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Risk Evaluation of Overseas Mining Investment Based on a Support Vector Machine

Hujun He [1,2,*], Yichen Zhao [1], Hongxu Tian [1] and Wei Li [1]

[1] School of Earth Science and Resources, Chang'an University, Xi'an 710054, China
[2] Key Laboratory of Western Mineral Resources and Geological Engineering, Ministry of Education, Xi'an 710054, China
* Correspondence: hsj2010@chd.edu.cn

Abstract: Analyzing the general method of establishing a support vector machine evaluation model, this paper discusses the application of this model in the risk assessment of overseas mining investment. Based on the analysis of the risk assessment index system of overseas mining investment, the related parameters of the optimal model were ascertained by training the sample data of 20 countries collected in 2015 and 2016, and the investment risk of 8 test samples was evaluated. All 8 samples were correctly identified, with an error rate of 0. South Africa's mining investment risk in 2016 was assessed using the risk evaluation model for overseas mining investment based on a support vector machine, and it was rated as grade IV (general investment risk). The results show that the model can provide a new solution for the judgment and deconstruction of the risk of overseas mining investment.

Keywords: support vector machine; overseas investment; risk evaluation; training sample; South Africa

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1. Introduction

The impact of the international financial crisis has continued to worsen during recent years, and all countries are facing the problem of insufficient follow-up for economic development, to varying degrees. Expanding economic cooperation and functional complementarity across many areas has become the consensus of world economic development.

With the global response to the Silk Road Economic Belt and the 21st Century Maritime Silk Road Initiative, Chinese enterprises have been investing more overseas, achieving a simultaneous increase in scale and efficiency, thus promoting globally related products, technologies, and services. The Belt and Road Initiative has given birth to a new model of international cooperation in the field of mineral resources and provides a new opportunity for China's mining industry to become global. Since the Belt and Road Initiative was launched in 2013, China's overseas direct investment in the mining industry has grown rapidly (Figure 1). In 2013, China's stock of outward foreign investment in the mining industry exceeded USD 100 billion for the first time, and at the end of 2020, China's outward foreign direct investment in the mining industry reached USD 175.88 billion, accounting for 6.8% of the total outward foreign direct investment, mainly in oil and gas exploration, the mining and mineral processing of nonferrous metals and ferrous metals, coal mining, etc. This is one of the six industries representing the stock size of one hundred billion US dollars [1,2]. As one of the five largest mineral resource countries in the world, South Africa is China's largest source of imports and its main trading partner on the African continent. The South African government encourages foreign mining investment, and it has a close and friendly relationship with China, so South Africa is one of the areas that Chinese mining enterprises focus on. However, the overseas investment project is large, the cycle is long, and the unpredictable factors are numerous, so the resource-based enterprises face a greater risk [3–5]. Therefore, to promote the sustainable, rational, orderly, and healthy development of overseas mining investment and to guide enterprises in the scientific assessment and prevention of overseas mining investment risks, an objective summary of the rules of overseas mining investment and protection against investment risks has strong research value [4,6–12].

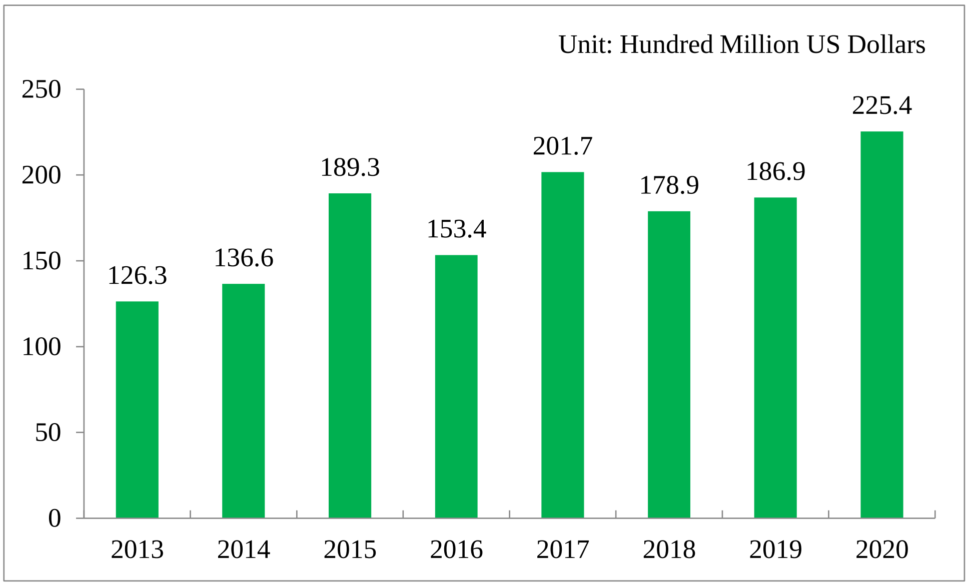

Figure 1. China's investment in the countries along the Belt and Road, 2013–2020 (Source: 2020 Statistical Bulletin of China's Outward Foreign Direct Investment).

Therefore, the aim of the present research was to explore how to use scientific methods to perform a quantitative and comprehensive evaluation of the risks faced by China's mining overseas investment, so as to guard against the risks of mining enterprises' overseas investment and protect the rights and interests of China's resources. We carry out a quantitative, comprehensive evaluation of the risks faced by China's overseas mining investment, which is of great practical significance for Chinese enterprises investing in overseas mining. The scientific assessment can promote the sustainable, rational, orderly, and healthy development of China's overseas mining investment and compensate for the shortage of mineral resources in China.

2. Literature Review

With the deepening of studies on the risk assessment of overseas investment in the mining industry, the analysis angle of the research has gradually changed from qualitative analysis to quantitative analysis, and more risk assessment methods have been put forward. For example, Charnes et al. [13] evaluated the relative effectiveness between departments through the data envelopment analysis (DEA) method. Campbell et al. [14] used a computer as the carrier to introduce an artificial neural network (ANN) method by inputting a large amount of sample data and simulating the thinking of human experts. Zhang and Da [15] used the gray relational analysis method to identify the risk pattern of enterprises. Yang and Zhang [16] established the investment priority model based on rough set information entropy theory. Huo and Lu [17] established a fuzzy mathematical model for the comprehensive assessment of the regional investment environment. Based on the sensitivity analysis method, Li [18] identified the key index that affects the mining investment environment grade according to the sensitivity of the index attribute value and the index weight. Carpenter and Vellat [19] proposed the planned economy country risk model (PERM) to determine the projected risk of developing countries in Southeast Asia. Liu et al. [20] used the analytic hierarchy process (AHP) to carry out quantitative analysis on the mining investment environment in 80 mining countries. Saaty et al. [21] calculated the priority weight via an analytic hierarchy process on the basis of dividing the complex system into several levels and elements. Zhang et al. [22] applied the value at risk (VaR) method to analyze the risks in mining investment. Mu and He [23] evaluated the oil investment environment of five major oil-producing countries (Nigeria, Angola, Algeria, Libya, and Egypt) in Africa via the entropy weight method and matter element model. Li [24] established a risk early-warning model for overseas direct investment based on full probability. Duan et al. [25] built a fuzzy integrated evaluation model of the overseas energy investment environment via entropy weight. Zheng and Hu [3] built an incentive variable weight assessment model of the overseas mining investment environment. Gu [5] established a risk assessment model of China's overseas mining investment in light of deep learning. Li et al. [26] studied the evaluation method for overseas oil and gas investment based on risk compensation. Wang et al. [27] proposed a new multiple-classifier fusion method to predict overseas investment risk. He et al. [28] constructed a comprehensive evaluation of the environmental risks of overseas mining investment based on game theory and our extension matter element approach.

In summary, fuzzy comprehensive evaluation, the analytic hierarchy process, gray theory, entropy weight, and BP neural networks are widely used in risk evaluation and have certain value and advantages in the risk analysis of mining investment. However, the influencing factors of overseas mining investment risk cover a wide range, have a complex structure, and have a certain fuzziness. Risk evaluation is a multi-level, multi-element, multi-objective, and complex system. The difficulty of traditional models in dealing with such complex data is mainly reflected in the following. First, dimensionality reduction may cause information loss, despite the existence of some dimensionality reduction techniques. Second, it relies mainly on artificial design features and inevitably involves the subjective factors of the researchers, and the characteristics of the design are too targeted and incomplete. Third, the traditional linear method also has strong linear settings, but the impact of various factors on risk is often nonlinear [3–5,28]. In recent years, the support vector machine has emerged as an artificial intelligence method based on statistical learning theory [29–32], which has better generalization performance, has a global optimal solution, and can effectively solve the computational complexity of the linear model via kernel mapping and linearization etc. Using the expansion theorem of special kernel functions, the nonlinear mapping formula does not need to be computed, to some extent, the problem of "dimensionality disaster" is avoided. Therefore, this method provides a possible and effective method for the risk assessment of overseas mining investment. As such, according to the existing research on risk assessment theories and methods of overseas mining investment, in this paper, we apply the idea of a support vector machine to oversee mining investment risk evaluation. The research establishes a risk assessment model of overseas mining investment on the basis of a support vector machine, which provides a new solution for overseas mining investment risk assessment.

3. Theoretical Background

3.1. Support Vector Machine

The support vector machine (SVM) method is a new general-purpose machine learning method that was introduced within the framework of statistical learning theory, and it can realize the optimal classification of linear and nonlinear separable data [29–37].

The main idea of a support vector machine is the process of constructing an optimal classification hyperplane by mapping an input vector to a high dimensional eigenspace via pre-selected nonlinear mapping. The support vector machine is developed from the optimal classification surface in the linear divisible case. The basic principle is shown in Figure 2. The rhombic and circular points in the figure represent the two types of samples respectively, and H is the classification line, H_1 and H_2 are the closest samples to the classification line and parallel to the classification line, and the distance between H_1 and H_2 is called the classification interval. The so-called optimal classification line is that the classification line can not only separate the two classes correctly, but also guarantee the maximum separation.

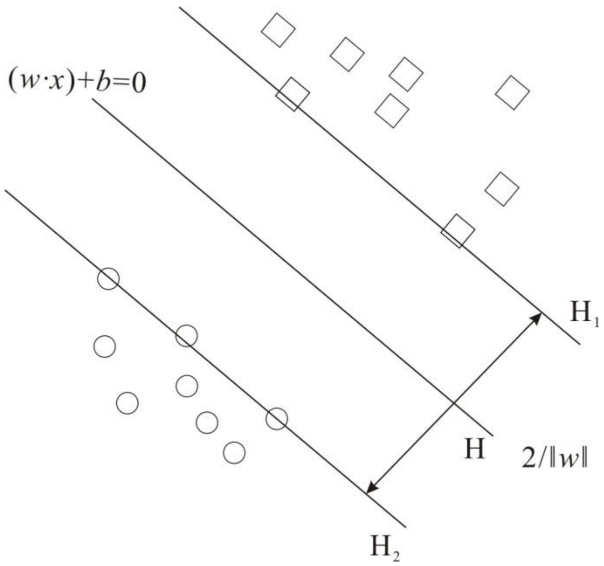

Figure 2. Schematic diagram of the optimal classification surface of two-type linear classification.

On the problem of optimal classification for linearly separable data, the training sample set $T = \{(x_1, y_1), (x_2, y_2) \cdots, (x_l, y_l)\}$, $x \in R^n, y \in \{-1, 1\}$ is given to find an optimal hyperplane $(w \cdot x) + b = 0$ which satisfies the problem, that is, to find the maximum interval of minimum $\|w\|^2/2$ for the interval of classification $2/\|w\|$, and for the subscript i of $y_i = 1$ and $y_i = -1$, there is $(w \cdot x) + b \geq 1$ and $(w \cdot x) + b \leq -1$. Then, the optimal classification hyperplane problem is found, that is,

$$\begin{gathered} \min \tfrac{1}{2}\|w\|^2 \\ s.t.\ y_i[(w \cdot x) + b] \geq 1, i = 1, 2, \cdots, l \end{gathered} \tag{1}$$

Using the Lagrange function, the dual objective function of Equation (1) is

$$\begin{gathered} \max W[\alpha] = \sum_{i=1}^{l} \alpha_i - \tfrac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i \cdot x_j) \\ s.t.\ \sum_{i=1}^{l} \alpha_i y_i = 0, \alpha_i \geq 0, i = 1, 2, \cdots, l \end{gathered} \tag{2}$$

To find the optimal solution α^* of the quadratic programming problem, and the classification threshold b^*, most samples have $\alpha^* = 0$. The corresponding samples for $\alpha^* \neq 0$ are only called support vector and determine the classification results. The optimal classification decision function is

$$f(x) = \operatorname{sgn}\{(w \cdot x) + b\} = \operatorname{sgn}\left(\sum_{i=1}^{n} \alpha_i^* y_i (x_i \cdot x) + b^* \right) \tag{3}$$

When the training set is a linear inseparability problem, the relaxation variable ξ_i, $i = 1, 2, \cdots l$ is introduced, and the optimal classification hyperplane problem is

$$\begin{gathered} \min \tfrac{1}{2}\|w\|^2 + C \sum_{i=1}^{l} \xi_i \\ s.t.\ y_i[(w \cdot x) + b] \geq 1 - \xi_i, \xi_i \geq 0, i = 1, 2, \cdots, l \end{gathered} \tag{4}$$

Here, C is the penalty parameter, and ξ_i is the relaxation variable. Using the Lagrange function, the dual objective function of Equation (1) is

$$\begin{gathered}\max_{\alpha} \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j (x_i, x_j) \\ s.t.\ C \geq \alpha_i \geq 0, i = 1, 2, \cdots, l \\ y^T \alpha = 0\end{gathered} \tag{5}$$

A classification hyperplane $(w^* \cdot x) + b^* = 0$ is constructed, and the optimal classification decision function is obtained.

$$f(x) = \mathrm{sgn}\{(w^* \cdot x) + b^*\} \tag{6}$$

For the nonlinear separable problem, the input vector can be mapped to a high dimensional feature space and an optimal hyperplane can be constructed in the feature space. The optimal hyperplane and decision function are $(w \cdot \Phi(x)) + b = 0$ and $f(x) = \mathrm{sgn}\{(w \cdot \Phi(x)) + b\}$, respectively, and the optimal classification hyperplane problem is

$$\begin{gathered}\min_{w,b,\xi_i} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^{l} \xi_i \\ s.t.\ y_i[(w \cdot \Phi(x)) + b] \geq 1 - \xi_i, \xi_i \geq 0, i = 1, 2, \cdots, l\end{gathered} \tag{7}$$

The dual optimization problem is also obtained.

$$\begin{gathered}\max W[\alpha] = \sum_{i=1}^{l} \alpha_i - \frac{1}{2} \sum_{i=1}^{l} \sum_{j=1}^{l} \alpha_i \alpha_j y_i y_j K(x_i, x_j) \\ s.t.\ 0 \leq \alpha_i \leq C, i = 1, 2, \cdots, l\end{gathered} \tag{8}$$

Here, $K(x_i, x_j) = \Phi(x_i) \cdot \Phi(x_j)$ is the kernel function, which is a concept introduced to overcome the increase of variable dimension in judging nonlinear functions. In order to realize the linear classification of nonlinear change, the kernel functions most commonly used are the Gauss radial basis function (Rbf), polynomial kernel function (Poly), Fourier kernel function (Fourier), multilayer neural network kernel function (Sigmoid), and so on. The optimal solution $\alpha^* = (\alpha_1^*, \cdots, \alpha_n^*)^T$ of the problem is calculated, and then $\omega^* = \sum_{i=1}^{n} \alpha_i^* y_i x_i$; the classification decision function is

$$f(x) = \mathrm{sgn}\left\{ \sum_{i=1}^{n} \alpha_i^* y_i K(x_i, x_j) + b^* \right\} \tag{9}$$

3.2. Risk Evaluation Model of Overseas Mining Investment Based on SVM

(1) The risk evaluation flow of overseas mining investment based on SVM

First, the factors affecting the risk of overseas mining investment are comprehensively analyzed, the key evaluation indices are selected, and the evaluation index system is constructed. The data sample set of evaluation indices is constructed via data collection. According to the grading standards of the evaluation indices, the original data are preprocessed. Then, training samples and test samples are selected from the preprocessed data, suitable kernel functions are selected, and the parameters are optimized. Support vector classification is trained with training samples. The risk evaluation model of overseas mining investment based on SVM is established to evaluate the risk level of the test evaluation samples. The specific evaluation flow based on SVM is shown in Figure 3.

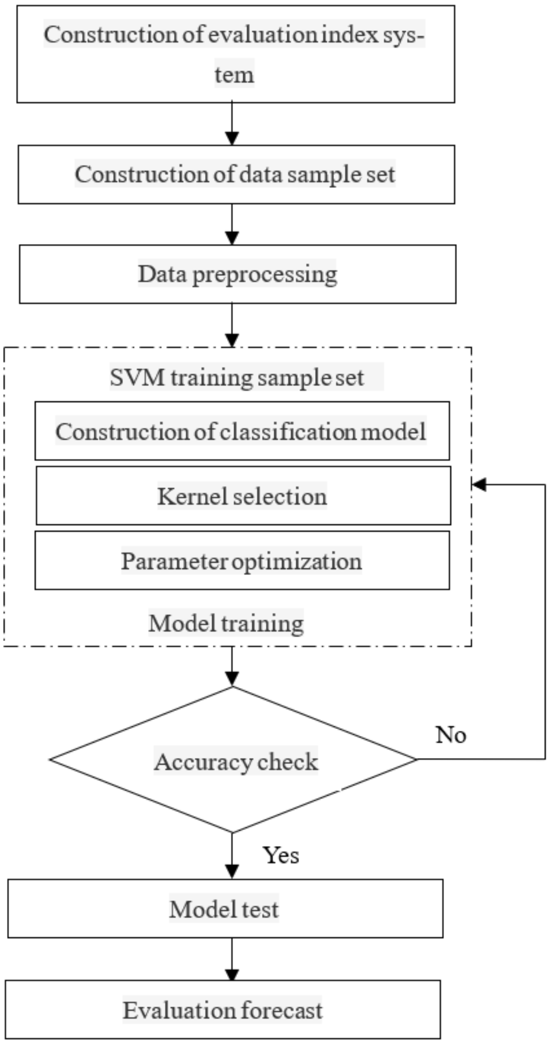

Figure 3. Flow diagram of risk assessment for overseas mining investment based on SVM.

(2) Risk evaluation index system

Based on the existing results achieved, 34 indexes of 16 items in 7 categories are selected as the risk assessment indexes of overseas mining investment (Table 1) [3–5,28]. After extensive investigation and research, according to the characteristics and measurement attributes of each index, the 0–10 value assignment criterion is set. For example, the resource potential (level three index) is assigned according to the best practice mineral resource potential index, and the specific assignment criteria are shown in Table 2. The assignment of other indexes is similar, and the assignment results are shown in Gu's reference [5]. According to the evaluation objectives and classification rules, the overall risk of overseas exploration and development of mining enterprises is divided into 5 grades by giving a mark, i.e., I (0–20), II (21–40), III (41–60), IV (61–80), V (81–100), which, respectively, represent no investment risk, serious investment risk, higher investment risk, general investment risk, and low investment risk [5].

Table 1. Risk evaluation index system for overseas mining investment.

Risk Evaluation Index System for Overseas Mining Investment		
Level One Index	**Level Two Index**	**Level Three Index**
Mineral resources	Resource status	Resource mining (ore and metal export index/%) Resource potential (best practice mineral resource potential index)

Table 1. *Cont.*

Risk Evaluation Index System for Overseas Mining Investment		
Level One Index	**Level Two Index**	**Level Three Index**
Politics and religion	Political stability	Civil war (degree of civil unrest) Regime change (form of regime change)
	Geopolitics	Peripheral relations (diplomatic hierarchy) The great power factor (great power intervention)
	Nationalities and religions	Religious influence (integration degree of church and state) Ethnic policy (harmony degree of ethnic policy)
Economics and finance	Economic situation	Economic growth (growth rate/%) Inflation (annual rate of inflation/%)
	Financial foreign exchange	Credit system (weighted asset ratio of regulatory capital and risk) Interest rate fluctuations (absolute value of the interest rate differential/%) Foreign exchange (freedom of foreign exchange) Exchange rate fluctuation (range of appreciation/depreciation/%)
Institutional operation	Mining tax	Subject of tax (number of tax) Total tax rate (DTF score of total tax rate)
	Legal governance	Legal system (level of legality) Law enforcement capacity (government efficiency)
	Operating environment	Social credit (DTF index of contract execution) Property registration (DTF index of property registration) Partner (director's level of responsibility)
	Invest in mining	Information disclosure (disclosure score) Foreign capital holding (proportion of foreign capital holding) Acquisition of mineral rights (difficulty of acquisition) Smelting requirements (difficulty of acquisition)
Community workers	Community organization	Public order (homicide rate) Community appeal (degree of community appeal)
	Labor employment	Labor policy (labor income as % of GDP) Risk of strike (annual total strikes)
Basic resources	Infrastructure	Infrastructure (Infrastructure score)
	Resource provision	Energy electricity (electricity availability index)
	Communication hygiene	Health (prevalence of tuberculosis per 100,000 population) Communication conditions (% of internet users)
Environmental protection	Environmental control	Environmental enforcement (environmental enforcement level)

Table 2. Assignment table of resource potential.

Best Practice Mineral Resource Potential Index	Risk Score
10<	10
10–20	9.0
20–30	8.0
30–40	7.0
40–50	6.0
50–60	5.0
50–70	4.0
70–80	3.0
80–90	2.0
>90	1.0

(3) Sample set of evaluation models based on SVM

A total of 40 datasets from 20 countries (North America: USA, Canada; Europe: Russia, Finland, Sweden, Turkey; Asia: Kazakhstan, Indonesia, Philippines, India; Latin America: Argentina, Peru, Brazil, Chile, Honduras, Guatemala; Africa: Zambia, Congo, Tanzania; and Oceania: Australia), collected in 2015 and 2016, provided by Gu [5], were used as learning samples; 32 samples from the first 16 countries were selected as training samples to construct the optimal support vector machine model, and 8 samples from the other 4 countries were used as test samples.

(4) Evaluation model based on SVM

In the risk evaluation model of overseas mining investment, the risk index data of the selected countries are input, and the features of the input data are extracted and expressed through classifier processing. Through layer-by-layer propagation, a continuous dimensionality reduction process is realized, which makes the representation of the data more and more abstract, and finally obtains the prediction result of the sample. The risk level of the sample mining countries is a very complex and abstract result, which needs many kinds of features to be combined to judge, and finally gets 5-level risk classification. In this paper, it is the process of reducing the input data from multi-dimension to 5-dimension.

The SVM model for the risk assessment of overseas mining investment is established using the knowledge from the training samples, the optimal kernel function parameter σ, and the penalty parameter C selected via the grid search method [33,35]. The SVM model is implemented using the latest open-source libSVM package in the Python environment, which was developed by Taiwanese professor Chih-Jen Lin [38], where the kernel functions are based on the commonly used Gauss radial basis function $K(x_i, x_j) = \exp\left(-\frac{|x_i - x_j|^2}{2\sigma^2}\right)$. After the model training, the optimal parameters of the SVM prediction model were obtained: penalty parameter $C = 32$, kernel parameter $\sigma = 0.0078125$, and the correct rate was 100%.

(5) Test of evaluation model based on SVM

Then, another l8 test samples were input into the trained evaluation model. The discrimination results are shown in Table 3, and the error rate was zero.

Table 3. The discrimination results of the test samples.

No.	Actual Grade	Test Grade	Prediction Result
1	III	III	True
2	III	III	True
3	III	III	True
4	IV	IV	True
5	IV	IV	True
6	IV	IV	True
7	IV	IV	True
8	IV	IV	True

4. Result Analysis and Discussion

4.1. Case Study

South Africa is located on the southern tip of the African Plateau, surrounded by the sea on the eastern, western, and southern sides and by mountains on the northern side, with high terrain in the north and low terrain in the south. South Africa has a total land area of 1,219,000 km^2 and is among the countries with the most abundant mineral resources in the world, being well-known for its resources and good occurrence conditions. The country houses the most important mineral resources, and there are now more than 70 types of mineral resources with proven reserves [4,7,39–42].

The relationship between South Africa and China has strategic importance throughout the African continent. With bilateral trade between China and South Africa reaching

USD 46 billion in 2015, China has been South Africa's largest trading partner for seven consecutive years. South Africa is China's largest source of imports and its main trading partner on the African continent. However, South Africa's mining industry has been in decline due to the poor global mining environment, and there are many problems in the mining investment environment of South Africa. Therefore, it is necessary to collate and analyze relevant documents to comprehensively study the mining investment environment in South Africa [4,7].

The risk profile data of South Africa in 2016 were evaluated, and they are presented in Table 4.

Table 4. The data of mining investment risk indices for South Africa in 2016.

Risk Evaluation Index System for Overseas Mining Investment			Data
Level One Index	**Level Two Index**	**Level Three Index**	
Mineral resources	Resource status	Resource mining (ore and metal export index/%)	23.58
		Resource potential (best practice mineral resource potential index)	57.69
Politics and religion	Political stability	Civil war (degree of civil unrest)	0.21
		Regime change (form of regime change)	4.00
	Geopolitics	Peripheral relations (diplomatic hierarchy)	4.00
		The great power factor (great power intervention)	6.00
	Nationalities and religions	Religious influence (integration degree of church and state)	4.00
		Ethnic policy (harmony degree of ethnic policy)	8.00
Economics and finance	Economic situation	Economic growth (growth rate/%)	0.57
		Inflation (annual rate of inflation/%)	6.33
	Financial foreign exchange	Credit system (weighted asset ratio of regulatory capital and risk)	15.93
		Interest rate fluctuations (absolute value of the interest rate differential/%)	1.04
		Foreign exchange (freedom of foreign exchange)	4.00
		Exchange rate fluctuation (range of appreciation/depreciation/%)	0.15
	Mining tax	Subject of tax (number of tax)	7.00
		Total tax rate (DTF score of total tax rate)	96.24
Institutional operation	Legal governance	Legal system (level of legality)	4.00
		Law enforcement capacity (government efficiency)	0.16
	Operating environment	Social credit (DTF index of contract execution)	66.14
		Property registration (DTF index of property registration)	65.50
		Partner (director's level of responsibility)	8.00
		Information disclosure (disclosure score)	8.00
	Invest in mining	Foreign capital holding (proportion of foreign capital holding)	6.00
		Acquisition of mineral rights (difficulty of acquisition)	6.00
		Smelting requirements (difficulty of acquisition)	6.00
Community workers	Community organization	Public order (homicide rate)	34.27
		Community appeal (degree of community appeal)	6.00
	Labor employment	Labor policy (labor income as % of GDP)	2.00
		Risk of strike (annual total strikes)	3.00

Table 4. *Cont.*

Risk Evaluation Index System for Overseas Mining Investment Level One Index	Level Two Index	Level Three Index	Data
Basic resources	Infrastructure	Infrastructure (Infrastructure score)	4.18
	Resource provision	Energy electricity (electricity availability index)	84.21
	Communication hygiene	Health (prevalence of tuberculosis per 100,000 population)	781.00
		Communication conditions (% of internet users)	54.00
Environmental protection	Environmental control	Environmental enforcement (environmental enforcement level)	6.00

South Africa's mining investment risk in 2016 was assessed using the risk evaluation model for overseas mining investment based on the support vector machine, and it was rated as grade IV (general investment risk).

4.2. Result Discussion

The results are consistent with those obtained by Gu [5] using the deep neural network (DNN) model, and the mining investment risk level in South Africa is general. In fact, there are many studies on the risk grade of mining investment in South Africa. For example, Jiang [4] evaluated the risk grade of mining investment in South Africa based on grey system theory, and Zheng and Hu [3] evaluated the environmental risk of mining investment in South Africa based on the incentive variable weight evaluation model. However, these studies assess the environmental risks of mining investment in South Africa in different years. Because the environment for mining investment in each country changes every year, and the researchers carried out their studies at different times, the final evaluation index system is different, the data collected are different, and thus the final results are different. Their research conclusions can only be used as a reference.

The results indicate that the multiclassification prediction model on the basis of SVM does not need much prior knowledge or learning samples, and it does not require many parameters to be adjusted in the prediction model, bringing convenience to training and study. Therefore, the application of the SVM classification model in the risk assessment of overseas mining investment is feasible, with high classification effectiveness and accuracy, which can provide a useful reference for practical projects.

Each method has its usefulness. When the implementation of statistical learning theory and the study of relatively new machine learning methods such as neural networks encounter some important difficulties—for example, how to determine the structure of the network, over-learning and under-learning, and local minimum problems—with the SVM's rapid development and improvement, it brings many unique advantages and good application prospects in solving practical problems. Therefore, the detection and evaluation of investment risk is essentially a high-dimensional classification problem of high complexity, and because the SVM has excellent learning ability, it has shown unique advantages and good application prospects in investment risk analysis.

5. Implications

5.1. Policy Implications

According to the above research results, the authors believe that before companies undertake such investment, they must fully understand the economic and trade policies of the target country, the investment environment of the industry, and the investment environment of the host country via the government platform or the employment of professional consulting firms; then, they should formulate a project schedule and an investment operation benefit plan according to the actual situation, in order to avoid blind investment or a loss of investment. When companies invest in the overseas mining industry, they should pay close attention to economic, social, and political development and update their evaluation results.

Mining, as one of South Africa's pillar industries, will not change in the next 20–30 years, given the government's policy of strongly encouraging and promoting mining development. However, mining development in South Africa faces a range of problems and challenges, although this is to be expected. The world's major mining countries also encounter such problems, but they are of different types and to different degrees. Thus, as long as mining enterprises deal with such situations and transform challenges into impetus, take positive action, follow good practices, and address malpractice, mining enterprises will be able to overcome these difficulties. Despite the challenges, South Africa's mining development still has considerable advantages and potential across the world.

Overseas mining investment is an economic activity with a large amount, long cycle, and high threshold. The risk changes at any time and is present throughout the whole process; in order to reduce the risk of mining enterprises, we should strengthen and perfect the service function of the government from the macro-perspective and guide and encourage enterprises to move abroad to exploit foreign mineral resources through policy support and macro-management. From the micro-perspective, regarding the risks of overseas investment, mining enterprises should take targeted measures to improve their international competitiveness.

5.2. Managerial Implications

With the continuous development and improvement of SVM technology, its superior performance (small sample size, generalization ability, etc.) has attracted wide attention. The practical application of this method in many fields is still in its infancy, and its application in mining investment is even smaller. Therefore, this paper attempts to introduce this method into the field of mining investment and apply it to assess the risk of overseas mining investment.

To summarize, the application of SVM in the risk assessment of overseas mining investment is entirely feasible, and by virtue of its powerful learning function, excellent generalization ability, the pursuit of optimal solutions, and nonlinear system modeling performance under existing information, it can provide a new means to solve "bottleneck" problems, such as "limited data" and "inaccurate evaluation parameters". Therefore, research on the application of SVM in mining investment is a new and promising research direction.

Although this paper has conducted a comprehensive and systematic study on the application of SVM technology in the risk assessment of mining investment, there are many factors affecting the risk of overseas mining investment. In this paper, the theoretical analysis, model simulation, and calculation were carried out with a certain simplification, and there were some factors that could not be considered. Therefore, it is inevitable that there will be some impact on the accuracy of sample testing and the capacity for model generalization. In the future, it is necessary to accumulate sample data of mining investment risk to enhance the application potential of SVM, so as to establish an evaluation model with more comprehensive consideration factors and stronger generalization ability.

6. Conclusions

(1) Based on problems existing in the theory and method of overseas mining investment risk evaluation, this paper introduces the idea of SVM for overseas mining investment risk assessment. The aim of the research was to establish a comprehensive risk evaluation model for overseas mining investment on the basis of SVM. The related parameters of the optimal model were ascertained by training the sample data.

(2) The model was applied to South Africa. The results showed that the mining investment risk level in South Africa was IV (signifying a general investment risk). The model was based on a small number of typical samples, had strong generalization abil-

ity, and could quickly obtain the investment risk grade of large-scale undetermined assessment units.

(3) To prevent the overseas mining investment risk for mining enterprises and protect the rights and interests of enterprise resources, before companies carry out such investment, they should consider due diligence and collect detailed data on the investment environment of the host country, including the mining investment environment indices, so as to undertake a risk assessment of the mining investment environment. Then, a decision can be made according to the result of the evaluation. After the investment, the investment environment risk should be carefully studied, and the corresponding risk prevention and control measures should be formulated according to the risk characteristics, so as to reduce the project operation risk and improve the success rate of the investment.

In this paper, a model of overseas mining investment risk assessment based on SVM was established for the first time and applied in an example. From the overall test results, the model has high accuracy and a good effect when used in the risk assessment of overseas mining investment, which proves the feasibility and scientific nature of this method for mining investment risk assessment; it provides a scientific evaluation of overseas mining investment to promote the sustainable and healthy development of overseas mining investment. However, in the course of the research, it was found that the establishment and selection of the kernel function for SVM and the optimal selection of related parameters in practical application need to be further studied. At the same time, considering that there are many factors affecting the risk of overseas mining investment, it is necessary to accumulate sample data on mining investment risk so as to exploit the application potential of SVM and establish an evaluation model with more comprehensive consideration factors and stronger generalization ability in the future.

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References

1. Chen, Q.S. *Global Mining Development Report 2019*; International Mining Research Center of China Mining News Agency: Beijing, China; China Geological Survey Bureau of Ministry of Natural Resources: Beijing, China, 2019.
2. Ministry of Commerce of the People's Republic of China; National Bureau of Statistics; State Administration of Foreign Exchange. *Statistical Bulletin of China's Outward Foreign Direct Investment (2003–2020)*; China Commerce and Trade Press: Beijing, China, 2020.
3. Zheng, M.G.; Hu, Z.L. Study on environmental risk evaluation of overseas mining investment. *Gold Sci. Technol.* **2018**, *26*, 595–604.
4. Jiang, Y. *Risk Evaluation of Overseas Mining Investment Based on Grey System Theory*; China University of Mining & Technology: Beijing, China, 2017.
5. Gu, C.Y. *Research on Risk Evaluation of China's Overseas Mining Investment Based on Deep Learning*; China University of Geosciences: Beijing, China, 2019.
6. Lei, L. *Study on the Philippine Mineral Investment Environment: With Nickel and Copper for Example*; China University of Geosciences: Beijing, China, 2015.

7. Xie, F.B. *Study on the Investment Environment of Mineral Resources in Africa*; China University of Geosciences: Beijing, China, 2015.
8. Bian, J.; Marchione, F. Business ethics and Chinese overseas investment. In *Regulations and Applications of Ethics in Business Practice. Accounting, Finance, Sustainability, Governance & Fraud: Theory and Application*; Bian, J., Çalıyurt, K., Eds.; Springer: Singapore, 2018; pp. 207–223.
9. Zeng, W. An analysis of the legal issues of China's overseas investment in the context of the 'belt and road' initiative. In *A Legal Analysis of the Belt and Road Initiative*; Martinico, G., Wu, X., Eds.; Palgrave Macmillan: Cham, Switzerland, 2020; pp. 199–219.
10. Hong, S.F.; Deng, Y.T.; Li, H.D. Risk evaluation of China's overseas mining investment based on structural power theory. *China Min. Mag.* **2021**, *30*, 24–31.
11. Zhang, D.Y.; Kong, Q.X. How does energy policy affect firms' outward foreign direct investment: An explanation based on investment motivation and firms' performance. *Energy Policy* **2021**, *158*, 112548. [CrossRef]
12. He, H.; Li, W.; Xing, R.; Zhao, Y. An evaluation of the petroleum investment environment in African oil-producing countries based on combination weighting and uncertainty measure theory. *Sustainability* **2022**, *14*, 5882. [CrossRef]
13. Charnes, A.; Cooper, W.W.; Lewin, A.Y.; Morey, R.C.; Rousseau, J. Sensitivity and stability analysis in DEA. *Ann. Oper. Res.* **1985**, *2*, 139–156. [CrossRef]
14. Campbell, J.P.; McCloy, R.A.; Oppler, S.H.; Sager, C.E. A Theory of Performance. In *Personnel Selection in Organizations*; Schmitt, N., Walter, C.B., Eds.; Jossey-Bass: San Francisco, CA, USA, 1993; pp. 35–70.
15. Zhang, Z.H.; Da, Q.L. Application of grey system theory in M & A risk decision. *Sci. Res. Manag.* **2003**, *24*, 1–5.
16. Yang, J.; Zhang, P.Z. An empirical study on the investment order based on rough set information entropy. *Econ. Manag.* **2004**, *14*, 18–22.
17. Huo, Z.Q.; Lu, H.S. Research on regional investment environment synthesis judgment and application. *China Bus. Mark.* **2008**, *2*, 62–65.
18. Li, Z.M. Research on sustainable optimization of the mining investment decision based on sensitivity analysis. *Public Financ. Res.* **2008**, *8*, 34–37.
19. Carpenter, S.; Vellat, M. The application of a planned economy country risk model to the assessment of market entry into the Chinese banking sector. *J. Financ. Serv. Mark.* **2009**, *13*, 345–356. [CrossRef]
20. Liu, S.; Wang, G.S.; Chen, C.; Ji, S.J. Study on global mining investment environment based on AHP. *Resour. Ind.* **2010**, *12*, 116–122.
21. Saaty, T.L.; Shang, J.S. An innovative orders-of-magnitude approach to AHP-based mutli-criteria decision making: Prioritizing divergent intangible humane acts. *Eur. J. Oper. Res.* **2011**, *214*, 703–715. [CrossRef]
22. Zhang, X.M.; Li, C.H.; Zhao, Y. Research on application framework of VaR method on risk management in overseas mining investment. *China Popul. Resour. Environ.* **2014**, *24*, 344–348.
23. Mu, X.Z.; He, F. Evaluation on the investment environment of top five oil-producing countries in Africa based on entropy weight method and the matter-element model. *Enterp. Econ.* **2015**, *5*, 119–122.
24. Li, Y.W. A risk early warning study on China's overseas investment. *Manag. World* **2016**, *9*, 178–179.
25. Duan, F.; Ji, Q.; Liu, B.Y.; Fan, Y. Energy investment risk assessment for nations along China's belt & road initiative. *J. Clean. Prod.* **2017**, *170*, 535–547.
26. Li, Z.X.; Liu, J.Y.; Luo, D.K.; Wang, J.J. Study of evaluation method for the overseas oil and gas investment based on risk compensation. *Pet. Sci.* **2020**, *17*, 858–871. [CrossRef]
27. Wang, D.L.; Tong, X.; Wang, Y.D. An early risk warning system for outward foreign direct investment in mineral resource-based enterprises using multi-classifiers fusion. *Resour. Policy* **2020**, *66*, 101593. [CrossRef]
28. He, H.J.; Xing, R.; Han, K.; Yang, J.J. Environmental risk evaluation of overseas mining investment based on game theory and an extension matter element model. *Sci. Rep.* **2021**, *11*, 16364. [CrossRef]
29. Lai, H.S.; Wu, C.F. Productivity evaluation of standard cultivated land based on rough set and support vector machine. *J. Nat. Resour.* **2011**, *26*, 2141–2154.
30. Liang, B.; Liu, Z.; Niu, Y.B. Shearer cutting pattern recognition based on multi-scale fuzzy entropy and support vector machine. *Coal Eng.* **2021**, *53*, 131–135. [CrossRef]
31. Reza, G.; Abbas, M.; Amirreza, B.; Emmanuel, J.M. Carranza regional-scale mineral prospectivity mapping: Support vector machines and an improved data-driven multi-criteria decision-making technique. *Nat. Resour. Res.* **2021**, *30*, 1977–2005.
32. Nasrin, T.; Majid, B. Multi-attribute selection for salt dome detection based on SVM and MLP machine learning techniques. *Nat. Resour. Res.* **2022**, *31*, 353–370.
33. Li, Y. *Prediction Method Study on Water Inrush through Coal Floor Based on SVM*; Xi'an Research Institute of China Coal Research Institute: Xi'an, China, 2007.
34. Huang, W.Y. *Study on Coal Gas Early-Warning Technology Based on Support Vector Machine and Data Fusion*; China University of Mining and Technology: Xuzhou, China, 2009.
35. Nie, X.F. *The Research on the Application of Fuzzy Rough Set and Support Vector Machines in Coal and Gas Outburst Prediction*; Liaoning Technical University: Fushun, China, 2009.
36. Wang, F. *Research on Methods of Traffic Flow Forecasting Based on SVM*; Dalian University of Technology: Dalian, China, 2009.
37. Cao, Q.K.; Zhao, F. Risk evaluation of water inrush from coal floor based on fuzzy-support vector machine. *J. China Coal Soc.* **2011**, *36*, 633–637.

38. Chang, C.C.; Lin, C.J. LIBSVM–A Library for Support Vector Machines. Available online: https://www.csie.ntu.edu.tw/~{}cjlin/libsvm/ (accessed on 1 January 2022).
39. He, J.X. Current situation, challenges and prospects for the mining industry of South Africa. *China Min. Mag.* **2019**, *28*, 48–51.
40. He, J.X.; Cui, R.G.; Xu, S.G.; Liu, W. Mining investment environment and trend in South Africa, Zambia, the democratic republic of congo and zimbabwe. *Land Resour. Inf.* **2021**, *5*, 10–19.
41. USGS (United States Geological Survey). 2016 Minerals Yearbook, The Mineral Industry of South Africa, Mineral Commodity Summaries, 2017. Available online: https://prd-wret.s3.us-west-2.amazonaws.com/assets/palladium/production/atoms/files/myb3-2016-sf.pdf (accessed on 1 January 2022).
42. Department: Mineral Resources Republic of South Africa, South Africa's Mineral Industry 2016/2017. Available online: http://www.dmr.gov.za//resources (accessed on 1 January 2022).