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Research Article

Research on Mining Balanced Competition Strategy in Financial Market Based on Computer Data Mining Method

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The mining process of traditional market equilibrium competition strategy is difficult to deal with massive data, resulting in the inability to accurately classify customer data in the process of competition strategy customization. Therefore, this paper proposes a strategy formulation method of balanced competition in the financial market based on computer data mining. Firstly, the process of the k-means clustering algorithm was optimized, and Murkowski distance and Markov distance were used as classification basis to find some potential information hidden in the data. Based on the optimized K-means clustering algorithm for data processing, in order to achieve effective data analysis, design customer behavior data mining process and analyze customer value matrix and customer pyramid. Finally, the layout framework of a balanced competition strategy in the financial market is established. The results show that the classification accuracy of the design method is higher than that of the traditional method in different states.

1. Introduction

Since the introduction of Internet technology into China after more than 20 years of in-depth development, it has had a very profound impact on national life and all walks of life. With the wide popularization of the Internet, Internet technology has developed very rapidly, which has derived some new concepts and applications. As the most basic resource allocation industry in the social economy, the financial market is inevitably affected by Internet technology and the popularity of the Internet. The development of Internet technology has increased the pressure on the competition in the financial industry [1–3]. The rise of Internet financial enterprises and the P2P financial model has brought profound changes to the whole financial industry. Especially for financial institutions, the traditional financial industry is facing great challenges. The development and growth of financial business on the Internet have caused a huge blow to the offline market and business income.

In this context, financial institutions need to formulate an effective strategy for balanced competition in the financial market according to the current form. In order to customize an effective balanced competition strategy, we need to sort out the internal information of current financial institutions in order to obtain accurate and complete enterprise financial behavior data. In the current financial institutions, such as some banks, insurance, securities, and other related institutions, in the daily customer maintenance, investment, and other operations, some operations and financial related data will increase exponentially every day. In the mining process of the traditional market equilibrium competition strategy, due to the lack of effective technical means, the accuracy in the process of data classification is low [4–6]. Therefore, this paper proposes a method to mine the balanced competition strategy of the financial market based on the computer data mining method. Through the analysis of these massive data, we can find some hidden potential information, and it can realize effective data analysis, and according to this information, excavate a complete set of competitive strategies in the balanced competition of the financial market, so as to enhance the competitiveness of financial institutions in the market.

This paper is divided into four parts as follows: introduction, mining balanced competition strategy in financial market, experimental results and discussion, and conclusion. Next mining balanced competition strategy in the financial market will be introduced below.

2. Mining Balanced Competition Strategy in Financial Market

2.1. Optimized Data Mining Algorithm. In the process of mining financial market equilibrium strategies, financial institutions first need to analyze customer behavior data and evaluate and cluster the risks of these data. Due to the large amount of data involved, this paper needs to use a data mining algorithm to process and classify the above data [7, 8]. In the process of data mining, this paper selects the K-means clustering algorithm to process data. Clustering is to classify the data according to some characteristics of the data, so that the data divided into one category have common characteristics in one aspect, and different categories of data need no obvious common characteristics. In the K-means clustering algorithm, clustering analysis is mainly based on the similarity of characteristics between individual data. Therefore, before clustering, it is necessary to measure the similarity of characteristics, which runs through the whole process of clustering analysis. In the measurement process, the similarity between individual data is generally expressed by distance [9, 10]. The commonly used clustering measurement distance types are Minkowski distance and Markov distance. It is assumed that two data are characterized by two points in space, which are respectively expressed as

$$\begin{cases} x(x_1, x_2, \dots x_n) \\ y(y_1, y_2, \dots y_n) \end{cases}. \tag{1}$$

Then, the Minkowski distance between these two points is calculated as follows:

$$d(x, y) = \left(\sum_{i}^{n} |x_i - y_i|^m\right)^{1/m}, m > 0. \tag{2}$$

In the formula, different distances will be obtained if the value of m is different. When the value of m is 1, the obtained $d(x, y)$ is called the absolute distance, which is recorded as

$$d(x, y) = \sum_{i}^{n} |x_i - y_i|. \tag{3}$$

When the value of m is 2, the obtained $d(x, y)$ is called the Euclidean distance, which is recorded as

$$d(x, y) = \sqrt{\sum_{i}^{n} |x_i - y_i|^2}. \tag{4}$$

When the value of m is infinite, the obtained $d(x, y)$ is called Chebyshev distance, which is recorded as

$$d(x, y) = \max_i |x_i - y_i|. \tag{5}$$

In the above Minkowski distance, no matter what the value of m is, it will meet the following properties:

$$\begin{cases} d(x, y) = d(y, x) \\ d(x, y) \le d(x, z) + d(z, y) \\ d(x, y) > 0, d(x, x) = 0 \quad x \ne y \end{cases}. \tag{6}$$

Using Minkowski distance alone will ignore the similarity between attribute individuals and focus on the similarity between numerical individuals. Due to the existence of dimensions, a single distance measurement will be affected by the data value, resulting in measurement error. Therefore, in the process of clustering, it is necessary to cooperate with Mahalanobis distance to be more accurate. The calculation formula of Mahalanobis distance is as follows:

$$d_m(x, y) = (x - y)\sum^{-1}(x - y)^T. \tag{7}$$

In the formula, $\sum^{-1}$ represents the covariance matrix between data. Under the action of this matrix, the influence of dimension on distance measurement can be eliminated. However, this clustering algorithm is easy to fall into local iteration in the process of classification cannot get the optimal solution in the global range [11, 12], and the obtained clustering results will produce different clustering results due to the change in the distance between individual data [13, 14]. Therefore, this paper needs to optimize the process of the K-means clustering algorithm. The optimization process is shown in Figure 1.

So far, the optimization of the data mining K-means clustering algorithm has been completed.

2.2. Data Processing Based on Optimized K-Means Clustering Algorithm. The K-means clustering algorithm can effectively classify customer data according to its characteristics. Its classification accuracy is higher than other clustering classification methods. Therefore, the K-means clustering algorithm is used to conduct clustering analysis in this paper. Under the optimization of the above K-means clustering algorithm, if you want to customize a balanced competition strategy in the financial market, you need to recommend personalized products and services for customers. On the basis of such recommendations, we need to have a large amount of customer data information, analyze and mine these data, find out the real needs of customers under these data, and provide customers with the correct products and services at the right time [15]. Under the mining of the K-means clustering algorithm, the mining process of data behavior is shown in Figure 2.

For financial institutions, customer value is the main evaluation index of the balanced competitiveness of the financial market. The level of customer value represents how much benefit it can bring to financial institutions. The division of customer behavior data based on value is to evaluate the contribution of future financial institutions based on customers. Customer value includes explicit value and value-added value. Explicit value refers to the profits that customers can create for financial institutions. The

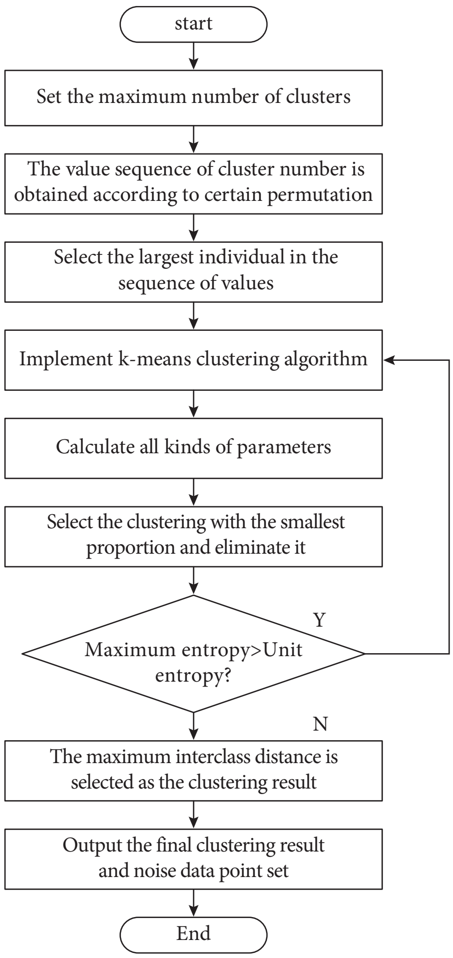

Figure 1: Optimization process of K-means clustering algorithm.

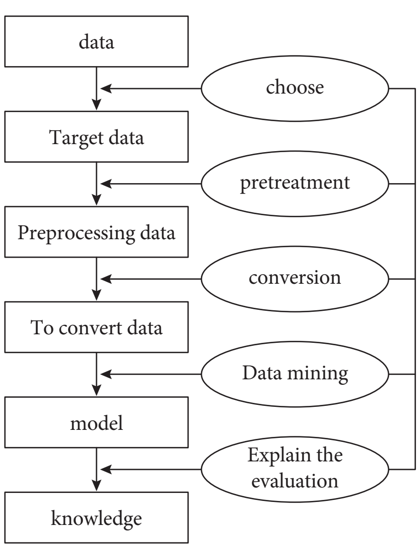

Figure 2: Customer behavior data mining process.

value-added value of customers refers to the potential value and future growth value of customers. The matrix thus established is shown in Figure 3.

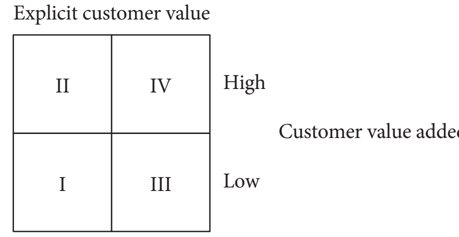

Figure 3: Customer value matrix.

In the figure , the value of class I~IV customers is ranked from low to high. Class I customers in the customer group have low explicit value and value-added value. They have low-profit contribution and business volume to financial institutions, but they require high service quality. Among class II customers, the current explicit value is relatively low, but its data operation shows that it has high value-added value and the total business volume is relatively large, but the business share invested in this financial institution is relatively small. Among class III customers, the business volume generated is basically in the financial institution, so it has high explicit value, but the value generated by such customers has entered a stable period, so the value-added value is relatively low. Class IV customers are the customers with the best value in financial institutions and can achieve common development with financial institutions.

In order to make financial institutions have certain competitiveness in the balanced competition of the market, it is necessary to classify customers. Based on the "28 rule," a "customer pyramid" is established for the above customer types. The tower type is shown in Figure 4.

By classifying the data, financial institutions can customize services for customers and complete data processing under the optimized K-means clustering algorithm.

2.3. Establishing the Layout Framework of Financial Institutions. After completing the relevant data analysis, we need to formulate our balanced competition strategy in the financial market according to the characteristics of financial institutions. According to the above analysis methods, if financial institutions want to customize a balanced competition strategy in the financial market, they need to combine market positioning, business transformation, and the current operation mode of the emerging Internet. Based on the main business of financial institutions, we need to establish a comprehensive competition layout structure from the coexistence of competition and cooperation, online and offline, and determine the business competition model framework under the background of computer data mining. In this process, we should first change the service model of the basic business of financial institutions and strengthen cooperation with existing Internet financial institutions. On this basis, correctly understand the transformation nature and characteristics of the financial market under the Internet environment, and establish a professional strategy for balanced competition. If you want to make great progress in the current financial market, you need to establish market

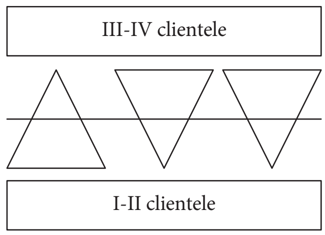

Figure 4: Customer pyramid.

orientation and brand positioning and maximize the customer resources in the Internet financial market. According to the above principles and development plan, the competition layout framework of financial institutions in the market is shown in Figure 5.

According to the framework in the figure above, under the excavation and formulation of a balanced competition strategy in the financial market, it is necessary to have a clear understanding of positioning transformation and competition layout reconstruction based on the environment and requirements of the development of emerging markets and the conditions and limitations of financial institutions. If you want to win the balanced competition in the market, the most important thing is to improve the customer service experience. Financial institutions need to improve the quality of offline services from the perspective of customer experience, mainly including strengthening the overall structural stability of offline main businesses and taking the main business as the starting point to radiate and guide the surrounding. At the same time, it also need to cooperate with publicity and promotion to promote the improvement of offline service quality. From the perspective of online service experience, we need to be based on humanization, reduce the threshold of service and transaction costs, and classify online app pages. A classified layout of special culture can be set to simplify service rates, taking the Internet as a breakthrough as a characteristic tool in the competition to establish an independent and diversified online customer group of the organization itself.

3. Experimental Results and Discussion

3.1. Experimental Design. In order to verify the effectiveness of the financial market equilibrium competition strategy based on computer data mining, this paper needs to design experiments and analyze the experimental results. In the process of experimental verification, the daily customer maintenance, investment, and other operational data of 1,500 enterprise customers of a financial institution are selected as the database in the experiment, and the selected experimental period is the average data between 2015 and 2018. In this experiment, the financial data provided by financial institutions are based on financial trade secrets, so the data provided are mainly the relevant attributes of the transaction database. After attribute transformation, we can get several attributes of financial indicators in relevant enterprises.

According to the availability and representativeness of data, this paper selects variables from customer information, credit card information, and transaction information to construct the analysis system. The computer data mining method of the financial market equilibrium competition strategy designed in this paper mainly relies on data mining technology. In the process of formulating a financial market equilibrium competition strategy, we first need to determine the target definition in the process of data mining. On the basis of data mining technology, customers will be reasonably and systematically customize a series of competitive strategies and marketing activities. In order to accurately find target customers and achieve balanced competition in the financial market, it is necessary to implement targeted precision marketing and clarify the objectives to be achieved by customer behavior data. Generally, it includes the analysis of the return on investment of financial institutions, which needs to provide personalized services according to the basic situation of customers, predict and judge the loss of customers, and finally carry out accurate targeted sales for a single financial product. The information provided for data mining in the experiment is shown in Table 1.

According to the priority indicators of financial institutions and the actual operation status of cooperative enterprises, the risk of competitive strategy is divided into four levels as follows: high, higher, medium, and low in the expert evaluation group. Among them, the high-risk strategy is the enterprise that uses the strategy and collapses during the research periothethe strategy with a higher risk level is the enterprise that uses the strategy and produces credit default during the research pthed; the strategy with a medium risk level is the enterprise that uses this strategy during the study period, although there is no credit default, the financial situation deteriorates.

Through the mining of competitive strategies in this paper, 10 decision trees are established for data mining and analysis. The decision tree is mainly constructed by randomly selecting 10 attributes from the financial indicators of relevant enterprises. The selected attributes are net profit of total assets, asset-liability ratio, quick freezing ratio, fixed assets ratio, interest protection multiple, return on assets, current ratio, capital adequacy ratio, working capital to total assets ratio, and total asset turnover ratio. The calculation formula for net profit P_{Ta} of total assets is as follows:

$$P_{Ta} = \frac{R_p}{(T_a + T_{a-1}) * 2}. \tag{8}$$

In the formula, R_p represents the net profit, T_a represents the total assets, and T_{a-1} represents the total assets of the previous period. The calculation formula for asset-liability ratio R_l is as follows:

$$R_l = \frac{D_l}{T_a}. \tag{9}$$

In the formula, D_l represents the total liabilities, and the calculation formula of the quick-freezing ratio Q_f is as follows:

$$Q_f = \frac{(C_a - I_w)}{F_l}. \tag{10}$$

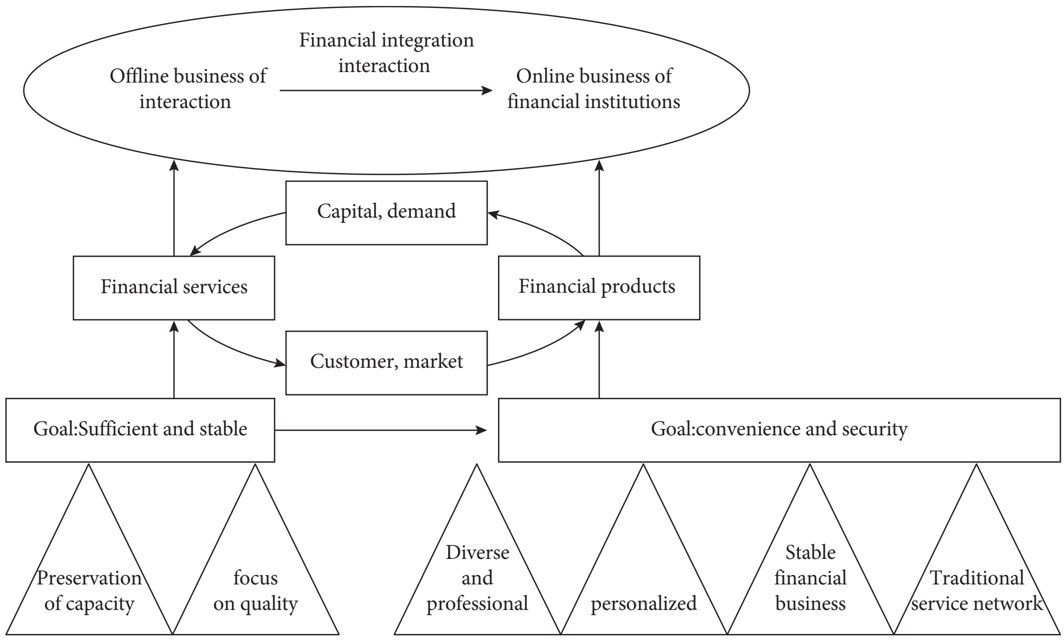

Figure 5: Framework of balanced competition in the financial market.

Table 1: Data information of financial institutions.

Classification	Field name	Information
Customer information	C_Number	Customer number
	C_Name	Customer name
	C_gender	Customer gender
	C_Birth_DT	Date of birth
	Cert_information	Certificate information
	UNIT_OCCUP_POSN	Work information
	C_Marry_CD	Marital status
	EDUC_LVL	Educational level
Credit/debit card information	CARD_Number	Card number
	CURR_Number	Currency
	CREDIT_LIMIT	Credit limit
	OPEN_CARD_DT	Card opening date
	CRD_TPY_BZ	Card type remarks
	LN_TOTL_AMT_HYPO	Account amount
Transaction information	ACCT_NO	Transaction account number
	CURR_IDEN	Note exchange identification
	Sa_tx_dt	Transaction date
	CR_tx_amt	Transaction amount
	DSCRP_COD	Summary code
	ACCT_BAL	Account balance

In the formula, C_a represents total current assets, I_w represents the net inventory value, and F_l represents the total current liabilities, and the calculation formula of the fixed asset ratio F_R^a is as follows:

$$F_R^a = \frac{F^a}{T_a}. \tag{11}$$

In the formula, F^a represents the total number of fixed assets, and the calculation formula of interest protection multiple M_{Ic} is as follows:

$$M_{Ic} = \frac{R_p + I_t + C_f}{C_f}. \tag{12}$$

In the formula, I_t represents income tax, and C_f represents financial expenses, and the calculation formula of return on assets R_a is as follows:

$$R_a = \frac{2R_p}{S_e + S_{e-1}}. \tag{13}$$

Table 2: Accuracy statistics of random sampling classification data of the strategy mining method in this paper.

Number of experiments	High risk/%	Higher risk/%	Medium risk/%	Low risk/%
1	69.6	69.33	73.33	83.69
2	76.3	68.66	76.63	76.93
3	79.5	70.05	75.51	85.32
4	68.4	69.22	72.25	82.20
5	72.1	71.11	74.35	73.21
6	72.2	70.44	78.38	86.34
7	75.0	72.57	79.25	78.62
8	68.3	73.60	73.12	82.50
9	65.6	75.52	72.45	82.22
10	75.5	74.43	71.66	86.54

Table 3: Accuracy statistics of random sampling classification data by traditional strategy mining methods.

Number of experiments	High risk/%	Higher risk/%	Medium risk/%	Low risk/%
1	32.23	46.62	53.33	63.3
2	33.25	43.32	56.20	72.6
3	26.31	55.22	65.12	65.2
4	32.61	41.52	52.01	76.5
5	32.22	50.65	63.54	62.3
6	23.25	45.22	55.55	61.4
7	30.65	43.25	60.66	60.7
8	24.55	56.52	51.49	72.0
9	35.59	45.56	62.25	73.2
10	20.36	58.25	65.11	75.3

In the formula, S_e represents the total amount of shareholders' equity, and S_{e-1} represents the total amount of shareholders' equity in the previous period, and the calculation formula of the current ratio C_R is as follows:

$$C_R = \frac{C_a}{F_l}. \tag{14}$$

The calculation formula of the capital adequacy ratio R_{ca} is as follows:

$$R_{ca} = \frac{S_e}{T_a}. \tag{15}$$

The calculation formula of the working capital to total assets ratio R_O is as follows:

$$R_O = \frac{C_a - F_l}{T_a}. \tag{16}$$

The calculation formula for the total asset turnover rate R_{AT} is as follows:

$$R_{AT} = \frac{2I_{mb}}{T_a + T_{a-1}}. \tag{17}$$

In the formula, I_{mb} represents the income of the main business. In the above attribute calculation, relevant data are obtained. The balanced competition strategy mining method and the traditional strategy mining method designed in this paper are used to correctly classify the risk of data.

3.2. Comparison and Analysis of Random Sampling Experimental Results. Under the above experimental data, two methods are used for multiple tests. The accuracy of strategy classification in multiple experimental tests obtained by this method is shown in Table 2.

It can be seen from the results in the above table that the classification accuracy of low-risk data can reach more than 75%, but the classification accuracy of high-risk data and high-risk data is maintained at about 70%.

The statistical results obtained by traditional mining methods are shown in Table 3.

It can be seen from the experimental results in the table above that the traditional method has high accuracy in the classification of medium risk and low risk. However, for high-risk and high-risk data, the classification accuracy is basically below 60%. Through the confirmation of the personnel of financial institutions, such classification accuracy has a certain reference value for the risk prediction of financial institutions. This paper comprehensively analyzes the problem of relatively low accuracy in the classification of high-risk and low-risk data in the traditional strategy mining methods. The main reason is that the amount of high-risk data is relatively small in the centralized state of training data, which leads to the defects of high-risk and low-risk data in training, so the classification accuracy is low.

After calculating the average value of the accuracy of the classified data of the above two strategy mining methods, the comparison results are shown in Figure 6:

From the comparison results of the above figure, it can be seen that the accuracy of data risk classification of mining financial market equilibrium competition strategy based on the computer data mining method designed in this paper is about 10% higher than that of traditional methods under different risk levels, which verifies the effectiveness of this method.

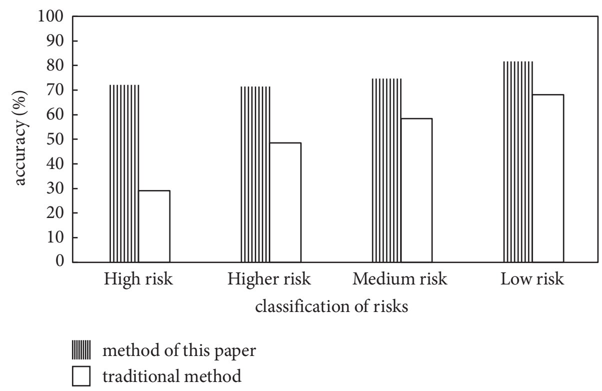

Figure 6: Comparison results of classification accuracy under average risk random sampling of different methods.

Table 4: Accuracy statistics of stratified sampling and classification data of strategy mining method in this paper.

Number of experiments	High risk/%	Higher risk/%	Medium risk/%	Low risk/%
1	73.63	82.33	73.42	83.33
2	86.32	82.32	86.33	86.80
3	72.51	72.65	75.56	82.52
4	73.45	82.52	87.55	84.25
5	70.10	75.22	81.54	81.53
6	71.26	81.34	82.51	90.25
7	74.32	75.64	80.87	85.56
8	76.53	88.41	73.48	84.52
9	82.52	78.15	85.18	90.55
10	73.85	88.25	87.55	88.52

Table 5: Accuracy statistics of stratified sampling and classification data by traditional strategy mining methods.

Number of experiments	High risk/%	Higher risk/%	Medium risk/%	Low risk/%
1	53.33	63.33	63.36	71.36
2	56.66	62.26	72.68	73.53
3	62.55	65.43	65.54	69.22
4	55.20	62.62	66.25	86.10
5	61.31	63.85	72.33	72.41
6	52.12	59.25	61.20	72.24
7	63.03	61.05	74.01	82.35
8	56.46	63.16	62.12	71.66
9	65.75	62.26	73.16	82.25
10	54.24	61.65	66.25	75.18

3.3. Comparison of Classification Accuracy under Stratified Sampling. In order to improve the accuracy of the experimental results and eliminate the influence of the amount of training data at different risk levels on the classification results, 300 data with high-risk evaluation were added to the training data set in the experiment, and the original random sampling classification method was changed to stratified sampling. According to the level of risk, the original data are stratified, and random sampling is adopted for each layer, which can ensure the number of data training with high-risk classification. Under the above experimental environment, the accuracy of strategy classification in the experimental test of this paper is shown in Table 4.

The statistical results obtained by traditional mining methods are shown in Table 5.

After calculating the average value of the accuracy of the classified data of the above two strategy mining methods, the comparison results are shown in Figure 7.

As can be seen from the experimental results of the above two tables, the classification accuracy of stratified sampling data is improved to some extent compared with that of random sampling data. Therefore, compared with the traditional random sampling method, the stratified sampling method has more advantages in the accuracy of data risk classification results. At the same time, the above analysis results also show that the results obtained by the K-means clustering method are relatively consistent with different sampling methods. This shows that the method has certain universality in practical application.

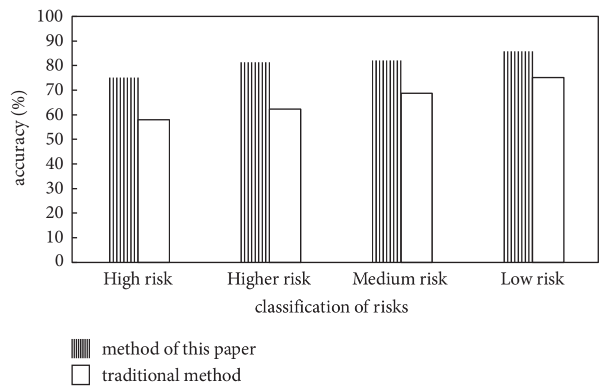

Figure 7: Comparison results of classification accuracy under average risk stratified sampling of different methods.

4. Conclusion

Based on data mining and equilibrium strategy competition of financial institutions, this paper proposes a method of mining equilibrium competition strategy of the financial market based on computer data mining method. This method effectively solves the problem that it is difficult to deal with massive data in the mining method of traditional market equilibrium competition strategy, and improves the accuracy of customer data classification in the process of competition strategy customization. This paper uses the K-means clustering method to analyze these massive data, which can find some hidden potential information and realize effective data analysis. According to this information, in balanced competition in the financial market, we can dig out a complete set of competitive strategies to enhance the competitiveness of financial institutions in the market.

Although the methods involved in this paper have been effectively verified in experiments, there are also some shortcomings. Due to the characteristics of the financial institution industry, the internal relevant data have a certain degree of confidentiality. The data and information collected in the experiment cannot be guaranteed to be the same as the real data, so there is a lack of a certain basis in the process of demonstration. Therefore, the effect of the proposed balanced competition strategy cannot be tested by practice. In future research work, we hope to improve and make up for the shortcomings of this method through practice. In future development, the strategy mining method proposed in this paper can be used in the practice of financial institutions.

Data Availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

References

[1] M. K. P. So, "Robo-Advising risk Profiling through content Analysis for Sustainable development in the Hong Kong financial market," *Sustainability*, vol. 13, no. 3, p. 1306, 2021.

[2] A. Reino, K. Rõigas, and M. Müürsepp, "Connections between organisational culture and financial performance in Estonian service and production companies," *Baltic Journal of Management*, vol. 15, no. 3, pp. 375–393, 2020.

[3] A. Wijekoon, S. Salunke, and G. A. Athaide, "Customer heterogeneity and innovation-based competitive strategy: A review, synthesis, and research agenda," *Journal of Product Innovation Management*, vol. 38, no. 3, pp. 315–333, 2021.

[4] E. Kang and H. Lee, "Employee Compensation strategy as Sustainable competitive Advantage for HR Education Practitioners," *Sustainability*, vol. 13, no. 3, p. 1049, 2021.

[5] A. Borodin, G. Panaedova, S. Frumina, A. Kairbekuly, and N. Shchegolevatykh, "Modeling the business environment of an energy Holding in the formation of a financial strategy," *Energies*, vol. 14, no. 23, p. 8107, 2021.

[6] J. Z. Zhan, T. T. Xu, X. Xu, and Y. Q. Jin, "Trade credit or vertical merger strategy for financial constrained retailer in a supply chain with asymmetric competing retailers," *RAIRO - Operations Research*, vol. 55, no. 3, pp. 1617–1641, 2021.

[7] T. T. Wang, S. C. Liew, and S. Zhang, "When blockchain meets AI: optimal mining strategy achieved by machine learning," *International Journal of Intelligent Systems*, vol. 36, no. 5, pp. 2183–2207, 2021.

[8] O. Abedi and S. Razaghi Kariznoi, "Load-balanced and energy-aware opportunistic routing with adaptive duty cycling for multi-channel WSNs," *The Journal of Supercomputing*, vol. 77, no. 2, pp. 1038–1058, 2020.

[9] B. Bruno and M. Faggini, "Sharing competition: An Agent-based model for the Short-Term Accommodations market," *The B.E. Journal of Economic Analysis & Policy*, vol. 20, no. 2, Article ID 20190231, 2020.

[10] X. Zhu, M. Wang, J. Pei, and P. M. Pardalos, "Investigating remanufacturing competition with yield uncertainty on market share, profit, and consumer surplus," *International Transactions in Operational Research*, vol. 27, no. 5, pp. 2584–2615, 2020.

[11] S. Hong, K. Serfes, and V. Thiele, "Competition in the venture capital market and the success of startup companies: Theory and evidence," *Journal of Economics and Management Strategy*, vol. 29, no. 4, pp. 741–791, 2020.

[12] R. Morandi Stagni, J. Santaló, and M. S. Giarratana, "Product-market competition and resource redeployment in multi-business firms," *Strategic Management Journal*, vol. 41, no. 10, pp. 1799–1836, 2020.

[13] H. Chen, S. Zeng, C. Wu, and H. Fu, "The dual effect of foreign competition on emerging market firms' internationalization," *Management Decision*, vol. 59, no. 9, pp. 2264–2285, 2020.

[14] L. Planer-Friedrich and M. Sahm, "Strategic corporate social responsibility, imperfect competition, and market concentration," *Journal of Economics*, vol. 129, no. 1, pp. 79–101, 2020.

[15] T. Ma, P. A. F. Fraser-Mackenzie, M. Sung, A. P. Kansara, and J. E. V. Johnson, "Are the least successful traders those most likely to exit the market? A survival analysis contribution to the efficient market debate," *European Journal of Operational Research*, vol. 299, no. 1, pp. 330–345, 2022.