Enterprise Financial Fraud Detection using GA-BPNN, Random Forest, and SVM with Multi-Modal Features

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This paper selected 22 indicators related to financial fraud, taking into account both financial and non-financial indicators from a machine learning perspective, and screened them through the IV value and Spearman correlation coefficient. Then, three algorithms, random forest (RF), support vector machine (SVM), and genetic algorithm-back-propagation neural network (GA-BPNN), were introduced, and experiments were carried out with the data of 784 fraudulent enterprises and 784 non-fraudulent enterprises sourced from the China Stock Market & Accounting Research Database as samples. The results indicated that using both financial and non-financial indicators yielded better identification results compared to using only financial indicators: the recall rate of the RF algorithm increased from 0.5762 to 0.6295, and the area under the receiver operating characteristic curve (AUC) increased from 0.6331 to 0.6874. The GA-BPNN algorithm exhibited the best performance in recognizing financial fraud behaviors, achieving a recall rate of 0.8256 and an AUC of 0.8537, which were the highest among the different algorithms. The shareholding ratio of the largest shareholder was the most important factor in identifying financial fraud, followed by the inventory turnover rate, which requires particular attention. The results demonstrate the usability of the GA-BPNN algorithm and the established indicator system, which can be applied in actual financial scenarios.

Povzetek: Študija pokaže, da lahko strojno učenje z uporabo finančnih in nefinančnih kazalnikov učinkovito izboljša prepoznavanje finančnih prevar v podjetjih.

1 Introduction

In the evolution of the capital market, there have always been some enterprises that have committed financial fraud in pursuit of illegal high returns. The existence of enterprise financial fraud has a significant influence on the development of the social economy [1], and research on its identification can provide technical support for investors and regulatory authorities, thereby maintaining the order and efficiency of the capital market [2]. The earliest fraud identification relied on the empirical judgment and analysis of auditors. Subsequently, statistical models such as logistic regression were applied in this field, improving the efficiency of identification. Compared with statistical models, machine learning methods exhibit better performance in identifying large amounts of data and have been widely applied in detecting financial fraud [2]. However, a single financial recognition indicator is often selected without considering non-financial indicators. From the perspective of machine learning, this paper studied the identification of enterprise financial fraud behavior and compared three different algorithms, with the aim of establishing a simple and reliable model to support practical work. Suppose that combining financial indicators with non-financial indicators can achieve a higher prediction accuracy compared to using only financial indicators. Assume that among different machine learning algorithms, the genetic algorithm-back-propagation neural network (GA-BPNN) can obtain superior performance than the random forest (RF) and the support vector machine (SVM). Through the empirical tests of fraudulent and non-fraudulent enterprises in the China Stock Market & Accounting Research Database (CSMAR), it is expected to construct a simple and reliable model for identifying corporate financial fraud behaviors and provide risk warning indicators with higher practical value for regulatory agencies and auditors.

2 Related works

Some related works are reviewed (Table 1).

Table 1: A summary of related works.

Literature	Method	Performance
Alghofaili et al. [3]	A financial fraud detection model based on long short-term memory	The model achieved an accuracy of 99.95% in less than one minute.
Binsawad [4]	Voted perceptron model	It was superior to competitors, with a low error rate and a high recall rate.
Li [5]	XGBoost model	The accuracy of short-term detection

		was higher than that of long-term detection, and two years was the optimal detection cycle.
Tong [6]	A metagraph fraud detection graph neural network	The F1-macro, area under the receiver operating characteristic curve (AUC), and geometric mean improved by 4.46%, 2.67%, and 8.59% respectively for the YelpChi dataset.

3 Financial fraud and machine learning

3.1 Enterprise financial fraud

Enterprise financial fraud refers to the act of an enterprise deliberately distorting true financial information in order to gain improper benefits [7]. The causes of fraud are complex, and the fraud triangle theory analyzes it from three perspectives: pressure, motivation, and excuse.

(1) Pressure: When faced with performance pressure and debt pressure, enterprises may choose to manipulate profits and hide debts.

(2) Motivation: When there are flaws in internal controls, information asymmetry, or regulatory loopholes, fraud can be carried out.

(3) Excuse: In cases where fraud is widespread in the industry or otherwise, enterprises can find excuses for the occurrence of fraud.

The existence of fraud directly affects the order of the capital market. When it is exposed, it will affect investors' confidence in investment. In general, enterprise fraud poses a great threat to the sustainable growth of the entire capital market [8]. Therefore, investigating methods for detecting fraud has become essential. From the perspective of machine learning, machine learning algorithms can be utilized to select a series of indicators related to fraud behavior to achieve identification.

3.2 Data description

In the study of this paper, Shanghai and Shenzhen A-share listed companies that were punished for financial fraud for the first time between 2000 and 2022 were used as fraud samples. Due to the significant differences in accounting between the financial sector and the non-financial sector, the financial sector was excluded from the sample selection, resulting in a total of 784 fraud samples. Then, the paired samples were selected in accordance with Beasley's pairing principle [9]:

(1) select enterprises that are in the same industry as the cheating company;

(2) the selected enterprises are not classified as tax assessment (TS), transfer pricing (TP), or *special treatment (ST), and the data is complete;

(3) the assets of the selected enterprises are comparable to those of the cheating enterprises.

Seven hundred eighty-four non-fraud samples were obtained. All data was sourced from the China Stock Market & Accounting Research (CSMAR) database (http://data.csmar.com).

3.3 Feature engineering

In the selection of indicators for enterprise financial fraud behavior, referring to the causes of fraud, in accordance with principles such as objectivity and operability, and considering both financial and non-financial aspects, an indicator system was established (Table 2).

Table 2: Indicator system for identifying financial fraud.1

Indicator type		**Indicator name**
Financial indicator	Development capacity	Growth rate of total assets
		Total profit growth rate
	Profitability	Net profit margin on total assets
		Net profit margin on current assets
		Return on net assets
		Operating profit margin
	Solvency	Current ratio
		Quick ratio
		Cash ratio
		Interest coverage ratio
		Asset-liability ratio
	Operational capacity	Accounts receivable to revenue ratio
		Accounts receivable turnover ratio
		Inventory turnover ratio
		Current asset turnover ratio
		Total asset turnover ratio
	Risk level	Financial leverage
		Combined leverage
Non-financial indicator	Equity structure	Shareholding ratio of the largest shareholder
	Board structure	Proportion of independent directors
	Corporate governance	Supervisory board shareholding ratio
	Audit	Types of audit opinions

As to the indicators in Table 2, except for the last one, all the others were numerical variables. The audit opinion type was a categorical variable, classified by whether a standard audit opinion was issued, with yes = 1 and no = 0.

For the features in Table 2, the missing values were imputed using the k-nearest neighbor method. The missing values of the categorical variable were filled in using the multiple imputation method. Then, the selected indicators were further screened.

First, the information value (IV) was calculated [10], which measures a variable's ability to distinguish the target event. When the IV value is lower than 0.02, the ability is weak, and its contribution to recognition is limited. Therefore, indicators with IV values less than 0.02 were excluded.

Then, the Spearman correlation coefficient was calculated [11]. The features in Table 1 may exhibit multicollinearity, which can lead to a decline in the stability and interpretability of the model. This coefficient measures the correlation between two variables and is more robust to non-normal distributions and outliers. When the result is greater than 0.7, it indicates a high degree of redundancy between the two variables and one should be removed. Through screening using the Spearman correlation coefficient, the feature combination can be optimized by eliminating multicollinearity, thereby constructing a more reliable model for identifying financial fraud behavior.

The indicators retained based on these two steps are displayed in Table 3.

Table 3: Financial fraud identification indicators after screening.

Indicator type		**Indicator name**	**Indicator number**
Financial indicators	Development capacity	Growth rate of total assets	X1
		Growth rate of total profit	X2
	Profitability	Net profit margin on total assets	X3
		Net profit margin on current assets	X4
		Return on net assets	X5
	Debt-paying ability	Cash ratio	X6
		Interest coverage ratio	X7
		Asset-liability ratio	X8
	Operational capacity	Accounts receivable to revenue ratio	X9
		Accounts receivable turnover ratio	X10
		Inventory turnover rate	X11
		Current asset turnover rate	X12
		Total asset turnover ratio	X13
	Risk level	Financial leverage	X14
Non-financial metrics	Equity structure	Shareholding ratio of the largest shareholder	X15
	Board structure	Proportion of independent directors	X16
	Corporate Governance	Supervisory board shareholding ratio	X17
	Audit	Types of audit opinions	X18

3.4 Model training

This article introduced three machine learning algorithms that are currently in use and perform well.

(1) Random forest (RF)

RF is an ensemble learning approach that uses decision trees as base classifiers and aggregates voting results from all decision trees. It has been widely applied in healthcare and cybersecurity lighting scenarios [12]. Here are the steps:

① based on the Bagging algorithm, sampling with replacement was used. To be specific, randomly select n training samples, and obtain k training sets after k rounds of sampling.

② train k decision trees;

③ vote and summarize the results of all decision trees to output the final financial fraud identification result.

(2) Support vector machine (SVM)

SVM, a generalized linear classifier, has good applications in scenarios such as text recognition and fault classification [13]. The principle of SVM is to establish a hyperplane (w,b) to maximize the distinction between positive and negative samples. The distance from any point x to hyperplane (w,b) can be written as:

$$r=\frac{|w^T x+b|}{||w||},$$

where w is the normal vector and b is the displacement term. Assuming hyperplane (w,b) can classify samples correctly, that is:

$$\begin{cases} w^T x_i + b \geq +1, y_i = +1 \\ w^T x_i + b \leq -1, y_i = -1 \end{cases}.$$

It is necessary to find w and b that can satisfy constraints to minimize interval $\frac{\|w\|}{2}$, that is:

$$\max_{w,b} \frac{\|w\|}{2},$$

$$s.t.\ y_i(w^T x_i + b) \geq 1,$$

Equivalent to:

$$\min_{w,b} \frac{1}{2}\|w\|^2,$$

$$s.t.\ y_i(w^T x_i + b) \geq 1.$$

(3) Back-propagation neural network (BPNN)

BPNN is one of the most commonly applied artificial neural network models [14]. With good autonomous training and learning capabilities, it is widely used in scenarios such as speech recognition and image processing. The advantage of BPNN lies in its learning ability, but it converges slowly [15]. It can be optimized in combination with a genetic algorithm (GA) to obtain the optimal weight threshold of BPNN. The steps of the GA-BPNN algorithm are as follows.

① Determine the topology of the BPNN and initialize the network.

② Determine the chromosome length and encode to obtain the initial population.

③ Take the reciprocal of the mean square error as the fitness function in the GA.

④ Perform genetic operations: use roulette for selection operations, and use real number crossover for crossover operations. For mutation operations, randomly select an individual and mutate it to obtain a new individual according to a certain probability.

⑤ Compute the fitness value and keep iterating until the termination condition is reached.

⑥ Obtain the weights and thresholds optimized by the GA and input them into the BPNN to complete the training.

4 Results and analysis

4.1 Experimental setup

All data processing and model construction were completed in the Python 3.8 environment. Before being input into the machine learning models, the data was standardized using Z-score normalization to transform it into a distribution with a mean of 0 and a standard deviation of 1. All models used the same input features and data partitioning method. The experiment employed five-fold cross-validation. RF and SVM determined their optimal parameters using the grid search method [16].

RF:
n_estimators: 500
Criterion: gini
max_depth: 10
min_samples_split: 5
min_samples_leaf: 2
random_state: 42
SVM:
C:1.0
Kernel: rbf
Gamma: scale
random_state: 42

In the GA-BPNN algorithm, the number of input nodes was 18 (18 indicators in Table 3), and there was one output node. The number of nodes in the hidden layer was determined using an empirical formula: $y=\sqrt{m+n}+a$, where $m = 1$, $n = 18$, and a is a constant between 1 and 10.

Then, each architecture was trained using the same hyperparameters. After the training was completed, the AUC value was calculated. The architecture that achieved the highest AUC value was selected as the final architecture. It was found that when the number of hidden layer nodes was 10, the AUC value was the highest. Therefore, the BPNN architecture was determined to be: 18-10-1. The optimal weight and threshold values of the BPNN were determined by the GA. In the GA, the population size was 50, the number of iterations was 100, and the probabilities of crossover and mutation were 0.8 and 0.1, respectively. During the training, the number of epochs was set to 300, the batch size was 32, the binary cross-entropy loss function and Adam optimizer were used, the learning rate was 0.001, and early stopping was enabled to prevent overfitting.

The recognition of enterprise financial fraud is a two-classification problem and therefore can be evaluated based on a confusion matrix (Table 4).

Table 4: Confusion matrix.2

	Identified as positive	**Identified as negative**
Actually positive	TP	FN
Actually negative	FP	TN

The specific evaluation indicators included:

$$Accuracy=\frac{TP+TN}{TP+FP+FN+TN},$$

$$Recall=\frac{TP}{TP+FN},$$

$$Precision=\frac{TP}{TP+FP},$$

$$F1=\frac{2\times Precision\times Recall}{Precision+Recall}.$$

AUC value: it denotes the area beneath the receiver operating characteristic curve, a graphical plot that uses the false positive rate (FPR) as the horizontal axis and the true positive rate (TPR) as the vertical axis [17]:

$$TPR=\frac{TP}{TP+FN},$$

$$FPR=\frac{FP}{FP+FN}.$$

However, in the identification of enterprise financial fraud, it is more essential to accurately identify enterprises with fraud, i.e., the recall rate is more important. AUC can comprehensively measure the discrimination ability of an algorithm. Therefore, this paper mainly used the recall rate and AUC value.

4.2 Analysis of results

Two experiments were designed:

(1) use only financial indicators;

(2) use both financial indicators and non-financial indicators.

The results of three machine learning algorithms for different features are displayed in Table 5.

Table 5: Recognition performance of different algorithms.3

		Recall rate	AUC
Financial indicators	RF	0.5762±0.021	0.6331±0.025
	SVM	0.6685±0.025	0.7346±0.026
	GA-BPNN	0.7742±0.027b	0.8009±0.027b
Financial indicators + non-financial indicators	RF	0.6295±0.023a	0.6874±0.026a
	SVM	0.7148±0.026a	0.7856±0.027a
	GA-BPNN	0.8256±0.028ab	0.8537±0.029ab

Note: a indicates $p < 0.05$ compared to using financial features only; b indicates $p < 0.05$ compared to RF and SVM.

According to Table 5, in terms of indicator selection, the recognition performance of several algorithms improved after adding non-financial indicators. For example, the recall rate of the RF algorithm rose from 0.5762 ± 0.021 to 0.6295 ± 0.023, and the AUC rose from 0.6331 ± 0.025 to 0.6874 ± 0.026. Statistical tests suggested $p < 0.05$. Similar improvements were observed in SVM and GA-BPNN. The results indicate that non-financial indicators can provide a lot of information related to financial fraud and are useful for identifying financial fraud in enterprises.

Then, when comparing different machine learning algorithms, the GA-BPNN algorithm outperformed the RF and SVM algorithms in both experiments ($p < 0.05$). When using both financial and non-financial indicators simultaneously, the recall rate of the GA-BPNN algorithm was 0.8256 ± 0.028, which was 31.17% higher than that of the RF algorithm and 15.5% higher than that of the SVM algorithm. The AUC value was 0.8537 ± 0.029, showing an increase of 24.19% over the RF algorithm and 8.67% over the SVM algorithm. The results demonstrated the superiority of the GA-BPNN algorithm in identifying enterprise financial fraud. This may be because there is a very complex and highly non-linear relationship between financial and non-financial indicators. In terms of automatically capturing and modeling this complex nonlinear interaction effect, BPNN has more advantages.

According to the feature importance of each variable obtained by the RF algorithm, the top five features are shown in Table 6.

Table 6: Analysis of feature importance.4

	Feature importance
Shareholding ratio of the largest shareholder	0.081
Inventory turnover rate	0.067
Asset-liability ratio	0.056
Growth rate of total assets	0.051
Financial leverage	0.043

It was seen from Table 6 that the shareholding ratio of the largest shareholder was the most important factor in identifying financial fraud in enterprises. In reality, the fraud of Kangmei Pharmaceutical is associated with the imbalance of the equity structure, and the major shareholder may manipulate financial data through acts such as fictitious transactions. The importance of the inventory turnover rate was secondary. For instance, Zhangzi Island's fraud used the means of falsely increasing inventory. Abnormal fluctuations in the asset-liability ratio suggest that there might be problems with the business. For example, Enron Corporation concealed its debts, which led to an undervaluation of the asset-liability ratio. The abnormal surge in the growth rate of total assets may be related to inflated assets. For example, Kangdexin Composite Material Group inflated profits of 11.9 billion yuan. In the fraud case of Yongcheng Coal and Electricity Holding Group Co., Ltd., its financial leverage was very high. Based on these results, these indicators can be focused on in practice.

5 Discussion

This paper constructed a financial fraud behavior identification indicator system that combined financial and non-financial indicators, and compared the performance of three machine learning models, namely RF, SVM, and GA-BPNN, in the identification of financial fraud behaviors. Experiments demonstrated that the GA-BPNN algorithm achieved the best performance in identifying financial fraud behaviors (recall rate: 0.8256, AUC value: 0.8537). From this result, it can be seen that the financial fraud behavior of enterprises is not a direct result of the abnormality of a single financial ratio but a complex phenomenon generated through the interaction of various factors. There is a highly complex and non-linear relationship between financial and non-financial indicators. Compared with RF and SVM, BPNN has a greater advantage in automatically capturing and modeling this complex interaction effect. Moreover, the introduction of GA effectively overcomes the inherent defects of traditional BPNN. It not only enhances the identification performance of the model but also improves the stability and robustness of training. Therefore, the GA-BPNN algorithm demonstrated the best performance in identifying financial fraud behaviors.

In current research on identifying financial fraud behaviors, most studies rely on logistic regression or use only a single financial indicator, resulting in poor identification effects. Moreover, the results of the feature importance analysis of RF showed that the "shareholding ratio of the largest shareholder" was the most important indicator for identifying financial fraud behaviors, effectively proving the importance of non-financial indicators. Moreover, the "inventory turnover rate", as the second most important identification indicator, showed that inflating profits by manipulating inventory is a common financial fraud behavior at present. This result strongly supports the hypothesis of this paper, i.e., combining financial and non-financial indicators can effectively strengthen the predictive power of the model.

Based on the research results, the GA-BPNN algorithm can be used as a tool for auxiliary auditing and regulatory screening, providing references for auditors, regulatory agencies, etc. However, in actual deployment, the limitations of the GA-BPNN algorithm need to be further considered. The performance of this model was verified on a specific Chinese A-share dataset. Its universality across countries and markets remains to be verified. Moreover, the input of the model depended on historical data, and the feature selection method was relatively simple. In the future, it is necessary to verify the results on a wider range of samples, explore more feature selection methods, and compare it with more deep learning and statistical methods.

The GA-BPNN algorithm combines the GA and neural network. Its training complexity is higher than that of RF and SVM. However, after the training is completed, BPNN has a relatively fast prediction speed, which can meet the needs of most real-time detections. In addition, as a black-box model, it is difficult to directly explain the decision-making logic of the GA-BPNN algorithm to auditors, regulatory agencies, or corporate management.

Moreover, with the popularization of such models, there is a risk that companies deliberately avoid the red lines of the model, i.e., the gaming indicator. The limitations of the GA-BPNN algorithm require the model to evolve from a static predictor to a dynamic adaptive system to ensure the robustness of the nonlinear multivariable system [18]. To overcome this defect, in future work, for the high-risk cases identified by the GA-BPNN algorithm, interpretable artificial intelligence technologies such as Shapley additive explanations can be employed to explain the decisions of the GA-BPNN algorithm, generating audit trails and reports for business and regulatory purposes. Additionally, exploring the construction of an online learning or continuous learning framework can enhance the model's dynamic adaptation ability.

6 Conclusion

This paper analyzed the identification of enterprise financial fraud from the perspective of machine learning and compared the identification performance of three machine learning algorithms. Experiments demonstrated that using financial and non-financial indicators can achieve better identification results compared to using only financial indicators. Among the three algorithms, the GA-BPNN algorithm demonstrated the best performance with a recall rate of 0.8256 ± 0.028 and an AUC value of 0.8537 ± 0.029. This algorithm can be applied to the identification of actual financial fraud in enterprises.

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