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A stacking ensemble model with SMOTE for improved imbalanced classification on credit data

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ABSTRACT

This research is based on a significant problem in credit risk analysis in the banking sector caused by class imbalance. We face the problem of the model's inability to accurately identify risks in the ''Charged Off'' class. As a solution, we propose a stacked ensemble approach that utilizes synthetic minority over-sampling technique (SMOTE) to balance the class distribution. Experiments were conducted by applying SMOTE to the training data before training the credit model using gradient boosting (XGBoost) and random forest (RF) algorithms in a single ensemble. The results show significant improvements in precision, recall, and F1-score after applying SMOTE on the unbalanced classes. The updated model achieved a striking accuracy rate of 0,97 on resampled training data. This re-search clearly identifies the problem of class imbalance as a major challenge in credit risk analysis. The application of SMOTE in a stacked ensemble was found to be effective in improving model performance, making a valuable contribution to the development of more reliable credit models for better risk management and revenue generation in financial institutions.

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1. INTRODUCTION

In the rapidly evolving landscape of credit risk management within the banking industry, there exists a persistent challenge-class imbalance in loan datasets [1]. The sheer volume of fully paid loans far surpasses that of charged off loans, impacting the efficacy of models in identifying ongoing credit risk [2]. This persistent issue necessitates innovative solutions to strike a balance between safety and profitability [3]. Against this background, credit risk management has become a critical aspect for banking institutions, demanding constant innovation to effectively handle the challenges posed by unbalanced data sets [4]. The increasing need for financial institutions to minimise credit risk while increasing revenue increases the urgency to explore new methodologies [5].

In the realm of credit analysis, the issue of class imbalance serves as a focal point for this research [6]. The skewed distribution poses a challenge, as inaccurate credit evaluations can have profound financial implications and erode customer confidence [7]. The substantial impact of bad debts on financial stability underscores the criticality of making accurate decisions to mitigate risks [8]. This is the crux of the problem that motivates our study. In addressing class imbalance in datasets, traditional machine learning models often struggle to capture the nuances of the minority class, leading to suboptimal performance, especially in the identification of high-risk loans [9]. The need for a robust solution becomes evident, prompting the exploration of innovative techniques that go beyond conventional methodologies.

In the contemporary landscape of credit risk management, addressing class imbalance in loan datasets has emerged as a crucial focal point [10]. As indicated by Ziemba *et al*. [11] the prevalence of fully paid loans significantly outweighs charged off loans, presenting a challenge in accurately identifying ongoing credit risks. Traditional machine learning models face limitations in capturing the nuances of minority classes, leading to suboptimal performance in high-risk loan identification [12]. This issue has prompted researchers to explore innovative techniques, such as the synthetic minority over-sampling technique (SMOTE), to rebal- ance datasets [13]. To address the prevalent issue of class imbalance, particularly in the banking industry, the study proposes a novel approach—SMOTE. Notably, the application of SMOTE is not confined to individual models but extends to the ensemble level, particularly within the innovative framework of stacking ensemble models [14]. This research seeks to systematically explore the integration of SMOTE with stacking ensemble models, shedding light on the impact of this combination on decision-making within the ensemble. By enriching the dataset through SMOTE, we aim to create a more balanced representation, enabling the underlying base models—gradient boosting (XGBoost) and random forest (RF)—to learn from a more diverse and evenly distributed information pool. This becomes a critical step in ensemble model development, given that balanced uniformity and diversity in the dataset greatly affect ensemble performance [15].

The primary contribution of this research lies in leveraging SMOTE within the context of ensemble stacking, aiming to substantially improve credit risk management practices. Our approach focuses on achieving a balance between precision and recall, thereby providing a more comprehensive and effective solution to credit risk assessment. Through this innovative contribution, we not only aspire to enhance model performance metrics but also deepen the understanding of how SMOTE, when applied at the ensemble level, can provide significant benefits.

2. METHOD

In this study, we propose the development of a stacking ensemble model using SMOTE to improve risk management and increase revenue on bank credit data is in Figure 1. A major challenge faced in credit analysis is class imbalance, where the number of fully paid loans far outnumber the charged off loans. Therefore, we apply SMOTE to the dataset to even out the class distribution, improving the model's ability to identify the true risk. Our method involves using base models, such as RF and XGBoost, which are then combined in a main model using the voting classifier (VC) technique. The SMOTE process is performed on the training data to ensure the main model gets balanced information from each class. The following diagram visualizes the steps of ensemble model development and SMOTE application on the credit dataset, which is expected to provide a more reliable and accurate solution in credit risk management.

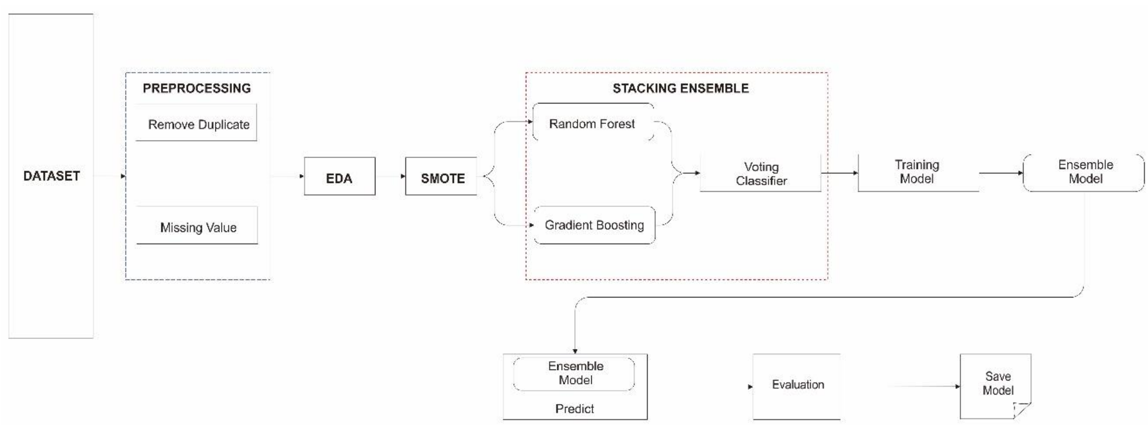

Figure 1. Stacking ensemble SMOTE of proposed method

2.1. Dataset

The dataset used in this research is a banking credit dataset obtained from Kaggle. This dataset consists of 19 features, namely loan ID, customer ID, loan status, current loan amount, term, credit score, annual income, years in current job, home ownership, purpose, monthly debt, years of credit history, months since last delinquent, number of open accounts, number of credit problems, current credit balance, maximum open credit, bankruptcies, and tax liens. This dataset provides an overview of borrower profiles and credit-related factors that can be used in risk analysis. A description of each feature in this dataset is provided in Table 1.

Table 1. Dataset features

Features	Description
Loan ID	Unique identifier for each loan record.
Customer ID	Unique identifier for each customer.
Loan status	Binary classification of the loan status (fully paid or charged off).
Current loan amount	The current approved loan amount.
Term	Duration of the loan (short term or long term).
Credit score	The credit score of the loan applicant.
Annual income	The annual income of the loan applicant.
Years in current job	The number of years the applicant has been in their current job.
Home ownership	The status of home ownership (own home, mortgage, or rent).
Purpose	The purpose of the loan.
Monthly debt	The total monthly debt payments.
Years of credit history	The number of years of credit history.
Months since last delinquent	The number of months since the last delinquent payment.
Number of open accounts	The number of open credit accounts.
Number of credit problems	The number of credit problems.
Current credit balance	The current outstanding credit balance.
Maximum open credit	The maximum open credit amount.
Bankruptcies	The number of bankruptcies.
Tax liens	The number of tax liens.

2.2. Preprocessing

Before starting the model building process, the first step is to preprocess the dataset. This process includes checking for data duplication and handling missing values [16]. From the results of the check, no data duplication was found in each dataset entry, indicating the cleanliness of the data used. However, a number of features were found to have missing values as shown in Table 2. To address these data gaps, the simple imputer method was used with a strategy of filling in the values using the mean [17]. This process provides a consistent solution and maintains the integrity of the dataset, allowing us to proceed to the next stage of ensemble model development. Subsequently, the missing values within each feature are replaced with their respective means [18]. This process ensures that the dataset becomes more complete, mitigating potential biases introduced by missing data during subsequent analysis.

$$\mu = \frac{\sum (available\ values)}{number\ of\ non\text{-}empty\ entries} \quad (1)$$

Table 2. Summary of missing values before imputation

Feature	Missing values
Credit score	1947
Annual income	1947
Months since last delinquent	5331
Bankruptcies	17
Tax liens	1

2.3. Exploratory data analysis

The initial analysis of this dataset focuses on the classification distribution of 'Loan Status' which is the target variable in this study. From the total data of 10,058, there are two main classifications, namely 'Fully Paid' and 'Charged Off'. The analysis shows that 7,744 entries indicate loans that have been fully repaid ('Fully Paid'), while 2,314 entries indicate loans that cannot be honored ('Charged Off'). The visualization shown in Figure 2 depicts the comparison between the 'Fully Paid' and 'Charged Off' classifications in the form of a bar chart. The graph provides a clear picture of how balanced or unbalanced the distribution is between loans that have been fully repaid and those that cannot be honored. This information is an important cornerstone in the initial understanding of the data characteristics, allowing researchers to identify class imbalances that might affect the performance of the classification model.

Next, we analyzed the distribution of risk categories based on credit scores. In this categorization, we divided the data into three categories: low risk, medium risk, and high risk. If the credit score is greater than or equal to 750, then the borrower is considered to have low risk. For credit scores in the range of 700 to 749, we categorize as medium risk. Meanwhile, credit scores below 700 are considered high risk. The results of this analysis show that there are 667 borrowers with low risk, 3591 borrowers with medium risk, and the remaining 5800 borrowers are categorized as high risk. A visualization of this analysis can be seen in Figure 3. The visualization shown in Figure 2 depicts the comparison between the 'Fully Paid' and 'Charged Off' classifications in the form of a bar chart. The graph provides a clear picture of how balanced or unbalanced the distribution is between fully paid and non-fulfilled loans. This information is an important cornerstone in the initial understanding of the data characteristics, allowing researchers to identify class imbalances that might affect the performance of the classification model.

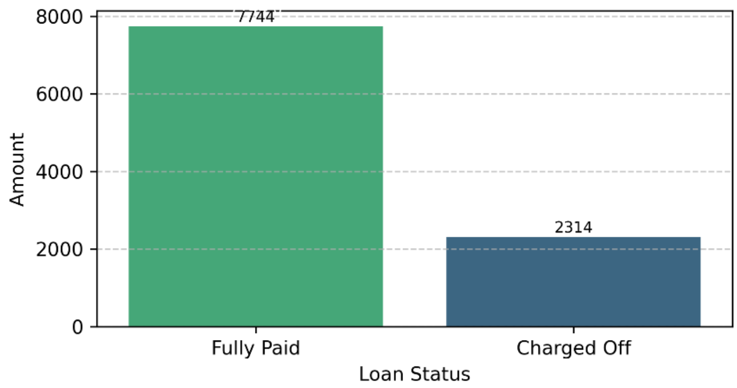

Figure 2. Loan status distribution (''Fully Paid'' vs. ''Charged Off'')

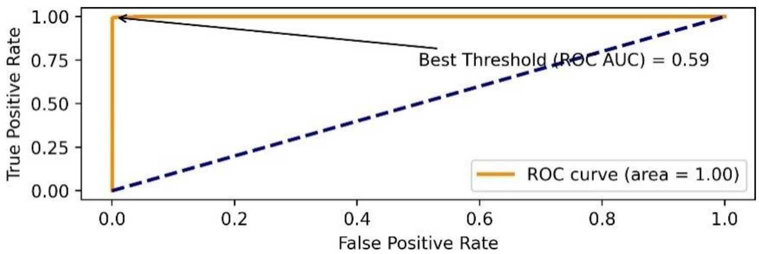

Figure 3. ROC curve

2.4. SMOTE

SMOTE is a valuable technique used to address class imbalance in machine learning datasets, a common issue where one class is significantly underrepresented. In our loan status dataset, SMOTE is applied to balance instances between "Fully Paid" and "Charged Off" classes. The fundamental concept of SMOTE involves generating synthetic samples for the minority class by interpolating between existing instances [19]. For a given minority class sample X_i, SMOTE selects k nearest neighbors (typically k=5) and creates synthetic samples using the formula:

$$X_{\text{new}} = X_i + \delta \times (X_j - X_i) \tag{2}$$

Here, Xi is the original minority class sample, Xj is a randomly chosen neighbor, and δ is a random value between 0 and 1, determining the interpolation extent [20]. This process is repeated to achieve the desired class balance. SMOTE enhances the model's generalization and prediction accuracy on the minority class by introducing synthetic samples [21]. This approach is particularly beneficial in scenarios like credit risk analysis, where accurate identification of default cases is crucial for effective risk management.

2.5. Stacking ensemble model

The method applied in this research carries the concept of stacking ensemble, a technique that combines predictions from several models [22]. The two basic models used are XGBoost classifier (GBC) and random forest classifier (RFC). The use of this combination was chosen with the consideration that both have their own advantages and disadvantages. According to Putrada *et al*. [23] the GBC tends to be accurate and can handle the complexity of non-linear relationships, while the RFC has the advantage of handling overfitting and reliability against unbalanced data [24]. The combination of XGBoost and RF in the base model is expected to provide better results as they complement each other's weaknesses. XGBoost can "learn" from previous model errors, while RF can help reduce variance and improve generalization. In addition, the base model is combined in the VC as the main model. In this concept, the final decision is taken based on the majority of votes from the base models.

RF works by creating a number of decision trees on the training data and combining the prediction results from each tree to give the final result [25]. XGBoost works by sequentially combining a number of weak models, in this case, decision trees. The resulting model places more emphasis on data that was deemed difficult to predict by the previous model. The general formula for XGBoost can be represented as (3):

$$F_m(x) = F_{m-1}(x) + \eta \cdot h_m(x) \tag{3}$$

Here, Fm(x) is the model prediction at the m-th iteration, Fm−1(x) is the model prediction from the previous iteration, η is the learning rate, and hm(x) is the weak model at the m-th iteration. VC combines predictions from multiple models by assigning weights to each model. One type of VC is hard voting, which selects the class based on the majority vote. The formula can be represented as (4):

$$VC(x) = \text{argmax}_c\left(\textstyle\sum_{i=1}^{N} w_i \cdot I(y_i(x) = c)\right) \tag{4}$$

Here, V C(x) is the prediction of the VC for sample x, N is the number of models, wi is the weight for the i-th model, and I(yi(x)=c) is the indicator function that is 1 if the i-th model predicts class c for sample x and 0 otherwise.

The formula for the stacking ensemble combination is:

$$\text{Ensemble Prediction} = VC\big(GBC(x), RFC(x)\big) \tag{5}$$

In other words, the final result of the stacking ensemble is the prediction of the VC using the predictions from the GBC and RFC as inputs.

3. RESULTS AND DISCUSSION

By applying the SMOTE to address class imbalance, the distribution of loan status is successfully balanced. Before the application of SMOTE, the dataset had 7744 instances of 'Fully Paid' and 2314 instances of 'Charged Off.' However, after the application of SMOTE, the two classes were successfully balanced, resulting in 6185 instances for 'Fully Paid' and 6185 instances for 'Charged Off,' creating a more balanced and robust training set for the classification model. Prior to the SMOTE process, the classification report shows results indicating good model performance on the class 'Fully Paid,' with an F1-score of 0.90, indicating high precision and recall. However, in the class 'Charged Off,' the model's performance dropped significantly with an F1-score of 0.41. This shows that the model has difficulty in identifying and predicting the 'Charged Off' class, indicating class imbalance and requires special handling such as the application of SMOTE to improve performance on minority classes. The comparison data of precision, recall and f1 score metrics before and after the SMOTE process is presented in Table 3.

Table 3. Comparison of results before and after SMOTE

Class	Precision before SMOTE	Recall before SMOTE	F1-Score before SMOTE	Support before SMOTE
Charged off	0.84	0.27	0.41	453
Fully paid	0.82	0.99	0.90	1559
Class	Precision after SMOTE	Recall after SMOTE	F1-Score after SMOTE	Support after SMOTE
Charged off	1.00	0.94	0.97	6185
Fully paid	0.94	1.00	0.97	6185

After applying the SMOTE technique to the dataset, the prediction using the main model showed very satisfactory results. The classification report on the resampled training data shows an accuracy rate of 0,97, with high precision, recall, and f1-score values in both the ''Charged Off'' and ''Fully Paid'' classes. In particular, the "Charged Off" class achieved a recall rate of 0,94, indicating the model's ability to correctly recognize high-risk loan cases. These results illustrate that the use of SMOTE successfully addresses class imbalance and improves model performance, especially in identifying potentially problematic loans (‘‘Charged Off”). This proves that addressing class imbalance with SMOTE contributes significantly to improving the accuracy and predictive ability of the model.

Before the SMOTE process, the model had an ROC AUC of 0.76 and a G-mean of 0.52. However, after implementing SMOTE, there was a significant improvement in model performance with an ROC AUC of 1.00 and a G-mean of 0.97. The ROC AUC and G-mean evaluation results of the classification model before and after the application of SMOTE show significant differences. Before the SMOTE process, the model showed an ROC AUC level of 0.76 and a G-mean of 0.52. In this context, a ROC AUC level that is less than 1.00 may indicate that the model performance can still be improved, and a low G-mean reflects an imbalance between sensitivity and specificity.

However, after the application of SMOTE, there was a marked improvement in the model evaluation. The ROC AUC level reached a value of 1.00, indicating that the model was able to perfectly distinguish between positive and negative classes. Meanwhile, the G-mean which increased to 0.97 illustrates the excellent balance between sensitivity and specificity. This improvement can be explained by the fact that SMOTE successfully addressed the class imbalance in the dataset, particularly in improving the representation of the minority class ”Charged Off”. By increasing the number of samples in the minority class, the model can learn better and produce more optimized results. In Figure 4, the G-mean curve results that have a value of ”best=1.00” indicate that the model has an excellent balance between true positive rate (recall) and true negative rate (specificity). In this context, a G-mean value of 1.00 indicates that the model can optimally classify both classes (positive and negative) without sacrificing performance in either class. Meanwhile, ”best threshold (G-Mean)=0.59” is the threshold value that gives the best G-Mean performance. This threshold value can be used as a decision boundary where the model classifies an instance as a positive or negative class. So, by using this threshold value, the model can achieve the optimal performance indicated by a G-mean of 1.00.

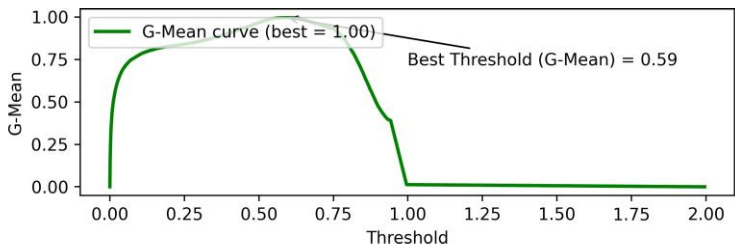

Figure 4. ROC curve

Research conducted by Al-Islam *et al.* [26] using SMOTE oversampling to handle imbalanced data and using ensemble stacking techniques with linear regression (LR), support vector machine (SVM), K-nearest neighbor (KNN), RF, and XGBoost classification models. The ensemble stacking models we used were GBC, RFC, and VC. We present the results of this model comparisonin Table 4.

Table 4. Comparison of stacking ensemble research results

Method	Accuracy	Precision	Recall
GB, RF, and VC	0.97	1.00	1.00
LR, SVM, KNN, RF, and XGBoost	0.91	0.90	0.90

4. CONCLUSION AND FUTURE WORK

In this study, we successfully explored and implemented a stacking ensemble approach involving base models, such as GBC and RFC as well as the main model VC. The use of SMOTE techniques to address data imbalance also proved effective in improving the performance of our classification models. Experimental results show significant improvements in evaluation metrics such as ROC AUC and G-mean, validating the effectiveness of this approach in handling classification cases on imbalanced datasets. While this study provides a better understanding of the application of stacking ensemble and SMOTE, there are still various areas for further research. First, further exploration and testing of various base models and parameter settings may provide additional insights into the best combination for specific datasets. In addition, it could be considered to integrate more advanced clustering techniques or more complex models in the stacking ensemble. Furthermore, in-depth research on feature engineering and feature selection can improve the model's ability to recognize patterns on more complex datasets. In addition, exploration of more advanced evaluation methods and development of model interpretation techniques could be an interesting research direction. Thus, future research can bring further contributions in dealing with classification challenges on imbalanced datasets.

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