Research on the Application of ANN in Enterprise Financial Risk Evaluation Information System with Digital Empowerment

Yixuan Guo(✉)

Economics and Management School, Jiangsu University of Science and Technology, Jiangsu, Zhenjiang, China
3087548445@qq.com

Abstract. This paper focuses on the field of enterprise financial risk, and innovatively proposes the application of artificial neural network (ANN) in enterprise financial risk evaluation information system, trying to highlight the superiority of ANN in enterprise financial risk evaluation information system, in order to provide information related to financial risk in a more intelligent and faster way, and provide timely early warning to managers.

Keywords: component · ANN · enterprise financial risk · evaluation information system formatting

1 Introduction

The application of emerging technologies has led to a shift from 'using digital' to 'living digital', including artificial intelligence, the Internet of Things, blockchain, etc. The ultimate goal is to provide effective and sufficient information for business decisions through models and algorithms, helping enterprises to improve the efficiency and effectiveness of management decisions. Enterprises improve their intelligent and forward-looking financial data intelligence information systems and establish intelligent, agile, systematic, in-depth and forward-looking digital and intelligent finances. These practices can largely avoid the phenomenon of data silos in corporate finance, and at the same time appear both important and urgent for the high-quality development of enterprises.

2 Literature Review

Research on the evaluation of financial risk has been at the forefront of attention of relevant scholars. Beaver, a professor of accounting at Stanford University in the US, innovatively used univariate analysis to link financial ratios to insolvency risk (Beaver, 1966) [1]. However, single-variable models have disadvantages such as harsh application conditions and narrow coverage. Haldeman and Narayanan extended the model into the ZETA model, which represents a wider marginal contribution than the previous model,

S. Tehseen et al. (Eds.): ICEDBC 2023, AEBMR 258, pp. 672–680, 2024.
https://doi.org/10.2991/978-94-6463-246-0_81

thus forming a second generation model (Haldeman & Narayanan, 1977) [2], Ohlson then refined the second generation model in his research to develop a predictive model for the probability of firm insolvency using conditional logistic analysis(Ohlson, 1980) [3]. In the 21st century, L. Molgedey et al. used the theory of information entropy to construct an early warning model for financial risk and concluded that this model is more comprehensive and accurate in determining the degree of financial risk of an enterprise among various early warning methods(L. Molgedey, 2000) [4], Ting and Morris use the entropy method to identify key indicators that have a significant impact on the financial crisis of a company and suggest effective ways to solve the financial crisis(Ting & Morris, 2001) [5], Aydogan uses the AHP method to determine the weights of the indicators in the TOPSIS method and uses them to evaluate the business performance of the company(Aydogan, 2011) [6].

Throughout the existing literature on the evaluation of corporate financial risk, there is less literature on the evaluation of corporate financial risk in combination with modern digital information technology, especially the use of neural network technology. This paper therefore introduces ANN into enterprise financial risk assessment information systems and explores the feasibility, adaptability and innovation of applying ANN to enterprise financial risk assessment information systems with digital empowerment.

3 ANN Introduction and Application

3.1 ANN Introduction

Neural Network (NN) is derived from the early neuronal models M-P and Hebb's learning law, and can be divided into two categories: Biological Neural Networks (BNN) and Artificial Neural Networks (ANN). (ANN for short). Artificial Neural Networks are widely used in Big Data technology and can be further classified into three categories: Feedforward Neural Networks, Feedback Neural Networks and Graph Networks.

ANNs are a hot topic of research in artificial intelligence that has emerged since the 1980's. ANNs abstract the neuronal network of the human brain from the perspective of information processing and build some kind of simple model to form different networks with different connections. In engineering and academic circles, it is often referred to as neural networks or neural-like networks. A neural network is an operational model consisting of a large number of nodes (or neurons) interconnected with each other. Each node represents a particular output function, called an excitation function. Each connection between two nodes represents a weighted value for the signal passing through that connection, called a weight, which is equivalent to the memory of an artificial neural network. The output of the network varies depending on how the network is connected, the weights and the incentive function. The network itself is usually an approximation of some algorithm or function in nature, or it may be an expression of a logical strategy.

3.2 ANN Application

Today, ANN is one of the frontier interdisciplinary disciplines that has been accelerating internationally. ANN emerged in the 1980s and has since accelerated to become one of the major topics of research in the new era of artificial intelligence, simulating the neural network of the human brain to obtain and process information on various aspects of data. In the study of modern neuroscience, ANN models have emerged. ANN techniques are also operational models, consisting of multiple simplistic network elements, with neurons being an important component of each simplistic network, and neurons are connected smoothly with the help of weights. From a theoretical point of view, the output of a neural network is inextricably linked to the form of the internal node connections and the weighting factor, and ANN technology involves a wide range of disciplines, such as computer science, mathematics and cybernetics, and is used in a variety of applications, for example, to collect data and information and to recognise images and languages. With ANN, machines can simulate the human brain and perform a range of operations on existing data and information, such as collecting, feeding back and scientifically 'predicting' the outcome of various aspects, automating certain complex tasks.

4 Introduction to Corporate Finance Risk

Corporate financial risk, also known as financial crisis or financial distress, refers to a situation where an enterprise is in a poor financial position for a specific period of time and faces a shortage of funds to make financial payments. Financial distress can worsen or even lead to bankruptcy if a business is exposed to financial risk and no timely action is taken. There are many reasons for financial crises, some of which are completely beyond the control of the business, such as the current Black Swan events that occur from time to time, causing a sudden downturn in the overall economy of many countries, which in turn leads to a significant drop in revenue for many companies. And more often than not, companies get into financial trouble because of their own mismanagement, such as over-borrowing and debt funding that does not yield benefits quickly enough, and companies get stuck in a quagmire of struggling to pay off their debts. Poor marketing decisions are also a common cause of financial risk. Expensive advertising campaigns that do not really translate into economic benefits can put a company in financial difficulty. Failure to collect receivables in a timely manner can also lead to serious cash flow problems for a business. Common remedial measures taken by businesses to mitigate financial distress include cutting costs, improving cash flow or revenue, and reducing the size of debt service through debt restructuring. The sooner a business takes steps to turn around its financial risk as it evolves from nothing to something less serious, the easier it is to turn the business around. Therefore, a deep insight into the financial situation and a keen awareness of financial risks are the primary prerequisites for financial risk management in an enterprise.

No matter how comprehensive the selection of financial risk indicators will never fully reflect the differences between enterprises. Between enterprises, and in particular, it is difficult to capture the differences in risk appetite, tolerance and acceptance levels. The incompleteness of financial risk indicators does not fully reflect The incompleteness of financial risk indicators also does not ensure that the existing evaluation methodologies are The incompleteness of financial risk indicators also does not guarantee the accuracy of risk evaluation results derived from existing evaluation methods. The incompleteness of financial risk indicators also does not guarantee the accuracy of risk evaluation results from existing methods. Relying solely on additional indicators is clearly not feasible. on the addition of indicators is clearly not feasible, although the increase in the number of calculations The increase in calculation volume is not a burden on modern computers and software. The increase in computational effort is not a burden on modern computers and software, but it will increase the cost of data acquisition and the independence of indicators. The independence between indicators is disturbed. This paper goes in the opposite direction. Instead of increasing the number of evaluation indicators, this paper considers the introduction of new indicators to correct the evaluation results. The paper goes in the opposite direction, instead of adding more indicators, it starts by correcting the evaluation results and considers the introduction of a factor reflecting the financial risk evaluation results by considering the introduction of a coefficient reflecting the variance of The paper does not add more indicators, but starts by correcting the evaluation results. This will make the evaluation results more accurate and refined.

5 Adaptation of ANN Technology to Evaluation

The complexity and diversity of corporate financial data, from which it is important and urgent to evaluate the financial risk of a company, also places more specific requirements on data structures and the handling of complex data, for example. The extent to which artificial neural networks are adapted to these requirements, and the extent to which they can solve the technical problems of traditional evaluation models, determines the feasibility of applying artificial neural networks to value-added evaluation practice.

5.1 ANN Technical Pathway and Evaluation Concept Adaptation

By applying ANN to the evaluation of corporate financial risk, the self-learning function of ANN can measure the explanatory weights of the independent variables on the dependent variable and analyze the 'net effect' of the reduction of corporate financial risk in terms of weight values.

In the new context, ANN technology continues to develop and continues to act as a pattern recognition, signal processing and decision aid. In optimising traditional forms of accounting information processing, companies can also take advantage of the diversity of ANN to increase the level of automated recognition of a large number of accounting elements on a daily basis. In the daily operation process, once the enterprise has economic matters occurring, economic matters can smoothly drive the event receiver of ANN under the role of relevant business modules, smoothly receive all kinds of economic matters data information generated in the process of carrying out economic activities, store them in a timely manner in the constructed resource processing system and, in turn, appear in the new economic matters document library under the role of the system. Usually, the system automatically makes use of the semantic network model and ontology knowledge tree structure to rationalise the description and scientifically identify the important business data generated in the course of the enterprise's daily operation according to various economic matters. Under the role of ANN, the business data information stored in the system has diverse characteristics, and the accounting data information obtained by the system must meet the objective requirements in terms of enterprise financial reporting, providing high reference value information data for other departments in the enterprise's internal operations, and providing a favourable guarantee for their scientific decision-making. In this way, objective presentation of all aspects of the process of carrying out various economic activities of the enterprise, for example, the flow of funds and information, real-time transmission of data on all aspects of accounting information of the enterprise, on the basis of scientific processing and automated clarification of the various elements of accounting.

In this process, enterprises can take advantage of their own operations in all aspects, cleverly use the advantages of ANN diversity, under the role of the event receiver, the scientific setting of efficient operation of the data interface, to ensure that the information management system built in the role of the data interface, regardless of time and space restrictions, at any time dynamic reception of various aspects of information data generated by the daily work of different departments.

5.2 ANN Flexibility and Evaluation Data Structure Adaptation

ANN can incorporate multiple feature variables into the input layer at the same time and its predictive models are constructed without the constraints of the statistical distribution of the data. This flexibility and openness allows for the adaptation of multiple layers of nested data in corporate financial risk assessment applications. At the same time, with its fully-connected topology and the 'squashed' nature of the activation function, ANN is highly tolerant and can indirectly increase the error tolerance of value-added evaluation in the data collection process, reducing the impact of missing and incorrect values to a minimum. In particular, the prediction accuracy of deep learning models such as ANN is significantly higher than traditional methods when dealing with large data sets.

Considering the nested data characteristics of value-added evaluation, if the data structure of the ANN middle layer is adaptively classified and transformed into a more flexible set of variables, it may simplify the complex coefficient correction procedure of the multilevel regression model and make the input process relatively independent between data. Thus, ANNs offer a degree of flexibility in data processing that is adapted to the nested interaction of multiple variables in value-added evaluation applications and to reduce the adverse effects of missing data to some extent.

5.3 ANN Inclusiveness Adapted to Evaluation Data Complexity

In terms of data complexity and model selection, ANNs eliminate the need to tediously query, represent and manipulate data, automatically approximating algorithmic functions that fit the pattern of the sample data and adaptively building relatively robust and widely used models. The more complex the influencing factors and the higher the degree of non-linearity, the more obvious this advantage of ANNs becomes. This is because ANNs are adaptive, self-learning and self-organising, and are adept at making decisions in an approximate, uncertain and even conflicting information environment. Its highly inclusive nature of complex data provides the basis for solving complex data and model selection problems in evaluation.

In addition, the ANN's 'input-implicit-output' structure can provide answers to the question of what to assess. If ANNs are used, they can be adaptive based on probabilistic

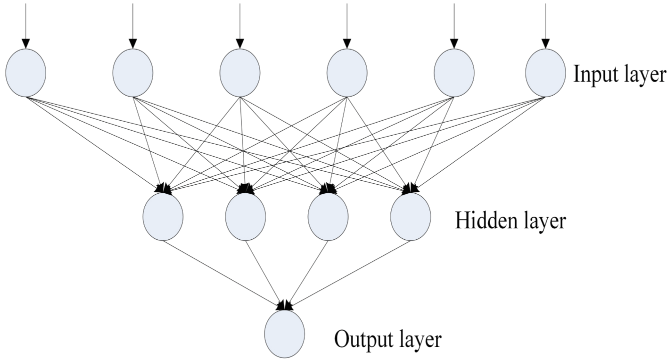

Fig. 1. ANN simulation structure diagram

logic through a multi-layered, two-way feedback mechanism, thereby incorporating non-linearly evolving core literacies into the assessment, overcoming the limitations of the assumption of constant efficacy in traditional models. As a result, ANNs are able to deal robustly with complex dependent variables that develop in a non-linear manner and are highly inclusive.

6 ANN in Evaluation Information System

6.1 Overall Application Process

According to the system requirements, the whole system is divided and designed into two parts The administration side, the back-end, is responsible for the management of operational data and user evaluation indicators. The front-end is the front-end of the system and is responsible for providing data when interacting with users. This is because the reliability and subjectivity of the system's indicator system varies. The evaluation results obtained are not comprehensive enough, so it is proposed to use data mining techniques to analyse previous historical datasets by using ANN to capture potential patterns and improve the accuracy of the evaluation model.

ANNs consist of neurons that are computationally capable and have some interconnectivity. Mature ANNs are designed to be divided into three layers; (i) an input layer, where the input data and n (neurons, neuron, are replaced by n in the text) (ii) a hidden layer, where n is a variable parameter; and (iii) an output layer, where the number of n to be consistent with the number of output targets. See Fig. 1 for a detailed diagram of the ANN simulation structure.

6.2 Specific Application Process

Two sets of models were designed for analysis, (i) a single ANN analysis model and (ii) an ANN network where all data was input into the model. The network input layer was disposed of using the mean values of reliability and subjectivity respectively, and the final expert manually aggregated ANN scores were manually set as the final evaluation model. Values as the final evaluation model. The problem design model was thrown into the conversation in order to be able to describe the model more clearly.

7 Experimental Platform

For ease of presentation, the various types of value-added evaluation models can be summarised in the following mathematical model: y = f (x1, x2,…, xn). Where y denotes the value-added outcome or exit score of the assessment object, f(x) denotes the value-added evaluation function, and {x1, x2,…, xn} denotes the associated influences on the score. Therefore, the objective of the construction and comparison of the evaluation model is to explore the evaluation function that can explain the relationship between y and x to the greatest extent possible. Accordingly, a basic strategy and workflow for the application of artificial neural networks in evaluation is proposed, as shown in Fig. 2, which first deals with the entrance problem on {x1, x2,…, xn}, including the selection, collection and standardisation of the input layer variables. The selection of variables is the key part.

Two sets of models were designed for analysis, a single ANN analysis model and an ANN network, where all data were entered into the model, the network input layer disposition was averaged with reliability and subjectivity respectively, and the evaluation values were manually set as training targets, and finally the experts manually aggregated the ANN scores as the final evaluation model. In order to be able to describe the model more clearly, the problem design model was thrown out to talk about. The set of assessment items is Q = $\{Y_1,Y_2,\ldots, Y_n\}$ and the items are Yk = $\{Yk_1,Yk_2\ldots..\}$, where Yk is the set of indicators and the number of indicators is used in the equation k_n, k = {1,2,3,…, n}.

Equation (1) is the first set of models. Model1 = ANN(Y1,Y2, ……) (1). The formula score all is the final output score, and the algorithm is used to train the training set obtained from the manual scoring of experts. Equation (2) is the second set of models. X1 = ANN(Y1,Score1),X2 = ANN(Y2,Score2),Xn = ANN(Yn,Scoren),Model_1 = ANN(X1,X2,…,Xn,scorenall). The second set of models ANN is theoretically superior to the first set of models, when multiple experts are required to join and requires the experts to evaluate each data item manually. It is because of the many practical limitations

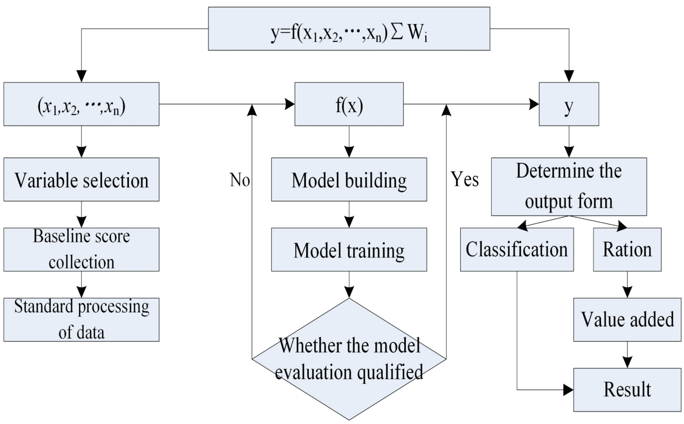

Fig. 2. ANN workflow of evaluation

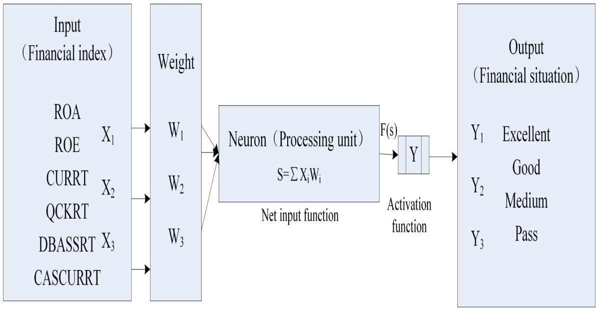

Fig. 3. ANN-based enterprise financial risk assessment information system for enterprises

that exist. It was not possible to obtain the support of multiple experts and sufficient real data to make a judgement on the validity of the student management assessment system. In order to demonstrate that the model captures the inherent patterns in the data, a set of random numbers with large values combined with variance is set up and trained with this set of data, using the experts' manual assessment data as real ratings to verify the validity of the model. See Fig. 3 for details of the process.

8 Concussion

Based on the basic theory of artificial neural networks, this paper demonstrates the adaptability of artificial neural networks in enterprise financial risk evaluation and proposes a basic application strategy. Artificial neural networks can not only adapt to the concept and technical requirements of enterprise financial risk evaluation, but also provide an intelligent path for enterprise financial risk evaluation, which has broad application prospects. At the same time, it is also necessary to deal objectively with the problems associated with artificial intelligence network technology. After dealing with the application process of variable input, model construction and result output, it is necessary to soberly understand and discover the application condition limitations and biases, and propose corresponding countermeasures to provide valuable references for the future use of artificial intelligence technology to promote enterprise financial risk evaluation reform.

References

1. BEAVER W H. Financial ratios as predictors of failure[J]. Journal of Accounting Research, 1966(4): 71–111.
2. ALTMAN E I, HALDEMAN R G, NAR AYANAN P. ZETATM analysis a new model to identify bankruptcy risk of corporations[J]. Journal of Banking & Finance, 1977, 1(1): 29–54.
3. OHLSON J A. Financial ratios and the probabilistic prediction of bankruptcy[J]. Journal of Accounting Research, 1980, 18(1): 109–131.
4. L. Molgedey, W. Ebeling. Local order, entropy and predictability of financial time series[J]. The European Physical Journal B, 2000(15): 733–737.

5. Ting Y. H., Morris H. L. Wang. Finding critical financial ratios for Taiwan's property development firms in recession[J]. Logistics Information Management, 2001(5/6): 401–412.
6. E. K. Aydogan. Performance measurement model for Turkish aviation firms using the rough-AHP and TOPSIS methods under fuzzy environment[J]. Expert Systems with Applications, 2011(4): 3992–3998.