-strategy combinations.

Algorithm	Baseline	Class weighting	SMOTE	Random undersampling
KNN	0.6632	0.6632	0.3811	0.2182
Gaussian Naive Bayes	0.1355	0.1174	0.1214	0.0897
SVM*	0.6499	0.3595	0.4569	0.2492
Logistic Regression	0.3842	0.1833	0.1805	0.1753
Random Forest	0.9126	0.9077	0.8944	0.8613
XGBoost	0.9299	0.9334	0.9146	0.8994

SVM used 20,000 stratified training observations, while the other classifiers used the full training set. KNN weighting denotes a post-fitting score adjustment.

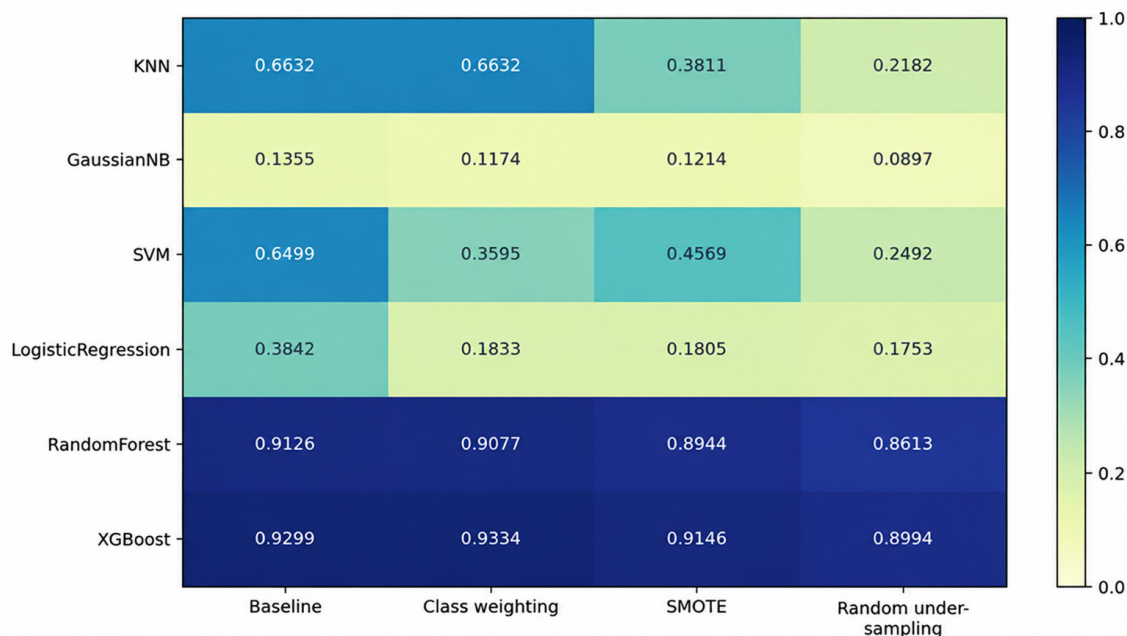


Figure 1. AP across classifiers and imbalance treatments on the temporal holdout.

Gaussian Naive Bayes, SVM, Logistic Regression, and Random Forest achieved their highest AP without balancing. KNN showed equal AP under baseline and weighting. Neither SMOTE nor undersampling improved AP.

2. Ranking and threshold-dependent performance

Balancing affected the metrics differently. For Random Forest, weighting increased Recall from 0.7642 to 0.9170 and Recall@5% from 0.9790 to 0.9903, although AP decreased from 0.9126. SMOTE increased Recall@5% to 0.9920 but reduced AP to 0.8944.

Baseline XGBoost achieved AP = 0.9299, while weighting increased AP to 0.9334, Recall to 0.9653, ROC-AUC to 0.9988, and Recall@5% to 0.9966. However, Precision decreased to 0.3883 and F1-score to 0.5539. For Logistic Regression, weighting increased Recall from 0.3159 to 0.8534 but reduced Precision from 0.7277 to 0.0593. These results at the fixed 0.5 threshold show that higher sensitivity may be accompanied by more false positives.

3. SHAP evidence

For class-weighted XGBoost, the most influential features were *amt* (3.80175), *avg_amt_last_7d* (1.09182),

hour (0.90091), num_txn_last_24h (0.33895), and category_shopping_pos (0.32451).

For avg_amt_last_7d, the upper-quartile mean signed SHAP value was 0.30204 and the lower-quartile mean was -1.70787, giving a difference of 2.00990. These values describe model prediction contributions and do not imply causal effects.

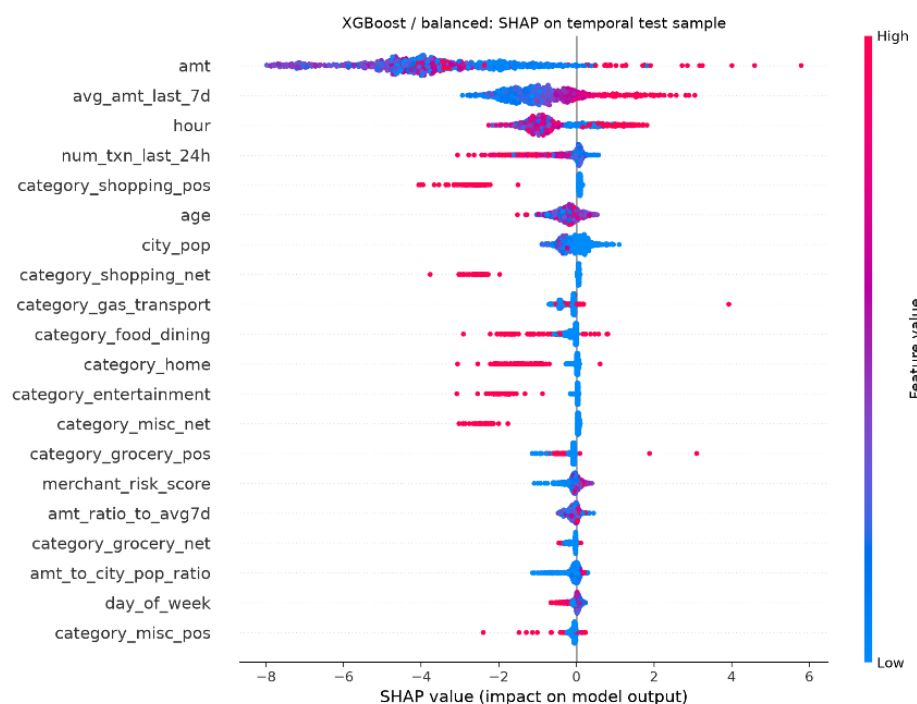


Figure 2. SHAP summary for class-weighted XGBoost using 1,000 randomly selected test observations.

4. Permutation evidence

The stratified permutation sample included 50,000 test observations, of which 190 were fraud cases. The baseline AP was 0.92569. Table 2 presents the mean AP decrease and standard deviation across three permutations for each feature.

Table 2. Permutation evaluation of engineered features.

Feature	Mean AP decrease	Standard deviation
amt_to_city_pop_ratio	+0.0045	0.00013
amt_ratio_to_avg7d	+0.0037	0.00129
haversine_distance_km	-0.0009	0.00102

Both amount-ratio features produced positive AP decreases, indicating predictive value in the fitted model. Geographic distance showed a mean decrease of -0.0009, suggesting no positive AP contribution in this experiment, although this does not imply that geographic information is generally uninformative.

The results show that severe class imbalance does not automatically justify resampling. Most classifiers achieved their highest AP without balancing, while class weighting produced only a small AP improvement for XGBoost. This supports evaluating the interaction between algorithm, imbalance treatment, and evaluation objective under a consistent temporal design.

SMOTE and undersampling may alter informative data structure, which may explain the observed AP reductions. However, these mechanisms were not tested directly, and the findings remain specific to the dataset and feature representation.

The distinction between ranking and threshold-dependent classification is important. AP evaluates performance across thresholds, whereas Precision, Recall, and F1-score depend on a selected threshold. Although weighting slightly improved XGBoost AP, it substantially reduced Precision at the 0.5 threshold. Therefore, model selection should consider ranking quality, false-positive burden, and operational thresholds together.

Recall@5% provides an alert-budget perspective, but a 5% review rate is not necessarily optimal. Appropriate alert volumes depend on investigation capacity, fraud losses, and false-positive costs [12].

SHAP and permutation analyses provided complementary evidence on feature importance. The amount-ratio features contributed useful predictive information, while the geographic-distance result was sample-specific. Neither method establishes causality, and correlated predictors may affect interpretation.

Limitations and future validation

The synthetic Sparkov dataset may not fully represent real banking transactions, so validation on real-world data is required. SVM was trained on only 20,000 observations, limiting direct comparison with models trained on the full dataset.

Model selection relied on a single temporal test set. The XGBoost AP improvement was only 0.0035 and was not confirmed through repeated temporal validation or an independent holdout.

The fixed 0.5 threshold was not optimized for operational costs or alert constraints. In addition, *merchant_risk_score* assumes immediate availability of prior fraud labels, whereas real fraud confirmation may be delayed.

Explainability analysis was limited to 1,000 SHAP observations and 50,000 permutation observations with three repeats. Larger samples, repeated temporal validation, and retraining-based ablation would provide stronger evidence.

CONCLUSION AND SUGGESTIONS

This study compared six machine learning algorithms under four class imbalance strategies, producing 24 configurations within a common temporal evaluation framework. Class-weighted XGBoost achieved the highest AP (0.9334), compared with 0.9299 for baseline XGBoost. Four classifiers performed best without balancing, while neither SMOTE nor random undersampling improved AP. These results indicate that imbalance treatments should be evaluated empirically rather than applied automatically.

The findings also highlight the difference between ranking and threshold-dependent performance. Although weighting slightly improved XGBoost AP and increased Recall at the 0.5 threshold, it reduced Precision and F1-score. Therefore, operational model selection should jointly consider AP, threshold-specific errors, Recall@5%, and available investigation capacity.

SHAP and permutation analyses showed that the fitted XGBoost model used both current transaction characteristics and historical behavioral information. However, the results remain specific to the synthetic Sparkov dataset and the evaluated temporal holdout. Future work should validate the models on real transaction data, apply repeated temporal validation and an independent holdout, account for delayed fraud labels, optimize thresholds and alert budgets, and use retraining-based feature ablation.

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