Financial Risk Early Warning Model of Listed Companies Under Rough Set Theory Using BPNN

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ABSTRACT

In order to reduce the risk of enterprise management, the financial risk early warning methods of listed companies are mainly studied. The financial risk characteristics of listed companies are analysed. With the help of rough set theory, the financial risk indicators are selected, and the financial risk early warning index system is established. The financial risk early warning model is constructed by using back propagation neural network (BPNN) algorithm based on deep learning. Finally, the accuracy and feasibility of the constructed neural network model are verified. The results show that rough set theory can be used to screen financial risk indicators and select important indicators, which can simplify the data and reduce the complexity of calculation. BPNN can calculate the simplified data and identify and evaluate the financial risk. Empirical analysis shows that the proposed method can shorten the training time of the model to a certain extent and improve the accuracy of financial risk prediction.

KEYWORDS

BPNN, Early Warning, Financial Risk, Rough Set Theory

INTRODUCTION

The rapid development of China’s national economy has led to the proliferation of enterprises. At the same time, the instability of the market environment means enterprises face increasing competitive pressure, and listed companies face even greater financial risks (Zaki, 2017). Finance is the foundation of an enterprise. In particular, for listed companies, once the financial risk of enterprises is out of control, it will lead to a certain financial crisis and even bankruptcy (Fichtner et al., 2017). Therefore, evaluating and predicting the financial risk faced by listed companies and giving early warning is the direction that companies need to focus on at present (He & Chen, 2020). In the market economy environment, financial risk runs through all the links of capital flows and the financial management of enterprises, which is the comprehensive, concentrated expression of various risks of enterprises and is also a serious problem faced by enterprises (Du et al., 2021). Therefore, to analyze enterprises’ financial risk and detect the occurrence signal of the financial risk in advance can enable the decision-
makers of enterprises to control the financial risk in time and take corresponding measures to prevent the occurrence of financial risks and reduce the bad influence on the enterprise.

Recently, the continuous development of science and information technology has brought new opportunities to all walks of life (Huang et al., 2018). The rapid and continuous changes of the market economy have led to a more diverse set of financial risks to enterprises, so traditional risk identification methods are limited (Lin et al., 2018). The continuous promotion of artificial intelligence and the popularization of neural network algorithms have injected new vitality into enterprise development. After the risk indicators for listed companies are simplified by rough set theory, the processed data are input into a back-propagation neural network (BPNN) to calculate listed companies’ financial risk assessment and prediction. The financial risks faced by listed companies are diverse and uncertain (Zhou et al., 2019; Liu et al., 2021). Therefore, they cannot meet the current needs to evaluate them through the existing historical data and experience. Rough set theory provides a powerful foundation for data mining and simplifies the risk data factors and supports selecting key risk indicators (Błaszczyński et al., 2021). Then, the BPNN algorithm trains and learns the risks to establish the financial risk assessment model and improve the scientific and intelligent financial risk early warning. By using scientific principles in the study of financial risk early warning models, listed companies can help enterprises avoid a crisis caused by financial risks and help them develop (Jin et al., 2018; Qiao et al., 2021; Wu et al., 2022; Yu et al., 2021). At the same time, it can also help enterprises make reasonable development plans and project decisions, reduce the adverse effects of market economic turbulence and enhance the ability to resist financial risks.

Based on the existing research, listed companies’ financial risk early-warning models are studied. First, the financial risk characteristics of listed companies are analyzed. Then, the financial risk index factors are simplified through rough set theory, the key indicators are selected, and the financial risk early-warning index system is established. Then, the BPNN algorithm is used to build a financial risk early-warning model to calculate, predict, and evaluate the simplified indicator data. Finally, through empirical analysis, the accuracy and feasibility of the neural network model are verified. At the same time, we briefly analyze the internal and external influencing factors and control methods of financial risk.

METHOD

Early Warning Based on Financial Risk

The concept of early warnings based on risk originates from military behaviors using early warnings and specific signals to warn of danger and risk. The degree of the risk is determined according to the signal, and control measures are taken to minimize the losses caused by war (Dong et al., 2018; Xiang & Qu, 2020; Ma et al., 2021). Kliestik et al. (2018) used a single financial variable to conduct bankruptcy prediction research. First, 19 companies were included in the sample, and they divided the sample data into bankruptcy vs. non-bankruptcy groups. Researchers paid attention to the financial early-warning model over the next ten years in the model. Helhel (2018) selected 30 financial indicators for 79 failed enterprises and 79 normal enterprises with similar industry types and asset scales in the United States for analysis. Their research methods include mean comparison, partition test, and likelihood analysis. Finally, Beaver’s investigation shows that the working capital flow/total debt indicator has the greatest discrimination in predicting financial crisis among the five financial indicators used. The accuracy rate of predicting enterprise failure in the year before enterprise failure is as high as 87%. The result far exceeds the random prediction model, followed by the discrimination effect of return on assets.
Using Neural Networks for Early Warnings

With the rapid development of computer technology, the neural network model was first proposed in the 1920s and gradually applied to company financial risk early warning. Geng et al. (2021) applied the neural network theory to the research of financial risk early warning systems, in which the input layer has five nodes and five financial ratios, the hidden layer has five nodes, and the output layer has one node. The data samples come from five types of financial data from 65 bankrupt and 64 non-bankrupt companies in recent 20 years. At the same time, they compare the neural network model with the multivariate discriminant analysis model. The test accuracy of the neural network model for samples was higher than the discriminant model method, which can better solve the problem of company classification. Xu et al. (2020) selected 59 bankrupted banks and the same number of non-bankrupted banks as samples and used neural networks, linear discriminant analysis, multiple logistic regression, decision tree algorithm, and k-nearest neighbor method for prediction. The comparison results show that the neural network model prediction accuracy is the highest.

The research and development of the financial risk early-warning model system have been carried out for decades, and many scholars have made many achievements in theoretical research. Foreign research on enterprise financial risk early-warning started earlier and presents rich research results. From single financial variable models to multivariable financial models, from logistic regression models to neural network models, and from financial indicators as to the center to introducing cash flow and non-financial indicator system, many results have been achieved in empirical research on risk early warning theory (Chung & Lee, 2019). However, there are several outstanding problems we address in the current research. First, the standard definition of whether to fall into a financial crisis is ST company, which is too limited and not scientific and rigorous. Second, the selection of an early warning indicator system is not comprehensive and often does not reflect the comprehensive financial situation of the company. Third, the neural network early warning system research method mostly adopts BPNN. We ignore the limitations of BPNN in determining weights and thresholds.

Basis of the Theoretical Research

This research draws on two theoretical foundations: rough set theory and BPNN.

Rough set theory can be used when fuzzy and uncertain knowledge are managed. The basic idea behind the theory is to derive classification rules of concepts through attribute reduction on the premise of keeping the ability of data classification unchanged. The factors that affect the ability of data classification are diverse, and different factors occupy different degrees of importance. Therefore, some factors will play a decisive role in the ability of data classification (Hu & Yao, 2019). A certain dependency relationship among the attributes can be analyzed and found through the rough set theory. Meanwhile, the dependency degree of the attributes can be calculated, the redundant attributes can be simplified, and the most important attributes can be selected (Das et al., 2018).

There are several important steps in the rough set, such as knowledge and knowledge base, indistinguishable relation, approximate set, information system and decision table, knowledge reduction, and acquisition and measurement of kernel decision rules. The rough set is domain \( U \), in which subsets are regarded as an abstract knowledge of domain \( U \), and a subset represents an information grain. The domain is defined, a set of equivalence relations \( S \) on the domain is given, and \( K=(U, S) \) is regarded as the knowledge base of the domain. If there is \( K=(U, S) \) and an equivalent relation \( P\Pi S \) in the knowledge base, and \( \forall R\Pi P \), when:

\[
IND(P) = IND\left( P - \{R\}\right)
\]

It is considered that knowledge \( R \) is not necessary in \( P \); otherwise, it is considered necessary. If \( G \) is independent and \( IND(G) \) is equal to \( IND(P) \), \( G \) is regarded as a reduction of \( P \), which is
represented by $G\overline{RED}(P)$. $RED(P)$ is used to represent the set of all attributes in $P$ after reduction. In the knowledge base, for any $R$, when:

$$IND(P) = IND(P - \{R\})$$

(2)

It is considered that $R$ is an indispensable knowledge in $P$, and the set composed of $R$ is regarded as the core of $P$, which is represented by $CORE(P)$. In rough set theory, the kernel is unique. There is a relationship $CORE(P) = \overline{RED}(P)$ between the core and the reduction, so every knowledge reduction contains the core, which is the basis of reduction.

The importance of the attribute can be determined by calculating the degree of interdependence between two attribute sets $P$ and $R$, and $\gamma R(P)$ is used to express the degree of dependence of attribute $P$ on $R$. The use of rough set theory can reduce the indicator attributes of financial risk, simplify the redundant data, and calculate the specific dependence of decision attributes on conditional attributes (Koyuncugil & Ozgulbas, 2012).

BPNN is an artificial neural network that simplifies, abstracts, and simulates the human brain neural network from the perspective of information processing through mathematical, physical, and other methods to solve uncertain and complex nonlinear problems (Yang & Wang, 2020). BPNN is a widely used artificial neural network with three components: an input layer, a hidden layer, and an output layer. Each node in the network represents a neuron, and there is no connection between nodes in the same layer of the network (Wang et al., 2017). Fig. 1 shows the information transmission process of a neural network. Fig. 2 shows the BPNN structure.

When BPNN is used for calculation, the neural network should be initialized first, and the weights and thresholds between the neural network layers should be given. The input layer data and the corresponding expected value should be selected randomly. The input data $S_j$ of each neuron in the hidden layer is calculated by connecting the weights, thresholds, and input layer network. The activation function $f(x)$ is used to process $S_j$, and the output value $b_j$ of each neuron is calculated. The input value $l_t$ of each unit in the output layer is calculated through the output value $b_j$ of the middle layer, the weight $V_{jt}$ of the connection layer and the threshold value $\gamma_t$. The response value $c_i$ of each element is calculated by $l_t$ and activation function $f(l_t)$. The calculation method is as follows.

$$c_i = f(l_t)$$

(3)

$$l_t = \sum_{j=1}^{P} V_{jt} \cdot b_j - \gamma_t$$

(4)

The correction error $d_t$ of each unit in the output layer is calculated through the expected output value $y_t$ and the actual output value $c_i$ of the network. The calculation method is as follows.

$$d_t = \sum (y_t - c_i) \cdot c_i (1 - c_i)$$

(5)

The correction error $e_j$ of the middle layer, the new connection weights between the middle layer and the output layer, and the new connection weights between the input and middle layers are calculated layer by layer. The next learning mode is trained randomly, and then it is necessary to return to the calculation step of the output value of each neuron in the hidden layer for repeated training. After all the training samples have completed the calculation training, samples are continuously selected for
Figure 1. Information transmission process of neural network (A: biological neural network information transmission process; B: artificial neural network information transmission process)

A

Nerve electrical pulse

Neurotransmitter production

Neurotransmitter release

Transmitter and receptor binding

Electrophysiological response

B

Data

Connection weight

Functional relationship

Output data

Figure 2. Structure of the BPNN

Data(x) → Input layer → Hidden layer

Desired output (y) → Compare → Output layer

Error
Figure 3. Learning process of BPNN

Table 1. Selection results of financial risk early warning indicators

<table>
<thead>
<tr>
<th>First level indicators $A_i$</th>
<th>Profitability $A_1$</th>
<th>Operation capability $A_2$</th>
<th>Debt-paying ability $A_3$</th>
<th>Development capacity $A_4$</th>
<th>Cash flow capacity $A_5$</th>
<th>Non-financial indicators $A_6$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return on assets $a_1$</td>
<td>Total assets turnover $a_3$</td>
<td>Asset current ratio $a_7$</td>
<td>Total assets growth rate $a_9$</td>
<td>Net amount / net profit $a_{12}$</td>
<td>Period total of guarantee $a_{15}$</td>
<td></td>
</tr>
<tr>
<td>Return on total assets ratio $a_2$</td>
<td>Turnover rate of accounts receivable $a_4$</td>
<td>Asset quick rate $a_7$</td>
<td>Revenue growth rate $a_{10}$</td>
<td>Net amount / current liabilities $a_{13}$</td>
<td>Executive consistency $a_{16}$</td>
<td></td>
</tr>
<tr>
<td>Inventory turnover $a_5$</td>
<td>Debt to asset ratio $a_8$</td>
<td>Net profit growth rate $a_{11}$</td>
<td>Net amount / liabilities $a_{14}$</td>
<td>Largest shareholder shareholding ratio $a_{17}$</td>
<td></td>
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</tr>
</tbody>
</table>
training until the global error value of the neural network reaches the allowable range or the maximum number of learning and training times of the neural network are reached. Finally, the training of the neural network is completed. Fig. 3 shows the learning process of BPNN.

**Indicator System Construction**

According to the previous construction process of financial risk early warning model of listed companies, and based on the analysis of existing research, six first-level indicators are proposed, namely profitability risk, operation capacity, debt-paying ability, development capacity, cash flow capacity risk, and non-financial indicator risk, represented by \( A_1, A_2, A_3, A_4, A_5 \) and \( A_6 \) in Table 1.

In addition, there are second-level indicators under the first-level indicators (Wang et al., 2017; Wang et al., 2018; Nurfalah et al., 2018; Piciullo et al., 2018; Deng et al., 2021; Liu, 2020). The risk early warning index system comprises six first-level and 22 second-level indicators.

**Establishment of the Early-Warning Model**

The financial risk early-warning model is constructed based on fair and effective capital market and real financial data (Chen et al., 2020). First, rough set theory is used to simplify the sample indicator system, and then SPSS 24.0 is used to classify the simplified indicators by using the hierarchical clustering analysis method to obtain the input value of the optimized BPNN model (Shen et al., 2019). After constructing financial risk model training, we use randomly generated samples for testing (Liu et al., 2021). Finally, the conclusion is drawn through the analysis of the results. Fig. 4 shows the research process used while building the model.

**Figure 4. Flow chart of financial risk early warning based on rough set and BPNN**

![Flow chart of financial risk early warning based on rough set and BPNN](image)

**Model Data and Parameters**

(1) Model data: in the model training process, the automobile industry of listed companies is taken as an example because this industry involves many data and receives a high degree of public attention. According to the industry classification of the China Securities Regulatory Commission in 2012, there are 99 listed companies in the automobile manufacturing industry (Feng et al., 2020). The background conditions of the selected sample companies are consistent with those of the predicted companies. Based on the automobile manufacturing industry division in the database, the different aspects of vehicle, parts and other industries are considered, and B shares and ST companies are excluded. Finally, 40 listed automobile manufacturing companies are selected as...
the research sample. The data are selected from the financial reports of various companies in 2018. Table 2 presents the sample codes.

Table 2. Sample codes of listed companies in the automobile industry

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Code</th>
<th>Abbreviation</th>
<th>Code</th>
<th>Abbreviation</th>
<th>Code</th>
</tr>
</thead>
<tbody>
<tr>
<td>Weichai Power</td>
<td>000338</td>
<td>FAW car</td>
<td>000800</td>
<td>West Pump Co., Ltd</td>
<td>002536</td>
</tr>
<tr>
<td>Jiangling Motors</td>
<td>000550</td>
<td>Ankai bus</td>
<td>000868</td>
<td>Wan’an Technology</td>
<td>002590</td>
</tr>
<tr>
<td>Wanxiang Qianchao</td>
<td>000559</td>
<td>ZCW</td>
<td>002085</td>
<td>Baling Technology</td>
<td>002592</td>
</tr>
<tr>
<td>Weifu hi tech</td>
<td>000581</td>
<td>Tianrun crankshaft</td>
<td>002283</td>
<td>BYD</td>
<td>002594</td>
</tr>
<tr>
<td>Chang An auto</td>
<td>000625</td>
<td>Asia-Pacific shares</td>
<td>002284</td>
<td>Longsheng Co., Ltd</td>
<td>002625</td>
</tr>
<tr>
<td>Tianxing instrument</td>
<td>000710</td>
<td>Xingmin Wheel</td>
<td>002355</td>
<td>Dongfeng Motor</td>
<td>600006</td>
</tr>
<tr>
<td>Steyr</td>
<td>000760</td>
<td>Jingu Co., Ltd</td>
<td>002488</td>
<td>Yutong Group</td>
<td>600066</td>
</tr>
<tr>
<td>JAC Motors</td>
<td>600418</td>
<td>King Long</td>
<td>600686</td>
<td>FAW Fuwei</td>
<td>600742</td>
</tr>
<tr>
<td>Shenyang Jinbei Auto</td>
<td>600609</td>
<td>Huayu Auto</td>
<td>600741</td>
<td>AVIC black leopard</td>
<td>600760</td>
</tr>
<tr>
<td>Great Wall Automobile</td>
<td>601633</td>
<td>Lifan Co., Ltd</td>
<td>601777</td>
<td>China Automotive</td>
<td>601965</td>
</tr>
<tr>
<td></td>
<td></td>
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<td></td>
<td>Research Institute</td>
<td></td>
</tr>
</tbody>
</table>

(2) Parameter setting: the input layer node is the number of core indicators after rough set filtering, which is 17. The output layer is the predicted category. According to the cluster analysis results, there are five types of corporate financial types, and the output layer is 5. The hidden layer belongs to the neural center of the neural network, which trains the internal rules of training samples, and the nodes of the hidden layer affect the learning effect. Too many nodes lead to a long learning time; too few nodes lead to poor fault tolerance. The number of nodes directly relates to the model’s performance, but there is no accurate model of nodes. We summarize the research experience and experimental data. The equation calculates the number of hidden layer nodes; that is, the maximum value of L is 12.

RESULTS

Reduction Results of Rough Sets

For the information system $S=\{U,A\}$ formed by the indicator system, the research sample field is: $U=\{1,2,3,\ldots,40\}$, the condition attribute is $A=\{A1,A2,A3,A4,A5,A6\}$, where $A1=\{a1,a2,a3,a4\}$, $A2=\{a5,a6,a7,a8\}$, $A3=\{a9,a10,a11\}$, $A4=\{a12,a13,a14\}$, $A5=\{a15,a16,a17,a18\}$, and $A6=\{a19,a20,a21,a22,a23\}$. The following results can be obtained by simplifying the first-level indicator A1.
To sum up, it can be obtained that: \( \text{U/ind}(A1) = \text{U/ind}(A1 - \{a3\}) = \text{U/ind}(A1 - \{a4\}) \) \( \text{U/ind}(A1 - \{a1\}) \) \( \text{U/ind}(A1 - \{a2\}) \). Therefore, indicators \( a1 \) and \( a2 \) are necessary attributes in \( A1 \), and indicators \( a3 \) and \( a4 \) are reduced. The first-level indicator \( A2 \) is simplified, and it can be obtained that:

\[
\begin{align*}
U / \text{ind} \left( A2 \right) &= \{2,24,30,38\}, \{2,24,30,38\}, \{2,4,21\}, \{37\}, \{9\}, \{6\}, \{34\} } \\
&= \{1\}, \{22,33\}, \{23,11,32\}, \{10,26\}, \{3,5,7\} } \\
&= \{8,12,13,14,15,16,17,18,19,20,25,27,28,29,31\} \\
\end{align*}
\]

\[
\begin{align*}
U / \text{ind} \left( A2 - \{a5\} \right) &= \{22,24,30,33\}, \{34\}, \{2,11,23,32\}, \{9\}, \{38\} } \\
&= \{26,10\}, \{4,21\}, \{6\}, \{1,3,13\}, \{37\}, \{5,7,8,12\} } \\
&= \{14,15,16,17,18,19,20,25,27,28,29,31,35\} \\
\end{align*}
\]

\[
\begin{align*}
U / \text{ind} \left( A2 - \{a7\} \right) &= \{2,4,21,38\}, \{1\}, \{26,3,10,13\}, \{37\}, \{19,35\} } \\
&= \{5,7,8,12,14,15\}, \{16,17,18,19,20,25,27\} \\
\end{align*}
\]

\[
\begin{align*}
U / \text{ind} \left( A2 - \{a8\} \right) &= \{24,30\}, \{2\}, \{9\}, \{34\}, \{22,33\}, \{11,23,32\} } \\
&= \{38\}, \{4,21\}, \{6\}, \{1\}, \{26,10\}, \{3,13\} } \\
&= \{5,7,8,12,14,15\}, \{16,17,18,19,20,25,27\} \\
\end{align*}
\]

To sum up, it can be obtained that: \( \text{U/ind}(A2) = \text{U/ind}(A2 - \{a8\}) \) \( \text{U/ind}(A2 - \{a5\}) \) \( \text{U/ind}(A2 - \{a6\}) \) \( \text{U/ind}(A1 - \{a7\}) \). Therefore, indicators \( a5, a6 \) and \( a7 \) are necessary attributes in \( A1 \), and indicator \( a8 \) is reduced. The first-level indicator \( A3 \) is simplified, and it can be obtained that:

\[
\begin{align*}
U / \text{ind} \left( A3 \right) &= \{14\}, \{25\}, \{3,1,11,22,33,38\}, \{1,37\} } \\
&= \{20\}, \{15\}, \{34\}, \{36\}, \{21,34\}, \{4,27\} } \\
&= \{10,28,32\}, \{6,17\}, \{23\}, \{7,30,31\}, \{9,16,26\} \\
\end{align*}
\]

\[
\begin{align*}
U / \text{ind} \left( A3 - \{a9\} \right) &= \{2,3,11,21,22,24,33,38\}, \{1,4,37,37\}, \{10,14\} } \\
&= \{6,15,17,25\}, \{13,23\}, \{7,8,30,31,34\}, \{9,16,26\} } \\
&= \{19,29\}, \{5,12,18,35,36,39,40\} \\
\end{align*}
\]
To sum up, it can be obtained that: \( U/\text{ind}(A3) \cap U/\text{ind}(A3 - \{a9\}) \cap U/\text{ind}(A3 - \{a10\}) \cap U/\text{ind}(A3 - \{a11\}) \). Therefore, the indicators \( a9 \), \( a10 \) and \( a11 \) are necessary attributes in \( A3 \), and there is no reducible indicator. The first level-indicator \( A4 \) is simplified, and it can be obtained that:

\[
U/\text{ind}(A4) = \left( \{16,13,20,23\}, \{22\}, \{15\}, \{3,36\}, \{18\}, \{37\} \right)
\]

\[
U/\text{ind}(A4 - \{a12\}) = \left( \{1,2,6,8,10,11,13,16,20,23,24\}, \{22,37\}, \{4,28\} \right)
\]

\[
U/\text{ind}(A4 - \{a13\}) = \left( \{1,3,6,13,15,20,23,36\}, \{18,22\}, \{31\}, \{2,5,7\} \right)
\]

\[
U/\text{ind}(A4 - \{a14\}) = \left( \{1,3,6,13,15,20,23,36\}, \{22,37\}, \{4,28\}, \{2,4,10,11\} \right)
\]

To sum up, it can be obtained that: \( U/\text{ind}(A4) \cap U/\text{ind}(A4 - \{a12\}) \cap U/\text{ind}(A4 - \{a13\}) \cap U/\text{ind}(A4 - \{a14\}) \). Therefore, indicators \( A12 \), \( A13 \) and \( A14 \) are necessary attributes in \( A4 \), and there is no reducible indicator. The first-level indicator \( A5 \) is simplified, and it can be obtained that:

\[
U/\text{ind}(A5) = \left( \{2,20\}, \{12\}, \{1,3,15,36\}, \{11,18\}, \{28\}, \{4\} \right)
\]

\[
U/\text{ind}(A5 - \{a15\}) = \left( \{2,20\}, \{12\}, \{1,3,15,36\}, \{4\}, \{7,9,10,26,29\} \right)
\]
Moreover, it is necessary to focus on the second-level indicators of enterprises, it is necessary to pay attention to the development of enterprises and improve the debt-paying ability and operation capability of enterprises. Therefore, to reduce the financial risk value of enterprises is the development capacity of enterprises, followed by the debt-paying ability of enterprises. Therefore, to reduce the financial risk value of enterprises is the development capacity of enterprises, followed by the debt-paying ability of enterprises.

Fig. 5 is the calculation results of the first level indicator weight. It suggests that the biggest impact on the financial risk of enterprises is the development capacity of enterprises, followed by the debt-paying ability and operation capability of enterprises. Therefore, to reduce the financial risk value of enterprises, it is necessary to pay attention to the development of enterprises and improve the debt-paying and operation ability of enterprises. Moreover, it is necessary to focus on the second-level indicators of enterprises, it is necessary to pay attention to the development of enterprises and improve the debt-paying ability and operation capability of enterprises.
level indicator, which accounts for a relatively large proportion under the first-level indicator, to improve enterprises’ ability to resist financial risks and maintain the long-term stable development of enterprises in Fig. 6.

**Figure 5. Calculation results of the first level indicator weight**

![Figure 5](image)

**Figure 6. Weight calculation results of the second-level indicators**

![Figure 6](image)
Data Standardization Processing

Based on the data value and importance, the first level indicator (A1 − A6) of the indicator system is weighted and evaluated according to the equation, and the standardized data of 30 research samples are obtained. The standardized data results of enterprises are in six aspects. Fig. 7 shows data standardization results. It reveals that the results of non-financial indicators are essentially stable, and the proportion of indicators is the smallest, while the proportion of other indicators in different listed companies is quite different.

Cluster Analysis of Financial Risk

Based on the data value and importance, the first-level indicator (A1 − A6) of the indicator system is weighted and evaluated according to the equation, and the standardized data of 30 research samples are obtained; that is, the standardized data results of enterprises have six key aspects. It suggests that the F-value of the first-level indicator A3 is the largest, showing that the difference is significant, and the differences among several indicators are obvious. The significance analysis shows that the indicators’ difference is less than the critical value of 0.05, suggesting statistical. Table 3 is a report of cluster analysis results from a one-way ANOVA.

Fig. 8 is the analysis report on clustering means. The results show that 17 companies have healthy financial risk levels and low risks, such as Weichai Power, Jiangling Motors, Yutong Group, and SAIC Motor. The financial situation of 16 companies, such as SG Automotive Group, Steyr, BYD, Dongfeng Technology, is good. China automotive research institute has a general financial situation. The financial situation of three companies, namely, Yaxing bus, Shenyang Jinbei Automotive, and AVIC black leopard, is in a light state of alarm, so managers should pay attention to their enterprise’s financial situation. The financial situation of three companies, namely, Baling technology, Weifu high tech, and Longsheng Co., Ltd., is in a severe state of alarm, so managers must pay attention to their company situation and take timely measures to avoid further losses.
An Empirical Study on the Financial Risk Model

The risk category is divided into five levels: health, good, general, light warning, and severe warning. The rough set BPNN financial risk early warning model is used to train and learn, verifying the model’s accuracy. Fig. 9 presents the analysis results. Fig. 9 shows that the accuracy of the proposed financial risk early-warning model results is over 90%, and the wrong data is less than one-tenth of the correct data, which proves that the model proposed has high calculation accuracy and the overall early warning effect is relatively good. Therefore, it can be applied to the actual financial risk early warning of listed companies, improve the efficiency and accuracy of financial risk early warning, and help enterprises resist further financial crisis. Enterprises should pay attention to and monitor the early warning results promptly. For the output of mild and severe early warning, they should pay more attention to it, take preventive and control measures, and formulate reasonable development

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Quadratic sum</th>
<th>df</th>
<th>Mean square</th>
<th>F</th>
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Table 3. Cluster analysis results from a one-way ANOVA analysis
measures, to minimize the financial crisis of enterprises and improve enterprises’ survival and development ability.

Figure 8. Clustering means analysis report

Figure 9. Accuracy analysis results of financial risk early-warning model
CONCLUSION

The primary focus of this investigation is the financial risk early-warning methods suitable for listed companies. The financial risk characteristics of listed companies were analyzed. With the help of rough set theory, financial risk indicators were selected and reduced. Through the importance degree, the key indicators were selected, and the financial risk early-warning indicator system was established. Then, the financial risk early warning model is constructed by the BPNN algorithm. The data processed by rough set theory is input into BPNN, and the financial risk was classified using hierarchical cluster analysis. Through neural network calculation, the financial risk level of listed companies was evaluated, and early warning alerts were generated. Finally, 30 listed companies were selected to verify the accuracy and feasibility of the neural network model. The empirical results show that the accuracy of the proposed method for the risk prediction results of listed companies is over 90%, which shows that the accuracy of the financial risk early warning model of listed companies is relatively high. Compared with the traditional methods, it can improve the scientific rigor of project decision-making and reduce the financial risk of enterprises. It is hoped that the model can be applied to real-world risk assessment processes to help enterprise managers make scientifically grounded decisions, promptly improve the deficiencies in the company’s development, control the financial risk according to the early warning risk outputs, and take reasonable and effective measures to reduce the probability of a financial crisis.

Due to the nature of the research, there are several limitations. Only 30 listed companies of the same type were selected for training and learning in the empirical analysis. Relatively speaking, the sample is not comprehensive, and sample data could be larger although the approach is demonstrated with this sample. It is hoped that in a follow-up study, the financial risks and early warnings for listed companies can be analyzed under the situation of multiple types and multiple data. The continuous development of deep learning and artificial neural network technology have increased enterprise risk assessment and early warning alerts. In the follow-up study, new technology can be applied to the enterprises’ financial risk early warning method, and the deficiencies of this study can be improved to enhance the model’s performance.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of interest: All Authors declare that they have no conflict of interest.

Human and animal rights: This article does not contain any studies with human participants or animals performed by any of the authors.

Informed consent: Informed consent was obtained from all individual participants included in the study.

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