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Research on International Trade Financial Risk Identification Based on Gbdt-Xgboost Algorithm

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Abstract. This paper employs the GBDT-XGBoost algorithm to explore the characteristics and identification strategies of international trade financial risks. Initially, historical data related to international trade, including import and export volumes, exchange rate fluctuations, and credit ratings among other multidimensional indicators, are collected using data mining techniques. Subsequently, the data undergo preprocessing and feature selection to extract effective risk factors. The study constructs a model based on a multi-layer GBDT fused with XGBoost to enhance the accuracy of identifying international trade financial risks. The model's parameters are optimally matched using Grid Search technology. Empirical tests conducted on historical datasets from various domestic and international financial institutions demonstrate that the model can predict trade financial risks with high accuracy. Compared to traditional risk assessment methods, it exhibits better resistance to overfitting and improved risk identification performance. Finally, based on the predictive outcomes of the model, international trade financial risk warning strategies are proposed, which hold significant practical importance in preventing major financial events. This research provides new analytical tools and decision-support systems for international trade risk management, playing an active role in strengthening risk prevention measures for international trade enterprises.

Keywords: Research model; International trade risk; GBDT-XGBoost; Machine learning; Risk identification.

1. Introduction

During the 2008 financial crisis that swept across the globe, there was a significant downturn in global demand, impacting foreign trade and international business operations. The challenges of consolidating foreign markets and a lack of orders destabilized many companies' capital chains. This was reflected in clear internal inflationary pressures and the rapid appreciation of the renminbi. The complex domestic and international economic environments substantially increased the financial risks associated with international commerce [1].

Finance plays a critical role in economic development and serves as the economic focal point of national development. In the face of a complex and volatile international market environment, it is imperative for countries to enhance financial security measures to mitigate financial risks and promote stable and healthy economic and social development, thereby continually boosting China's economic strength and stature. To effectively prevent financial risks, companies must accurately understand these risks and their contextual knowledge, fully grasp the causes and types of financial risks, establish crisis awareness, develop risk prevention and early warning systems, accurately predict factors that could lead to risks, and enhance their ability to cope with financial risks. This will invigorate companies with renewed vitality in the marketplace [2-3].

However, enterprises engaged in foreign trade often lack a comprehensive and systematic understanding of their financial risks when conducting international business. The financial risk control systems have yet to be established, and numerous cases of financial risks threaten the survival and development of institutions. Compared to the relatively sophisticated financial risk control systems of Western countries, the risk control and early warning systems of foreign trade business institutions are significantly underdeveloped. Therefore, this study examines various financial risks faced by foreign economic and trade institutions in their international operations, aims to establish and enhance the financial control systems of these risk-bearing enterprises, reduce financial risks, and improve the early warning and prevention capabilities of foreign economic and trade enterprises. This holds significant practical importance for widespread competition in the international market [4].

This paper aims to utilize the Xtreme Gradient Boosting (XGBoost) algorithm to comprehensively analyze the various financial risks faced by international economic and trade institutions in managing international business, effectively reducing the financial risks of foreign trade institutions in their international operations and promoting comprehensive, coordinated, and sustainable development of foreign economic and trade institutions.

2. Analysis of the Causes of Financial Risks in International Business for Enterprises

Financial risk is a product of the international capital market economic environment, influenced by external objective factors and the enterprise's own business model. It is primarily manifested in the following three dimensions. The specific limiting factors are shown in Figure 1.

2.1. Lack of Necessary Financial Risk Awareness and Related Legal Knowledge

The rapid development of the knowledge economy market has highlighted an increasing number of disadvantages, significantly impacting the internationalization of enterprises. The root cause is the lack of necessary financial risk awareness and related legal knowledge among enterprises. Massive changes in the economic environment have not been accompanied by timely adjustments in corporate ideologies and economic structures, resulting in a lag in enterprise development relative to economic transformations [5].

2.2. Inadequate Internal Management Systems in Small and Medium Enterprises

Currently, small and medium enterprises (SMEs) form the backbone of China's trade sector. These enterprises often lack a systematic, scientific, and rigorous internal management structure. Their systems are not well-developed, and their leaders lack the necessary professional capabilities, as well as management philosophies and experience. This deficiency hampers their ability to discern the essence of issues during international trade processes, leading to erroneous decision-making. There is a notable lack of investment in training and development for specialized risk management personnel within these enterprises. Internal crisis awareness is weak, risk management practices are not highly regarded, trade operation procedures are not proficient, and compliance issues frequently arise. These factors can lead to disruptions in the enterprise's production chain, thereby triggering financial risks.

2.3. Influences of Social, Economic, and Policy Factors

The changes and stability in the market economic environment are direct causes of financial risks. Adjustments and changes in domestic and international economic policies, legal provisions, social events, and trade measures lead to corresponding changes in trade conditions such as tax rates and costs. For instance, the anti-dumping strategies, trade protectionism, and trade barriers implemented by the United States to protect its interests have adversely affected the survival and development of Chinese SMEs, making them susceptible to financial risks. Additionally, fluctuations in exchange rates during debt settlement can lead to economic losses [6].

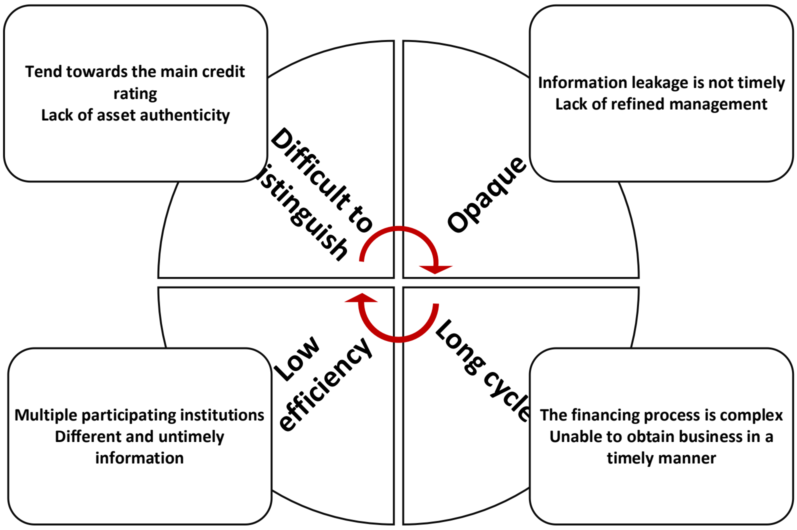

Figure 1. Current Issues in International Trade Finance

3. Construction of the International Financial Trade Risk Indicator System

3.1. Economic Dimensions and Their Impact on International Trade

Economic factors, serving as the cornerstone of international trade, revolve around domestic gross product (GDP), interest rates, inflation rates, and trade volumes, all of which influence the demand and vitality of international markets. Changes in GDP and trade volumes directly indicate the vitality of economies and the potential demand in markets, while interest rates and inflation rates indirectly affect trade processes by influencing the costs and purchasing power of businesses and consumers. These economic indicators not only shape trade scales but also form the basis for the formulation of trade policies and market strategies.

3.2. Financial Dimensions on International Trade

The stability of financial markets and the fluctuation of currency values significantly impact the fluidity of international trade. Exchange rate volatility affects the pricing of import and export goods, while stock market indices and banking liquidity reflect the health of financial markets and the adequacy of funds. The activity level of financial derivatives trading and sovereign credit ratings are important financial domain indicators in international trade, together shaping the contour of financial risks in international trade.

3.3. Political Dimensions on International Trade

Political stability and policy continuity are crucial for the development of international trade. The level of political risk, the frequency and complexity of policy changes can either weaken or enhance the trust and willingness to cooperate among trade partners. A mild political environment and clear policy directions can reduce uncertainties in the trading process, benefiting the orderly conduct of international trade.

3.4. Social Dimensions on International Trade

Social factors such as employment status, consumer confidence, and the integrity of the public sector provide a societal foundation for international trade. A stable social environment helps to create a favorable business atmosphere, enhances the national international image, attracts foreign investment, and promotes international trade. However, fluctuations in social factors may lead to a decline in market confidence, adversely affecting international trade. Consequently, the resulting indicator system is presented in Table 1.

Table 1. Financial Trade Risk Indicator System [7-10]

Primary Indicator	Secondary Indicator	Indicator No.	Variable Unit
Economic factors (A1)	GDP	X1	Billion USD
	Central Bank Base Rate	X2	%
	Inflation Rate	X3	%
	Trade Volume	X4	Billion USD
Financial factors (A2)	Forex Rate	X5	Currency per USD
	S&P 500 Index	X6	/
	Bank Liquidity Ratio	X7	%
	FxSwaps	X8	Billion USD
	Sovereign Credit Rating	X9	/
Political factors (A3)	Political Risk Index	X10	/
	Policy Change Index	X11	/
	Business Regulatory Complexity	X12	/
Social factors (A4)	Unemployment Rate	X13	%
	Consumer Sentiment Index	X14	/
	Corruption Perceptions Index	X15	/

4. GBDT-XGBOOST Model Construction

XGBoost is a powerful machine learning algorithm within the ensemble learning category, specifically under Boosting algorithms. Proposed by Tianqi Chen and others, it is designed to handle large-scale data and deliver efficient predictive performance. XGBoost enhances model prediction accuracy by iteratively adding new tree models (Tree Boosters) to reduce prediction errors in the current model. Compared to standard Gradient Boosting Machines (GBM), XGBoost incorporates regularization terms during the optimization process to reduce model complexity, enhance generalization, and prevent overfitting. The XGBoost algorithm has performed exceptionally well in various data mining and machine learning competitions and is widely applied to tasks such as classification, regression, and ranking, especially suited for dealing with complex datasets with high-dimensional features. It implements machine learning algorithms under the framework of Gradient Boosting Decision Tree (GBDT) and optimizes the objective function using the second-order Taylor expansion. The addition of regularization to the loss function aims to control the complexity of the model. The optimized objective function of XGBoost is as follows:

$$Obj^{(m)} = \sum_{i=1}^{n}((y_i, \hat{y}^{(m-1)}) + f_m(x_i)) + \Omega(f_m) + C \tag{1}$$

In the equation: *Obj*(*t*) represents the objective function during the *t*-th training iteration; *yi* represents the true value of the *i*-th sample; $\hat{y}$(*t* - 1) is the predicted value of the model from the (*t*- 1) th iteration; *l* is the loss function; *ft* (*xi*) denotes the function value in the *t*-th round for input *xi*; *Ω*(*ft*) is the regularization term; *C* is a constant. Using the second-order Taylor expansion, equation (1) is rewritten as follows:

$$Obj^{(m)} \approx \sum_{i=1}^{n}[l(y_i, \hat{y}^{(m-1)}) + h_i f_m(x_i) + \frac{1}{2} g_i f_m^2(x_i)] + \Omega(f_m) + C \tag{2}$$

$$h_i = \delta_{\hat{y}^{(m-1)}} l(y_i, \hat{y}^{(m-1)}) g_i = \delta_{\hat{y}^{(m-1)}}^2 l(y_i, \hat{y}^{(m-1)}) \tag{3}$$

During model training, equation (2) can be expressed as:

$$Obj^{(m)} = \sum_{j=1}^{m}[(\sum_{i \in I_j} h_i)\theta_j + \frac{1}{2}(\sum_{i \in I_j} g_i + \lambda)\theta_j^2] + \gamma T \tag{4}$$

$$G_j = \sum_{i \in I_j} h_i \, , H_j = \sum_{i \in I_j} g_j \tag{5}$$

In equations (4) and (5), I_j is defined as the set of indices for samples located at each leaf node j, $I_j = \{q(x_i) = j\}$, where $q(x_i)$ represents the set of samples on each leaf. This step is because the second part of XGBoost's objective function adds two regularization terms: the number of leaf nodes T, and the scores of leaf nodes w.

5. Construction of Algorithm Validation Metrics

When evaluating the model's fit and prediction accuracy, it is essential to use various error calculation methods for a comprehensive and objective assessment. Common statistical measures to assess the closeness of model fit to actual data include Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Coefficient of Determination (R^2), and Mean Absolute Percentage Error (MAPE). This study has selected MSE and another metric to measure the accuracy of the XGBOOST model in prediction. MSE is a commonly used measure to assess the deviation between predicted values and actual values, and its formula is as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2 \tag{6}$$

In the formula, n represents the number of samples; y is the actual value of the i-th experimental data; y is the predicted value of the i-th experimental data; The range of MSE values for is [0,10], where a smaller value indicates a smaller error between model predictions and actual values, thus higher prediction accuracy.

Coefficient of Determination (R^2). The R-Square reflects the model's fit to the observed values, calculated as follows:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2}{\sum_{i=1}^{n}\left(y_i - \bar{y}_i\right)^2} \tag{7}$$

In the formula, y is the average value of the experimental data. The range of R^2 values for is [0,1], where a larger value indicates a better fit of the model.

6. Empirical Analysis

6.1. Data Collection

The dataset was collected from macroeconomic databases from multiple countries worldwide, covering the period from 2018 to 2023. Sources include, but are not limited to, the World Bank database, the International Monetary Fund (IMF), the United Nations Trade Database, and financial statistics released by central banks of various countries. The primary considerations during data collection were the authority of these sources and the reliability of the data, ensuring accuracy and representativeness of the information. In the preprocessing stage, data were first cleaned by removing outliers and missing values, and standardization was applied to different statistical indicators to ensure comparability. Subsequently, normalization transformations were performed to reduce potential biases among data from different sources. Additionally, dimension reduction techniques were used to minimize the impact of irrelevant variables, thereby enhancing the accuracy of the analysis. Table 2 displays the descriptive statistical analysis of the data.

Table 2. International Financial Trade Risk Indicator System

Indicator Name	Maximum value	Minimum value	Mean value	Standard deviation
GDP	25376.8	1092.3	13704.9	6459.34
Interest Rate	25.32	0.28	4.12	6.25
Inflation Rate	15.89	-3.47	2.47	3.86
Trade Volume	7235.9	362.4	1687.01	1134.89
Forex Rate	1.8	0.6	0.79	0.28
Stock Market Index	37826.4	12675.9	22705.7	8684.56
Bank Liquidity Ratio	26.5	9.8	14.35	4.24
FxSwaps	93650	2500	22150	13035.4
Sovereign Credit Rating	95	50	65.78	9.64
PoliticalRisk Index	85	1	26.58	22.45
Policy Change Index	20	1	7.98	4.72
Business Regulatory Complexity	85.6	25.3	50.21	14.36
Unemployment Rate	22.1	2.5	9.96	5.24
Consumer Sentiment Index	140.5	39.8	85.67	28.99
Corruption Perceptions Index	92.7	16.5	44.27	18.69

Through an analysis spanning five years, we observed that GDP growth rates across nations exhibit significant volatility in the short term while demonstrating stable trends in the long term. Interest rates and inflation have experienced varying degrees of fluctuation, which are often closely linked to the conditions of financial markets and policy adjustments. Trade volumes and foreign exchange rates directly influence the cost and competitiveness of goods import and export. Stock market indices and bank liquidity reflect the stability of the financial system and the prosperity of markets. These data provide essential insights into the state of international trade and financial markets. Indices of political risk and policy changes significantly impact the international trade environment. Social factors, such as consumer confidence and unemployment rates, also directly drive or inhibit trade demand. By delving into these data, this study aims to explain how economic, financial, political, and social factors collectively shape the landscape of international trade, providing empirical support for the formulation of related economic policies. Through the analysis of these composite factors, this research hopes to offer readers a comprehensive new perspective on the global trade situation.

6.2. Model Calculations

By invoking the XGBOOST method within a pertinent computational tool, six elements serve as predictors, while the closing prices for the Shanghai and Shenzhen 300 are the criterion variable. The model's tree count is increased by increments of one hundred, ranging between one hundred and one thousand. For the dataset, 70 percent is allocated to training, with the remaining 30 percent designated for verification, employing L2 regularization. The outcomes of the prediction accuracy are depicted in the specified Table 3 and Figure 2. The importance of secondary indicators is illustrated in Figure 3, and the importance of primary indicators is also shown in Figure 4.

Table 3. Model accuracy demonstration

Number	R^2	MAE
100	0.985	4.242
200	0.925	0.025
300	0.855	0.001
400	0.885	0.001
500	0.99	0.001
600	0.92	0.001
700	0.98	0.001
800	0.97	0.001
900	0.935	0.001
1000	0.945	0.001

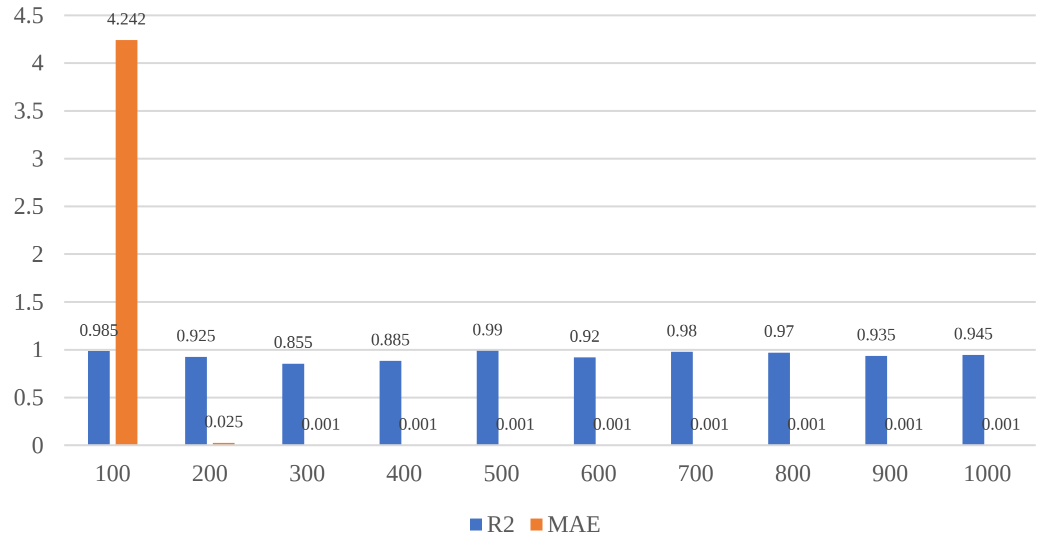

Figure 2. Model accuracy demonstration

The precision of the machine learning model is optimal when it includes 500 decision trees, achieving an R-squared of 0.99 and a mean absolute error of 0.001.

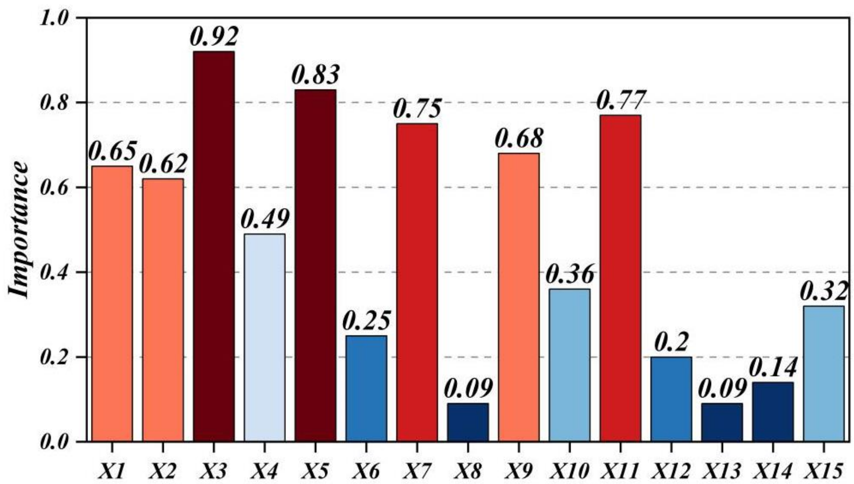

Figure 3. Importance of Secondary Indicators

A deep analysis of each economic indicator's impact on international financial trade reveals varying degrees of importance at both macro and micro levels, as demonstrated in Figure 3. Taking GDP as an example, while it is a common standard for measuring national economic growth, its role in promoting international trade is not irreplaceable. In contrast, political stability and policy continuity, such as the "Political Risk Index" (0.36) and "Policy Change Index" (0.77), exert a more direct influence. Additionally, indicators such as foreign exchange rates, stock market indices, and bank liquidity play significant roles in guiding business transactions and trade flows.

When considering the overall situation of international trade, it is also essential to pay attention to other social and political factors, even though their impact may not be as apparent as economic and financial indicators. The complexity of regulation, unemployment rates, consumer sentiment, and perceptions of corruption may not play a direct leadership role, but together they shape a country's economic environment, continuously influencing market stability and long-term economic development. Policymakers and entrepreneurs should holistically assess these complex factors to optimize trade strategies and seek competitive advantages on the global economic stage.

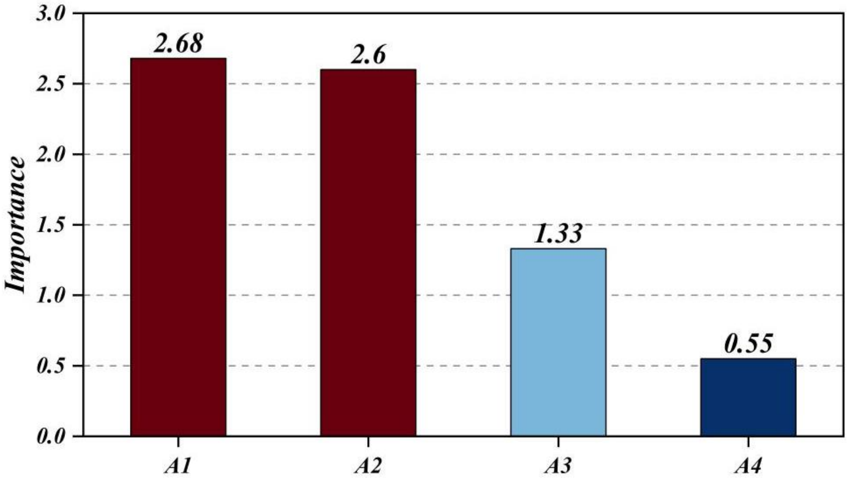

Figure 4. Importance of Primary Indicators

The data in Figure 4 highlights that economic factors are the most prominent among the four groups of macro factors, with a significant score of 2.68. Following closely are financial factors (2.6), indicating that capital flows, investment environments, and fluctuations in financial markets are equally important in influencing trade dynamics. In contrast, political factors (1.33) and social factors (0.55) have relatively weaker impacts. These low associations remind us that while political stability and social health are the cornerstones of national security and long-term economic development, their direct influence on trade flows through ideological and cultural characteristics is not significant. Therefore, in the process of forecasting and decision-making based on existing data, economic and financial environments should be prioritized, while the indirect roles of political and social factors should not be overlooked. A deep understanding of the interactions and potential impacts of these factors will aid in developing a more comprehensive international trade strategy.

7. Conclusion

International trade is a crucial economic activity for foreign trade enterprises, and in their development, companies inevitably face various financial risks that adversely affect their healthy growth. Financial risks have a wide range of impact, significantly affecting internal cash flow and potentially disrupting the capital chain, leading to a survival crisis for the business. In this study, the GBDT-XGBoost algorithm was adopted and applied to effectively enhance the accuracy of identifying financial risks in international trade. Empirical analysis has demonstrated the high efficacy of the model in practical risk assessment scenarios. Compared to traditional assessment tools, this model exhibits significant anti-overfitting advantages and superior predictive performance. For decision-makers in financial institutions and foreign trade companies, the new decision support system provided by this research markedly improves the capability to quickly identify trade risks. Moreover, the model offers a more scientific risk management system for international trade enterprises, which not only aids in strengthening internal controls and early warning mechanisms but is also expected to significantly enhance their competitiveness in complex financial environments. Additionally, it provides technological support for formulating more reasonable international trade financial strategies.

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