Credit fraud modeling is a crucial area of research that is highly relevant to the credit loan industry. Effective risk management is a key factor in providing quality credit services and directly impacts the profitability and bad debt ratio of leading organizations in this sector. However, when the distribution of credit fraud data is highly unbalanced, it can lead to noise errors caused by information distortion, periodic statistical errors, and model biases during training. This can cause unfair results for the minority class (target class) and increase the risk of overfitting. While traditional data balancing methods can reduce bias in models towards the majority class in relatively unbalanced data, they may not be effective in highly unbalanced scenarios. To address this challenge, this paper proposes using Bagging algorithms such as Random Forest and Bagging to model highly unbalanced credit fraud data. Bayesian optimization is utilized to find hyperparameters and determine the accuracy of the minority class as an optimization function for the model, which is tested with real European credit card fraud data. The results of the proposed packing algorithms are compared with traditional data balancing methods such as Balanced Bagging and Balanced Random Forest. The study found that traditional data balancing methods may not be compatible with excessively unbalanced data, whereas Bagging algorithms show promise as a solution for modeling such data. The proposed method for finding hyperparameters effectively deals with highly unbalanced data. It achieved precision, recall, and F1-score for the minority category of 0.94, 0.81, and 0.87, respectively. The study emphasizes the importance of addressing the challenges associated with unbalanced credit fraud data to improve the accuracy and fairness of credit fraud models

Keywords: unbalanced data, Bayesian optimization, random forest, majority and minority class

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UNBALANCED CREDIT FRAUD MODELING BASED ON BAGGING AND BAYESIAN OPTIMIZATION

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1. Introduction

The banking industry's growth has led to increasing market volatility and credit fraud, and the widespread use of financial derivatives has further contributed to this trend. One of the critical challenges in credit fraud detection is to accurately rate an applicant's creditworthiness based on the objective laws present in the credit data. The rating is a binary classification problem determining whether the applicant has committed credit fraud [1, 2]. The identification and early warning of credit fraud are crucial, and the success of the risk identification model is closely related to data balance. Thus, finding models unaffected by data imbalance, as with credit fraud, is highly useful. Borrowers who appear reliable have a high success rate and exhibit a low default rate [3, 4]. Current research focuses on overcoming the problem of model bias towards the majority category by comparing the effects of data balancing methods. The main data balancing methods include changing data distribution and improving the algorithm's level. The former involves over-sampling algorithms, such as SMOTE [5] and ADASYN [6], combined with under-sampling algorithms [7–12], which generate new samples.

However, overfitting of the classifier may occur when the imbalance ratio is too large, and poor classification results may occur in the test set if a large number of majority class samples are discarded. The latter approach involves cost-sensitive methods that assign different misclassification costs to different classes and higher misclassification costs to minority class samples erroneously classified as the majority class [13, 14]. However, determining the cost factor for misclassification is challenging. Alternatively, ensemble learning, which combines multiple learners to obtain better learning effects than a single learner, can be used [15]. Boosting, a commonly used ensemble method can model unbalanced data sets. However, the subjective cost function can lead to difficulties in defining it. Therefore, most scholars focus on the ensemble classification algorithm based on data processing, which includes combining oversampling and boosting [16] and SMOTBoosting [17, 18]. Despite the above methods, unbalanced data classification algorithms still have some drawbacks, especially when the imbalance ratio is large. Therefore, studies that are devoted to addressing the challenges associated with unbalanced credit fraud data are of scientific relevance in the modern credit loan industry.

2. Literature review and problem statement

The paper [19] proposes a feature fusion-based machine learning model for fraud detection, which showed promising results in identifying fraudulent transactions. However, there are still unresolved issues related to the class imbalance problem in credit card fraud datasets, which affects the accuracy of traditional machine learning algorithms.

The paper [20] provides a comprehensive review of ensemble learning algorithms, which combine multiple models to improve performance. The paper discusses various ensemble techniques, including bagging, boosting, and stacking, and highlights their advantages and disadvantages. However, the review does not specifically address the issue of class imbalance.

The paper [21] proposes a hybrid data-level ensemble approach that combines under-sampling, over-sampling, and bagging to address the issue of class imbalance. The proposed approach achieves high performance on imbalanced datasets, but the study is limited to a specific type of ensemble learning.

The paper [22] proposes a biased random forest algorithm that adjusts the sampling rate of the majority and minority classes to improve performance on imbalanced data. The algorithm uses a threshold to determine the sampling rate, which is a limitation as it may not work well on datasets with varying levels of imbalance.

The paper [23] proposes a twin bounded support vector machine algorithm that combines a robust loss function with a regularization term to handle outliers and imbalanced data. The proposed algorithm outperforms existing methods on several benchmark datasets, but the study does not provide a comparison with other algorithms.

The paper [24] proposes an entropy-based fuzzy least squares twin support vector machine algorithm that addresses the issue of class imbalance by adjusting the class weights in the objective function. The proposed algorithm performs highly on imbalanced datasets, but the study is limited to binary classification problems.

The paper [25] proposes a credit card fraud detection system that uses naive Bayesian and C4.5 decision tree classifiers. The study compares the performance of the two classifiers on imbalanced datasets and shows that the naive Bayesian classifier outperforms the C4.5 decision tree.

The paper [26] proposes a multiple classifiers system that combines six classifiers to detect anomalies in credit card data with overlapped and imbalanced classes. The study shows that the proposed system achieves high performance on the imbalanced dataset, but the study is limited to a specific application domain.

Despite the existing methods, there are still unresolved issues related to handling class imbalance in credit card fraud datasets. Therefore, the overall problem addressed in this study is to propose a bagging algorithm that effectively models highly unbalanced credit fraud data and improves the accuracy of credit fraud detection in the banking industry.

3. The aim and objectives of the study

The aim of this study is to develop and evaluate a bagging algorithm for modeling highly unbalanced credit fraud data and compare its performance with traditional data balancing methods.

To achieve this aim, the following objectives are accomplished:

– to model excessively unbalanced data, as in the case of credit fraud data, it is suggested to use bagging algorithms and measure their efficiency;

– to improve the prediction accuracy, the study proposes to develop a random forest classifier model and use Bayesian optimization to find the hyperparameters and prove that finding the appropriate hyperparameters improves the balancing of the model;

– to know the performance of the models accurately, the confusion matrix and other measures (recall, accuracy, and F1-score) were used for both categories (minority and majority) to compare the performance of credit fraud detection algorithms for the minority category.

4. Materials and methods of research

4. 1. Object and hypothesis of the study

The object of this study is the effectiveness of the Random Forest with Bayesian Optimization (RFBO) pipeline in improving the evaluation performance of machine learning models for credit card fraud detection in the banking industry. The working hypothesis is that utilizing the Random Forest with Bayesian Optimization (RFBO) pipeline will improve the model's performance in identifying credit fraud cases by recommending optimal hyperparameter combinations and addressing the imbalance in the dataset. The researchers hypothesize that by employing the RFBO pipeline, which incorporates Bayesian optimization to determine the best hyperparameters for the model, they will achieve higher accuracy and better credit card fraud detection compared to traditional methods. The hypothesis is based on the understanding that random forests are highly accurate and robust classifiers, especially when dealing with incomplete or imbalanced datasets. By leveraging the ensemble method and optimizing the model's parameters through Bayesian optimization, the researchers expect superior performance in identifying credit card fraud cases.

Bagging is the most straightforward way to improve or «boost» a classifier's performance. It necessitates repeating the first classifier on resampled copies of the training sample, with no new information in the training sample, either in more variables or additional observations. The decision tree is chosen as the basis classifier [27]. Most software packages include decision trees, which are strong nonparametric classification algorithms. According to Breiman, they are suitable candidates for the bagging technique since they are high-performing yet unstable classifiers. When tiny changes in the dataset are made, «instability» refers to classifiers that alter considerably. Because Bagging, i.e. Bootstrap, averages predictions across a set of bootstrap samples, the variance of the prediction is reduced, enabling the classifier's predictive accuracy to be improved [28, 29]. The basic idea of random forest is that if the classification accuracy is regarded as the core objective of the prediction model, then the single classifier can be completely excluded, and the ensemble method can be used. Random forest is one of the most cutting-edge methods among all randomization-based ensemble methods. Random forest is a machine learning theory proposed [30]. It first uses the bootstrap resampling method to select n samples from the original data set and then builds a decision tree for each sample, requiring all attributes. Randomly select m attributes from and select the best segmentation attribute as a node. Repeat the above steps k times to build k decision trees. These k decision trees will form a random forest, and each tree will pass the prediction. The target class votes, and finally, the output result with the most votes is used as the predicted classification result of the data through statistical voting. Many research results have confirmed that random forest has high prediction accuracy and high tolerance to outliers, strong robustness to noise, and is not prone to overfitting. It can be said that a random forest is a natural nonlinear modeling tool that only needs to train samples and mine information separately [31].

Furthermore, it is also an adaptive method that is good at dealing with problems without explicit rules or prior knowledge. A random forest can give reliable results even when the dataset is incomplete, so it outperforms traditional forecasting methods, inefficiently extracting information from the data. Similar to the Classification and Regression Tree (CART), random forests can be divided into two types: Random Forests for Classification (RFC) and Random Forests for Regression (RFR). The main criterion for distinguishing the two lies in the type of dependent variable. If the dependent variable is categorical, you can use RFC; otherwise, if the dependent variable is continuous, then RFR is more appropriate [32, 33]. Fig. 1 shows how the outputs of the random forest results are integrated.

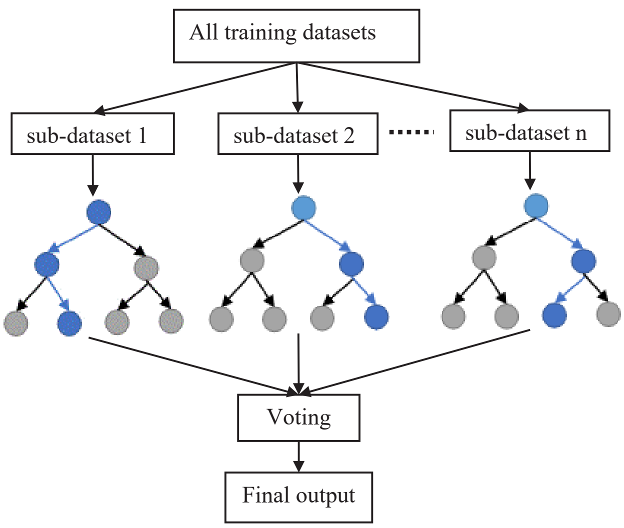

Fig. 1. Illustrating Random forest classifier

As illustrated in Fig. 1, a sub-dataset is generated after the sampling with replacement is taken from the original dataset and the sampling with replacement is taken from the sub-dataset. The sub-dataset has an identical data volume similar to the main dataset. Repetition is possible across items in distinct sub-datasets and between elements within the same sub-dataset. First, create sub-datasets and sub-decision trees, insert the data into each sub-decision tree, and finally output the result. Lastly, imagine that there is fresh data and that the classification result has to be achieved via a random forest algorithm. In such a situation, by voting on the judgment result of the sub-decision tree, the output result of the random forest can be produced [32, 34].

4. 2. Data description

The experimental data in this paper were selected from credit card fraud data collected from European cardholders [35]. The experimental data set contains a total of 284,897 samples and 31 features. The sample category is represented by 0 and 1, where 0 is a good credit sample (also known as a negative sample), the majority category, and 1 represents a fraud sample (also known as a positive sample). It is a minority sample category. There are 492 samples from the minority group and 284,405 samples from the majority group, and the imbalance ratio is 0.173, which is very unbalanced.

4. 3. Model construction

A pipeline known as Random Forest with Bayesian Optimization (RFBO) was developed to enhance the evaluation performance of machine learning models while dealing with excessively imbalanced credit fraud data. This pipeline employs Bayesian optimization for the machine learning model to recommend the optimal combination of hyperparameters for model variables, training, and processing of imbalanced data sets for the model to be trained on. An RFBO-based random forest classifier was developed as an example to demonstrate the efficiency of RFBO in increasing the model's performance in the detection of credit fraud in the banking industry. Fig. 2 describes the process of building a Random Forest with Bayesian Optimization model.

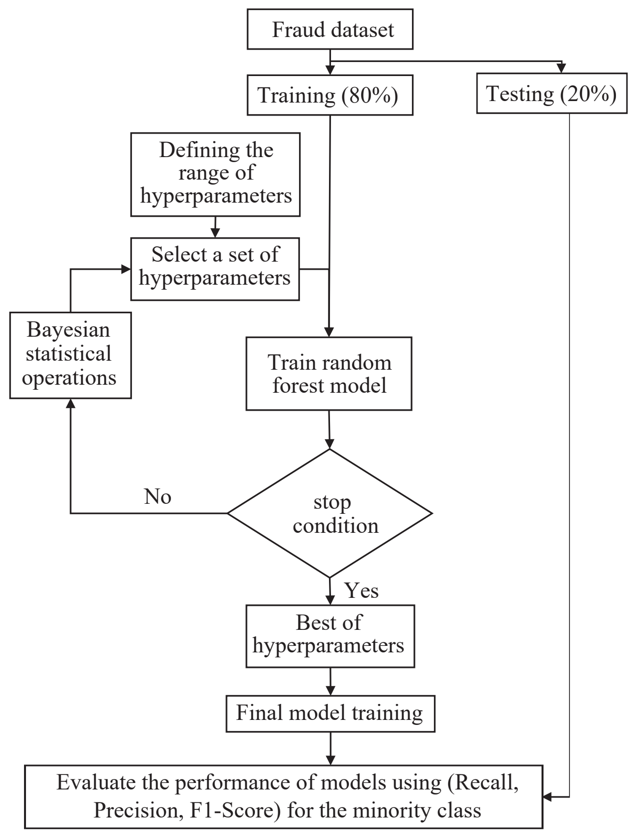

Fig. 2. The process of building a Random Forest with Bayesian Optimization model

As shown in Fig. 2, the data set was divided into a training set and a test set. Determining the range of hyperparameter values with a training set as input to a pipeline that combines a random forest model and Bayesian optimization to create a final model.

Usually, the processing class imbalance learning algorithm can be evaluated by the area under the AUC curve [36]. However, when the number of negative and positive samples is quite different, it is difficult for the AUC of ROC to discriminate significantly between classifier performance. In the confusion matrix, TN represents correctly identified negative samples, FP represents incorrectly identified negative samples, FN represents incorrectly identified positive samples, and TP represents correctly identified positive samples [37–39]. Fig. 3 represents a visualization of the confusion matrix and the intersection of actual and expected values.

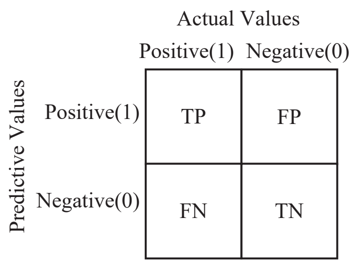

Fig. 3. Confusion matrix

Just looking at the absolute and relative indicators of each value of the confusion matrix is likely to ignore the real situation of credit fraud. This study uses the confusion matrix and other measures (Recall, Precision, F1-Score) for both categories (minority, majority):

$$Precision = \frac{TP}{TP + FP}, \quad (1)$$

$$Recall = \frac{TP}{TP + FN}, \quad (2)$$

$$F1 - Score = 2 * \frac{Precision * Recall}{Precision + Recall}. \quad (3)$$

Recall (also known as sensitivity) measures the proportion of actual positive cases that were correctly identified by the model, while precision measures the proportion of predicted positive cases that were actually positive. F1-score is the harmonic mean of precision and recall, providing a balanced measure of the model's performance. By evaluating the model's performance on both the minority and majority classes, the study can provide a more nuanced understanding of how well the model identifies cases of credit fraud, especially since the minority class is often the one of greater interest in these types of analyses.

5. Evaluation of Bagging Models and the Proposed Random Forest with Bayesian Optimization Model

5. 1. Bagging models for unbalanced credit fraud modeling

The performance of four bagging learning models (Bagging, Balanced Bagging, Random Forest, and Balanced Random Forest) is compared in terms of precision, recall, and F1-score for credit fraud detection in the minority class. Table 1 shows that the Balanced Bagging and Balanced Random Forest models achieved the highest recall scores of 0.94, indicating their ability to detect the minority class, while the Bagging and Random Forest models achieved high precision scores of 0.90 and 0.93, respectively.

Based on the comparison of the four bagging learning models, it can be observed that the Balanced Bagging and Balanced Random Forest models outperformed the Bagging and Random Forest models in terms of recall score. This means that the Balanced Bagging and Balanced Random Forest models are better at detecting instances of credit fraud in the minority class. However, the Bagging and Random Forest models achieved higher precision scores, which means that they have a lower false positive rate.

Table 1

Comparison of bagging learning algorithms for credit fraud detection for the minority class

Evaluation indicator	Bagging	Balanced Bagging	Random Forest	Balanced Random Forest
precision	0.90	0.07	0.93	0.05
recall	0.82	0.94	0.79	0.94
F1-score	0.86	0.12	0.85	0.10

5. 2. Results of Random Forest performance with Bayesian optimization (RFBO)

The performance of the proposed RFBO model, a Random Forest classifier model with Bayesian optimization, is evaluated and compared with the results of the previous subsection. Table 2 shows that the RFBO model achieved a precision score of 0.94, a recall score of 0.81, and an F1-score of 0.87, indicating an improvement in overall performance compared to the previous models.

Table 2

Random Forest performance with Bayesian optimization (RFBO)

Evaluation indicator	RFBO
precision	0.94
recall	0.81
F1-score	0.87

The results of the RFBO model show that it outperforms the previous bagging models in terms of precision and F1-score while maintaining a reasonable recall score. This indicates that the RFBO model is better at detecting credit fraud cases while minimizing false positives than the previous models. Using Bayesian optimization to tune the model's hyperparameters likely contributed to this improved performance. Overall, the RFBO model shows promise as an effective tool for credit fraud detection.

5. 3. Comparison of models based on confusion matrices

The confusion matrices of the algorithms in this experiment are compared to evaluate their performance for both categories (minority and majority). The confusion matrices in Fig. 4 compare the performance of five different models:

a) Bagging;

b) Balanced Bagging;

c) Random Forest;

d) Balanced Random Forest;

e) RFBO in detecting credit fraud cases in the minority and majority classes and that the RFBO model achieved the highest true positive rate for the minority class (74 out of 98), indicating its ability to accurately detect credit fraud cases in the minority class while minimizing false positives in the majority class.

The proposed RFBO model outperformed traditional bagging models in detecting credit fraud cases in the minority class, demonstrating the potential of bagging algorithms in modeling highly unbalanced data. Bayesian optimization was also shown to be effective in finding optimal hyperparameters and improving the model's overall performance.

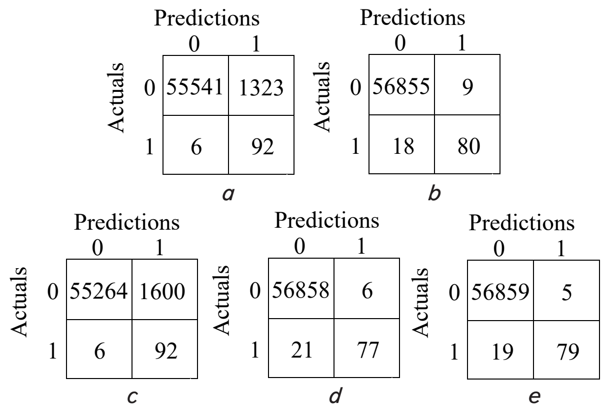

Fig. 4. Comparison of confusion matrices of: *a* – Bagging; *b* – Balanced Bagging; *c* – Random Forest; *d* – Balanced Random Forest; *e* – Random Forest with Bayesian optimization

6. Discussion of the performance of the proposed Random Forest with Bayesian optimization and traditional bagging models

The obtained results can be explained by the following key points. Firstly, the RFBO algorithm outperformed traditional bagging models in detecting credit fraud cases in the minority class due to its ability to find optimal hyperparameters through Bayesian optimization (Fig. 4). The use of Bayesian optimization allows for a more thorough search for the best hyperparameters, resulting in improved performance compared to traditional grid search methods. The higher precision, recall, and F1-score achieved by the RFBO model demonstrate its effectiveness in accurately detecting credit fraud cases while minimizing false positives (Table 2).

Secondly, the advantages of the proposed RFBO model can be attributed to the combination of Random Forest and Bayesian optimization. Random Forest is a robust classifier that handles imbalanced and incomplete datasets well, making it suitable for credit card fraud detection. By incorporating Bayesian optimization, the model's hyperparameters can be fine-tuned, leading to improved performance and better identification of fraud cases (Table 2). The RFBO model leverages the ensemble method of Random Forest and the optimization capabilities of Bayesian optimization, resulting in superior credit card fraud detection compared to traditional methods.

This study has some limitations that may impact the generalizability of the results. The study uses a single dataset and focuses on credit fraud detection, limiting its applicability to other domains. Additionally, the study does not explore the impact of the dataset's size on the models' performance.

One potential disadvantage of this study is that it does not consider other ensemble learning methods, such as boosting, which can provide better performance in highly unbalanced data. Future studies can explore these methods' effectiveness compared to bagging algorithms. Additionally, future studies can use multiple datasets and explore the dataset size's impact on the models' performance.

The development of this research can lead to the improvement of fraud detection methods in highly unbalanced data, which is a critical issue in many domains. Future research can explore other optimization techniques, such as genetic algorithms, to find optimal hyperparameters for bagging algorithms. Mathematical and computational difficulties may arise in exploring the effectiveness of these methods, which may require the development of new algorithms and computational methods.

The results obtained in this study show that the proposed Random Forest with Bayesian optimization (RFBO) model outperforms traditional bagging models in detecting credit fraud cases in the minority class while minimizing false positives in the majority class. The use of Bayesian optimization in tuning the model's hyperparameters likely contributed to this improved performance, as it allowed for a more thorough search for optimal hyperparameters compared to traditional grid search methods.

Compared to existing works, the use of bagging algorithms for modeling highly unbalanced data is not a new approach. However, including Bayesian optimization in the RFBO model is a novel contribution that has not been extensively explored in the literature for credit fraud detection. One limitation of the study is that it only evaluated the performance of the models on a single dataset. Further research is needed to evaluate the proposed method's generalizability and performance on other datasets.

Overall, the proposed RFBO model shows promise as an effective tool for credit fraud detection, particularly in cases where the data is highly unbalanced. The use of Bayesian optimization in tuning hyperparameters may also be applicable to other machine learning models and domains, providing a valuable contribution to machine learning.

7. Conclusions

1. The proposed bagging algorithm, Random Forest with Bayesian Optimization (RFBO), outperforms traditional data balancing methods in modeling highly unbalanced credit fraud data. The model showed an increase in precision, recall, and F1-score for the minority category compared to other traditional models. It achieved 0.94, 0.81, and 0.87, respectively.

2. The use of Bayesian optimization to find the optimal combination of hyperparameters significantly improves the prediction accuracy of the random forest classifier model. By fine-tuning the hyperparameters, the balancing of the model improved. The model showed an increase in precision, recall, and F1-score for the minority category compared to other traditional models. It achieved 0.94, 0.81, and 0.87, respectively.

3. The confusion matrix and other measures such as recall, accuracy, and F1-score were used to evaluate the performance of credit fraud detection algorithms for both minority and majority categories. The proposed RFBO model better detected fraud cases among the minority category, as in Fig. 4. Therefore, it can be concluded that the proposed bagging algorithm using random forest and Bayesian optimization is a promising solution for modeling highly unbalanced credit fraud data, and it outperforms traditional data balancing methods. Furthermore, fine-tuning hyperparameters using Bayesian optimization leads to improved model balancing and prediction accuracy. The evaluation metrics used confirm the superiority of the proposed model in detecting fraud cases among the minority category.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

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Data availability

The manuscript has associated data in a data repository.

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