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Building a Financial Integration Algorithm for Mobile Internet and Accounting Information System Collaboration

Shuyu Hu[1] and Ming Huang[1,*]
[1] School of Economics and Management, Hunan Open University, Changsha, Hunan, 410004, China
Corresponding authors: (e-mail: 13973183761@163.com).

Abstract Nowadays, modern technology represented by unstructured text data information is widely used in all walks of life. According to the company's unstructured text data information, the establishment of the most advanced company's financial accounting artificial intelligence model has gradually become the yearning goal of Chinese companies to carry out financial work. In order to solve many problems such as low efficiency of traditional financial accounting and insufficient risk early warning ability, this paper used the Naive Bayes algorithm based on the unstructured text data of enterprises. It can improve the early warning accuracy of enterprise financial analysis and solve the problem of low efficiency of financial accounting, thereby promoting the transformation of financial accounting into an artificial intelligence model. By comparing the accuracy of financial risk early warning with the help of Naive Bayes algorithm and traditional manual mode, it was concluded that the Naive Bayes model algorithm based on enterprise unstructured text data had higher accuracy in corporate financial risk early warning, generally around 98%. It improved the accuracy by about 10% compared with the traditional manual mode, which was conducive to the continuous enhancement of financial accounting data collection, processing, and analysis capabilities.

Index Terms Financial Accounting Transformation, Artificial Intelligence Model, Unstructured Text Data, Naive Bayes Model

I. Introduction

As an important part of the refined management of enterprises, financial accounting is becoming more and more important in shaping the core competitiveness of enterprises [1], [2]. More and more corporate executives are gradually realizing the necessity of financial accounting to enhance the core competitiveness of enterprises. Under the conditions of the new market economic system, financial accounting can improve a full range of financial data and information for enterprise operation and management. Various problems have appeared in traditional financial work, which has been unable to meet the new financial needs of social enterprises, and even seriously affect the governance and judgment of group companies. The emergence and perfection of enterprise unstructured text data makes enterprise financial work and computer technology perfectly integrated, and solves many financial work problems for enterprises [3], [4]. Naive Bayesian algorithm helps artificial intelligence model finance to provide newer and better solutions to the problem of overly complex corporate financial processes. Based on enterprise unstructured text data, financial staff can further improve work efficiency and work quality, and reasonably save various costs that may be used in accounting work. At the same time, the accuracy of accounting can be improved. This can promote the further transformation of enterprise financial accounting into advanced artificial intelligence model.

With the continuous development of enterprises' requirements for financial accounting skills, enterprises put forward higher requirements for the development of accounting, which promotes the transformation of accounting to advanced models. Hu Z M made use of the OBE (Outcomes-based Education) teaching mode to analyze the reconstruction of the "higher financial accounting" teaching mode under its mode, and finally put forward the reform strategy of the teaching mode based on the OBE teaching concept [5]. Based on the enterprise financial sharing service platform and the strategic needs of enterprises, Xiong I provided strong endogenous vitality and support for enterprise management and promoted the development of enterprise scale economy [6]. Yang Y used the force field analysis method to study the Financial Shared Service Model and constructed the force field model of the impact mechanism [7]. Shevtsiv LY developed theoretical and practical approaches to corporate accounting policy in the context of accounting coordination and reporting, in accordance with management objectives. In order to optimize the accounting process, and in the effective management system of commodity classification, a decomposition information model of accounting policy was proposed [8]. Among the studies made by these scholars, few studies have considered the transformation of financial accounting into advanced artificial intelligence models based on enterprise unstructured text data. For this, based on enterprise unstructured text data, this paper further studied the transformation of financial accounting into an advanced artificial intelligence model.

Research on unstructured text data has always been very hot, and related research reports are emerging one after another. Gong L believed that computational methods using machine learning can identify disease entities associated with autism spectrum disorder (ASD) from textual data collections. Disease-related entities were extracted from autism-related biomedical literature through deep learning using bidirectional long-short-time chronotypes and conditional random field models [9]. Ning Y believed that data sharing sometimes brings the risk of privacy leakage, so he proposed a deep learning-based product identification (PI) method for unstructured text. This method can extract PI from unstructured text [10]. In order to better interpret the controlled source electromagnetic (EM) data on the topographic seafloor, Zhang J proposed an unstructured grid-based inversion method for oceanographic controlled source electromagnetic measurements. This method can use unstructured tetrahedral elements to discretize the model domain, and calculate the response time and sensitivity of the method of seabed controlled source electromagnetic (MCSEM) [11]. Hou B presented an audit data analysis framework based on text mining, which created entity models based on clear audit requirements and analyzed audit data. [12]. Among these scholars, the research on unstructured text data is to use unstructured text data to analyze different things. Therefore, the application scope and research objects of unstructured text data are very wide, which shows that the subject of this paper is valuable.

The transformation of financial accounting based on enterprise unstructured text data into an artificial intelligence model can not only maximize the efficiency of enterprise financial accounting, but also effectively detect possible financial risks, so as to avoid the leakage of company financial information. The use of corporate unstructured text data can help corporate financial accountants improve their professional knowledge and better use the artificial intelligence model for financial management, thereby ensuring the normal operation of the company's finances. By using enterprise unstructured text data and combining with the Naive Bayes model algorithm, accountants can perform financial work anytime and anywhere, which can further promote the transformation of accounting in the direction of intelligence and digitization.

II. Financial Accounting Based on Enterprise Unstructured Text Data

II. A. Unstructured Text Data

The principle of unstructured text data is to convert unstructured data into text data information, and gradually process text data into semi-structured or structured data information [13], [14]. The specific process is shown in Figure 1.

When converting unstructured data into textual data information, the data is in a semi-structured state and must be repaired with existing NLP (natural language processing) and SNA (Social Network Analysis) algorithms. The most typical text solving algorithms include term frequency-inverse document frequency (TF-IDF), text ranking (TextRank), and Naive Bayes model. Various algorithms have clear application domain characteristics, as shown in Table 1.

Table 1: Common text algorithms

Algorithm	Tntroduce	Advantage	Ahortcoming
TF-IDF	Analyze keywords based on statistical methods	Easy to understand	Over reliance on word segmentation results
TextRank	Graph based sorting algorithm for text	Keywords can be extracted by using the information of a single document	Slow extraction speed
Naive Bayes model	The knowledge of probability statistics is used to classify the sample data set	Low misjudgment rate and fast extraction speed	The algorithm is somewhat complex and difficult to understand

II. B. Opportunities Brought by Unstructured Text Data to Financial Accounting

The first is the unstructured text data technology can effectively reduce the frequency of manual work by financial personnel, and solve a lot of cumbersome, mechanical and inefficient work. For example, unstructured text data can efficiently process massive amounts of information; the work of mining, sorting, and analyzing data can be completed efficiently; it can also accurately perform large-capacity retrieval and storage. The transformation of enterprise financial accounting based on unstructured text data can not only carry out independent accounting, but also work 24 hours without downtime with a very low error rate [15], [16].

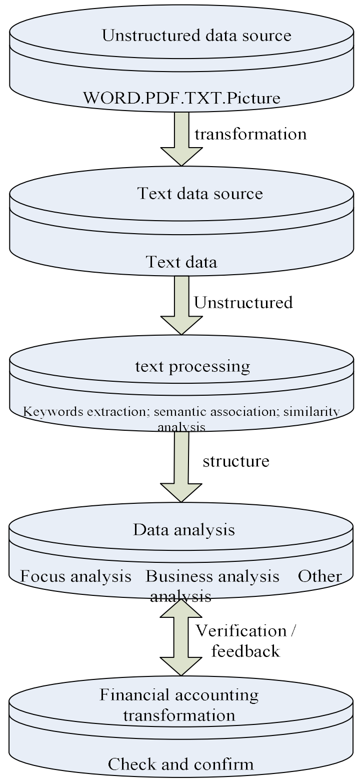

Figure 1: Unstructured data analysis process

The second is to improve the quality of accounting information, because the traditional financial accounting work only applies to structured data and very little unstructured data, and the risk description is not sufficient and systematic, so it cannot effectively reflect the value of the data. After the application of unstructured technology, it is possible to dig deep into the data first and obtain valuable data as quickly as possible, so as to fill in the deficiencies in the analysis of structured data; then, the data can be fully integrated, especially the correlation between the data, and the value of the data can be improved. The most difficult thing for companies to control is the problem of false or leaked accounting information. One of the main reasons why this problem has existed for a long time and cannot be completely eliminated is that the moral literacy of financial personnel cannot be controlled artificially, and some insiders may consciously tamper or leak information for personal gain. However, the transformation of enterprise financial accounting based on unstructured text data makes the accounting work mainly generated automatically by the system. Therefore, it is more difficult for financial personnel to tamper with and leak information privately, which improves the problem to a certain extent [17], [18].

The third is to promote the transformation of corporate financial personnel to management accounting. It has become inevitable for financial robots to replace traditional accounting, but artificial intelligence cannot completely replace accountants. Because artificial intelligence model accounting still has some shortcomings and limitations. At present, the development of artificial intelligence in positions requiring planning ability and cross-domain thinking is relatively weak, so it can promote the upgrading of the skills of corporate financial and accounting personnel [19], [20].

II. C.Naive Bayes Algorithm

Naive Bayesian algorithm refers to the assumption of characteristic conditional independence. Classification shall be carried out before calculation, and the probability shall be calculated [21], [22]. The formula for calculating the prior probability is:

$$F(Y = D_k) = \frac{\sum_{i=1}^{N}(Y=D_k)}{N} \tag{1}$$

Among them, *N* is the total number of texts in the training set, and refers to the *k*-th category. When the characteristic conditions are independent of each other, that is, the characteristic words are independent of each other, the financing debt risk of the financial risk of the enterprise is substituted into it, and the conditional probability formulas are:

$$F(X = x|Y = D_k) = F\left(X^{(1)} = x^{(1)}, X^{(2)} = x^{(2)}, \ldots X^{(n)} = x^{(n)} | Y = D_k\right) \tag{2}$$

$$F(X = x|Y = D_k) = \prod_{i=1}^{n} F\left(X^{(i)} = x^{(i)} | Y = D_k\right) \tag{3}$$

After substituting the enterprise risk type factors into the algorithm basis again, the checking probability formulas can be written as:

$$\text{GaussianNB}F(X = x|Y = D_k) = \frac{F(Y=D_k)F(X=x|Y=D_k)}{F(X=x)} \tag{4}$$

$$F(X = x|Y = D_k) = \frac{F(Y=D_k)\prod_{i=1}^{n} F(X^{(i)}=x^{(i)}|Y=D_k)}{F(X=x)} \tag{5}$$

In addition, since F(X=x) is the same for the same text, only the numerator needs to be considered:

$$y = \arg\max F(Y = D_k) \prod_{i=1}^{n} F\left(X^{(i)} = x^{(i)} | Y = D_k\right) \tag{6}$$

In general, after the text to be classified is represented by feature items, the category with the largest posterior probability is used as its final category. GaussianNB assumes that the conditional probability distribution of features satisfies a Gaussian distribution. The Gaussian distribution has two parameters, namely the mean μ and the variance. The specific expression is Formula (7):

$$F(X = x|Y = D_k) = \frac{1}{\sqrt{2\pi\vartheta_k^2}} e^{\frac{(x-\mu)^2}{2\vartheta_k^2}} \tag{7}$$

Among them, can be estimated by the sample mean of *X* in the training sample of, then can be estimated by the sample variance of *X* in the training sample of. represents the probability when the category belongs to and the feature item takes *x*.

When the attribute category is a discrete attribute, the multinomial Bayesian classifier MultinomialNB is generally considered [23], [24]. There are:

$$N_k = \sum_{i=1}^{N} L(y_i = D_k) \tag{8}$$

$$N_{kj} = \sum_{i=1}^{N} L\left(y_i = D_k, X^{(j)}\right) = a_{ij} \tag{9}$$

$$F(X^{(j)} = a_{ij}|Y = D_k) = \frac{N_{kj}+\gamma}{N_k+n\gamma} \tag{10}$$

Among them, indicates the number of samples belonging to category, and indicates the number of samples whose category is and feature item $X^{(i)} = a_{ij}$; indicates that the number of values of feature item is, and is the smoothing coefficient.

The specific process of the Naive Bayes algorithm is shown in Figure 2.

II. D.Evaluation Indicators

The evaluation indexes include precision, recall, precision and recall. Before introducing these evaluation indicators, some commonly used character concepts and classification confusion matrices need to be introduced first, as shown in Table 2.

Table 2: Classification confusion matrix

Forecast results / True category	Positive example	Counterexample
Positive example	TP	PN
Counterexample	FP	TN

The accuracy is generally the percentage of the number of classified positive samples in the total number of samples judged to be positive. The formula is as Formula (11):

$$P = \frac{TP}{TP+FP} \tag{11}$$

The recall rate generally refers to the percentage of the number of classified positive samples in the total number of positive samples in the classified samples. The formula is as Formula (12):

$$R = \frac{TP}{TP+FP} \tag{12}$$

Precision and recall are two different indicators to measure the classification effect. The formula is as Formula (13):

$$F1 = \frac{2PR}{P+R} \tag{13}$$

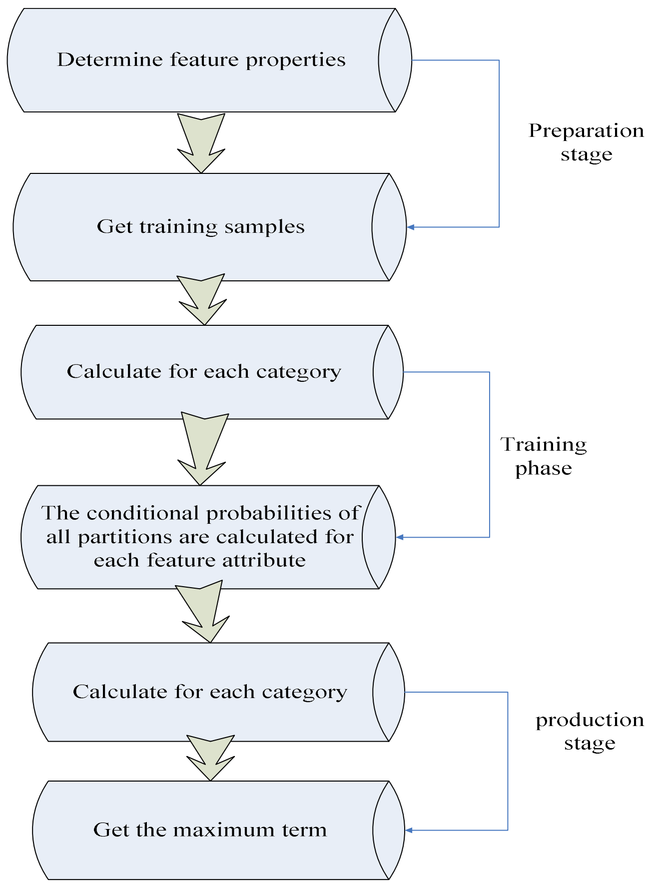

Figure 2: Flow chart of naive Bayesian algorithm

III. Transformation of Financial Accounting Based on Enterprise Unstructured Text Data into Artificial Intelligence Model

In the era of rapid increase in the amount of unstructured text data, if according to the traditional mode, accounting personnel only rely on manual inspection and accounting of the overstocked financial documents of enterprises, it would inevitably slow the progress of enterprise accounting and affect the efficiency and speed of financial accounting audit [25]. Under the background of enterprise unstructured text data, the Naive Bayes model algorithm can be used to quickly identify and analyze the company's financial data documents, and speed up the development of enterprise financial work, thereby improving the quality of work. In order to prove this, the financial data of a company at the end of 2021 was collected. By comparing the traditional manual method of reading and accounting for data and the method of using the Naive Bayes model algorithm to read and calculate data through the server, it was tested whether the use of Naive Bayes model algorithm based on enterprise unstructured text data can promote the transformation of financial accounting to artificial intelligence model. The comparison results are shown in Figure 3.

It can be clearly analyzed from Figure 3 that in the case of a large amount of corporate financial text data, with the help of the Naive Bayes model algorithm, the retrieval speed of financial data was greatly increased. When there were only 100 files, the Naive Bayes model algorithm took the shortest time to read and calculate, which only took 0.1 days. When the number of documents increased, the time for review and accounting also increased, but the increase was very small. When there were 1,000 financial data files to be accounted for, it only took 0.4 days. However, if the company's financial documents were reviewed and calculated according to the traditional financial accounting manual, when there were only 100 documents, the traditional manual method took 0.5 days. When the number of documents increased, the reading and accounting time also increased, and the increase was gradually larger. When there were 1000 financial data files to be accounted for, it took 4 days. The traditional manual calculation of 100 documents took longer than the calculation of 1000 documents using the Naive Bayes model algorithm, which showed that the use of the Naive Bayes model algorithm can help enterprises to upgrade their finance from manual mode to artificial intelligence mode. It greatly improved the work efficiency of enterprise financial accounting, and enhanced the ability to efficiently process massive information. In addition, it can also enable the precise retrieval of data. Therefore, the calculation speed of the financial system of the artificial intelligence model was significantly higher than that of human.

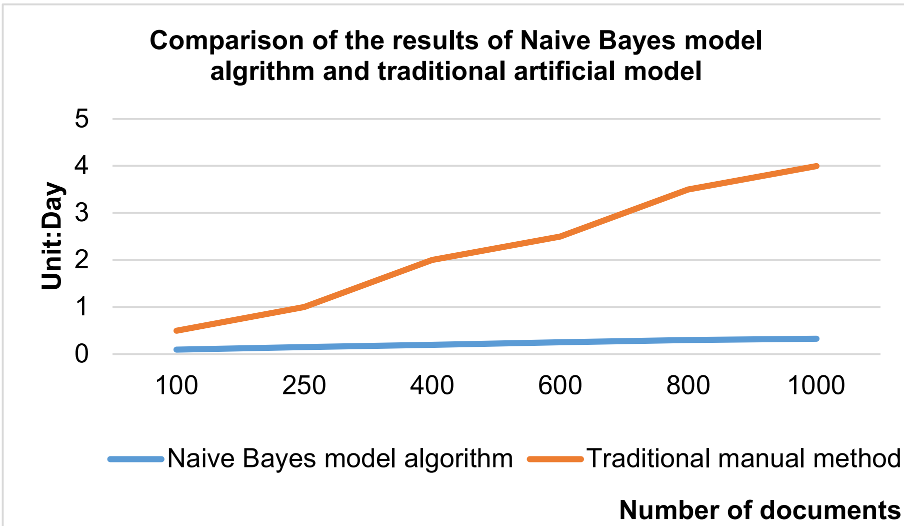

Figure 3: Comparison results of naive Bayes model algorithm and traditional artificial model on accounting time of financial data

Enterprises would have financial risks in the process of development. Financial risks may have a direct impact on the realization of an enterprise's financial management goals, which is very unfavorable to the future development of the enterprise. In particular, in the case of unstructured text data, the financial data of enterprises increases greatly, and the hidden financial risks are also increasing. The increase of these risks is not conducive to the transformation of enterprise financial accounting and the establishment of enterprise artificial intelligence financial accounting models. There are mainly several types of financial risks in enterprises, as shown in Table 3.

Table 3: Main types of enterprise financial risk

Serial number	Risk event
1	Financing debt risk: insufficient capital budget
2	Guarantee risk: lack of systematic evaluation on the solvency of the guaranteed enterprise
3	Risk of cost rise: increase in labor and management costs
4	Tax risk: improper use of tax reduction and exemption policies of the project increases the tax burden of the enterprise
5	Investment risk: lack of correct estimation of the project
6	Interest rate risk: interest rate change is not found in time

By observing Table 3, it can be found that there are six main types of financial risks in general enterprises, namely financing debt risk, guarantee risk, risk of cost rise, tax risk, investment risk and interest rate risk. In the case of enterprise unstructured text data, corporate finance cannot eliminate possible risks through risk composition or substitution. With the gradual growth of unstructured data, corporate financial accounting may not be able to fully grasp the overall financial risk situation of the company in daily work, and the breadth and depth would be affected by data diversity and data volume, which would lead to an increase in the risk accumulation effect. With the help of unstructured data analysis methods, the Naive Bayes model algorithm is used to comprehensively analyze and utilize the data to form an overall risk map, which can effectively reduce the accumulation of financial risks in the process of enterprise development.

In view of the verification of the accuracy of Naive Bayes model algorithm on the early warning of different financial risks of enterprises, the six common corporate financial risks of financing debt risk, guarantee risk, risk of cost rise, tax risk, investment risk, and interest rate risk listed in Table 3 were arranged in the order of No. 1, No. 2, No. 3, No. 4, No. 5 and No. 6. The six types of financial risk data of Chinese enterprises over the years were collected and input into the established artificial intelligence model financial system to form a basic database. Machine learning training was performed on the intelligent system using the underlying database. The financial data of each period from 2020 to 2021 were selected respectively. The financial system of the artificial intelligence model established by the Naive Bayes model algorithm was compared with the traditional model by using the comparative analysis method to see whether the naive Bayes model algorithm has better accuracy in early warning of different financial risks of enterprises. The specific results are shown in Figure 4.

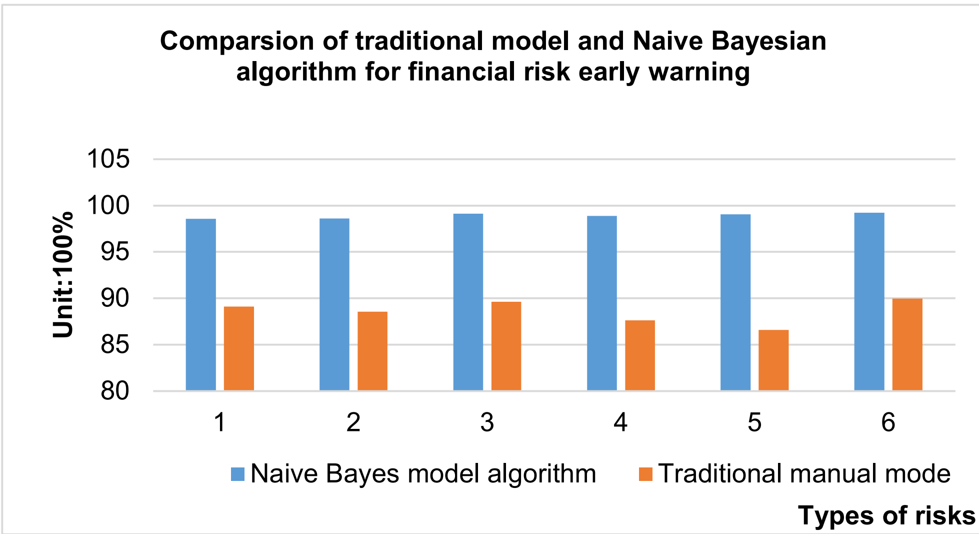

Figure 4: Comparison results of accuracy of traditional model and naive Bayes model algorithm for enterprise financial risk early warning

It can be clearly analyzed by careful observation of Figure 4 that in the case of enterprise unstructured text data, the enterprise financial model established by using the Naive Bayes model algorithm had a much higher degree of early warning than the traditional manual model in risk warning. By using the Naive Bayes model algorithm, the early warning accuracy rate for these six common financial risks of enterprises was all over 98%. Among them, the early warning accuracy rate of guarantee risk was 98.61%, and the risk of cost rise was 99.12%; the highest pre-warning accuracy rate was interest rate risk, and uped to 99.23%; the lowest pre-warning accuracy rate was financing debt risk, and uped to 98.56%. The accuracy rate of early warning for these six common financial risks of enterprises using traditional manual mode was all below 90%. The risk of cost rise was 89.63%, of which the highest rate of early warning accuracy was interest rate risk, which was 89.98%; the lowest rate was investment risk, which was only 86.59%.

Although the highest accuracy rate of financial risk warning of the two was interest rate risk, the model established using the Naive Bayes model algorithm was 9.25% higher than the traditional manual model, and the lowest financing debt risk using the Naive Bayes model algorithm for financial risk warning was 8.58% higher than the highest interest rate risk of the traditional manual model. Therefore, in terms of corporate financial early warning, machine intelligence was more forward-looking, and the accuracy of financial early warning that can be made was higher. This was because the use of the Naive Bayes model algorithm can help financial accounting transform into an artificial intelligence model with powerful computing power, so that it can make predictions in multiple different scenarios at the same time and give more decision-making options. Machine intelligence also made financial forecasts more dynamic, and can make timely revisions to financial forecasts based on the latest data obtained simultaneously. As a result, AI models outperformed humans with lower error rates in terms of analyzing and predicting errors.

In the case of enterprise unstructured text data, the transformation of enterprise financial accounting may encounter sensitive text data, because the sensitive information involved is different and can be divided into many types. By comparing and using the Naive Bayes model algorithm, keyword matching technology and convolutional neural network detection technology, the experimental analysis was carried out. In order to prove that the sensitive information detection method of enterprise financial text based on the Naive Bayes model algorithm is more effective, various methods of sensitive information detection of unstructured text were tested experimentally, and the advantages of the method were reflected from the accuracy rate.

According to the actual collected financial accounting sensitive text data, these collected data were divided into training set, test set and verification set according to the ratio of 4:1:1. The financially sensitive texts and financially non-sensitive texts of each part should be in a ratio of 1:1 as much as possible to ensure data balance, which is more conducive to improving the detection effect after the model is established, and is conducive to the transformation of financial accounting into advanced artificial intelligence models. The specific data are shown in Table 4.

Table 4: Data set splitting

Data set	Financial sensitive text	Financial non sensitive text	Total
Training set	4300	4000	8300
Validation set	900	1000	1900
Test set	1000	900	1900
Total	6200	5900	12100

The reason why the unstructured text sensitive information detection method based on the Naive Bayes model algorithm was proposed is because the method is better for unstructured text sensitive information detection, which can be confirmed by the following experiments. In order to prove that the text sensitive information detection method based on the Naive Bayes model algorithm is more effective, the dataset was tested with 1900 test sets. The obtained results are shown in Table 5.

Table 5: Comparative experimental results of various detection methods

Experimental method	Accuracy	Result analysis
Using naive Bayes model detection technology	98.12%	The effect is expected and the detection time is fast
Keyword matching technology	74%	Financial non sensitive texts containing financial sensitive information cannot be accurately distinguished and the detection time is long
Convolutional neural network detection technology	90%	The extraction process is complex and takes a long time

A careful observation of table 5 showed that for unstructured financial accounting sensitive text data, the accuracy of using the Naive Bayes model detection technology was as high as 98.12%; the accuracy rate of keyword matching technology was only 74%, and the accuracy rate of detection technology using convolutional neural network was 90%. The Naive Bayes model detection technique was much more accurate than the other two detection techniques; it was 24.12% more accurate than the keyword matching technique and 8.12% more accurate than the convolutional neural network detection technique. In particular, the Naive Bayes model detection technology was easier to achieve than the other two detection technologies, and the detection time was faster and the extraction process was simpler. It can correctly distinguish financially non-sensitive texts containing financially sensitive information. After these experiments, it can be seen that the detection method adopted in this paper had a significant improvement in accuracy compared with the keyword matching technology and the convolutional neural network detection technology. It had the advantages of automatic extraction of text semantics, elimination of human emotional factors, and combination of text context information compared with the other two methods.

The detection method of unstructured text sensitive information based on the Naive Bayes model algorithm had a shorter detection time for financial sensitive text data than keyword matching technology and convolutional neural network detection technology. The specific results are shown in Figure 5.

From Figure 5, it can be known that for the 1900 test sets extracted for verification to detect financially sensitive texts, the Naive Bayes model algorithm reduced the detection time by 9 seconds and 3 seconds compared with the other two algorithms, and the detection speed was also improved many times. Therefore, in the case of unstructured text-based data, when faced with sensitive texts in finance, the detection time can be greatly shortened by using the Naive Bayes model algorithm to establish an artificial intelligence model, which was conducive to the transformation of the traditional artificial model financial accounting model to an advanced artificial intelligence model.

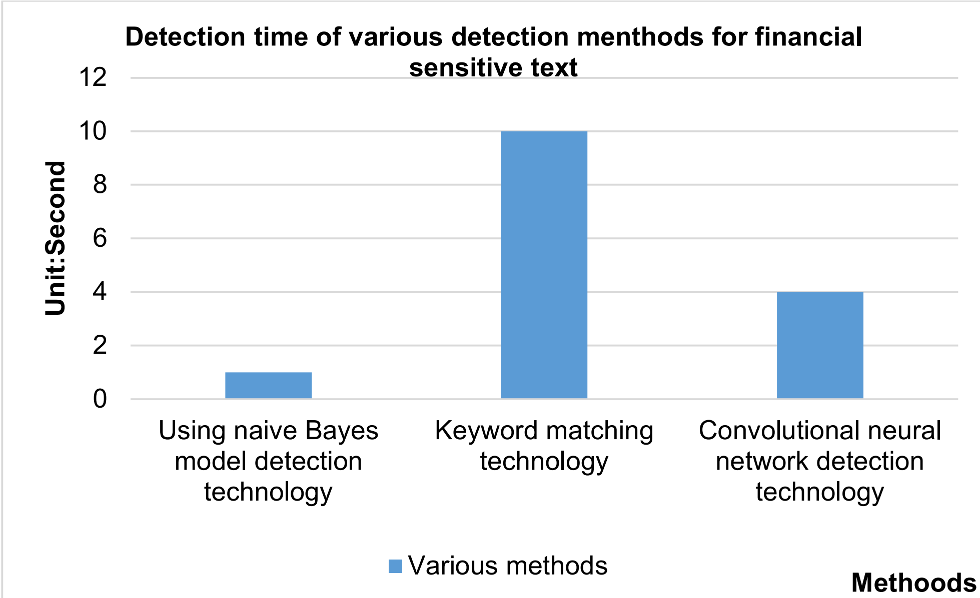

Figure 5: Detection time of various detection methods for financial sensitive text

IV. Conclusions

The organic combination of unstructured text data and corporate financial accounting has become an inevitable trend. However, this does not mean that financial workers and financial accounting work would withdraw from the historical stage, because data based on unstructured text also has some risks to corporate finance, which may increase the risk of corporate financial information leakage and increase the cost of corporate financial management. In addition to risks, the benefits of the organic combination of unstructured text data and corporate financial accounting are more. In this paper, the transformation of financial accounting to a higher level was mainly based on unstructured text data technology, and the Naive Bayes model algorithm was used to study the financial risk early warning error and the accounting speed of financial data. By comparing with the traditional manual model and the Naive Bayes model algorithm, it was found that when developing the unstructured text data of the enterprise, the use of the Naive Bayes model algorithm to calculate the financial data was very fast, and the accuracy of financial risk early warning was very high and stable. It can be seen that the financial accounting transformation research based on the Naive Bayes model algorithm can not only enables corporate financial workers to strengthen their own strength, but also enables them to continuously improve their comprehensive quality and strengthen the times, which provides a guarantee for corporate financial development.

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