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Risk Assessment Algorithm of Financial Big Data Based on Human-Computer Interaction Emotion Recognition

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Abstract For enterprises, the losses caused by financial risks are extremely terrifying, and strengthening financial risk assessment is conducive to the safe operation of enterprises. Big data (BD) not only strengthens the relationship between enterprises and customers, but also increases the difficulty of enterprise financial risk assessment. The current risk assessment is more of an assessment of financial BD. Many financial BD risk assessment algorithms have emerged on the market, but these algorithms generally have the problems of incomplete and inaccurate assessment, and the assessment efficiency is not very high. Human-computer interaction (HCI) technology makes the connection between the user and the machine more closely, and also makes the data calculation closer to the user's expectation. This paper studied the risk assessment algorithm of financial BD based on HCI emotion recognition, and proposed a new risk assessment algorithm by combining AHP, grey relational method and support vector machine. A related mathematical model is constructed, and the application effect of the algorithm is improved by using HCI technology. The experimental results showed that the new risk assessment algorithm improved the accuracy of financial BD risk assessment, and the assessment efficiency was also enhanced. Compared with other algorithms, the efficiency was 6.7% higher.

Index Terms Risk Assessment Algorithm, Financial Big Data, Human-computer Interaction, Emotion Recognition

I. Introduction

Financial data holds the economic lifeline of an enterprise, and the advent of the technological era has made financial BD even more important. What financial personnel need to do is to carry out accurate risk assessment of financial BD, so as to avoid enterprises from falling into financial crisis and ensure the smooth operation of related businesses. At present, most of the risk assessment algorithms in enterprises are outdated and perform poorly in terms of assessment accuracy and efficiency. In order to accurately assess enterprise BD, algorithms must be optimized and upgraded. It is an attempt and an innovation to apply HCI emotion recognition technology to financial BD risk assessment algorithms.

Risk assessment can reduce risks and losses to a certain extent. At present, many scholars have also joined the research ranks of risk assessment. Daly M B studied the application of quantitative regional risk assessment methods in oil and gas storage safety planning. The results showed that the individual risk and social risk of the storage area exceeded the allowable risk standard due to the high population density [1]. Keshavarzi B proposed a new method of groundwater pollution risk assessment suitable for different regions and different types of pollution, and finally found that the concentrated distribution of pollution sources would increase the risk of groundwater pollution [2]. Kullak-Ublick G A applied cloud computing technology to asset risk assessment, which ultimately improved the processing speed of assessment work [3]. Nielsen G D developed a lightning strike risk assessment method based on the direct acquisition of lightning strike characteristic parameters. Practice has shown that high-precision evaluation results can be obtained by applying these parameters [4]. Zhang Y designed a chemical technology risk assessment model based on inherent safety, which was more rational and can give better process selection results [5]. Liu X proposed a natural disaster risk assessment method, which comprehensively considered the environmental problems and economic losses caused by natural disasters, and provided a certain reference value for post-disaster reconstruction work [6]. Jiang X proposed a smart sensor-based postoperative risk assessment method. Practice has shown that this method has a good effect in postoperative risk assessment, which brought a lot of convenience to medical staff and patients [7]. These research contents on risk assessment have certain reference value, but they are not related to financial BD.

HCI technology makes the connection between machines and users more closely, and its related research is also more and more. Hibbeln M proposed an intelligent English teaching system based on HCI. Experiments show that the system can significantly improve students' interest in learning [8]. Chakraborty B K applied HCI technology to the daily fitness system, making the fitness system more humanized and intelligent [9]. Michalakis K developed a user information collection system combined with HCI. Test results showed that the proposed system is a promising user authentication tool [10]. Greenberg S proposed a mobile nursing system based on HCI. Practice has shown that the system greatly improved the nursing work efficiency and guarantees the postoperative treatment of patients [11]. Devi N designed a smart home power management HCI system, which was not only rich in functions, but also provides security for various circuits in the home [12]. Rozado D proposed a car music system based on HCI. Practice showed that the system can accurately recommend different types of songs according to user preferences [13]. Mueller S introduced a road tracking method based on HCI. Experimental results showed that the method is efficient and reliable, and can save a lot of cost compared with traditional manual maps [14]. These research works on HCI are relatively specific, but there is no mention of applying this technology to financial BD risk assessment.

This paper first introduced the background significance of financial risk assessment and HCI, then described a lot of research work on these two aspects, and then elaborated the emotion recognition function in HCI. Finally, the problems existing in the current financial risk assessment were listed, and a financial BD risk assessment model based on HCI emotion recognition was constructed according to the problems. Finally, the experiment proves that the new algorithm has certain reference significance.

II. Concept of HCI and Process of Emotion Recognition in HCI

As shown in Figure 1, HCI refers to the process in which a person (user) and a computer use a specific conversational language to complete the information exchange process between the person and the computer in a specific communication method. The part of HCI that is in direct contact with the user is called the human-computer interface. When a user uses a device such as a computer, the user must use a human-computer interface to communicate and dialogue with the computer.

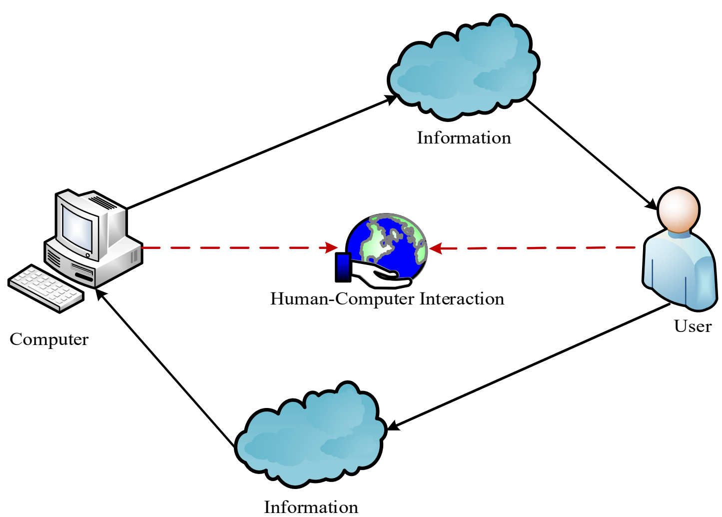

Figure 1: Schematic diagram of HCI

Both emotion recognition and agents are important content in affective computing. In a specific emotional interaction task, emotion is embodied as emotion. The agent would use its own autonomous perception and emotional expression ability to perceive the user's emotion and situation, make corresponding emotional response through internal learning, and then establish emotional communication with the user.

Usually, the emotional communication between the user and the agent is bidirectional, one is that the emotion is transmitted from the user to the agent, and the other is that the emotion is transmitted from the agent to the user [15]. As shown in Figure 2, when emotions are transmitted from the user to the agent, the user expresses his emotions during the interaction. The emotion can be happy, sad or calm, and then the emotion is transmitted to the agent through the perception module. After capturing the user's emotions, the agent would use the learning module to customize the emotional expression to meet the user's personalized emotional communication needs. Similarly, when emotions are transmitted from the agent to the user, the agent would have an effect on the user's emotion. The specific performance is that after the agent performs actions such as anger, sadness and happiness, the user's emotions would change accordingly. In general, the emotion model can use algorithms to realize the quantitative expression of emotions, and satisfy the user's emotional experience by creating a pleasant human-computer interface.

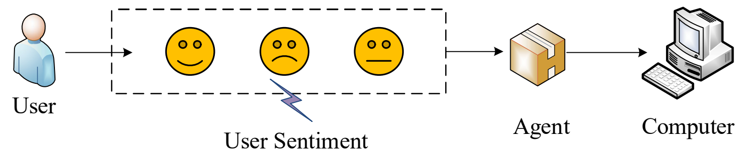

Figure 2: Emotional communication in HCI

III. Common Problems and Related Algorithms of Financial BD Risk Assessment

With the development of science and technology, there are more and more algorithms for risk assessment. It is very important to use these algorithms to solve the problems that arise in the risk assessment of financial BD.

(1) Frequently Asked Questions

Risk awareness is weak. Enterprise founders are not all professionals who have been systematically trained, and it is inevitable that there would be inappropriate handling during the operation of the enterprise. Especially after the enterprise reaches a certain scale, financial risks are easily ignored in the financial management concept and institutional environment, resulting in a lack of financial risk awareness in actual operation. This ultimately deepens the financial risk and jeopardizes the survival of the business.

Rating mechanisms and rating algorithms are not healthy. Enterprises do not have a deep understanding of the use of internal funds and human resources, and lack an effective financial risk assessment mechanism and corresponding supervision mechanism. People do not pay enough attention to actual or potential future financial risks, let alone specific preventive measures, which would eventually lead to huge economic losses for enterprises. In addition, conventional risk assessment algorithms can no longer meet the risk assessment requirements in the era of BD, and the algorithms must be upgraded and optimized, or new assessment algorithms must be used.

Businesses ignore financial risk assessments. For the purpose of financial management, the company blindly expands the production and operation field and production scale of the enterprise, and only pursues the maximization of the enterprise's interests but ignores the operation ability of funds, which leads to financial crisis.

(2) Common algorithms

As shown in Figure 3, common financial BD risk assessment algorithms include analytic hierarchy process, grey relational method, support vector machine and efficacy coefficient method.

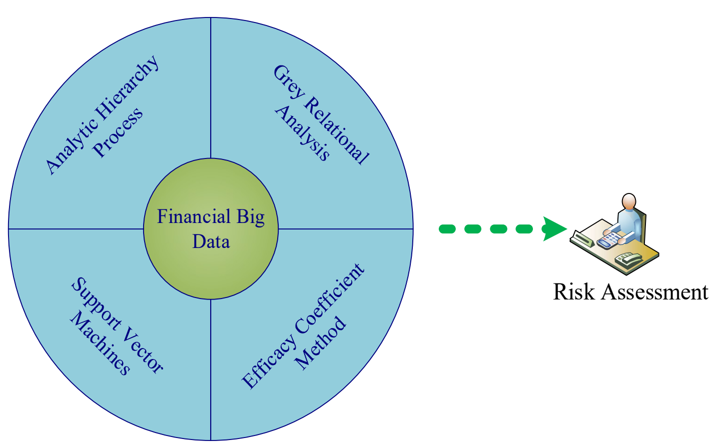

Figure 3: Common financial BD risk assessment algorithms

(3) Financial risk assessment algorithm based on HCI emotions

Combined with the specific situation, this paper applied the first three common algorithms to the risk assessment of financial BD, and improved the effect of the algorithm with the help of HCI emotion recognition technology. The implementation process is shown in Figure 4. First, the financial BD is input into the input specific algorithm according to the algorithm principles and steps, and the data processed by the algorithm is again transmitted to the HCI emotion recognition system for further analysis, and finally the evaluation result is given.

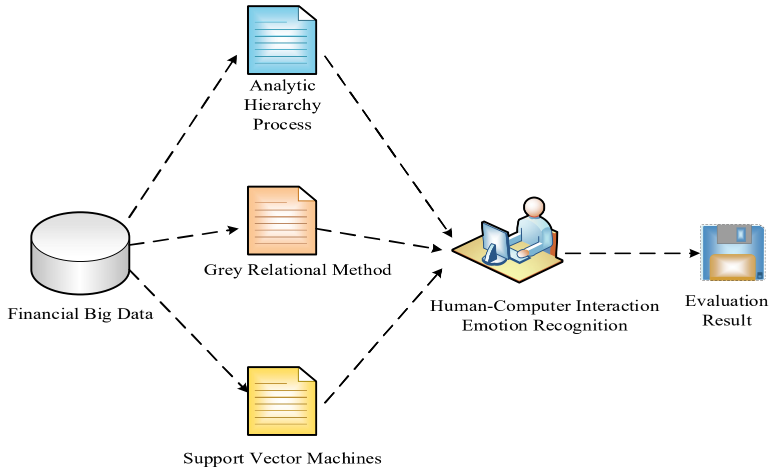

Figure 4: Implementation process of financial risk assessment algorithm based on HCI emotion recognition

The principles and steps of the three algorithms are as follows:

AHP is to decompose the complex financial BD components into sub-component problems at multiple levels, then analyze and compare the weight of each component, and finally analyze the arrangement and optimize the component relationship in a more intuitive way. Analytic hierarchy process usually establishes a hierarchical structure first, and then constructs two-by-two matrices, that is, after comparing each index in pairs, the relative order of each rating index is arranged according to the quantile ratio, and the judgment matrix of the evaluation index is constructed in turn.

As a development branch of grey theory, the basic idea of grey correlation method is to use various factors in financial BD to form a coordinate curve, and to use the degree of similarity or area difference between two curves to quantitatively and qualitatively study the degree of correlation between data. The more similar the two curves are, the greater their correlation is, and vice versa, the smaller their correlation is.

The main idea of SVM is to first transform the input data space into a high-dimensional space through nonlinear transformation, and then obtain the optimal linear interface in this high-dimensional space. The nonlinear transformation is achieved by defining a suitable inner product function [16]. The application of support vector machine in risk assessment is to select a part of the data in the sample set as a training sample to create a classification model, and the other part as a test set to check the accuracy of the model, and finally make a judgment based on the data category.

IV. Financial BD Risk Assessment Algorithm Model Based on HCI Emotion

The changes of financial BD risk assessment are dynamic and non-linear, and at the same time, they are affected by many factors, such as national policies, corporate rules, capital status, etc., which make the financial BD risk assessment process quite complicated. Assuming a total of m risk assessment indicators for financial BD, denoted as $\{x_1, x_2, ..., x_m\}$, then the financial risk assessment level can be described as:

$$y = f\left(x_1, x_2, ..., x_n\right) \tag{1}$$

It can be seen from formula (1) that in order to establish a better financial BD risk assessment model, the optimal $f(\cdot)$ must be found. This function is mainly used to fit the changes of financial BD risk assessment indicators and financial risk levels. The working framework of the financial BD risk assessment algorithm based on HCI emotion recognition is shown in Figure 5.

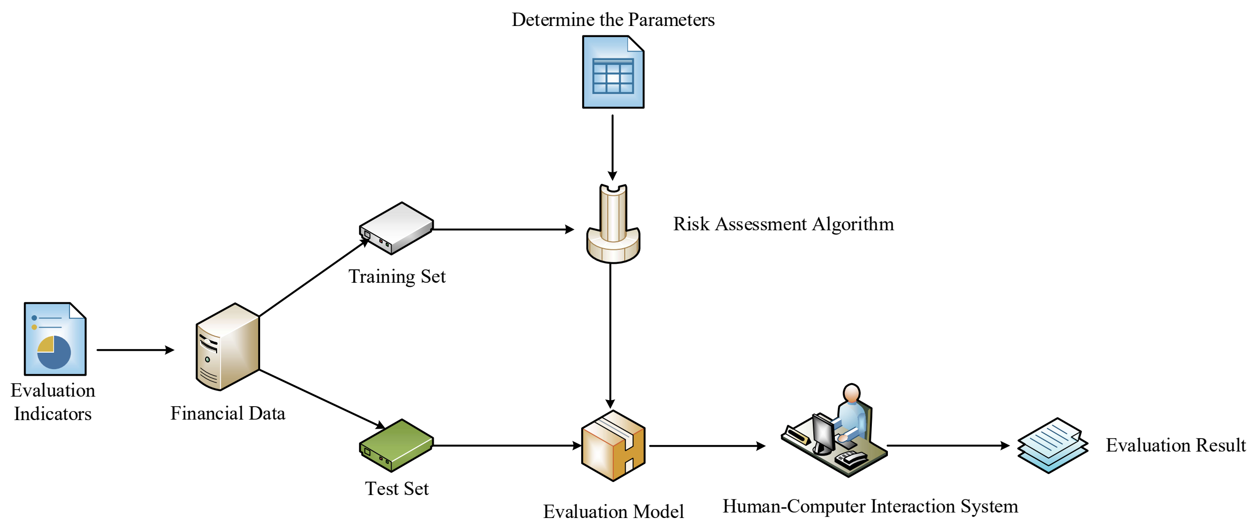

Figure 5: Working framework of financial BD risk assessment algorithm based on HCI emotion recognition

The first is to establish risk evaluation indicators, and then integrate and collect financial BD. Usually financial BD is divided into two parts, including training set and test set. The training set would be input into the risk assessment algorithm after the parameters are determined, and the test set would be input into the risk assessment model. Finally, the final evaluation result is given through the processing of the HCI emotion recognition system.

(1) Establish financial BD risk assessment indicators through AHP

AHP is an index analysis method. The consistency index (CI), the consistency ratio (CR) and the average random consistency index (RI) are the three important contents of this method [17]. This paper introduces it into the construction of financial BD risk assessment. First, the corresponding financial BD risk assessment indicators can be collected, and then the eigenvectors and the maximum eigenvalue $\lambda_{\max}$ of the risk assessment indicators can be calculated, and then the consistency test can be carried out. The consistency test results are as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{2}$$

In the formula, n represents the order of the financial BD risk assessment matrix.

As shown in formula (3), if the random one-time ratio CR satisfies this condition, it means that the user is satisfied with the financial BD risk assessment judgment matrix, which is acceptable, then the financial BD risk assessment index system can also be expressed as:

$$CR = \frac{CI}{RI} < 0.1 \tag{3}$$

In the formula, RI is the average random consistency index. According to the financial BD risk assessment judgment matrix, the hierarchical model of the financial BD risk assessment index can be constructed.

(2) Using the grey relational analysis method to analyze the relationship between financial BD risk assessment indicators

Grey relational analysis is a method to analyze the relationship between two objects [18]. At the same time, the introduction of grey theory can simplify the analysis process. The specific process is as follows:

a) Let the financial BD risk assessment data be: $x_i(k), k = 1, 2, ..., n$, so the data form is a sequence $X_i = (x_i(1), x_i(2), ..., x_i(n)), i = 1, 2, ...m$.

b) The dimensionless operation of X_i can be performed to obtain $\vec{X}_i$, and the selected part can be used to form the reference sequence $\vec{X}_i = (\vec{x}_i(1), \vec{x}_i(2), ..., \vec{x}_i(n)), i = 1, 2, ...m$ for financial BD risk assessment.

c) It can calculate the difference between all financial BD risk assessment reference sequences, namely $\Delta_i(k)=\left|x_i(k)-\vec{x}_i(k)\right|$, and then find the maximum difference and minimum difference of the sequence, which can be specifically expressed as: $M=\max_i \max_k \Delta_i(k)$ and $m=\min_i \min_k \Delta_i(k)$.

d) The gray correlation coefficient $r_i(k)$ of the financial BD risk assessment index can be calculated, and the calculation method is as follows:

$$r_i(k)=\frac{n+\zeta M}{\Delta_i(k)+\zeta M} \tag{4}$$

In the formula, ζ is the resolution coefficient.

e) To find the grey comprehensive correlation degree r_i, the specific calculation form is:

$$r_i=\sum_{k=1}^{m}\omega_i r_i(k) \tag{5}$$

In the formula, ω_i is the weight. According to the value of the grey comprehensive correlation degree, the financial BD risk assessment index can be obtained, and the degree of influence of this value on the financial BD risk assessment result can also be analyzed.

(3) Financial BD risk assessment model based on support vector machine

SVM is a common classification algorithm in machine learning [19]. Its classification goal in this paper is to find an optimal classification hyperplane, then distinguish the risk data in all financial BD, and maximize the distance between all samples and the classification hyperplane.

Let the risk assessment data of financial BD be: $\{x_i,y_i\},x_i\in R^n,i=1,2,...,n$, where x_i represents the input of financial BD risk, y_i represents the risk level of financial BD, then the optimal classification plane can be expressed as:

$$y=w^T\varphi(x)+b \tag{6}$$

In the formula, w represents the weight of the optimal classification plane.

In order to solve formula (6), the offset value of the optimal classification plane must be found, and a non-negative relaxation factor is introduced for transformation to obtain:

$$\min J(w,\xi)=\frac{1}{2}\|w\|^2+c\sum_{i=1}^{n}\xi_i \tag{7}$$

$$s.t \quad y_i\left(w\cdot\varphi(x_i)+b\right)\geq 1-\xi_i \tag{8}$$

$$\xi\geq 0,i=1,2,...,n \tag{9}$$

In the formula, ξ_i represents the relaxation factor, and c is the penalty degree of the error.

In order to further obtain the solution process of the above formula and speed up the risk assessment of financial BD, the Lagrange multiplier (Lagrange multiplier) α_i is used to obtain the corresponding dual problem [20], specifically:

$$\max W(\alpha)=\sum_{i=1}^{l}\alpha_i-\frac{1}{2}\sum_{i=1}^{l}\alpha_i\alpha y_i x_i\cdot x_j \tag{10}$$

$$s.t.\begin{cases}\sum_{i=1}^{l}\alpha_i y_i=0\\ c\geq\alpha_i\geq 0\\ i=1,2...,l\end{cases} \tag{11}$$

The calculation formula of the weight vector w is:

$$w = \sum \alpha_i y_i \varphi(x_i) \cdot \varphi(x) \tag{12}$$

Then the financial BD risk assessment function based on support vector machine is:

$$f(x) = \operatorname{sgn}\left(\alpha_i y_i \varphi(x_i) \cdot \varphi(x) + b\right) \tag{13}$$

In order to reduce the space complexity of financial BD risk assessment modeling, using kernel function $k(x, x_i)$ instead of dot product $\varphi(x_i) \cdot \varphi(x_j)$ has:

$$f(x) = \operatorname{sgn}\left(\alpha_i y_i k(x, x_i) + b\right) \tag{14}$$

Selecting the radial basis function as $k(x, x_i)$, there are:

$$k(x, x_i) = \exp\left(-\frac{\|x - x_i\|}{2\varepsilon^2}\right) \tag{15}$$

The financial BD risk assessment function becomes:

$$f(x) = \operatorname{sgn}\left[\alpha_i y_i \exp\left(-\frac{\|x - x_i\|}{2\varepsilon^2}\right) + b\right] \tag{16}$$

Therefore, the specific workflow of the financial BD risk assessment model based on HCI emotion recognition can be summarized as follows:

a) Collect financial BD risk assessment indicators for analysis, and then establish an indicator system for college students' entrepreneurial risk assessment.

b) Collect evaluation data according to the indicators of financial BD risk assessment, and use the following formula to process the evaluation indicators.

$$\vec{x}_i = \frac{x_i}{x_{\max}} \tag{17}$$

c) The analytic hierarchy process can be used to determine the index level of financial BD risk assessment, and the grey relational analysis method can be used to test the risk assessment indicators, and select the indicators that have a significant impact on the financial BD risk assessment results.

d) Support vector machines can be used to learn the training samples of financial BD risk assessment, and determine the corresponding parameters to establish a risk assessment model.

e) The financial BD risk assessment model can be used to test the corresponding test samples and output the risk assessment results.

V. Experimental Results of New Financial BD Risk Assessment Algorithm

Although HCI emotion recognition has been used in many fields, its application in financial risk assessment algorithms is still rare. This paper applies the HCI emotion recognition to the financial BD risk assessment algorithm, and finally forms a new algorithm model. Whether the new algorithm can be recognized or not, this paper investigates the satisfaction of 200 financial personnel and management personnel in a large enterprise, including 100 financial personnel and 100 management personnel. The survey results are shown in Table 1.

Table 1: Satisfaction of financial staff and managers with the new algorithm

satisfaction	Financial officer		manager	
	number of people	proportion	number of people	proportion
dissatisfied	3	1.5%	8	4%
satisfy	43	21.5%	51	25.5%
Very satisfied	54	27%	41	20.5

From the data in Table 1, it can be seen that the number of people who are dissatisfied with the new algorithm is less than 10, whether it is financial staff or administrators. There are more than 180 people who are satisfied and very satisfied, accounting for more than 90% of the total number. Obviously, financial personnel and managers are quite satisfied with the new algorithm, which also shows that the application of HCI emotion recognition to financial BD risk assessment algorithm is correct and effective.

Under the current situation, financial risk assessment is more about the assessment of financial BD. With the continuous expansion of enterprise scale, enterprise BD would become more and more complex, which requires the ability of risk assessment algorithm to process data must be more outstanding. In order to verify the data processing capability of the new algorithm (that is, the algorithm model proposed in this paper), the evaluation volume of the algorithm on 100,000 financial BD of an enterprise was tested, and the data evaluation volume under the conventional algorithm was compared. The specific time is set at 5 hours, as shown in Figure 6.

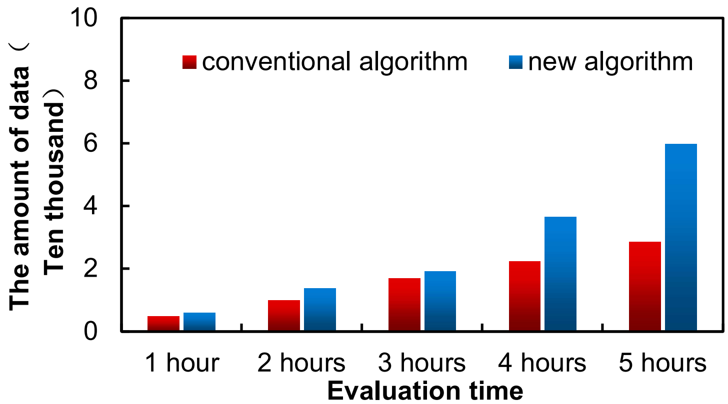

Figure 6: Data evaluation amount of the two algorithms

As can be seen from the histogram in Figure 6, the data evaluation amount of the two algorithms is less than 10,000 in one hour. In contrast, the evaluation amount of the new algorithm is more than that of the conventional algorithm. As time increases, so does the amount of data evaluation. Two hours later, the data evaluation volume of the conventional algorithm still did not exceed 10,000, while the data evaluation volume of the new algorithm has far exceeded 10,000. When the evaluation time reaches 5 hours, the data evaluation amount of the conventional algorithm would reach nearly 30,000. At this time, the data evaluation amount of the new algorithm is close to 60,000, which is more than twice the evaluation amount of the conventional algorithm. Overall, the performance of the new algorithm in terms of data evaluation volume is still very good, and the increase in evaluation volume would further promote the improvement of evaluation efficiency.

In order to further test the evaluation performance of the financial BD risk assessment algorithm based on HCI emotion recognition, simulation experiments were carried out on 20 core data in the financial BD of company A. The data numbers are 1-20 in sequence, and the test tool adopts the Matlab (Matrix Lab) toolbox. The test results are shown in Figure 7.

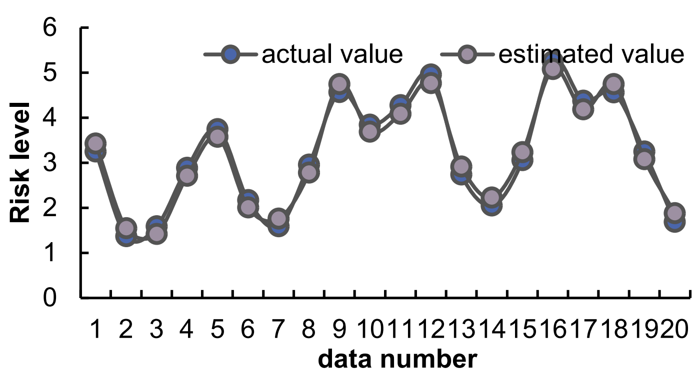

Figure 7: Evaluation performance test results of financial BD risk assessment algorithm based on HCI emotion recognition

According to the analysis of the line graph in the test results, it can be concluded that the financial BD risk assessment value under the financial BD risk assessment algorithm based on HCI emotion recognition is very close to the actual risk value, and the deviation is small. It can also be said that the algorithm has obtained high-precision financial BD risk assessment results, which also shows that the evaluation performance of this algorithm is very excellent.

In order to more intuitively understand the change results of the new algorithm evaluation accuracy, we still use the financial BD of company A as the experimental sample. The change of the data evaluation accuracy rate of the new algorithm within 7 hours was tested, and the change of the evaluation accuracy rate under the conventional algorithm was compared. The comparison results are shown in Figure 8.

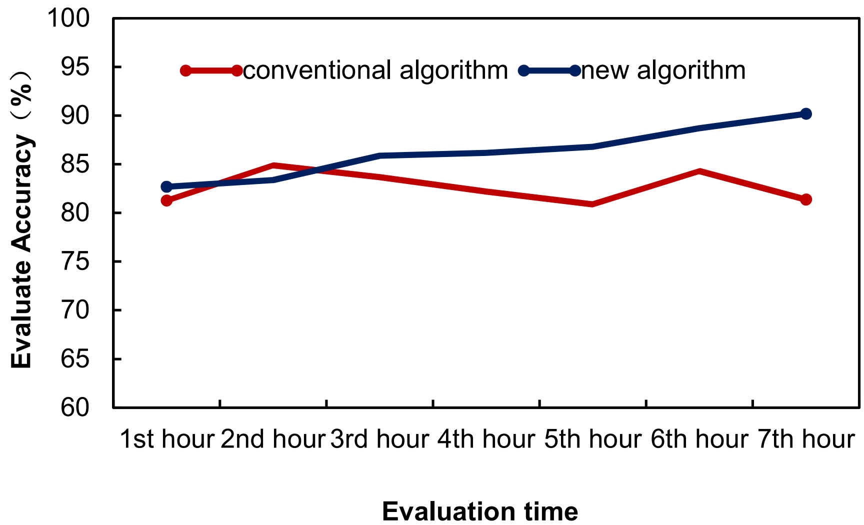

Figure 8: Changes in the accuracy of data evaluation for the two algorithms within 7 hours

It can be clearly seen from the line graph in Figure 8 that at the first hour, the evaluation accuracy of both algorithms exceeds 80%. The new algorithm is lower than the conventional algorithm because the new algorithm has just been implemented and is not very sensitive to some data. Since the second hour, the evaluation accuracy rate under the new algorithm has maintained an upward trend, and even exceeded 90% at the highest point. In contrast, the evaluation accuracy rate under the conventional algorithm began to decline from the second hour, until the sixth hour, and then began to decline again. Overall, the evaluation accuracy of the new algorithm is higher than that of the conventional algorithm, and it is relatively stable.

Financial BD risk assessment in the new era requires higher assessment efficiency. In order to verify the risk assessment efficiency of the new algorithm, the changes in the risk assessment efficiency of financial data within 12 hours of the new algorithm were tested, and compared with the assessment efficiency under the conventional algorithm. The test sample is the financial data of Company A, and the test results are shown in Figure 9.

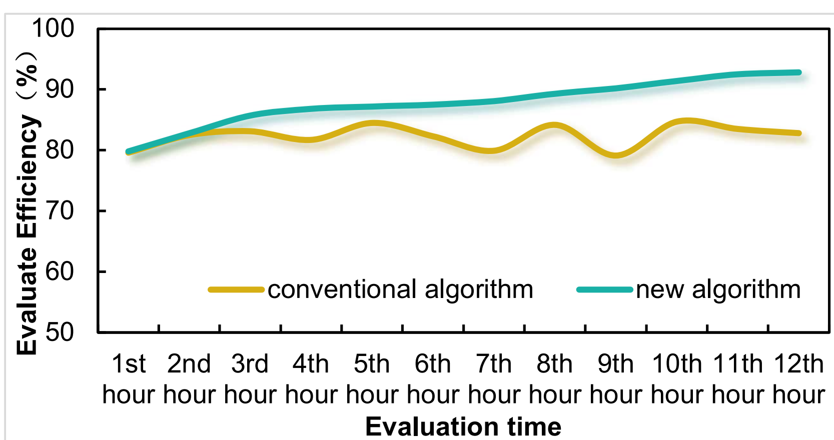

Figure 9: Changes in the efficiency of financial data risk assessment for the two algorithms within 12 hours

It can be seen from the graph that the evaluation efficiency of the two algorithms is basically the same at the first hour and the second hour, but from the third hour, the evaluation efficiency is significantly different. The evaluation efficiency under the new algorithm has been on a steady upward trend since the third hour, and the highest efficiency reached nearly 93%. In contrast, the evaluation efficiency under the conventional algorithm has been high and low since the third hour, the fluctuation trend is obvious, and the efficiency is also below 85%. The comparison curve is easy to draw, and the risk assessment efficiency under the new algorithm is 6.7% higher than that of the conventional algorithm.

VI. Conclusion

Whether it is a large enterprise or a listed company, financial risk assessment is essential. With the progress of the times and the development of science and technology, financial risk assessment has gradually become accurate financial BD risk assessment. Most of the current financial BD risk assessments have the problems of inaccurate assessment and low assessment efficiency. In order to carry out accurate risk assessment of financial BD, it is necessary to use relevant intelligent technologies and assessment algorithms. The application of HCI emotion recognition technology to financial BD risk assessment algorithm is the combination of artificial intelligence and assessment algorithm, which has certain reference value for the optimization and upgrading of enterprise financial BD risk assessment and assessment work.

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