SIN-CHN SCIENTIFIC PRESS PTE.LTD.

Molecular & Cellular Biomechanics 2024, 21(4), 920.
https://doi.org/10.62617/mcb920

Article

Risk prediction of computer investment database information management system based on machine learning algorithms

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CITATION

Guo Y. Risk prediction of computer investment database information management system based on machine learning algorithms. Molecular & Cellular Biomechanics. 2024; 21(4): 920. https://doi.org/10.62617/mcb920

ARTICLE INFO

Received: 26 November 2024
Accepted: 5 December 2024
Available online: 10 December 2024

Abstract: In recent years, with the continuous development of the financial market, the risk prediction of computer investment database information management systems (IMS) has high practical value. At present, there are risk issues in the information management system, which may cause drawbacks to investment data processing. To address these issues, this article used Machine Learning (ML) algorithms to analyze the risk prediction of computer investment database IMS. This article introduced and utilized typical Self-Organizing Map (SOM) and Artificial Neural Network (ANN) combination algorithms, regression algorithms, and Gradient Boosting Decision Tree (GBDT) algorithms to compare and analyze the prediction accuracy of these three algorithms. This article found that the GBDT algorithm has the highest prediction accuracy. Through a large amount of experimental data, it has been proven that the average testing accuracy using regression algorithms was 3.5% higher than that using neural network algorithms. It was found that the average test accuracy using the GBDT algorithm was 7.2% higher than the average test accuracy using the regression algorithm. The study also explores the combination of physiological and behavioral data collected by wearable devices to provide more comprehensive risk assessment and decision support, which provides an important reference for the optimization of enterprise risk management. Through this innovative data source integration, this paper provides a new perspective for the application and development of machine learning algorithms in computer investment database IMS.

Keywords: machine learning algorithms; computer investment database; information management system; risk profile

1. Introduction

In the context of modern financial technology, the accurate acquisition and real-time processing of data is particularly important. The rapid development of wearable sensor devices has opened up new possibilities for data acquisition, with the ability to monitor users' physiological states and behavioral patterns in real time, thus providing additional context for financial decisions. For example, measuring the user's heart rate, activity level, stress value and other data can help investment institutions understand the user's risk tolerance and investment behavior pattern. This biometric data, which is closely related to investment decisions, can be combined with IMS to provide a more holistic view of risk assessment. With the improvement of Internet security, users' trust in wearable devices has also increased significantly, and the business value of IMS has increased. Therefore, combining data collected by wearable sensors with machine learning (ML) algorithms to analyze users' personal data and investment records can provide more accurate risk predictions. The study not only focuses on traditional financial data, but also physiological and behavioral data from wearable devices, which will provide deeper support for individual credit risk assessment and investment decisions.

The security issue of IMS is currently one of the most popular subjects online, and many experts have analyzed it. Lee In combined emerging internet technologies such as big data (BD) and artificial intelligence (AI) to introduce a theoretical framework for internet risk in response to the current large-scale attacks on the internet. He explored the evaluation methods of internet risk and conducted in-depth research on the security issues of IMS in the internet based on practical cases [1]. Rahmani, Koshal Rahman conducted a security evaluation of the security and operability of IMS, and identified the prioritization of security risks based on effective guidelines for system vulnerability [2]. Dhar, Suparna analyzed various security issues faced by current IMS and established a security system for IMS based on "zero trust" and "blockchain". On this basis, he improved the access characteristics and communication protocol uniformity of IoT nodes by dividing their risks [3]. Jakka, Geethamanikanta effectively controlled internet crime through the use of AI, emphasizing the important role played by AI in controlling the dangers of cyber-attacks. He explored the incidence of network attacks and the network security issues of IMS [4]. Dong, John Qi constructed a research framework based on information technology innovation and corporate governance mechanisms. Investment in information technology can help enterprises identify problems and create innovations that can compensate for performance differences. These would help to better understand the security issues and their consequences in investment in IMS [5]. Due to the need for IMS to store and process a large amount of data, there is a lack of relevant analysis of IMS using data processing algorithms in current research.

With the application of BD in IMS, many experts and scholars have analyzed it. Park, Jong-Hyun believed through Analytic Hierarchy Process and Regression Analysis that BD, technological capabilities, financial investment capabilities, and data quality are the determining factors for risk prediction in IMS. Policies related to BD, security, and privacy would also have a significant impact on BD adoption [6]. Setyowati, Widhy used e-mail, bulletin board, electronic cash and other BD technologies, which can facilitate the application of information management system in business activities [7]. Gao and Jun [8] conducted research on company financial and accounting information management in the BD environment, and analyzed the company financial information management system in the BD environment. Cao, Guangming explored how to use BD and market analysis to enhance the competitiveness of IMS. He used BD to achieve good results in enterprise marketing strategy, marketing execution, brand management, customer relationship management and marketing strategy [9]. Ashta, Arvind analyzed the uncertainty of non-representative BD and the subjective bias of representative BD, as well as the selection of algorithms, and studied the application of BD in the interpretation of IMS [10]. Although BD brings benefits to the management of IMS, there is a lack of application of ML algorithms in it.

This article explores how to strengthen risk management in computer information system integration projects by improving actual operational effectiveness. This article first analyzes the structure of computer data IMS and the current problems in management, and then attempts to provide a more detailed discussion on how to strengthen risk management. In response to these issues, this article proposes a risk prediction model and explores the use of ML methods for credit risk assessment in the field of venture capital. This article designs three schemes and calculates the proportion of defaulters in the three schemes. Through comparative analysis, it is found that the proportion of defaulters in Scheme 3 is lower than that in Scheme 2. This article evaluates the prediction accuracy of various machine algorithms and finds that the GBDT algorithm has the highest prediction accuracy for computer investment database IMS.

2. Computer database information management system

2.1. Structure of database management system

Due to the complexity of the hierarchical structure of a database management system, when analyzing a database management system, one can start from the aspect of processing objects in the database management system. Usually, the regional management and operability of the entire system are carried out through the hierarchical structure of the computer's database. Therefore, the hierarchical structure within the system plays a crucial role in maintaining and managing the entire system.

2.2. Application of database management system

Computer database management can achieve the analysis, accounting, and resolution of relevant data, reduce errors and other issues encountered by staff during use, and greatly improve the efficiency of the entire construction and management. The use of computer database management can greatly reduce the problems of high data information recording and complex operations caused by the complexity of information, and can also classify and manage data and conduct overall analysis of data groups.

Integrating database management systems with database technology can not only increase the practical application of database technology, but also increase the efficiency of database management systems. The combination of the two has become a trend in multimedia production. The recording, encryption, and analysis of information not only need to be operated through computer database management. It also requires specialized processing of independent data models and important confidential information using computer database management to enhance the security of receiving or transmitting important information. In addition, computer database management is established by using multiple types of databases, such as hierarchical database, relational database and mesh database, to manage and plan the overall information in the database in an orderly manner.

The technical and management personnel operating computer database management systems manipulate the permissions of different types of users through setting access permissions for various users in their work, with the aim of ensuring the security of user data. The computer database information management system studies sustainable industrial development from three aspects: production decision-making information system, real-time sensor network, and AI technology. The performance of the manufacturing system can be evaluated using the relevant information provided [11]. The main variables that affect the adoption level of computer investment database information management system users include performance expectations, investment expectations, acceptability, information security and confidentiality, credibility, etc. [12]. In the context of BD, computer investment database IMS based on deep learning algorithms can be used for book data management [13].

The computer investment database information management system represented by BD is penetrating into various industries. In order to achieve sustainable development, modern supply chain management would also be integrated with the progress of technology [14]. The computer investment database information management system promotes the development of information technology and finance, creating unique value for the development of finance [15]. The computer investment database information management system is developed to discover, manage, and utilize geospatial information. It aims to build highly accurate Earth models or "digital twins" to monitor and predict environmental changes and human impacts, supporting sustainable development [16]. The computer investment database information management system has carefully considered the management and control of data. In the policy implementation process targeting teachers and students, this information system would provide leaders with a development overview [17].

It is necessary to use computer firewall management technology to reduce the network risk of users during use, prevent illegal infringement of the internal network, and resist the access requirements of illegal users. The use of data backup technology to backup computer database data is an effective method in the event of unforeseeable errors or intrusion in the database. After the accident occurs, relevant personnel can perform a powerful and unified restoration of all information based on the backed-up database information. This ensures the consistency and integrity of data, reduces unnecessary investment in database reconstruction, and improves the security management of computer databases. Therefore, user authentication management technology can be used to authenticate and verify the identity of relevant data access users to protect the interests of users and prevent their infringement.

With the popularization of computer databases, their security issues have received great attention, and a large amount of bad news about data leakage has emerged. Therefore, there is an urgent need to improve their security and confidentiality performance. After continuous improvement and repair of the database, the security of the database has been greatly guaranteed, making it difficult for some criminals to break through the database, and the data in the database would not be leaked or files would be lost.

At the same time, the research combines computer database management with wearable sensors, which can significantly improve efficiency and accuracy when processing and analyzing data. The data generated by these wearable devices contains the user's physiological indicators and behavioral habits, and this information can be integrated into the database, thereby reducing the complexity of human input and organization. Computer database management not only deals with traditional financial data, but also needs to effectively manage data from wearable devices, such as heart rate, amount of walking, and sleep quality. This integration can reduce errors in information sharing and enhance the basis for investment decisions, making information management systems more responsive to complex data challenges.

By combining data collected by wearable sensors with traditional investment data, the database can provide a comprehensive picture of the user's health and behavior, providing more dimensions of data support for risk assessment and decision making. For example, if a user's physiological state shows a high level of stress response, an investor may consider adjusting its investment advice to reduce risk more effectively.

2.3. Outlook of computer database systems in information management

With the development of the times, people's demand for information technology is also increasing. In this context, higher requirements have been put forward for the informationization construction of enterprises.

Risk monitoring refers to the comprehensive monitoring of the development and changes of risks during project operation [18–20]. Its focus is to implement existing risk control plans, especially in accordance with the risk control process. Usually, when independently executing a risk management plan, attention should be paid to making a risk decision based on the specified risk content, and implementing a risk reduction strategy [21].

In summary, risk management is a relatively complex process in computer information system integration projects, and the specific operation methods are also very cumbersome [22–24]. Therefore, at the beginning of the project, the project leader should conduct a risk analysis of the entire process and start from three perspectives, namely: improving the risk entire process mechanism, quantifying risks, and monitoring risks.

In today's information construction continues to mature, the trend of combining wearable sensor equipment and computer investment database IMS is becoming more and more obvious [25–27]. In the future, organizations can integrate data from these devices for real-time risk monitoring. This monitoring can focus not only on a user's financial behavior, but also on changes in health status and lifestyle habits [28–30]. Such data interaction will bring dynamic risk assessment to projects and investments, helping project leaders make timely decisions in risk management.

As technology advances, risk management will apply more real-time data analysis techniques, and the physiological and behavioral information provided by wearable devices will play an important role in this. By quantifying the health and behavior characteristics of users, enterprises will better understand the risk characteristics of customers to improve the risk control process and decision-making mechanism. This development is expected to push the financial industry towards a more personalized and intelligent direction, thus achieving greater competitive advantages in the new economic situation.

3. ML algorithms

In today's continuously improving computing performance, ML has once again become the focus of attention. Compared with conventional algorithms, this method can repeatedly learn data, allowing computers to extract more information from it. ML is a method of extracting potential patterns from social networks. Based on the observation results of existing annotated training samples, the annotation of new samples can be identified.

Among them, data preprocessing, model selection, analysis and evaluation and overfitting are the main links of ML research. In the process of ML, data preprocessing is a crucial step, and the selection of preprocessing methods often has a significant impact on the effectiveness of the algorithm. In the absence of data or errors, the data can be completed or corrected, but because it is not the original data, the completed data differs from the actual data.

In ML, the most fundamental problem is how to select a suitable model, which can ensure both fast algorithm speed and accuracy. The accuracy of conclusions depends on feedback on the learning process, thereby adjusting the parameters of the model. Therefore, the selection of conclusions can also have a certain impact on the conclusions. After selecting the evaluation criteria, it is generally believed that if the algorithm performs better in the training set, the model and parameters would be better. In reality, if an algorithm performs too well on the training set, it means that it tends to over learn. Among them, the emergence of overfitting problem increases the difficulty of ML, and simply improving the performance of the model would lead to the decline of its universality. The simplest explanation is that due to the complexity of the model, it leads to overfitting, and the way to optimize it is to simplify it to the minimum.

The prediction algorithm based on ML fully utilizes human intelligence characteristics and has wide applications in venture capital prediction, stock market prediction, bidding, and other aspects. When studying bank loan risks, they can be classified into financial risk, non-financial risk, cash flow risk, and credit support risk based on their essential characteristics. Among these elements, financial element is the most basic one, and evaluating the financial condition of financial institutions is crucial for their debt repayment ability. Credit guarantee refers to the borrower's credit as collateral, providing secondary repayment resources for the loans they pay.

3.1. Risk prediction based on neural network combination

The neural network is determined based on the number of selected indices and the number of output categories. SOM can be combined with ANN, and the SOM network adopts two neurons like network topologies. Its function is to collect data. The integration of SOM and ANN methods can effectively improve the accuracy of risk prediction. In addition, this method can also utilize financial data from various stages to analyze the evolution process of the enterprise and determine its competitive position among peers.

3.2. Prediction based on neural networks and analytic hierarchy process

Analytic Hierarchy Process (AHP) can be combined with Self-Organizing Feature Mapping (SOM). AHP and SOM methods can be used to establish a bidding evaluation method based on distributed and high-dimensional samples, and apply it to bidding. The prediction model of a ML algorithm is shown in **Figure 1**.

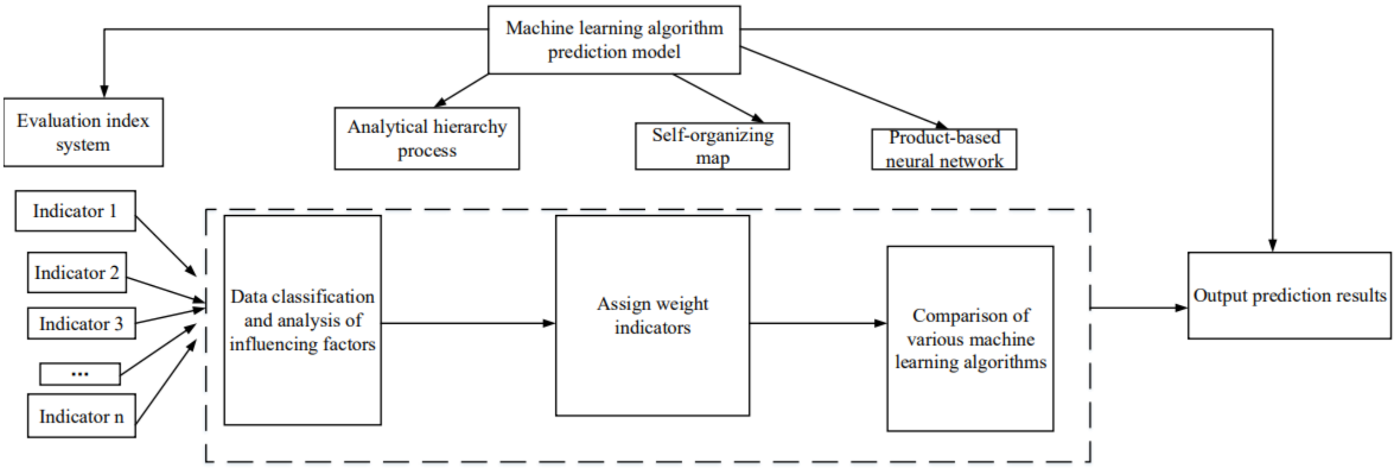

Figure 1. ML algorithm prediction model.

4. Risk prediction model

With the rapid development of the economy, the banking industry has also experienced rapid development. In the current field of online finance, the issue of assessing the credit risk of borrowers is also increasingly attracting people's attention. The essence of the credit risk assessment problem for bank customers is a classification problem, which involves dividing existing bank users into reputation and non-reputation processes.

4.1. Data preprocessing

This article would classify and process the data used to determine whether users have potential default risks, mainly including customer bank information records, third-party payment records, etc. The specific financial information of the customer account is shown in **Table 1**.

Table 1. Customer account specific financial information.

Data type	Information type	Specific classification
Dynamic data	Basic user information	Identification card information
		Education Information
		Marital status
	Account income and expenditure situation	Income amount
		Expenditure amount
		Consumption amount
		Investment

During the lending process, users must first submit relevant information when requesting a loan from relevant financing institutions, and then the relevant financing platform simulates the user's information.

4.2. Prediction model algorithm

1) Regression algorithm

In view of characteristics of the data, a more mature approach can be chosen, among which a regression model containing dummy variables is the best model to establish this model.

$$f(x_{n-1}) = w_1 + w_2 x_1 + w_3 x_2 + \ldots + w_n x_{n-1} + e \tag{1}$$

Among them, x_{n-1} is the dummy variable, w_n is the weight coefficient, and e is the error value.

2) GBDT algorithm

The Gradient Boosting Decision Tree (GBDT) algorithm is an iterative method. Suppose that the loss function of the learner is $L\left(f\left(x_i\right), e\right)$.

3) Comparison of Two Algorithms

Comparing the regression algorithm with virtual variables and the GBDT algorithm, it can be found that this method has the following advantages: simple modeling, and at the same time, based on the data collected by the bank, it can more conveniently increase or decrease relevant parameters. When conducting scientific research work, the simplest approach is usually adopted to solve problems. In practice, due to various reasons, the customer information collected by banks is not entirely accurate, so in the end, they still adopted the GBDT algorithm to build this model.

4.3. Algorithm implementation

Let the collective sample be the maximum number of iterations N and the loss function L. The final output learner is g (x). The initial learner function is

$$g_0(x) = \sum_{i=1}^{m} L\left(f(x_i), e\right) \tag{2}$$

After iteration, there are:

The negative gradient calculation formula for the sample dataset is

$$g_{n-1}(x) = -\frac{\partial L\left(f\left(x_i\right), g\left(x_i\right)\right)}{\partial g\left(x_i\right)} g\left(x\right) \tag{3}$$

5. Experimental results and investment data

Firstly, this article categorizes users in the investment database. Based on customer details and related algorithmic data, customers can be split into 4 categories: Both the user information and the management system are judged to be reputable customers recorded as a. The user information is a reputable customer. If the management system determines that it is a non-reputable customer, it is recorded as b, and the user information is a non-reputable customer. The management system determines that a reputable customer is recorded as c, while both the user information and management system determine that a non-reputable customer is recorded as *d*. Assuming the accuracy rate of the management system judgment is R_1 and the error rate is R_2, the calculation formulas for accuracy and error rate can be obtained as follows:

$$R_1 = \frac{d}{c+d}, \quad R_2 = \frac{b}{a+b} \tag{4}$$

This article selects 10,000 customers in the bank, extracts the bank's daily records and user information, designs three schemes, and conducts comparative analysis. Option 1: This article divides all investment users into an average of 10 groups, with each group consisting of 1000 people and 60 non reputable customers. This article conducts practical analysis of the data and directly calculates the proportion of defaulters. Option 2: This article divides users into 10 groups of 1000 people each. Based on the number of defaults per user, this article calculates the probability of default and uses a random function to sort users. Option 3: Similarly, this article divides investment users into 10 groups with an average of 1000 people each. ML algorithms are used to calculate the number of defaults by users and calculate the default ratio. This article would use ML algorithms to process and plot the proportion of non-reputable customers in Plan 1, Plan 2, and Plan 3. The comparison of the proportion of default cases among the three options is shown in **Figure 2**.

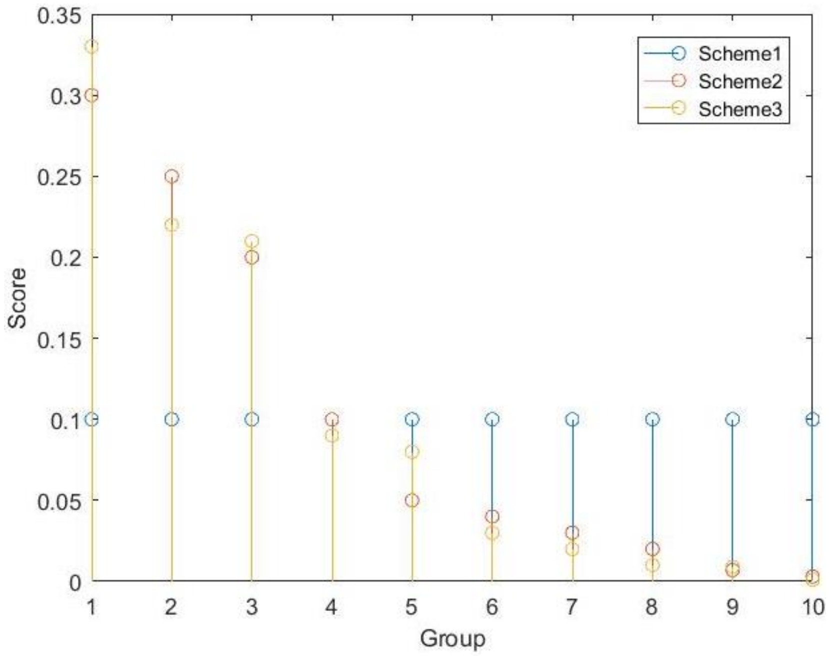

Figure 2. Proportion of the number of defaults in the three schemes.

From **Figure 2**, it can be seen that the proportion of defaulters in Scheme 1 was the same, all at 10%. The proportion of defaulters in Option 2 was gradually decreasing. This is because Scheme 2 was arranged in descending order of probability, resulting in the lowest proportion of defaulters in Group 10. Option 3 was allocated using ML algorithms. Observing the data in the graph, it can be seen that the lowest proportion of defaulters in Group 10 was 0.1%. In the 10th set of data, the proportion of defaulters in Scheme 3 decreased by 0.2% compared to Option 2.

This article selects 10,000 users from the bank user data and divides them into 10 groups. Based on the calculation formulas for accuracy and error rates, the accuracy and error rates of the management system's judgments are obtained. The accuracy and error rate of the computer investment database information management system judgment are shown in **Table 2**.

Table 2. Accuracy and error rate of judgment in computer investment database information management system.

Group	Before using ML algorithms		After applying ML algorithms	
	Accuracy	**Error rate**	**Accuracy**	**Error rate**
1	73%	27%	78%	22%
2	64%	36%	66%	34%
3	71%	29%	74%	26%
4	65%	35%	68%	32%
5	70%	30%	72%	28%
6	68%	32%	70%	30%
7	69%	31%	71%	29%
8	74%	26%	77%	23%
9	72%	28%	75%	25%
10	66%	34%	68%	32%

In **Table 2**, the average accuracy of the management system judgment before using ML algorithms was 69.20%, and the average error rate was 30.80%. The average judgment accuracy of the management system using ML algorithms was 71.90%, and the average error rate was 28.10%. Therefore, ML algorithms are more effective in determining the efficiency of management systems, with an overall average accuracy improvement of 2.7%.

This article compares and analyzes the neural network algorithm, regression algorithm, and GBDT algorithm in ML algorithms. This article uses these three algorithms to predict the default probability of users, and uses relevant examples to illustrate. This article compares and analyzes the testing accuracy of three algorithms in computer investment database IMS, and selects 10 sets of user data. This article averages the testing accuracy obtained from the test data samples, and the comparative analysis of the testing accuracy of the three algorithms is shown in **Figure 3**.

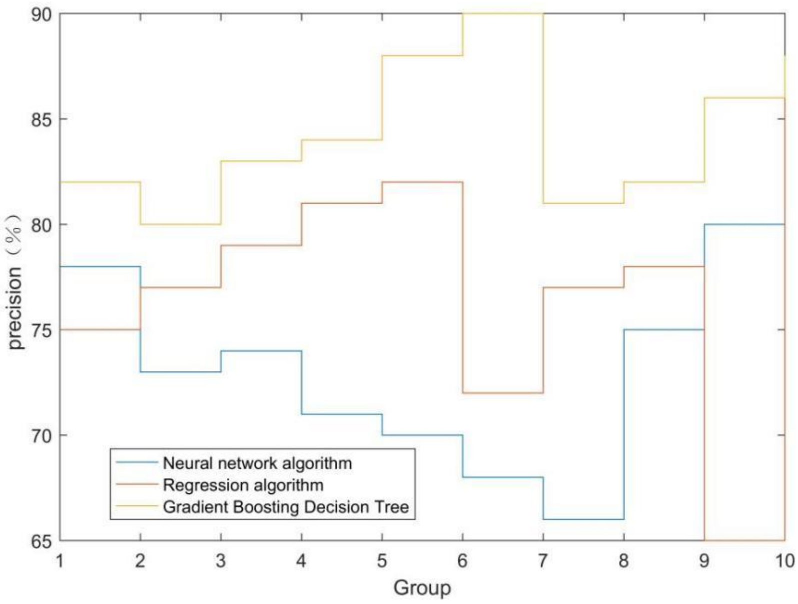

Figure 3. Comparative analysis of testing accuracy of three algorithms.

From the data in **Figure 3**, it can be seen that the average test accuracy calculated using neural network algorithm was 73.7%, the average test accuracy calculated using regression algorithm was 77.2%, and the average test accuracy calculated using GBDT algorithm was 84.4%. The average test accuracy using regression algorithm was 3.5% higher than that using neural network algorithm, and the average test accuracy using GBDT algorithm was 7.2% higher than that using regression algorithm. In order to compare the advanced nature and reliability of the proposed methods more comprehensively, more comparison methods and evaluation indicators are used for analysis. Comparison methods include random forest (RF), support vector machine (SVM), K-nearest neighbor (KNN), and evaluation indicators include Precision, Recall, and F1 scores. The results are shown in **Table 3**.

Table 3. Comparison results of the advancement and reliability of different methods.

Algorithm	**Accuracy**	**Recall**	**Precision**	***F*1 score**
Research method	0.844	0.805	0.857	0.829
RF	0.810	0.795	0.820	0.807
SVM	0.785	0.760	0.795	0.777
KNN	0.752	0.705	0.760	0.731

Table 3 results show that the research method shows the highest accuracy (0.844), recall rate (0.805), accuracy rate (0.857) and *F*1 score (0.829), which clearly has excellent identification and classification ability in the field of risk prediction. Compared with RF (0.810 accuracy) and SVM (0.785 accuracy), it also showed obvious advantages. The results emphasize the technical advantages of the research method in dealing with unbalanced data sets and its significance in financial risk management, provide a feasible model optimization scheme for future research, and provide an accurate and effective tool for decision support in practice.

The computer investment database information management system optimizes and distributes data in the computer through the construction, management, and application functions of the entire computer database. Currently, many industries are using computer databases, which are the most effective way to organize databases. This is very beneficial for promoting the development of engineering, multimedia technology, information technology, and so on. With the continuous progress of computer technology, the system has been greatly improved in various aspects, and its applications in various aspects have also been further expanded. However, there are still many urgent problems that need to be solved, which requires scientific and technological personnel in the field of computer technology and information management to continue exploring and researching this. Only in this way can the functionality of the computer database system be improved. At the same time, database technology can also better serve society. While information technology has driven the growth of the computer industry, it has also triggered a huge transformation and transformation. In terms of production and technology, information integration also has an impact on the operation of traditional industries. Due to its increasingly widespread and in-depth application in engineering, engineering management has become increasingly difficult. Among these factors, risk management has become a new model that has received increasing attention in recent years. Strengthening research on risk management is also a major method for promoting innovation in computer information management methods.

6. Conclusions

This article took the credit risk issue in the internet finance industry as the research object, analyzed the structure, development status, and application prospects of database management systems, and also studied several ML algorithms. This article established a credit risk prediction model by comparing and analyzing, selecting suitable ML algorithms, and using ML algorithms. In terms of data processing, in addition to using classic basic user information, bank journal logs and financial information records, other relevant data has also been introduced. This article analyzed neural network algorithms and regression algorithms, as well as the predictive accuracy of the GBDT algorithm. Through experimental data research, it is found that the GBDT algorithm has the highest operational accuracy in computer investment database IMS. This article also designed three schemes, and after comparing the proportion of account defaults, it was found that Option 3 had the best processing effect.

Ethical approval: Not applicable.

Conflict of interest: The author declares no conflict of interest.

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