



Comparing the Power of Predicting Financial Helplessness in the Deep Learning Method Based on the Gray Wolf Optimization Algorithm with the Artificial Neural Network Method

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ABSTRACT

Financial institutions model potential counterparty distress before lending to potential counterparties in an attempt to mitigate such losses. Therefore, one of the ways to help in the correct use of investment opportunities and also to prevent the wastage of resources is to predict financial helplessness. In this regard, in this research, a new model related to the prediction of financial helplessness is presented, in which the deep learning method based on the gray wolf optimization algorithm will be used. Then the predictive power of this model is compared with the artificial neural network method. For this purpose, the information of 160 selected firms admitted to the Tehran Stock Exchange during the period of 2016 to 2022 was used. The findings of the research related to predicting the helplessness of firms based on the deep learning method based on the gray wolf meta-engineering algorithm, showed that the percentage of success of this model in predicting the helplessness of companies is equal to 98.33%, while the power of prediction the artificial neural network method was for 94.45%. Based on this, it can be concluded that the deep learning method based on the gray wolf meta-engineering algorithm has a higher level of accuracy than the artificial neural network method in predicting the helplessness of the investigated firms.

Considering the high accuracy of the deep learning method based on the gray wolf optimization algorithm and its better performance in comparison with the ANN method algorithm, the gray wolf optimization algorithm can be used to predict the financial helplessness of Tehran Stock Exchange companies, whether for the purposes of investment and crediting or for the purpose of using the company's internal management.

Keywords: Financial Helplessness, Artificial Neural Network Method, Deep Learning Method, Gray Wolf Meta-Heuristic Algorithm



1. Introduction

One of the ways to help in the correct use of investment opportunities and also to prevent the waste of resources is to predict financial distress. In this regard, first, by providing the necessary warnings, companies can be informed of the occurrence of financial distress so that they can take the necessary measures according to these warnings, and secondly, investors can distinguish between favorable and unfavorable investment opportunities for investing their resources (Liu and Pang, 2022).

On an intuitive level, it is important to be able to predict the possibility of financial distress. Clearly, efforts to do so have been widely used. Suppose the (default) cost of financial distress is assumed to be zero, and the rights of stakeholders (for example, creditors, employees, shareholders) can be renegotiated without cost. In that case, the value of the company can be independent of the probability of financial distress. However, even in this case, it may be important to assess the likelihood of financial distress from the stakeholders' perspective, as it determines the distribution of profits associated with their investment. Of course, empirically, the costs of financial distress and renegotiation are not zero, and the value of the company may be affected by the possibility of financial distress (Ashraf et al., 2019).

Previous studies have shown that predicting the financial distress of a business or organization is very important. Since the failure of a company is clearly related to the financial features and background of the company, modeling and predicting the probability of financial distress of companies is a possible and, at the same time, necessary task. Previous studies have focused on developing statistical models and machine learning to predict financial problems. Researchers have identified warning patterns of economic problems in various sectors, but their accuracy needs to be improved. Many algorithms consider the prediction of financial distress as a binary problem, ignoring the actual duration. Also, variables and features may not be related. Based on this and according to the concepts raised and the valuable and irreplaceable role of financial distress in the development of industries and in maintaining and increasing the level of sustainable employment in the country, the present study deals with the design of a model based on deep learning to predict financial distress.

The structure of this study is such that while presenting the literature review, the GWO algorithm-based deep learning method and ANN method will be explained. Then, the research method will be introduced, and data analysis will be done. Finally, the summary and conclusion will be presented.

2. Theoretical Foundations and Research Background

During the global financial crisis in recent years, many companies have faced financial distress and bankruptcy. Currently, economic enterprises operate in a very variable and competitive environment. A quick and correct reaction against highly variable market conditions plays a significant role in the position of enterprises. With the development of monetary and financial markets and the subsequent competition, many bankrupt companies leave the competition. This causes the owners of capital to worry, and in order to prevent the wasting of their capital, they are looking for ways to predict the financial crisis of companies (Emtaj and Amini, 2022).

Predicting financial distress by providing necessary warnings can alert companies to the occurrence of financial distress and bankruptcy so that they can take appropriate measures according to these warnings. From an economic point of view, financial distress can be interpreted as the loss of the company, in which case the company has failed. In this case, the return on investment rate is lower than the cost of capital rate. Another form of financial distress also occurs when the company fails to comply with one or more clauses related to the debt contract, such as maintaining the current ratio or the net worth ratio to total assets according to the contract. This is called technical default. Other situations of financial distress are when the company's net worth becomes negative (Ebrahimi Sarvolia et al., 2019).

Finally, by predicting the financial crisis, investors not only avoid the risk of losing their capital but also use it as a tool to reduce the risk of their investment profits. Business unit managers can also take preventive measures if they know about the risk of bankruptcy in time. In this way, banks and credit institutions can avoid the risk of non-payment. Therefore, predicting bankruptcy is an important category for success in the economy. The reason for this importance is because financial distress and

bankruptcy bring a lot of costs and cause irreparable damage to a country's economy. Therefore, one of the ways that can help prevent financial distress is predicting financial distress (Mathew et al., 2021).

In this regard, various techniques have been used to design predictive models of financial distress. In general, the predictive models of financial distress can be classified into three groups: statistical, artificial intelligence, and theoretical models. Statistical models are divided into two groups: univariate and multivariate. Multivariate statistical models consist of multiple discriminant analyses, linear probability, logit, and probit models, cumulative sum, and incomplete adjustment processes. ANNs, genetic algorithms, recursive partitioning, hard sets, support vector machines, and fuzzy logic constitute artificial intelligence techniques, and theoretical models also include balance sheet decomposition/entropy theory, speculator bankruptcy theory, cash management theory, and credit risk theory.

There are three popular approaches for bankruptcy predictive models:

- 1) Accounting approach (for example, Altman, 1968).
- 2) Contingent claim approach that represents equity as an option on assets (for example, Min and Lee, 2005).
- 3) Risk models that calculate the probability of bankruptcy using accounting and market data (for example: Shamavi, 2001).

Accounting models have always been used as a tool to predict the financial distress of companies. However, many researchers found the use of accounting models ineffective in estimating bankruptcy risk because accounting models use information from financial statements, and the said data only reports the past performance of the company. Secondly, accounting conventions such as historical cost and conservatism limit the scope of accounting information, so the value of the assets in the financial statements is expressed less than the reality. Third, accounting data shows an image of the company's value at a specific point in time, while market data is prospective. Accounting numbers are also subject to management manipulation. In addition, companies prepare accounting statements under the assumption of continuity of activity, which assumes that the company will never go bankrupt. Another important shortcoming and defect of these criteria is their failure to pay attention to the volatility

of assets, which makes the probability of bankruptcy of companies with similar ratios considered exactly the same. However, volatility is an essential variable in predicting the distance to default because it indicates the probability that the company's assets are insufficient to cover its commitments. In addition, using the credit rating as a criterion to measure the probability of default is not without problems. First, a company's creditworthiness can change significantly before its credit rating is readjusted. Secondly, using the credit rating to estimate the probability of default implies that two companies with the same credit rating will have the same probability of default. Also, it should not be forgotten that some companies, especially small market companies, are not given a credit rating, and this issue can lead to size bias in the statistical sample of the research (Li et al., 2021).

An alternative to the methods of estimating the probability of default mentioned above is the conditional claim approach. Structural models are one of the types of conditional claim approach models. These models measure the probability of default directly based on the variables related to the company, such as its stock value, and also use market information to predict the credit risk of customers of customers. By using structural models, volatility, distance to default, and default probability can be estimated, and based on their outputs, the companies can be ranked in terms of credit risk. Option pricing models are among structural models (Zhou et al., 2022).

Black and Scholes (1973) first presented a basic formula for option pricing, and Merten (1974) extended it with debt pricing. The Black and Scholes (1973) and Merten (1974) model is a bankruptcy prediction model based on option pricing principles and a combination of accounting and market data. The option pricing principles are that in the basic option pricing model, the loan paid to the borrower is considered equivalent to the purchase of an option right. This means that the default will occur when the company or the borrower does not exercise the right to purchase the company's shares in exchange for the repayment of the debt when the debt is due. The price that the company pays to buy this option is equivalent to the amount of risk that is considered in the interest rate.

Finally, Shawi (2001) presented a simple risk model using accounting and market data to calculate

the company's bankruptcy risk at any point in time. He stated: When static models give conflicting and biased estimates of the probability of bankruptcy, the risk model is generally inconsistent and, in some cases, without bias.

The users of financial statements, especially investors and creditors, are interested in knowing about the continuity of the business unit activity in the future. Financial distress and bankruptcy models are important tools to achieve this target. Based on this, financial researchers, based on inter- and intraorganizational information, have provided different models for predicting the financial distress and bankruptcy of companies over the past years, and the study of these models, solely from their methodology, is a great help in diagnosing and Identifying factors affecting the financial distress of companies. For this purpose, a review of the research related to predicting financial distress and the methods used by previous researchers will be done.

3.1. Research Background

Among the latest domestic and foreign research that has examined the issue of predicting financial distress, the following can be mentioned.

Based on the investigations and a review of the studies mentioned above, it is clear that no independent research has been done on designing a deep learning model to predict financial distress with the deep ANN method and the GWO algorithm. Research that has been mentioned in the background of domestic and foreign research has not provided this model.

3. Research Method

According to the literature related to the financial distress of companies, the factors affecting financial distress, and predicting the financial distress of companies, in order to evaluate and provide a model to predict the bankruptcy of companies, financial ratios can be used as predictive model inputs. In this regard, the independent variables of the model are the financial ratios of the companies, and the dependent variables of the model are the considering the status of the companies in terms of being financially healthy or distressed. Based on this introduction, the independent variables are thirty-four of the most important financial ratios of companies, which are mentioned in the following Table:

Table (1): Summary of previous studies

No.	Authors (year)	Research title	Conclusion
1	Esmaili & Gogerdchian (2017)	Prediction of financial bankruptcy using the ANN approach	The ANN model has the power to predict the bankruptcy of companies in Iran.
2	Khodakarimi & Piri (2017)	Prediction of financial distress with logistic regression approach	A combination of accounting and market data has the power to predict companies' distress.
3	Ebrahimi Sarvolia et al. (2019)	A model for dynamic prediction of financial distress using survival analysis	Using the Cox model, the dynamic prediction model of financial distress of companies admitted to the Tehran Stock Exchange was estimated, and its accuracy was confirmed.
4	Khoshkar et al. (2019)	The relationship between profitability financial ratios and bankruptcy prediction in Tehran Stock Exchange companies	The results of both the above statistical methods confirm the existence of a significant relationship between profitability financial ratios and bankruptcy prediction at the error level of 5%.
5	Dabbagh & Sheikh Baglo (2020)	Bankruptcy prediction of Tehran Stock Exchange companies with ANN methods and Fulmer model	Using the results and models presented in the research, it is possible to properly prevent companies from suffering from financial crises, bankruptcy, and its consequences.
6	Sadehvand et al. (2022)	Study and comparison of the performance of conventional and hybrid models in predicting financial distress	Compared to the hybrid and Merton model, Altman's model has better predictive power for healthy and unaided companies.
7	Bargbid et al. (2022)	A 3D hybrid model (financial, economic, sustainability) in predicting financial distress of companies	The results showed that the 3D hybrid model (financial, economic, sustainability) has a high predictive power for distress.
8	Rahimi et al. (2022)	Explanation of financial variables effective in predicting financial distress: the application of ANN	By comparing the prediction made by the ANN method with the actual values of the dependent variable in 2019, it was found that this method correctly predicted companies' financial distress in more than 97% of cases.

No.	Authors (year)	Research title	Conclusion
9	Lotfi et al. (2024)	Prediction of financial distress with a hybrid model	The hybrid model has better explanatory power than the Merton model and the binary logistic regression model.
10	August Gonzalez et al. (2017)	Prediction of financial distress using macro and accounting variables	The results of their research showed that a combination of macroeconomic variables and accounting variables can predict the financial distress of companies.
11	Matin et al. (2019)	Prediction of financial distress using deep learning method	Unstructured data provides a statistically significant increase in predictive performance of financial distress, especially for large companies where accurate predictions are critical.
12	Al-Hasani et al. (2020)	A deep learning-based model for predicting financial distress	The results point to the superiority of the adaptive whale optimization algorithm with deep learning technique over other compared techniques.
13	Li et al. (2021)	A deep learning-based approach to make domain sentiment vocabulary: A case study in predicting financial distress	Deep learning-based models can achieve satisfactory results in generating Chinese financial words, which mainly cover four aspects of sentiment words, including capital market, stock market, internal business conditions of companies, and politics.
14	Yu and Li (2023)	An ensemble learning model based on case-based reasoning for predicting financial distress with missing data	An ensemble learning model based on case-based reasoning can be used as a competitive solution for predicting financial distress.

Table (2): Input variables (independent) of the model to predict the financial distress of companies

No.	Variables	Symbol	Pearson correlation test result (significant relationship)
1	Net profit margin (net profit/income)	X1	Confirm
2	Gross profit margin (gross profit/income)	X2	Confirm
3	Operating profit margin (operating profit/income)	X3	Confirm
4	Gross profit margin (gross profit/income)	X4	Confirm
5	Profit to gross profit (profit/gross profit)	X5	Confirm
6	Return on assets (net profit/total assets)	X6	Confirm
7	Return on capital (net profit/capital)	X7	Confirm
8	Return on equity (net profit/equity)	X8	Reject
9	Return on working capital (net profit/working capital)	X9	Reject
10	Return on fixed assets (net profit/fixed asset)	X10	Confirm
11	Assessing the usefulness of the loan (return on assets/return on equity)	X11	Confirm
12	Current ratio (current assets/current debts)	X12	Confirm
13	Quick ratio (current assets without considering inventory and prepayments/current debts)	X13	Confirm
14	Liquidity ratio (cash assets/current debts)	X14	Confirm
15	Current assets ratio (current assets/total assets)	X15	Reject
16	Cash adequacy ratio (operating cash/divided cash profit, purchase of fixed assets, repayment of long-term debts, interest paid for financial facilities)	X16	Confirm
17	Cash flow ratio (operating cash/current debts)	X17	Confirm
18	Net working capital (current assets/current debts)	X18	Confirm
19	Inventory turnover period (inventory*365)/cost of goods sold)	X19	Confirm
20	Receivables collection period (Average accounts receivable*365/Sales)	X20	Confirm
21	Goods to working capital ratio (inventory of goods/working capital)	X21	Confirm
22	Current capital turnover (sales/working capital)	X22	Reject
23	Fixed assets turnover (net sales/fixed assets)	X23	Confirm
24	Total assets turnover (net sales/total assets)	X24	Confirm
25	Debt ratio (total debts/total assets)	X25	Confirm
26	Long-term debt to net worth ratio (total debts/net worth ¹)	X26	Confirm
27	Long-term debt to net worth ratio (long-term debts/net worth)	X27	Confirm

¹ Net worth is recognized as the book worth of assets or shareholders' equity.

No.	Variables	Symbol	Pearson correlation test result (significant relationship)
28	Current debt to net worth ratio (current debts/net worth)	X28	Confirm
29	Ownership ratio (sum of equity/total assets)	X29	Confirm
30	Debt coverage ratio (net operating income/debts)	X30	Reject
31	Interest coverage ratio (operating profit/financial cost)	X31	Reject
32	Debt-burden ratio (profit before deducting interest and tax/(Interest paid from the loan/ 1-tax rate))	X32	Confirm
33	Financial costs to net profit (financial cost/net profit)	X33	Reject
34	Financial costs to operating profit (financial cost/operating profit)	X34	Reject

(Source: Wang et al., 2017)

To identify the desired financial indicators that are supposed to enter the model, the data of 163 selected companies from 2017 to 2022 were first extracted. Then, the relationship between the variables was examined with the Pearson correlation test. Out of 34 financial ratios, 25 ratios had a significant relationship.

The statistical population includes the companies admitted to the Tehran Stock Exchange that have joined the stock exchange since 2017. In this research, the systematic elimination method was used to ensure that the statistical sample was a suitable representative of the desired statistical population. If a company met all the criteria, it was selected as one of the sample companies.

- 1) During 2017 to 2022, there is no change in the financial year and no stop of operations.
- 2) The financial statements and explanatory notes of the companies in the studied period are available on reliable websites related to the Tehran Stock Exchange.
- 3) Be admitted to the Tehran Stock Exchange before 2017.
- 4) Their stops should not exceed three months.
- 5) The target companies do not include financial intermediation investment companies and monetary institutions.

After considering all the above criteria, 160 companies remained as the screened population, all of which were selected as the research sample. Therefore, according to the 6-year period of the research (2017-2022), observations reach 960 years per company (6 years x 163 companies).

In this research, the required data related to the research literature and theoretical foundations have been extracted from the library method, document analysis, scientific databases, and internal and external articles. To collect data, financial statements of companies, information banks of Tehran Stock

Exchange Organization and Tehran Stock Exchange Technology Management Company, information banks of Rahevard Novin software, as well as reports and announcements published on the Codal network will be used.

To predict the financial distress of companies in this research, the GWO algorithm-based deep learning method and ANN method are used. Deep learning is a subset of machine learning and artificial intelligence methods that mimic the way humans learn. Deep learning is one of the main foundations of data science and is especially widely used in statistics and predictive modeling. This method has helped data scientists by speeding up the processes of data collection and, analysis and interpretation. Simply put, deep learning is a way to automate predictive analytics. Unlike linear machine learning algorithms, deep learning hierarchical algorithms increase their complexity and abstraction at each phase.

An advanced type of machine learning algorithm called ANN forms the basis of most deep learning models. This is why sometimes deep learning is called with titles such as practical neural learning or deep neural networking. There are different types of neural networks. Some of these types are Recurrent Neural Networks (RNNs), Convolutional Neural Networks (CNNs), ANNs, and Feedforward Neural Networks (FNNs). Although each of these neural networks has different advantages and applications, almost all of them work similarly. All these neural networks are fed with data and provide the possibility of correcting the interpretation of the data for the model.

4. Data Analysis

4.1. Prediction of financial distress based on the GWO algorithm-based deep learning meta-heuristic method

In the first phase, the data collected from the selected companies of the Tehran Stock Exchange was ranked based on Article 141 of the Trade Law (data related to the fiscal year 2017 to 2022), which included 102 successful companies and 58 distressed companies. In the second phase, the research variables are calculated (sorting, ranking, and performing calculations to obtain the variables are done through an Excel spreadsheet). In the third phase, the data is transferred to the database in Access to be used in the GWO algorithm-based deep learning meta-heuristic method and stored in the form of specific tables that will be referred to.

Considering that the algorithm must consider all the combined states of the coefficients and test all of them in order to extract the optimal combination, therefore it is necessary to consider all pure subsets of the variables (pure subsets are all subsets of a set other than the set itself). To obtain pure subsets, the following relation is used:

$$2^n - 1 = \text{number of pure subsets}$$

$$2^{11} - 1 = 32768 - 1 = 32767 = \text{the number of subsets of this research}$$

In fact, to obtain the optimal state in the first phase, the variables above have combined with their coefficients 32767 times.

3.2. Extraction of coefficients of variables:

In order to prepare the data for the execution of the first phase, coefficients should be assigned to the variables. In this regard, according to the results calculated in the first part of the research, a coefficient was assigned to each of the ten studied variables; these ratios change during the initial execution of the algorithm, according to the skewness coefficient of the studied variables, and finally, the initial coefficients of the first phase are prepared. After preparing the

coefficients, it is time to enter the cycle of data mining through the GWO meta-heuristic algorithm.

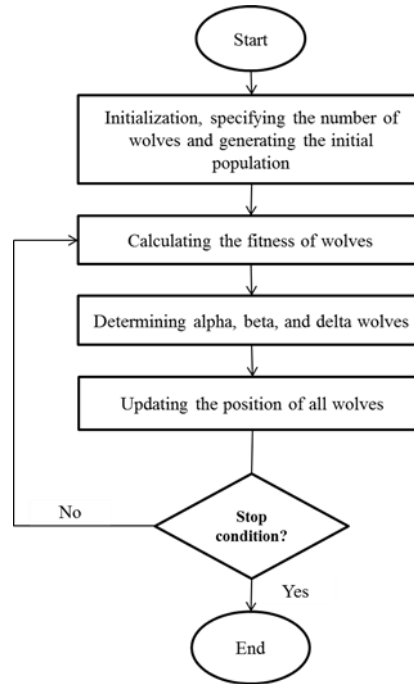


Fig. (1): Flow chart of the initial coefficients selection program (data mining)

The GWO algorithm has parameters whose values should be determined. Alpha, beta, gamma, and omega wolves are parameters of the GWO algorithm. The value of these parameters should be determined in a way that leads to the optimal solution in the model. Algorithms do their determination. These values are initially determined randomly by the algorithm itself; then, the above values are changed with each iteration to reach the best solution. The GWO algorithm determines its initial values randomly. The number of iterations in the GWO algorithm is 150. In 66 iterations, the GWO algorithm achieved the values that provide the optimal solution. The optimal solution was obtained after 66 execution steps as follows:

Table (3): The optimal solution of variables

No.	Variable	Description	Optimal parameters
1	X1	Net profit margin (net profit/income)	-1.256
2	X2	Gross profit margin (gross profit/income)	0.358
3	X3	Operating profit margin (operating profit/income)	-0.695

No.	Variable	Description	Optimal parameters
4	X4	Gross profit margin (gross profit/income)	-0.125
5	X5	Profit to gross profit (profit/gross profit)	-0.320
6	X6	Return on assets (net profit/total assets)	-0.523
7	X7	Return on capital (net profit/capital)	-0.012
8	X10	Return on fixed assets (net profit/fixed asset)	-0.320
9	X11	Assessing the usefulness of the loan (return on assets/return on equity)	-0.125
10	X12	Current ratio (current assets/current debts)	-0.025
11	X13	Quick ratio (current assets without considering inventory and prepayments/current debts)	-0.133
12	X14	Liquidity ratio (cash assets/current debts)	-0.307
13	X17	Cash flow ratio (operating cash/current debts)	-0.783
14	X18	Net working capital (current assets/current debts)	-0.286
15	X19	Inventory turnover period (inventory*365)/cost of goods sold)	-0.209
16	X20	Receivables collection period (Average accounts receivable*365/Sales)	-0.248
17	X21	Goods to working capital ratio (inventory of goods/working capital)	-0.117
18	X23	Fixed assets turnover (net sales/fixed assets)	0.355
19	X24	Total assets turnover (net sales/total assets)	-0.088
20	X25	Debt ratio (total debts/total assets)	-0.343
21	X26	Long-term debt to net worth ratio (total debts/net worth)	-0.203
22	X27	Long-term debt to net worth ratio (long-term debts/net worth)	1.549
23	X28	Current debt to net worth ratio (current debts/net worth)	-0.282
24	X29	Ownership ratio (sum of equity/total assets)	-0.659
25	X32	Return on equity (net profit/equity)	-0.220

Source: Research Findings

For $Z \geq 0$, the company is healthy, and for $Z < 0$, the company is considered distressed.

In order to validate the results of predicting financial distress based on the GWO meta-heuristic algorithm in the deep learning method, the data is divided into training and testing. The model is created using the training data, and then the results are examined on the testing data. Finally, the accuracy of the model is calculated. To evaluate prediction methods (the difference between the actual value and the predicted value), the Mean Square Error (MSE), Root Mean Square Error (RMSE), Pearson correlation coefficient (r), and coefficient of determination (R^2) have been used.

Table (4): The results of training data applications, validation, and evaluation of neural network

	MAP	RMSE	r	R2
Total data	0.0015	0.0425	0.68	0.85
Training data	0.0008	0.0512	0.71	0.89
Testing data	0.0004	0.0398	0.70	0.92
Validation data	0.0002	0.0459	0.61	0.93

Source: Research Findings

The low values of MSE and RMSE obtained, as well as the appropriate correlation coefficient between the model's output and the target's output, indicate that the GWO meta-heuristic algorithm in the deep learning method can model the data optimally.

After obtaining the optimal solution, it is time for the most important part of the research: testing the model on the financial ratios of the studied companies and testing the hypothesis. The test results of the mentioned model for the first, second, and third years were obtained as follows.

Table (5): The status of companies based on the collected data

Total number of companies	The number of bankrupt companies	The number of healthy companies
160	58	102

Source: Research Findings

The results related to predicting the financial distress of companies based on the GWO meta-heuristic algorithm in the deep learning method showed that this model's success percentage in predicting the financial

distress of companies is 98.33%. In other words, the GWO algorithm has been able to correctly predict 101 companies out of 105 healthy companies, which indicates a predictive power of 98.23%.

Table (6): The results of the financial distress test for the studied companies

Total number of companies	The number of healthy companies	The number of bankrupt companies	The success percentage of the model
160	101	59	98.33%

Source: Research Findings

4.2. Prediction of financial distress based on the ANN model

In the design of ANNs, in which MATLAB version 8 software is used, It is necessary for network programming to determine effective factors in network performance, which include the number of hidden layers of the network, the number of neurons in each layer, learning algorithm, transformation function, performance function, learning rate, number of iterations, data normalization, training and testing set size. Most of the previous research results in the field of financial distress classification and prediction show that having a hidden layer in the network is enough to solve this type of problem. For example, Odom and Sharda (2000), Tom and Kiang (2002), Zang et al. (2019), and Fallahpour (2014) can be mentioned. Therefore, in this research, a hidden layer has been used in the design of neural networks. In classification-type problems, the number of input layer neurons is equal to the number of predictor variables. Therefore, the number of input layer neurons is equal to five. Considering that the network has one output, then the number of neurons in the output layer is equal to one. Determining the number of neurons in the hidden middle layer is not an easy task, and it is mostly done by trial and error so that the total performance of the network improves; after iterated trials and errors, the best mode of network performance with high generalization power was the considering four neurons in the middle layer. It should be said that for each layer, a network is also considered. The error backpropagation learning algorithm has been used to train neural networks. The transformation function used in the output layer is a linear function, and in the hidden layer, it is a sigmoid function whose relation is equal to:

Equation1

$$f(NET) = (1 + e^{-NET})^{-1}$$

NET means the weighted sum of input variables from the previous layer. Using this function, the value of the output variable will be a number between zero and one. The network training performance function is the MSE. This performance function is usually used in the design of multilayer feedforward neural networks, which is calculated from the following relation:

Equation2

$$MSE = \frac{1}{N} \sum_{i=1}^N (e_i)^2$$

In relation to the learning rate, it should be said that if the learning rate is small, the learning is done slowly, and if it is chosen large, it will cause high fluctuation and instability of the system. The learning rate used in this research was chosen as 0.1 due to the use of the MSE performance function and several times of testing. The number of iterations depends on the learning rate and the desired target in relation to the performance function. With a learning rate of 0.1 and an MSE of 0.01, the number of iterations for the neural network was 7236. The target of 0.01 was also chosen after several tests, as there was little improvement in the total performance of the network after this point. In some previous research, it has been stated that there is no need to normalize the input data in predicting financial distress using ratios. In this research, due to the favorable results of using normal data, data normalization was not done.

The resulting neural network architecture includes eight input layers, one middle layer with 1 unit, and two output layers. The performance function used in the middle layer is the hyperbolic tangent function, and the error function used is entropy. It should be noted that 0.7% of data (equivalent to 807 data) were used as training samples, and 29.3% of data (equivalent to 345 data) were used as testing samples. The functions used in the middle layer are linear function, exponential function, and hyperbolic tangent. In this research, the software automatically selected the hyperbolic tangent function to fit the model in the final layer because it gave the least error.

The error value obtained from fitting the model is 0.07 in the training sample and 0.02 in the testing sample. Since the error value obtained in the testing sample is

lower than the training sample, therefore the fit of the model is acceptable.

Table (9) shows the importance of the independent variables in the deep neural network structure model based on research backgrounds.

After fitting the model using ANN, the significance level obtained from the prediction of the model for the independent and dependent variables is shown in Table (10).

Table (7): Allocation of the number of sample members

		Number	Percentage
Sample	Training	756	70.7%
	Testing	395	29.3%
Total		1120	100%

Source: Research Findings

Table (8): A summary of the results of the ANN model

Input layer	Independent variables	Net profit margin (net profit/income)
		Gross profit margin (gross profit/income)
		Operating profit margin (operating profit/income)
		Gross profit margin (gross profit/income)
		Profit to gross profit (profit/gross profit)
		Return on assets (net profit/total assets)
		Return on capital (net profit/capital)
		Return on fixed assets (net profit/fixed asset)
		Assessing the usefulness of the loan (return on assets/return on equity)
		Current ratio (current assets/current debts)
		Quick ratio (current assets without considering inventory and prepayments/current debts)
		Liquidity ratio (cash assets/current debts)
		Cash flow ratio (operating cash/current debts)
		Net working capital (current assets/current debts)
		Inventory turnover period (inventory*365)/cost of goods sold
		Receivables collection period (Average accounts receivable*365/Sales)
		Goods to working capital ratio (inventory of goods/working capital)
	Fixed assets turnover (net sales/fixed assets)	
	Total assets turnover (net sales/total assets)	
	Debt ratio (total debts/total assets)	
Long-term debt to net worth ratio (total debts/net worth)		
Long-term debt to net worth ratio (long-term debts/net worth)		
Current debt to net worth ratio (current debts/net worth)		
Ownership ratio (sum of equity/total assets)		
Return on equity (net profit/equity)		
	The number of input layers	8
	Scaling method	Standardization
Middle layer	The number of middle layers	1
	The number of units in the middle layer	1
	Function used	Hyperbolic tangent
Output layer	Dependent variable	Z
	The number of middle layers	2
	Scaling method	Standardization
	Function used	Softmax
	Error function	Entropy error

Table (9): Comparison of model fit error in testing and training samples

Training	Error	0.07%
Testing		0.02%

(Source: Research Findings)

Table (10): How to enter the variables into the deep neural network model

Independent variables	The degree of importance	Priority
Net profit margin (net profit/income)	0.092	First
Gross profit margin (gross profit/income)	0.085	Second
Operating profit margin (operating profit/income)	0.081	Third
Gross profit margin (gross profit/income)	0.075	Fourth
Profit to gross profit (profit/gross profit)	0.070	Fifth
Return on assets (net profit/total assets)	0.0062	Sixth
Return on capital (net profit/capital)	0.060	Seventh
Return on fixed assets (net profit/fixed asset)	0.059	Eighth
Assessing the usefulness of the loan (return on assets/return on equity)	0.054	Ninth
Current ratio (current assets/current debts)	0.051	Tenth
Quick ratio (current assets without considering inventory and prepayments/current debts)	0.049	Eleventh
Liquidity ratio (cash assets/current debts)	0.043	Twelfth
Cash flow ratio (operating cash/current debts)	0.040	Thirteenth
Net working capital (current assets/current debts)	0.038	Fourth
Inventory turnover period (inventory*365)/cost of goods sold)	0.033	Fifteenth
Receivables collection period (Average accounts receivable*365/Sales)	0.031	Sixteenth
Goods to working capital ratio (inventory of goods/working capital)	0.028	Seventeenth
Fixed assets turnover (net sales/fixed assets)	0.022	Eighteenth
Total assets turnover (net sales/total assets)	0.021	Nineteenth
Debt ratio (total debts/total assets)	0.019	Twenty
Long-term debt to net worth ratio (total debts/net worth)	0.015	Twenty-first
Long-term debt to net worth ratio (long-term debts/net worth)	0.011	Twenty-second
Current debt to net worth ratio (current debts/net worth)	0.009	Twenty third
Ownership ratio (sum of equity/total assets)	0.005	Twenty fourth
Return on equity (net profit/equity)	0.004	Twenty-fifth

(Source: Research Findings)

Table (11): A significance level of variables in deep ANN model

Variable		Spearman's correlation coefficient		
		Correlation coefficient	Significance level	Sample size
Net profit margin (net profit/income)	X1	-2.5982	0.0000	960
Gross profit margin (gross profit/income)	X2	-1.2536	0.0000	960
Operating profit margin (operating profit/income)	X3	-0.2301	0.0425	960
Gross profit margin (gross profit/income)	X4	-1.3501	0.0312	960
Profit to gross profit (profit/gross profit)	X5	-0.3628	0.0012	960
Return on assets (net profit/total assets)	X6	1.2350	0.0000	960
Return on capital (net profit/capital)	X7	-0.4589	0.0000	960
Return on fixed assets (net profit/fixed asset)	X10	0.2365	0.0025	960
Assessing the usefulness of the loan (return on assets/return on equity)	X11	-0.1250	0.0365	960
Current ratio (current assets/current debts)	X12	0.3625	0.0021	960
Quick ratio (current assets without considering inventory and prepayments/current debts)	X13	-7.2515	0.0000	960
Liquidity ratio (cash assets/current debts)	X14	-6.0365	0.0000	960
Cash flow ratio (operating cash/current debts)	X17	-0.9525	0.0425	960
Net working capital (current assets/current debts)	X18	-1.3620	0.0312	960
Inventory turnover period (inventory*365)/cost of goods sold)	X19	-0.6254	0.0012	960
Receivables collection period (Average accounts receivable*365/Sales)	X20	5.9669	0.0000	960
Goods to working capital ratio (inventory of goods/working capital)	X21	-4.3642	0.0000	960
Fixed assets turnover (net sales/fixed assets)	X23	0.3620	0.0082	960
Total assets turnover (net sales/total assets)	X24	-0.3611	0.0368	960
Debt ratio (total debts/total assets)	X25	0.5212	0.0020	960

Variable		Spearman's correlation coefficient		
		Correlation coefficient	Significance level	Sample size
Long-term debt to net worth ratio (total debts/net worth)	X26	-5.3625	0.0000	960
Long-term debt to net worth ratio (long-term debts/net worth)	X27	-4.9522	0.0000	960
Current debt to net worth ratio (current debts/net worth)	X28	-0.5621	0.0362	960
Ownership ratio (sum of equity/total assets)	X29	-1.3625	0.0251	960
Return on equity (net profit/equity)	X32	-0.2536	0.0011	960

(Source: Research Findings)

The accuracy of the model and the estimation of the coefficients of the variables in the deep ANN method in order to predict the financial distress of the companies is also shown in the following Table.

Table (12): The accuracy of the model and estimation of the coefficients of the variables in the deep ANN method

Sample	Observed	Predicted		The correct percentage
		0	1	
Training	0	392	0	93.85%
	1	0	423	
	Total percentage	93.90	6.10	
Testing	0	295	0	94.45%
	1	0	520	
	Total percentage	95.12	4.85	

(Source: Research Findings)

In the above Table, the meaning of the input layer is the independent variable, and the meaning of the output layer is the dependent variable. The column of the middle layer (1:1) is the estimation of the coefficient of independent variables by the deep ANN method.

4.3. Comparison of financial distress predictions

This section compares the results of predictions based on two GWO algorithm-based deep learning methods and ANN.

Table (13): Comparison of financial distress prediction based on two GWO algorithm-based deep learning methods and ANN

Model	Success percentage	Top model
GWO algorithm-based deep learning method	98.23%	GWO algorithm-based deep learning method
ANN	94.45%	

(Source: Research Findings)

As can be seen, the GWO algorithm's predictive power was higher than that of the deep ANN model in predicting the financial distress of the studied companies from 2017 to 2022.

5. Conclusion

The increasing expansion of joint-stock companies, the diversification of their capital structure, and the emergence of severe financial crises in macro and micro-economic dimensions caused the owners and stakeholders of various companies to seek to create a shield to protect themselves against such risks. This issue has made them aware of the use of tools and models predicting the financial helplessness of companies. The crisis in the world's financial markets has also created new conditions for Iran's economy. Although at the beginning of the crisis, some people were of the opinion that this crisis would not have much effect on the economy of the country due to Iran's low communication with other countries and the sanctions imposed against Iran, it seems that everyone now confirms that Iran, like other world economies, will not be immune from the world's great financial crisis (credit and economic crisis of 2009) and the resulting recession. Therefore, according to the competitive conditions of countries' economies and the economic crises created at the international and domestic levels, the need to develop a suitable model for predicting the financial helplessness of companies admitted to the Tehran Stock Exchange was felt. Based on this, the effect of 25 indicators of net profit margin, gross profit margin, operating profit margin, gross profit margin, profit to gross profit, return on assets, return on capital, return on fixed assets, assessing the usefulness of the loan, current ratio, quick ratio, liquidity ratio, cash flow ratio, net working capital, inventory turnover period, receivables collection period, goods to working capital ratio, fixed assets turnover, total assets turnover, debt ratio, debt to net worth ratio, long-term debt to net worth ratio,

current debt to net worth ratio, ownership ratio and return on equity have been studied on the probability of financial helplessness by using deep learning method based on the gray wolf optimization algorithm and ANN method.

The results related to predicting the financial distress of companies based on the GWO algorithm-based deep learning method showed that the success percentage of this model in predicting the financial distress of companies is 98.33%. In other words, the GWO algorithm has been able to properly predict 101 companies out of 105 healthy companies, indicating a predictor power of 98.23 %. Other findings of the research showed that the predictive power of the ANN method was 94.45%. Based on this, it can be concluded that the GWO meta-heuristic algorithm-based deep learning method has a higher level of accuracy than the ANN method in predicting the financial distress of the studied companies.

This result is in agreement with Esmaili & Gogerdchian (2017), Dabbagh & Sheikh Baglo (2020), Rahimi et al. (2022), Mateen et al. (2020), Al-Hasani et al. (2010), Li et al. (2021) that they have shown that methods based on deep learning approach and the use of meta-heuristic algorithms can be highly accurate in predicting the strength of financial distress of companies.

According to the results, it is suggested that company managers use the variables of net profit margin, gross profit margin, operating profit margin, gross profit margin, profit to gross profit, return on assets, return on capital, return on fixed assets, assessing the usefulness of the loan, current ratio, quick ratio, liquidity ratio, cash flow ratio, net working capital, inventory turnover period, receivables collection period, goods to working capital ratio, fixed assets turnover, total assets turnover, debt ratio, debt to net worth ratio, long-term debt to net worth ratio, current debt to net worth ratio, ownership ratio and return on equity with more weight and importance to predict the financial helplessness of companies. It is also recommended that managers, banks and credit institutions, rating and insurance companies, as well as other capital market actors, including actual and potential investors, as well as investment companies, use the gray wolf optimization algorithm to assess the risk of financial helplessness so that each of them can take the necessary decisions and actions according to their information needs.

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