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Integrating Financial and Non-Financial Indicators through RF-SVM-Stacking Model for Accurate Green Credit Risk Assessment

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Abstract

Green credit has emerged as a crucial financial mechanism to promote sustainable economic development and mitigate environmental degradation. However, the evaluation and risk assessment of green credit remain a significant challenge due to the complexity of environmental factors and the limitations of traditional financial scoring models, which primarily rely on quantitative financial data. This study aims to develop a more accurate and comprehensive green credit scoring approach by integrating financial and non-financial indicators into an advanced hybrid model. To achieve this, an RF-SVM-Stacking integrated model is proposed, combining Random Forest (RF) for feature importance ranking and Support Vector Machine (SVM) for credit scoring. The model incorporates conventional financial indicators along with non-financial factors, including green credit risk characteristics, innovation input indicators, and ESG (Environmental, Social, and Governance) ratings. Methodologically, the stacking ensemble technique is employed to enhance prediction accuracy and robustness across datasets. The empirical analysis demonstrates that the proposed RF-SVM-Stacking model achieves higher accuracy and better generalization capability compared to baseline models such as SVM with Bagging or AdaBoost, neural networks, and Gradient Boosted Decision Trees (GBDT). The findings suggest that incorporating non-financial and sustainability-related metrics significantly enhances the accuracy of green credit risk assessment. These results have important implications for financial institutions and policymakers, suggesting that adopting integrated machine learning approaches can effectively support the development of a sustainable financial system and guide more responsible investment practices aligned with global environmental objectives.

Keywords: *Credit Risk; ESG Rating; Green Credit; Integrated Learning; Random Forest; Support Vector Machine.*

A. Introduction

The accelerated industrial growth and urban expansion worldwide have exacerbated environmental degradation into a pressing global issue. Worsening pollution levels and the rapid exhaustion of natural resources have propelled environmental conservation to the forefront as both an urgent priority and a formidable challenge for the international community. As China's economic development transitions to a phased approach, shifting from high-input, high-emission development patterns to an efficiency-driven, sustainable model has become imperative. In this context, green finance mechanisms have emerged as a critical policy instrument for steering business practices toward ecological responsibility, particularly in guiding developing economies to align industrial progress with environmental governance (Chen et al., 2023). Since

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2007, China has gradually introduced a series of policies to promote the development of green financial products, including green credit, green insurance, and green securities, marking the official beginning of the green credit era. A significant milestone was the release of the Green Credit Guidelines by the China Banking Regulatory Commission (CBRC) in 2012, followed by the introduction of the Green Credit Statistics System in 2013 (Luo et al., 2021).

Green lending represents a paradigm shift from conventional financing by prioritizing the ecological benefits and long-term sustainability of funded projects. Defined as commercial banks' provision of credit to environmentally sustainable enterprises or initiatives, this financing mechanism serves a dual purpose: it actively channels capital toward green development while systematically restricting access to credit for high-pollution industries. This is achieved through two key mechanisms: first, by imposing environmental compliance requirements on lending institutions themselves, and second, by mandating the integration of comprehensive environmental and social risk assessments into traditional credit evaluation frameworks. Such an approach transforms financial institutions into gatekeepers of sustainable development, aligning capital flows with ecological priorities (An et al., 2021; Wen et al., 2021). As a new financial instrument that utilizes financial means to support green industries and environmental projects, green credit serves as a crucial lever for integrating social and economic benefits (Feng et al., 2024). This type of financing is essential for promoting the development of the green industry.

The risks associated with developing green loans differ from those of traditional loans. The environmental protection industry is exposed to higher levels of risk, and variations in environmental policies across countries have a significant impact on international investment risk. (Criscuolo & Menon, 2015). Research on green lending typically approaches the topic from the selection of green scoring indicators and the development of evaluation models.

To establish a green credit scoring model, it is important to build a comprehensive index system. Environmental factors significantly affect loan success rates, interest rates, and default rates, and have been considered as important evaluation indicators for credit assessment (White, 1996). Meanwhile, numerous studies suggest that the environment poses direct or indirect risks to banks (Thompson, 1998; Campbell & Slack, 2011). These include considering factors such as market and weather risk (Lohmann, 2010). Engaging in environmental risk management not only enables the effective evasion of environmental and social risks but also prevents related risks, such as credit and reputation risks, thereby reducing the occurrence of bank bad debts (Chami et al., 2002). From the perspective of green development, sustainable development ability and moral risk are taken as green credit scoring index (He & Liu, 2018).

Several effective green credit scoring models incorporating hybrid techniques have been proposed in recent years. Many traditional credit scoring methods are also used for green credit scoring, such as the 3σ rule (Kobayashi & Tanaka, 2021), network analysis method (Ngan, et al., 2018), KMV model (Wang & Xu, 2023), etc. With the rapid advancement of technologies such as machine learning, big data, and cloud computing, artificial intelligence is also being applied in green credit scoring. The latest machine learning methods, such as random forest (Ech-Chafiq, et al., 2023), LightGBM algorithm (Guo, et al., 2022) and BP neural network (Li and Wu, 2010) are commonly used in green credit scoring. They can effectively prevent subjective errors and improve prediction accuracy. To improve prediction accuracy, scholars have combined various methods to construct a green credit scoring model. Farquad and Sriramjee (2011) employed a method that combines PCA and SVM models, where the PCA model is used for dimensionality reduction, followed by the SVM model for classification. Vicente and Marqués (2014) evaluated algorithms such as decision trees, support vector machines, and K-nearest neighbors using different data samples and methods. The support vector machine algorithm performed much better than the other algorithms in terms of overall performance. Green credit scoring models that combine different methods, choosing to use multi-classifier systems, i.e., ensemble algorithms, to improve the model's generalization ability are also proposed, and ensemble learning algorithms are significantly superior to single algorithms in classification capability (Singh, 2017).

Machine learning methods can effectively improve the efficiency and accuracy of green credit scoring. However, due to the differences in datasets, the performance of models will vary significantly, making it challenging to find methods that are suitable for various situations. Based on the characteristics of actual data, this paper introduces innovation investment, ESG rating indicators, and the BSMOTE method to develop an RF-SVM Stacking model for green credit scoring. An integrated algorithm for green credit scoring is proposed. The remainder of this paper is organized as follows: Section 2 introduces the related methods; Section 3 presents the proposed model; Section 4 describes the sources of experimental data and evaluation metrics; Section 5 analyzes the experimental results; Section 6 draws conclusions and compares the superiority of the model.

B. Methods

This study employs a quantitative experimental-comparative design aimed at developing and evaluating an integrated predictive model for green credit risk assessment. This design was selected to enable the identification of causal relationships between financial and non-financial variables, while ensuring high analytical accuracy through the application of machine learning techniques. The proposed RF-SVM-Stacking model combines the strengths of the Random Forest (RF) algorithm, which identifies the relative importance of features, with the Support Vector Machine (SVM), which performs classification and scoring of credit risk. The primary objective of this design is to construct a more accurate and adaptive model than conventional approaches, such as SVM enhanced with Bagging or AdaBoost, as well as Neural Network and Gradient Boosted Decision Trees (GBDT) models.

The research procedure begins with the formulation of indicators encompassing both financial and non-financial variables, including green credit risk characteristics, innovation input indicators, and ESG ratings. Data are collected from financial statements, ESG databases, and relevant green credit portfolios. The subsequent steps involve data preprocessing, which includes cleaning, handling missing values, normalization, and encoding of categorical variables. The dataset is then divided into training, validation, and testing sets using k-fold cross-validation to ensure model robustness. Feature selection is conducted using RF, followed by SVM training and the construction of a stacking model that integrates predictions from multiple base learners through a meta-learner to enhance overall performance.

The data collection techniques employed in this study rely on both primary and secondary sources. Primary data are obtained from financial institutions that provide green credit portfolios, loan performance data, and project documentation. Secondary data are gathered from public financial reports, global ESG databases, and relevant macroeconomic datasets that support environmental risk analysis. Sampling is conducted using a purposive approach to ensure data completeness and representativeness. Ethical research principles are strictly maintained by anonymizing sensitive information and complying with data protection regulations.

Data analysis is conducted through several stages, including exploratory analysis, feature selection, and the construction of machine learning models. The Random Forest algorithm is employed to determine the importance of each feature, while the Support Vector Machine performs the final classification task. The Stacking Ensemble method integrates the predictive outputs of base models to achieve higher stability and accuracy. Model evaluation is conducted using metrics such as Accuracy, Precision, Recall, F1-Score, and AUC-ROC, followed by statistical comparison with benchmark models. The findings are expected to enhance the accuracy of green credit risk assessment and contribute to the advancement of sustainable financial systems based on artificial intelligence and environmentally responsible decision-making.

C. Results and Discussion

1. Related work

The proposed model mainly involves three algorithms: the random forest algorithm, Borderline SMOTE, and the support vector machine, which are vital fields in credit scoring and machine learning. Some representative studies are presented in this section.

Random Forest

The random forest algorithm was developed by Breiman in 2001. It is a tree-based ensemble learning method that consists of decision tree forests and is widely used in classification and regression tasks. The random forest algorithm increases the diversity of trees by constructing decision trees from bootstrap samples and random subsets of input features. In addition, aggregating the predicted results of all different decision trees can significantly eliminate the influence of noise in the dataset and reduce the overall variance of the model.

Compared to traditional machine learning algorithms, the random forest algorithm can evaluate the relative importance of input features, which helps reduce dimensionality and improve the model's performance on high-dimensional problems. Since the dataset for each tree is generated by replacement sampling or bootstrapping, some data may be duplicated, and some data may not be selected. On average, approximately one-third of the samples in the dataset are not used in constructing a tree and are referred to as out-of-band (OOB) samples for that tree. The random forest algorithm can provide an unbiased estimate of the generalization error without using external datasets based on the OOB samples of each tree. The OOB samples are actually considered as a test dataset for each tree. By adding random noise to change the value of a certain feature and comparing the decrease in the prediction accuracy of OOB samples, the importance of features can be evaluated. The greater the reduction, the more important the feature is. Not only can the impact of individual features be considered, but also the interaction between multiple feature pairs can be taken into account.

This article's green credit risk assessment indicator system includes two parts: financial indicators and non-financial indicators. We use the random forest method to select the top 18 indicators that contribute to 90% of the importance from the original indicator system, which contains 21 explanatory variables. Three unimportant indicators are then removed to construct a new indicator system. The indicators for evaluating each type of capability are not evenly distributed, with the debt-paying ability and operational ability comprising four indicators, and the development ability and profitability comprising three indicators. This breaks the traditional mode where all indicators are evenly distributed under each type of capability and focuses on the overall importance of the indicator system rather than a single capability. Finally, the importance of R&D investment proportion and ESG rating are among the top, indicating that R&D investment and environmental protection are also key factors affecting enterprise credit ratings. Therefore, including R&D investment proportion and environmental protection in the green credit risk evaluation indicator system has a certain practical basis. The final constructed indicator system is shown in Table 1.

Table 1. Index system after screening

Debt Servicing Ability	Quick Ratio (X2)
	Interest Coverage Ratio (X3)
	Cash Ratio (X4)
	Equity Multiplier (X5)
Operating Efficiency	Accounts Receivable Turnover Ratio (X6)
	Inventory Turnover Ratio (X7)
	Current Asset Turnover Ratio (X8)
	Total Asset Turnover Ratio (X9)
Development Capability	Capital Accumulation Rate (X10)
	Total Asset Growth Rate (X11)
	Operating Profit Growth Rate (X12)
Profitability	Return on Assets (X14)
	Return on Equity (X16)
	Operating Net Profit Margin (X17)
Non-financial Indicators	R&D Expenditure Ratio (X18)
	Environmental Rating (X19)
	Social Rating (X20)
	Governance Rating (X21)

Borderline SMOTE

SMOTE is commonly used to handle imbalanced data by synthesizing minority class samples to balance their numbers with those of the majority class samples. However, due to the algorithm itself, this method generates mostly noise samples, which provide little useful information and may negatively impact the model's performance. The BSMOTE used in this article is a variant of SMOTE. BSMOTE can make data generation more targeted by concentrating the generation of new data around difficult-to-classify boundary data points. BSMOTE has been demonstrated to enhance classification performance across various datasets and classifiers.

Based on this, the BSMOTE algorithm is employed to balance the sample data and obtain a more balanced dataset. From Table 2, it can be seen that the sample distribution in the original dataset was very imbalanced, with a ratio exceeding 6:1. After balancing, the gap in sample distribution is reduced, and the ratio of both is close to 1:1, which can effectively solve the problem of prediction bias caused by imbalanced samples and make the classification results of the model more reasonable.

Table 2. Sample equalization distribution

Before Balancing	**Raw Data**	**784**	**123**	**907**	**86.44%**	**13.56%**
	Training Set	549	86	635	86.44%	13.56%
	Test Set	235	37	272	86.44%	13.56%
Balancing	New Training Set	549	549	1098	50.0%	50.0%

Support Vector Machine

The Support Vector Machine (SVM) is a statistical machine learning method that has been applied to various regression and classification problems, including text/face recognition, medical diagnosis, and market analysis. To classify non-separable datasets, SVM nonlinearly maps the data to a higher-dimensional space, allowing for linear separation by a hyperplane. Finding the best separating hyperplane is the core concept of the SVM model classification, and it is crucial to find a hyperplane that can separate the two classes to the maximum extent. Data points that only act to form the hyperplane are called support vectors, which are the closest data points to the hyperplane in each class and are the only data points that affect the construction of the classifier. The principle is shown in Fig 1.

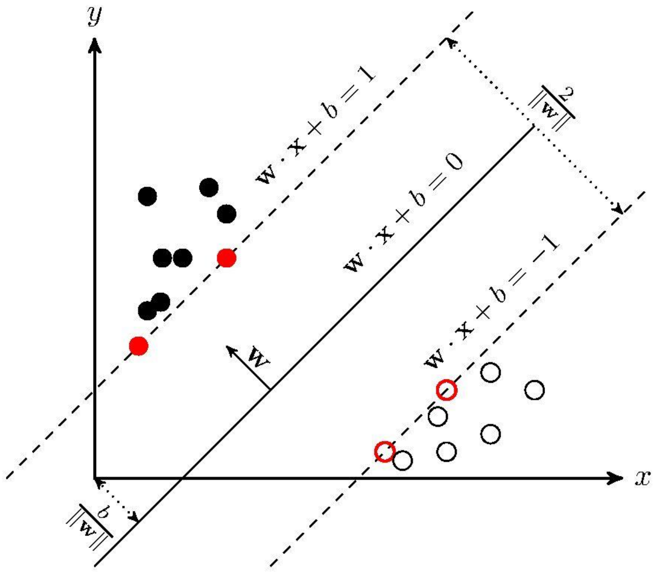

Figure 1. Support vector machine

2. Modeling

This article examines the characteristics of imbalanced sample data and green credit by introducing innovative inputs, including ESG rating indicators and the BSMOTE method. It proposes an RF-SVM stacking model that is more suitable for green credit risk assessment, thereby enhancing the performance of the base model. The process of building the model is illustrated in Fig. 2. An ensemble learning algorithm is a method that combines multiple algorithms to form a more powerful predictive model. Each basic algorithm in ensemble learning is referred to as a weak classifier, and when these basic algorithms are combined using an ensemble algorithm, they form a strong classifier. In this article, the three most widely used ensemble algorithms —Bagging, AdaBoost, and Stacking —are employed for model integration.

Bagging Ensemble Algorithm

The main principle of the Bagging ensemble algorithm is to train each base model with a sub-sample randomly selected from the original training dataset, and the output is the linear combination of all base models. The best way to maximize the accuracy of Bagging-based models is to use very unstable and fast base models. When small differences in a model's training data set can result in highly different predictive models, it is usually unstable, so hundreds of models need to be built during the training step. The training process of the Bagging Ensemble Algorithm is illustrated in Fig 3.

AdaBoost Ensemble Algorithm

Adaboost is an ensemble algorithm with adaptive adjustment capability, which has two typical features. Firstly, in each iteration, Adaboost increases the weight of misclassified samples to construct a new training set, allowing the model to focus more on these misclassified samples. Secondly, after each iteration, the algorithm generates a classification model (called a "weak classifier"), and the weights of each weak classifier are adjusted based on their classification accuracy, with weak classifiers with higher classification accuracy receiving higher weights. Therefore, the Adaboost ensemble algorithm constructs a powerful classifier by combining multiple weak classifiers. The AdaBoost algorithm can integrate multiple low-precision models into an accurate model with strong classification ability, while reducing the complexity of model design. The training process of the Adaboost algorithm is shown in Fig. 4.

Stacking ensemble algorithm

A stacking ensemble algorithm is a fusion method that allows each base classifier to be trained on the same original training dataset, and the results trained by each base classifier are combined into a new dataset, which is then used to train and classify with a new classifier. The advantage of this method is that it can effectively integrate different types of classifiers, thereby improving the model's ability. The working principle of the Stacking ensemble algorithm is shown in Fig. 5.

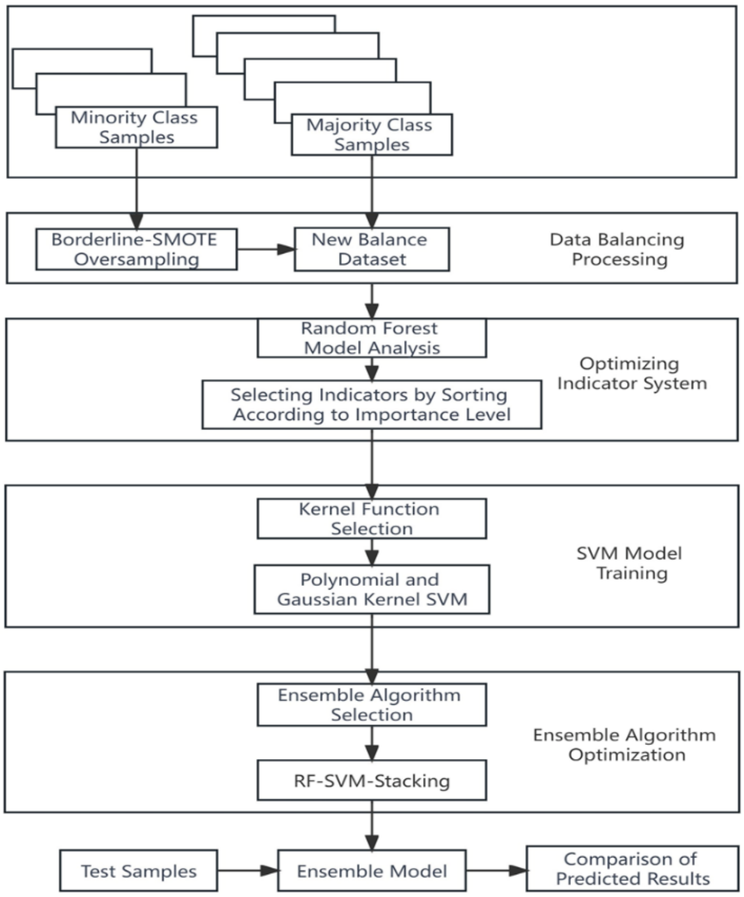

Figure 2. Flowchart of RF-SVM-Stacking model construction

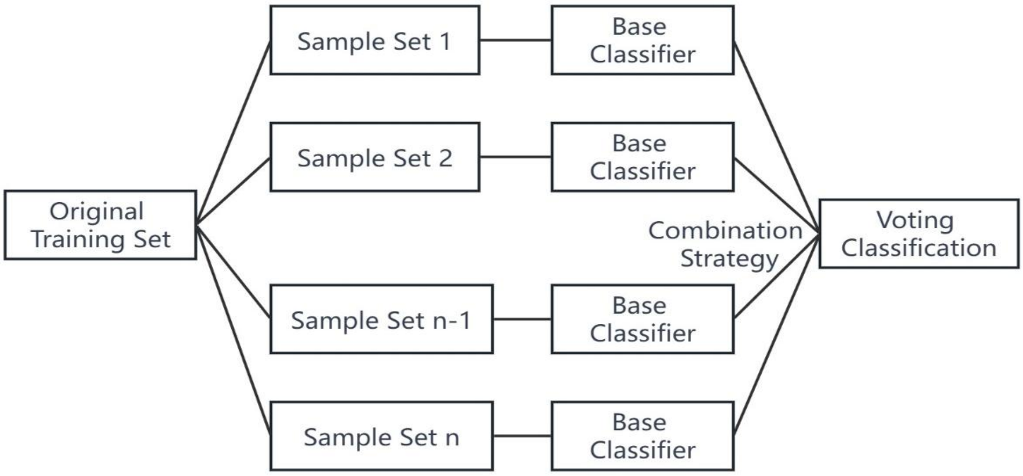

Figure 3. Principle of Bagging algorithm

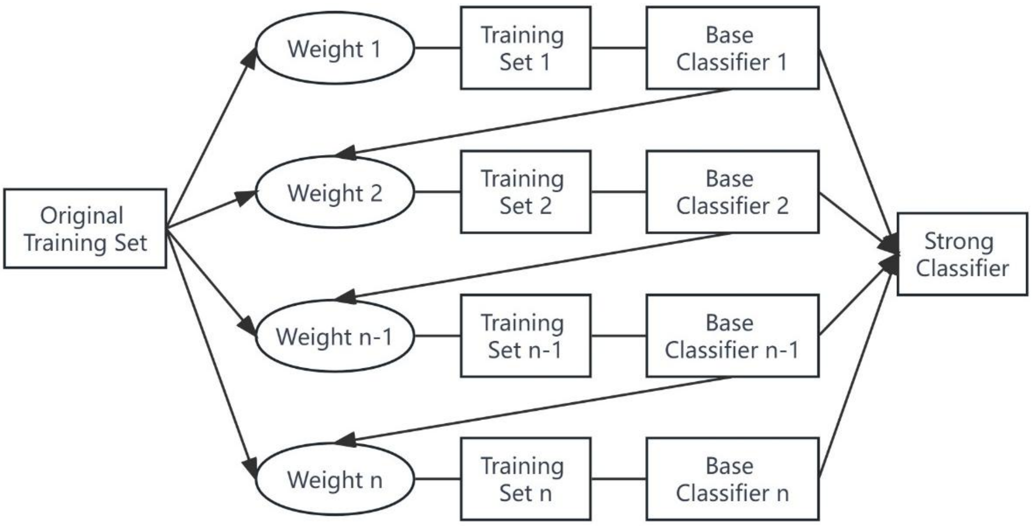

Figure 4. Principle of Adaboost algorithm

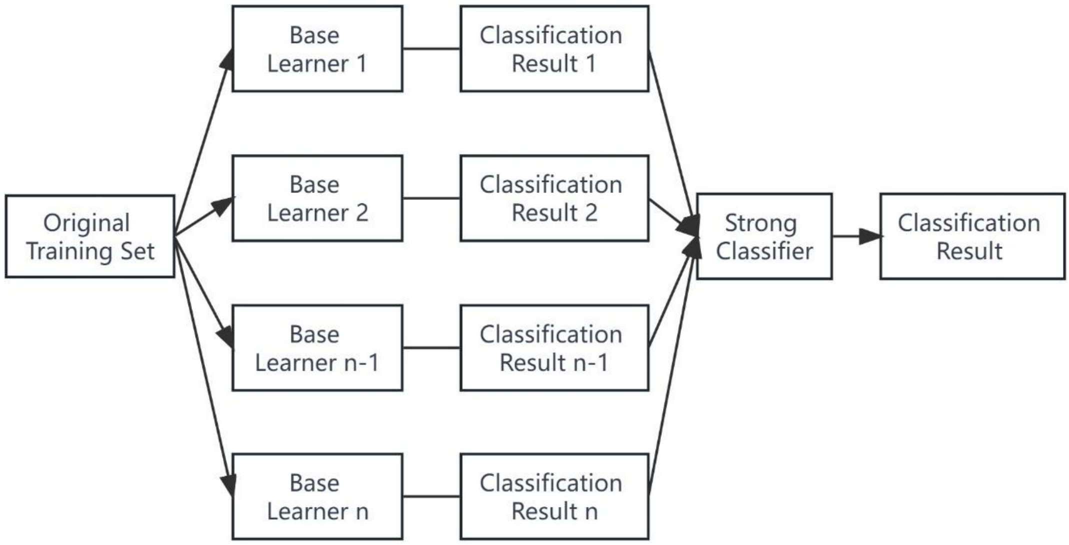

Figure 5. Stacking algorithm principle

3. Experiment

Dataset description and data preprocessing

This paper selects relevant indicator data from publicly issued information of Chinese listed companies since 2024. The data sources include GTA (Guotai An), Wind, publicly available government data, and the database of the People's Bank of China. After excluding companies with missing ESG rating indicator data and enterprise credit rating data, a total of 907 listed companies remain in the sample dataset for this article. In terms of credit rating classification, the company categories are based on enterprise credit rating data. To reflect the strict requirements of green credit, the credit rating is divided by the "AA-" level. The sample companies with a credit rating above (including the "AA-" level) are classified as high-credit-rating, with the indicator set to 0, while those below this level are classified as low-credit-rating, with the indicator set to 1.

Evaluation indicators

In this study, four evaluation indicators were adopted: accuracy, F-score, ROC, and AUC. The higher the indicator value, the better the model's classification performance. Accuracy refers to the ratio of the number of correctly identified samples to all samples participating in classification. The accuracy of the positive class is TP/(TP + FP), and the accuracy of the negative class is TN/(TN + FN). The overall accuracy is (TP + TN)/(TP + FP + TN + FN).

Recall refers to the proportion of correctly classified samples to the total number of samples in the actual class. The recall rate of the positive class is TP/(TP + FN), and the recall rate of the negative class is TN/(TN + FP). Precision refers to the probability that a sample predicted as positive or negative is truly positive or negative.

Table 3. Confusion matrix

Prediction Actual	Positive Class	Negative Class
Positive Class	TP	FP
Negative Class	FN	TN

Note: Here, TP (true positive) refers to the part that is accurately predicted as a positive class, and FP (false positive) refers to the part that is actually a negative class and is wrongly predicted as a positive class. Similarly, TN (true negative) refers to the part that is correctly predicted as a negative class, and FN (false negative) refers to the part that is actually a positive class but is wrongly predicted as a negative class. F1 score is the harmonic mean of precision and recall. Its formula is:

$$\mathrm{F1-score_i} = 2 \times \frac{\mathrm{precision_i} \times \mathrm{recall_i}}{\mathrm{precision_i} + \mathrm{recall_i}} \times (\mathrm{i = Positive\ class,\quad negative\ class})$$

The ROC curve is a tool for evaluating the performance of classifiers, which shows the relationship between the true positive rate and the false positive rate of the classifier. Generally, we hope that the true positive rate is higher and the false positive rate is lower. The larger the slope of the ROC curve, the better the classifier's performance. The value range of the AUC area is between 0 and 1; the performance of different classifiers can be evaluated by comparing the size of their AUC areas. Generally, the larger the AUC value, the better the classifier's performance.

4. Experimental analysis

Evaluation of the Support Vector Machine Model

Demonstrate the effectiveness of the Support Vector Machine (SVM) model by evaluating the results using the three evaluation indicators listed below. From the results in Table 4, it can be seen that the RBF kernel function has slightly lower F1 scores than the poly kernel function, but has a higher accuracy rate and AUC values than the other two kernel functions.

Table 4. Comparison of kernel functions

Linear Kernel Function	**0.7580**	**0.8248**	**0.7816**
Ploy Kernel Function	0.8832	0.8906	0.8952
Rbf Kernel Function	0.8854	0.9637	0.8789

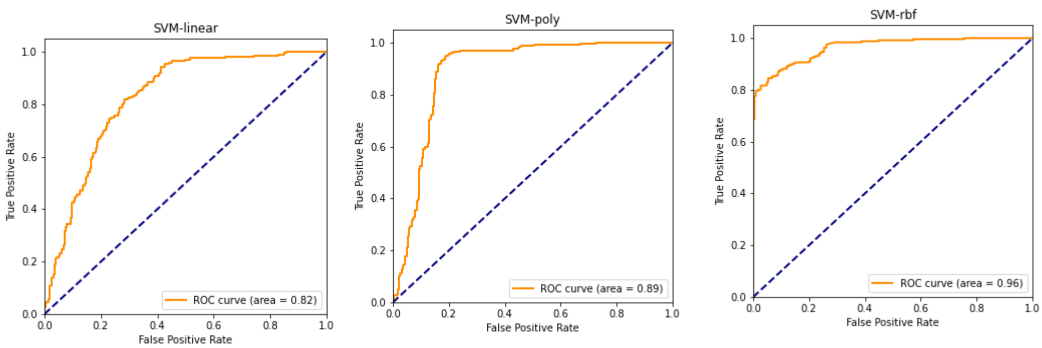

Figure 6. ROC curves of three kernel functions

The performance of the support vector machine model is compared with that of other single classification models, including logistic regression, K-nearest neighbor, naive Bayes, and decision tree models, in the dataset, as shown in Table 5. The results show that compared with other models, the support vector machine model has significant advantages in all aspects. The logistic regression and naive Bayes models do not perform well in the test set, while the K-nearest neighbor and decision tree models have relatively good accuracy rates, F1 scores, and AUC values.

Table 5. Comparison of different algorithms

Logistic Regression	0.7517	0.8200	0.7646
K-Nearest Neighbors	0.8684	0.8636	0.8852
Naive Bayes	0.6561	0.7795	0.6010
Decision Tree	0.8386	0.8566	0.8550

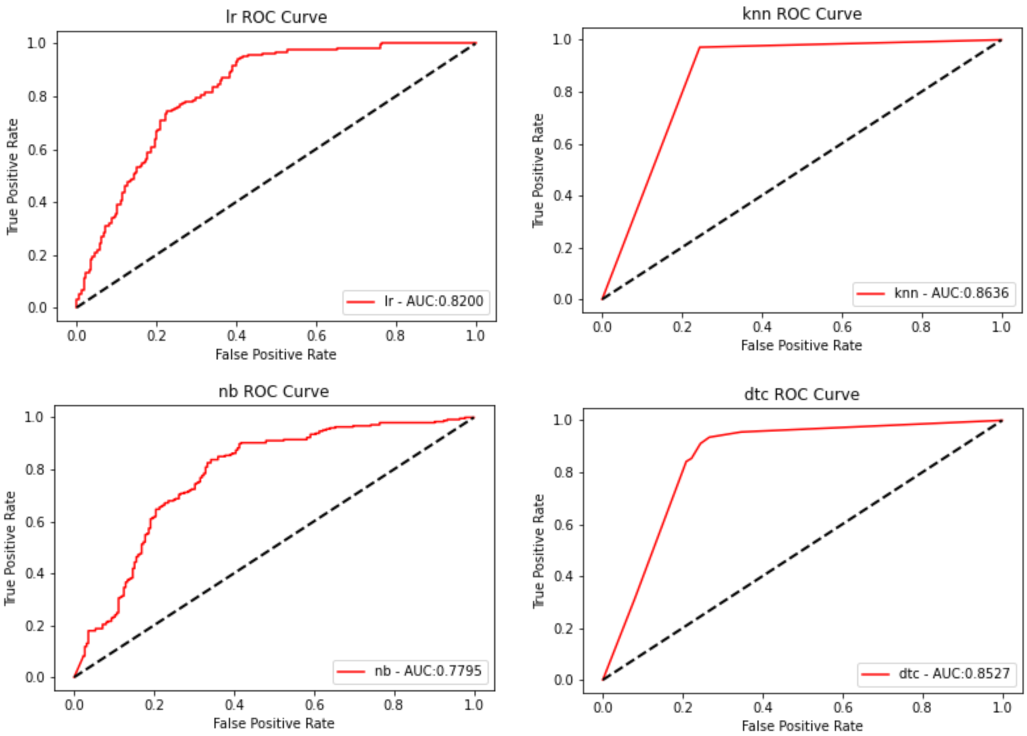

Figure 7. ROC curve of logistic regression and K-nearest neighbor and Naive bayes and decision tree model

Ensemble learning

To further optimize the model and enhance its performance, this paper utilizes the Stacking ensemble method to integrate the previous Random Forest model with the well-performing Polynomial and Gaussian kernel Support Vector Machine (SVM) models, constructing the RF-SVM-Stacking ensemble model. By calling the Stacking Classifier function, the random forest model and the well-performing polynomial and Gaussian kernel function support vector machine models are utilized as the first-layer base classifiers, while the logistic regression model serves as the second-layer classifier for integration. The results are shown in Table 6.

Table 6. Comparison of integration learning results

Function Type	Accuracy	AUC	F1
RF-SVM-Stacking	0.9193	0.9836	0.9212
Ploy Kernel Function	0.8832	0.8906	0.8952
Rbf Kernel Function	0.8854	0.9637	0.8789

From Table 4.5, it can be seen that the constructed ensemble model has significant improvements in all three indicators compared to the original two support vector machine models. The accuracy rate has increased from about 0.88 in the basic model to 0.9193, the AUC value has increased to 0.9836, and the F1 score has increased to 0.9212. The ROC curve is shown in Fig 8.

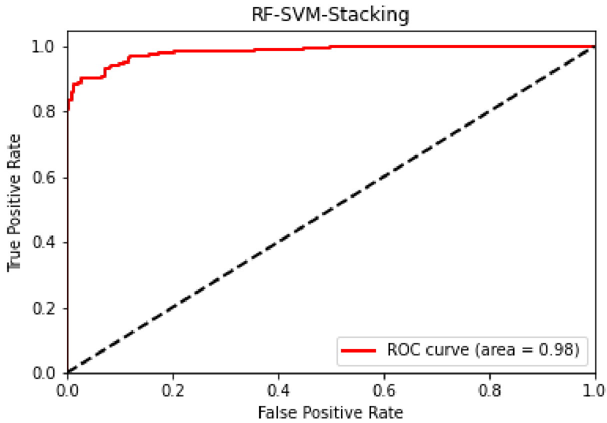

Figure 8. ROC curve of RF-SVM-Stacking model

To verify the effectiveness of the ensemble algorithm, it is compared with models using SVM models with three kernel functions for Bagging and AdaBoost ensembles. The results are presented in Table 7, and the ROC curves for each model are illustrated in Fig. 9.

Table 7. Comparison of different algorithms

Function Type	Accuracy	AUC	F1
linear--Bagging	0.7643	0.8304	0.7811
poly-Bagging	0.8089	0.8805	0.8085
rbf-Bagging	0.8896	0.9609	0.8855
linear-Adaboost	0.7601	0.8153	0.7823
poly-Adaboost	0.8960	0.9277	0.9041
rbf-Adaboost	0.8726	0.9646	0.8618

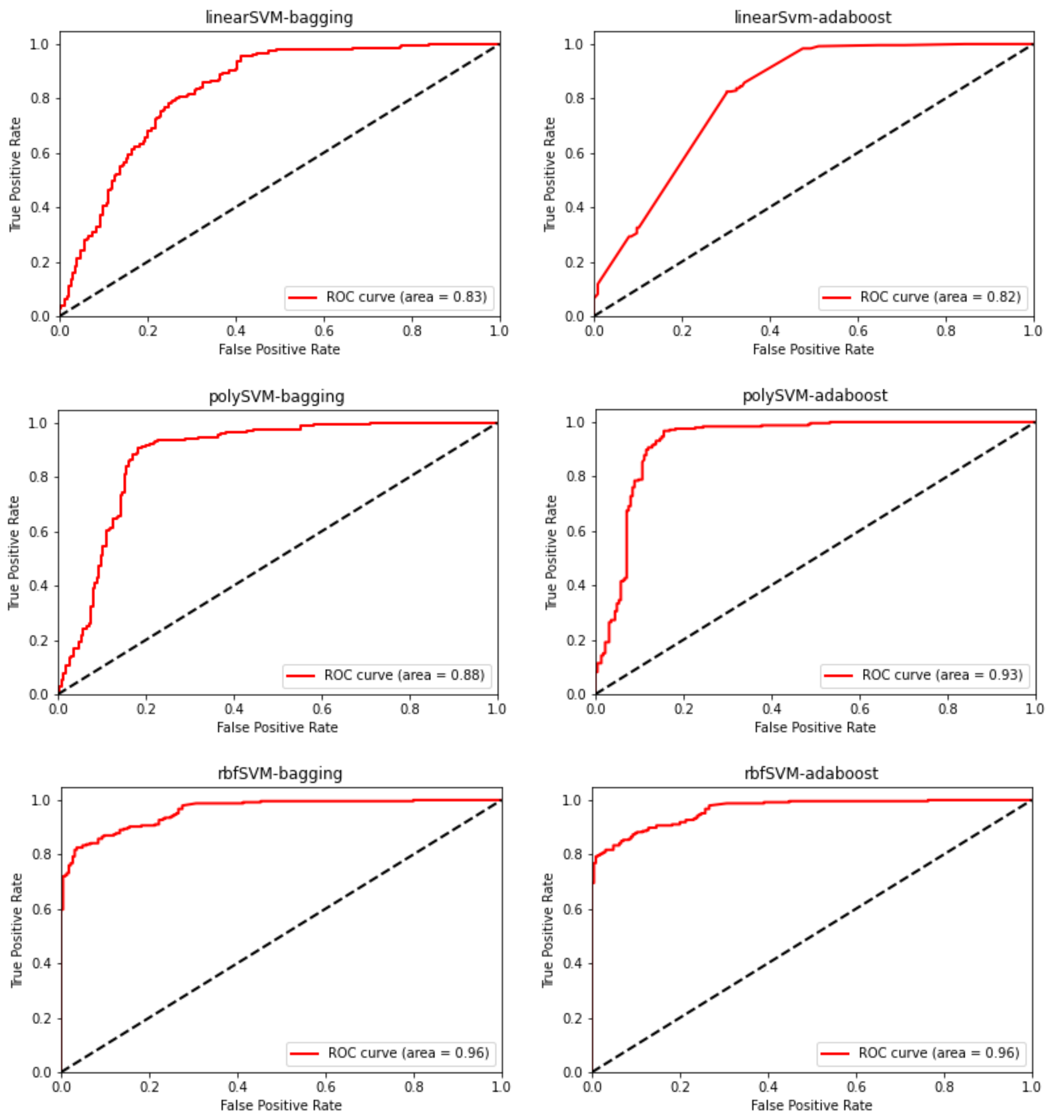

Figure 9. Results of integration of three SVMs under the Bagging and Adaboost methods

From the results in Table 4.6, it can be seen that the SVM model with a linear kernel function using Bagging and AdaBoost ensemble methods has achieved some improvement in various indicators compared to its basic model. However, the polynomial kernel SVM has slightly different results after the ensemble. The performance of the model is improved after being integrated using the Adaboost method, while its performance is slightly reduced after being integrated using the Bagging method. The Gaussian kernel SVM model itself performs well, and the performance improvement after using these two ensemble methods is not significant. At the same time, their performance did not exceed that of the RF-SVM-Stacking ensemble model.

To further verify the effectiveness of the RF-SVM-Stacking ensemble model, it is compared with other common ensemble models and neural network models. It is found that the values of the RF-SVM-Stacking ensemble model are higher in terms of accuracy rate, F1 score, and AUC value, and its performance is more excellent. The comparison of the model results and ROC curves is shown in Table 8 and Fig. 10.

Table 8. Comparison of different algorithms

Function Type	Accuracy	AUC	F1
RF-SVM-Stacking	0.9193	0.9836	0.9212
Neural Network	0.8854	0.9386	0.8963
GBDT	0.8684	0.9367	0.8798
Adaboost	0.8238	0.8854	0.8376

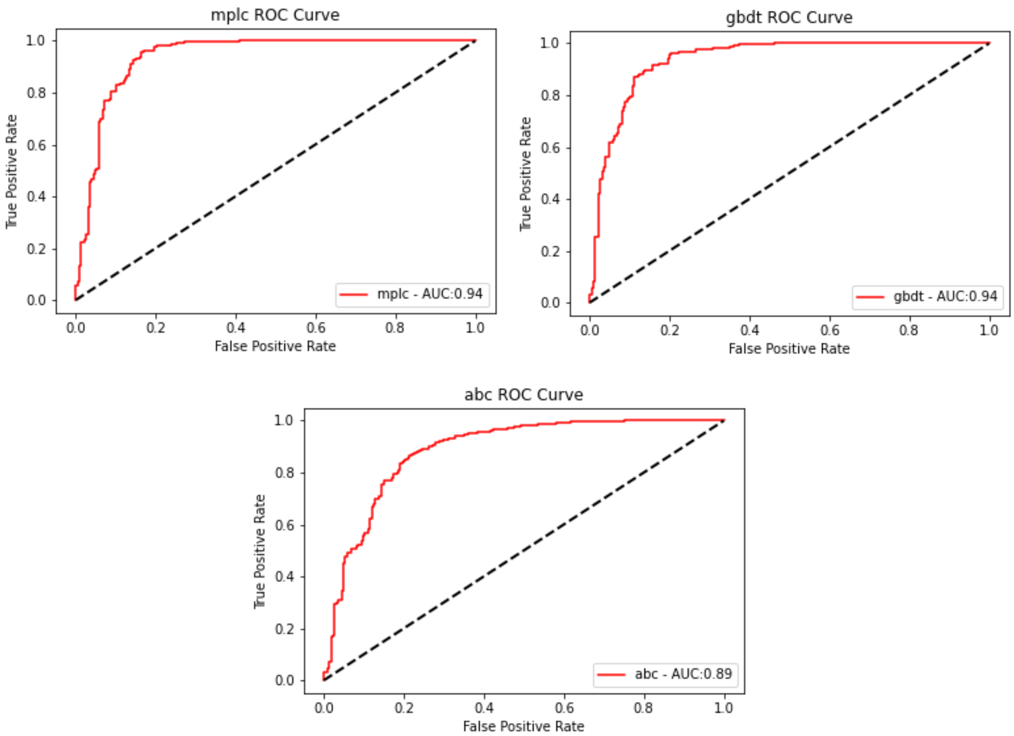

Figure 10. ROC curve of neural network and GBDT and Adaboost models

From Table 4.3, it can be observed that the three types of kernel Support Vector Machine (SVM) models exhibit varying performance on the sample data. In terms of results, the Polynomial kernel and Gaussian kernel SVM models demonstrate higher F1 scores and AUC areas, making them more suitable for classifying green credit risks. Table 4.4 reveals that logistic regression and Naive Bayes models have significant advantages in green credit risk assessment, but they are still inferior to the Polynomial and Gaussian kernel SVM methods. Regarding the construction of ensemble models, as shown in Table 4.5, the RF-SVM-Stacking ensemble model proposed in this paper has achieved further improvement over the base Support Vector Machine models. Moreover, compared to Bagging and Adaboost ensemble algorithms, it exhibits the best performance.

D. Conclusion

In constructing the evaluation indicator system, this article introduces enterprise innovation investment and ESG rating indicators, finding that R&D investment, ESG ratings, and corporate development indicators are among the most important, with a significant impact on the green credit risk assessment of enterprises. Banks and other financial institutions should pay closer attention to these indicators when conducting green credit business, incorporating these factors into their credit risk assessment indicator systems to effectively identify the environmental performance of companies and make more precise assessments of their green credit risks.

The RF-SVM-Stacking ensemble model presented in this article for green credit risk assessment exhibits a high level of precision and superior performance compared to other machine learning algorithms. Although the ensemble SVM model constructed using Bagging and AdaBoost ensemble algorithms has some improvement on its basic model, its performance is weaker than that of the RF-SVM-Stacking ensemble model. Furthermore, compared with single models such as logistic regression, K-nearest neighbor model, naive Bayes model, and decision tree model, as well as ensemble models such as GBDT and Adaboost models, the performance of the RF-SVM-Stacking ensemble model is more excellent.

Acknowledgements

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