# USING GLOW-WORM ALGORITHM TO PREDICT COMPANIES' FINANCIAL DISTRESS

## UTILIZACIÓN DEL ALGORITMO GLOW-WORM PARA PREDECIR LAS AFLICCIONES FINANCIERAS DE LAS EMPRESAS

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## ABSTRACT

One important research issue in the risk management area is to predict the financial distress of companies. This case has received great attention from banks, companies, managers, and investors. Although there are many studies on this case, the hybrid models (mixed feature selection and classifier models) have been used by researchers in recent years. The main objective of this study is to propose a high-performance predictive model and compare its results with other models that are commonly used for financial distress prediction. To do this, the Glowworm optimization algorithm-based hybrid neural network model was employed. Moreover, the neural network and logistic regression model, which is one of the statistical classifier models were used. The results indicated that the glowworm optimization algorithm (also known as firefly optimization algorithm)-based hybrid neural network model had higher performance compared to the neural network and logistic regression models.

**Keywords:** Glowworm Algorithm; Financial Distress; Hybrid Models; Neural Network.

**RESUMEN**

Un tema de investigación importante en el área de gestión de riesgos es predecir las dificultades financieras de las empresas. Este caso ha recibido gran atención por parte de bancos, empresas, gestores e inversores. Aunque hay muchos estudios sobre este caso, los modelos híbridos (modelos mixtos de selección de características y clasificadores) han sido utilizados por los investigadores en los últimos años. El objetivo principal de este estudio es proponer un modelo predictivo de alto rendimiento y comparar sus resultados con otros modelos que se utilizan habitualmente para la predicción de dificultades financieras. Para hacer esto, se empleó el modelo de red neuronal híbrida basado en el algoritmo de optimización Glowworm. Además, se utilizó la red neuronal y el modelo de regresión logística, que es uno de los modelos clasificadores estadísticos. Los resultados indicaron que el modelo de red neuronal híbrida basado en el algoritmo de optimización de luciérnaga (también conocido como algoritmo de optimización de luciérnaga) tuvo un mayor rendimiento en comparación con la red neuronal y los modelos de regresión logística.

**Palabras clave:** algoritmo Glowworm; dificultades financieras; modelos híbridos; red neuronal

## INTRODUCTION

The increased number of economic firms and companies today and their competition for higher profit have made companies seek a larger share of product and service markets. Moreover, the limited available resources have increased the probability of bankruptcy and financial distress in these companies (Grice & Ingram, 2001). Hence, a model should be designed to warn managers before bankruptcy and the loss of public and individual capital. In this way, managers can prevent such issues timely making the right decisions. On the other hand, banks and financial providers play a vital role in financing production, commercial, consumption, and even governmental sectors in all countries. In Iran, the banking network is responsible to finance real economic sectors owing to the type of economic structure, undeveloped capital markets, and other non-bank and contractual networks in Iran. Now, the survival of Iranian banks and activities depends on governmental support. The considerable volume of non-performing and overdue loans of banks implies the lack of suitable and specialized models in the credit systems of banking networks (Fadaei & Eskandari, 2011). Financial distress prediction is a solution for the proper use of investment opportunities and efficient resource allocation. This prediction warns firms about possible financial distress so they can take the required measures. On the other hand, investors and creditors can use this technique to identify optimal opportunities and undesired cases and invest their resources in proper cases. In this research, the financial distress criterion of companies is included in Article 141 of Trade Law. It should be mentioned that financial distress does not necessarily lead to bankruptcy, while bankruptcy is a consequence of financial distress that occurs at the last stage of bankruptcy (Medsker et al., 1993; Jabeur et al., 2021).

Since bank arrears and inaccurate management are the most important problems in the Iranian economic system, the extant study can play a vital role in helping financial institutions to make decisions on granting their loans to companies. This study also can assist managers to make the best decisions by warning them at the right time. The fourth and fifth development plans have emphasized presenting solutions to reduce bank arrears, manage companies accurately, and increase national output regarding the firms' privatization (Menhaj, 2007).

Financial distress prediction can help managers in making decisions and preventive measures to prevent financial distress. Banks and credit providers can use these models to make decisions and control risks caused by granting loans and credits to companies. Many companies deal with daily issues and forget system control, so they cannot detect financial distress at the right time because these are problems that occur gradually (Medsker et al., 1993). Therefore, a model must be designed to warn companies timely and make them dynamic. Increased possibility of bankruptcy is a problem that companies confront when experiencing financial distress that, in turn, causes higher costs rather than financial distress for stakeholders, managers, and creditors (Dabagh & Sheikhbeiglou, 2021).

According to the abovementioned points, a mixed method of Glowworm algorithm-based feature selection and neural network is used in this research to design a model with high accuracy in finding the best subset of features out of 18 variables (features) of problem input. Artificial Neural networks and Logistic Regression are used as competitor models that are widely used to predict bankruptcy and financial distress. Finally, methods are compared in terms of their overall accuracy and precision then their relevant hypothesis test is done. A cross-validation method is used to compare mentioned methods.

## RESEARCH THEORETICAL FOUNDATIONS

### 1. Predicting Financial Distress

Many models are used to predict financial distress and bankruptcy (Rahman et al., 2021). There are three general categories of statistical methods, heuristic techniques, and theoretical models that are used to predict bankruptcy. The mentioned methods consist of various subgroups. These models are used in chronological order to predict firms' bankruptcy: univariate models, multiple diagnostic analytics, Logit and Probit analysis, Recursive Algorithm, and Artificial Neural Network (ANN).

Commercial institutions developed various financial ratios in the 1920s. After the U.S. Securities and Exchange Commission was created, financial ratios were extremely developed and used. The studies conducted during that decade indicated that bankrupt companies have different financial ratios compared to non-bankrupt firms (Altman, 1968). Winakor and Raymond analyzed the process of financial ratios of bankrupt companies in 1930 and 1935. They analyzed the 10-year trend of financial ratios in these companies using 21 financial ratios, and concluded that the working capital-to-total assets ratio was the most suitable index for solvency. The lack of a control group comprising non-bankrupt companies was the limitation of this study (Horrigan, 1968).

William Beaver was the first person who used statistical techniques and financial ratios to predict companies' bankruptcy, and Edward Altman was the first researcher who used multiple discriminant analysis (MDA) to predict bankruptcy (Altman, 1968). The mentioned researchers found that some specific financial ratios markedly change when companies approach the bankruptcy stage. The univariate statistical techniques were methods firstly used to predict bankruptcy. This analysis can be used to examine the predictive potential of various financial ratios. This technique addresses one ratio in each turn. The current ratio was one of the oldest financial ratios used in 1870 to evaluate credit situations (Beaver, 1966).

The main objective of MDA is to detect the difference between groups and predict the probability at which a company belongs to a certain group. MDA uses several independent quantitative variables for prediction (Altman, 2013). MDA is a statistical technique that is used to classify observations into predetermined groups (Altman, 1968). MDA set a linear combination of different features based on the interaction between variables and the regression formula. Therefore, a company can be categorized as a sound company or a financially distressed firm. Univariate models address a metric each time and do not consider interactions between variables. Therefore, there is more likely wrong classification is formed in studies (Dabagh & Sheikhbeiglou, 2021).

### 2. Artificial Neural Network (ANN) Prediction Model

Odom and Sharda (1990) were the first persons who used different statistical techniques and computational methods of neural network models to predict bankruptcy in a non-empirical study. They found the neural network approach superior to other prediction methods. Neural networks can analyze complicated plans more efficiently rather than other statistical methods. Statistical constraining assumptions are not required in neural networks. The mentioned advantages allow the neural networks model to provide high accuracy. They used a Three-Layer Feedforward Network (Odom & Sharda, 1990).

Tam and Kiang (1992) compared neural networks with the linear discriminant model, logistic regression model, nearest neighbor algorithm, and decision tree model. To do this, they used data from 59 bankrupt banks and 59 non-bankrupt banks between 1985 and 1987. Results indicated better performance of the neural networks model compared to other models (Tam & Kiang, 1992).

Zhang et al. (1999) proposed a model using ANN, data of 220 firms (including 110 bankrupt and 110 non-bankrupt firms), and six variables. The results indicated that the overall prediction precision of neural networks exceeded logistic regression.

## RESEARCH METHODS

The extant study was applied in terms of objective and descriptive research in terms of method. The studied population comprised all companies listed on Tehran Stock Exchange from 1996 to 2014. The sample size consisted of 120 manufacturing companies of them a list of financially distressed companies (n=103) was prepared based on the number of exchange companies contained in Article 141 of Trade Law. Sixty companies with available information were chosen, and 60 sound and healthy companies were selected using random sampling. In total, 120 companies were studied.

In this research, the main sample was randomly divided into ten 12-member parts each of them comprising six companies with financial distress and six companies without financial distress. Then these categories (n=12) were used to form subsamples. In this case, 9 groups of 12-member categories were used for neural training and one group for model testing. In this regard, a 12-member group of the training group is replaced with a 12-member test group in each subsample. Therefore, 108 companies were assigned to neural training and 12 companies for the model test. Finally, the overall accuracy of the model is measured based on the mean accuracy rates of 10 subsamples.

## 1. Hypotheses

Main hypothesis: The hybrid Glowworm algorithm-based neural network model has higher overall accuracy for financial distress prediction compared to the artificial neural network model and logistic regression model.

This research hypothesis has been divided into six statistical hypotheses for years t, t-1, and t-2 to be testable. Year t is considered as the year in which forms of financial distress have been included in Article 141 of Trade Law and the year in which health companies' data are gathered.

The following six statistical hypotheses are designed:

| | |
|---|---|
| **HYPOTHESIS 1** | $H_0$: there is no difference between the hybrid glowworm algorithm-based neural network-feature selection model and the logistic regression model in terms of overall prediction accuracy in year t.<br>$H_{1:}$ there is a difference between the hybrid glowworm algorithm-based neural network-feature selection model and logistic regression model in terms of overall prediction accuracy in year t. |
| **HYPOTHESIS 2** | $H_0$: there is no difference between the hybrid glowworm algorithm-based neural network model and logistic regression model in terms of overall prediction accuracy in year t-1.<br>$H_1$: there is a difference between the hybrid glowworm algorithm-based neural network model and logistic regression model in terms of overall prediction accuracy in year t-1. |
| **HYPOTHESIS 3** | $H_0$: there is no difference between the hybrid glowworm algorithm-based neural network model and logistic regression model in terms of overall prediction accuracy in year t-2.<br>$H_1$: there is a difference between the hybrid glowworm algorithm-based neural network model and logistic regression model in terms of overall prediction accuracy in the year t-2. |

| | |
|---|---|
| **HYPOTHESIS 1** | $H_0$: there is no difference between the hybrid glowworm algorithm-based neural network-feature selection model and the artificial neural network (CNN) model in terms of overall prediction accuracy in year t.<br>$H_{1:}$ there is a difference hybrid glowworm algorithm-based neural network-feature selection model and the artificial neural network model in terms of overall prediction accuracy in year t. |
| **HYPOTHESIS 2** | $H_0$: there is no difference between the hybrid glowworm algorithm-based neural network model and artificial neural network model in terms of overall prediction accuracy in year t-1.<br>$H_1$: there is a difference between the hybrid glowworm algorithm-based neural network model and artificial neural network model in terms of overall prediction accuracy in year t-1. |
| **HYPOTHESIS 3** | $H_0$: there is no difference between the hybrid glowworm algorithm-based neural network model and artificial neural network model in terms of overall prediction accuracy in year t-2.<br>$H_1$: there is a difference between the hybrid glowworm algorithm-based neural network model and artificial neural network model in terms of overall prediction accuracy in years t-2. |

After studying and reviewing previous studies and available information of selected firms, 18 variables of important financial ratios used in former papers were selected as input variables. Table 1 reports these 18 variables.

**Table 1.** Research variables

| NAME | NO. | NAME | NO. |
|---|---|---|---|
| NET WORKING CAPITAL | $V_1$ | Gross profit-to-sale | $V_{10}$ |
| COLLECTION PERIOD | $V_2$ | Operating profit | $V_{11}$ |
| CURRENT CAPITAL TURNOVER | $V_3$ | Return on assets (ROA) | $V_{12}$ |
| FIXED ASSET TURNOVER | $V_4$ | Return on investment (%) | $V_{13}$ |
| TOTAL ASSET TURNOVER | $V_5$ | Return on equity (ROE) | $V_{14}$ |
| DEBT RATIO | $V_6$ | Return on fixed asset | $V_{15}$ |
| OWNERSHIP RATIO | $V_7$ | Current ratio | $V_{16}$ |
| DEBT COVERAGE RATIO | $V_8$ | Quick ratio | $V_{17}$ |
| NET PROFIT-TO-SALE | $V_9$ | Liquidity ratio | $V_{18}$ |

These variables are defined as follows:

$V_1$: net working capital is the difference between current assets and liabilities.

Current assets are cash, and assets be expected to be sold, consumed, or exhausted within one year. Current liabilities are debts are to be settled from current assets or other current liabilities within one year. Net working capital is the security margin for creditors. A firm that deals with borrowing problems in short term require a high working capital balance.

(1) $$V_2 = \frac{\text{Comercial Accounts Receivable} + \text{Other Coomercial Accounts Receivable}}{\text{Total revenue}} \times 365$$

(2) $$V_3 = \frac{\text{Total revenue}}{\text{Total current assets} - \text{Total current debts}} \times 100$$

(3) $$V_4 = \frac{\text{Total revenue}}{\text{Net fixed assets}} \times 100$$

(4) $$V_5 = \frac{\text{Total revenue}}{\text{Total assets}} \times 100$$

(5) $$V_6 = \frac{\text{Total debts}}{\text{Total assets}} \times 100$$

(6) $$V_7 = \frac{\text{Equity}}{\text{Total assets}} \times 100$$

(7) $$V_8 = \frac{\text{Net fixed assets}}{\text{Long-term debts}} \times 100$$

(8) $$V_9 = \frac{\text{Profit (loss) after interest rate and tax}}{\text{total revenue}} \times 100$$

(9) $$V_{10} = \frac{\text{Groos profit (loss)}}{\text{Total revenue}} \times 100$$

(10) $$V_{11} = \text{Revenue - Cost of Goods Sold}$$

(11) $$V_{12} = \frac{\text{Profit (loss) after interest rate and tax}}{\text{total assets}} \times 100$$

$$(12) \quad V_{13} = \frac{Profit\ (loss)\ after\ interest\ rate\ and\ tax}{capital} \times 100$$

$$(13) \quad V_{14} = \frac{Profit\ (loss)\ after\ interest\ rate\ and\ tax}{Shareholders'\ equity} \times 100$$

$$(14) \quad V_{15} = \frac{Total\ Revenue}{Net\ fixed\ assets} \times 100$$

$$(15) \quad V_{16} = \frac{Total\ current\ assets}{total\ current\ liabilities}$$

$$(16) \quad V_{17} = \frac{Total\ current\ assets - Inventory}{Total\ current\ liabilities}$$

$$(17) \quad V_{18} = \frac{Short-term\ investments - Cash\ and\ equivalent}{Total\ current\ liabilities}$$

The glowworm swarm optimization algorithm (or glowworm algorithm) was introduced by Krishnanand and Ghose (2005). They developed the theoretical foundations of this algorithm between 2006 and 2008. The Swarm Intelligence that occurs in natural communities is the outcome of swarm agents' actions, which are done based on local information. In regular, swarm behavior seeks more complicated swarm objectives. Some samples of this phenomenon are seen in groups of ants, bees, birds, and so forth. Various algorithms have been designed to solve sophisticated problems, such as optimization, multiagent, and robotic decision-making inspired by noncentralized decision-making mechanisms observed in these samples and other natural species. This algorithm initiates randomly by placing an n-member population of glowworms in different places of the optimization problem's search space. All glowworms gave an equal quantity (1) of luciferin at the first stage. Every replication of the algorithm includes two phases: update luciferin and glowworm's place.

The dependent variable generates two outcomes in many studies and can take only zero and one value. Value one indicates the event occurrence, while zero is vice versa. We can find the logistic regression model as a generalized linear model that uses the Logit function as the link function, and its error follows a polynomial distribution.

Table 2 reports the model accuracy and precision.

**Table 2.** Determine model accuracy

| | PREDICTED MEMBERSHIP IN THE GROUP | |
|---|---|---|
| ACTUAL MEMBERSHIP IN THE GROUP | Bankrupted | Non-bankrupted |
| BANKRUPTED | T | $F_1$ |
| NON-BANKRUPTED | $F_2$ | T |

Where T represents true classification and F indicates false classification. $F_1$ and $F_2$ indicate type I and type II errors, respectively. The true classifications are divided by the total number of samples to measure the percent of correctly-classified companies. All modeling and programming phases have been done through MATLAB and MS Excel software.

## RESULTS AND DISCUSSION

Table 3 reports the results of prediction accuracy of ten subsamples for the hybrid neural network model in years t, t-1, and t-2.

**Table 3**. Prediction accuracy of subsamples' models in all three years

| YEAR | SUB 1 | SUB 2 | SUB 3 | SUB 4 | SUB 5 | SUB 6 | SUB 7 | SUB 8 | SUB 9 | SUB 10 | TOTAL |
|---|---|---|---|---|---|---|---|---|---|---|---|
| T | 100.0% | 91.7% | 100.0% | 83.3% | 100.0% | 100.0% | 100.0% | 100.0% | 91.7% | 100.0% | 96.67% |
| T-1 | 91.7% | 100.0% | 100.0% | 100.0% | 91.7% | 100.0% | 83.3% | 83.3% | 91.7% | 75.0% | 91.67% |
| T-2 | 83.3% | 91.7% | 83.3% | 83.3% | 83.3% | 91.7% | 91.7% | 83.3% | 91.7% | 83.3% | 86.6% |

The value of 91.7% of Sub2 in year t indicates that the determined model had 91.7% accuracy in this subset, which comprises 108 companies (54 non-bankrupted and 54 bankrupted companies) for training and extracting the model and 12 companies (6 on-bankrupted and 6 bankrupted companies) for model testing. Then the 12-member experimental category of Sub2 is replaced with one of nine training categories, and a new model is created to measure Sub3. The model accuracy equaled 100% after using the experimental model in the next step. Finally, the overall accuracy of the model was measured by averaging the subsets' accuracy. According to the table, the total accuracy of model prediction equaled 96.67%, 91.67%, and 86.67% for years t, t-1, and t-2, respectively (Table 4).

**Table 4.** Prediction accuracy of logistic regression model

| STUDIED YEAR | ACCURACY |
|---|---|
| T | 90% |
| T-1 | 50.82% |
| T-2 | 17.79% |

According to the comparison between results obtained from the studied model and logistic regression model and data reported in Tables 8 and 9, the total accuracy of the hybrid glowworm algorithm-based neural network was greater than the prediction accuracy of the logistic regression model in all three years.

**Table 5.** Results of prediction accuracy of models obtained from subsamples in all three years

| YEAR | SUB 1 | SUB 2 | SUB 3 | SUB 4 | SUB 5 | SUB 6 | SUB 7 | SUB 8 | SUB 9 | SUB 10 | TOTAL |
|---|---|---|---|---|---|---|---|---|---|---|---|
| T | 83.3% | 91.7% | 91.7% | 91.7% | 91.7% | 91.7% | 91.7% | 100.0% | 91.7% | 91.7% | 91.67% |
| T-1 | 91.7% | 75.0% | 91.7% | 83.3% | 75.0% | 91.7% | 83.3% | 83.3% | 83.3% | 83.3% | 84.17% |
| T-2 | 83.3% | 75.0% | 91.7% | 83.3% | 83.3% | 83.3% | 75.0% | 83.3% | 83.3% | 75.0% | 81.67% |

According to the comparison between the results of the hybrid neural network model and artificial neural network and information reported in Tables 3-7 the total accuracy of the hybrid glowworm algorithm-based model was greater than the prediction accuracy of the artificial neural network in all three years.

**Table 6.** Prediction accuracy of models used for distress year (t)

| METHOD | TYPE | MEAN VALUE OF TOTAL PREDICTION ACCURACY (%) |
|---|---|---|
| HYBRID GLOWWORM OPTIMIZATION ALGORITHM-BASED NEURAL NETWORK MODEL | Artificial intelligence | 96.67 |
| ARTIFICIAL NEURAL NETWORK (NORMAL) | Artificial intelligence | 91.67 |
| LOGISTIC REGRESSION | Statistical | 90 |

**Table 7.** Results of a paired comparison test of the research model and logistic regression in year t

| DESCRIPTION | HYBRID GLOWWORM OPTIMIZATION ALGORITHM-BASED NEURAL NETWORK MODEL | LOGISTIC REGRESSION METHOD |
|---|---|---|
| ACCURACY MEAN VALUE (%) | 96.67 | 90 |
| T-VALUE | 2.6832 | |
| P-VALUE | 0.01581 | |
| HYPOTHESIS TEST | $H_0$ is rejected | |

There is a significant difference between the total prediction accuracy of the hybrid glowworm optimization algorithm-based neural network model and the logistic regression model because of the p-value<α at the confidence level of 95% .

**Table 8.** Results of a paired comparison test of the research model and artificial neural network in year t

| DESCRIPTION | HYBRID GLOWWORM OPTIMIZATION ALGORITHM-BASED NEURAL NETWORK MODEL | ARTIFICIAL NEURAL NETWORK |
|---|---|---|
| ACCURACY MEAN VALUE (%) | 96.67 | 91.67 |
| T-VALUE | -2.25 | |
| P-VALUE | 0.03719 | |
| HYPOTHESIS TEST | $H_0$ is rejected | |

Based on table 8, there is a significant difference between the total prediction accuracy of the hybrid glowworm optimization algorithm-based neural network model and the artificial neural model because of the p-value<α at the confidence level of 95%.

**Table 9.** Results of a paired comparison test of the research model and logistic regression in year t-1

| DESCRIPTION | HYBRID GLOWWORM OPTIMIZATION ALGORITHM-BASED NEURAL NETWORK MODEL | LOGISTIC REGRESSION METHOD |
|---|---|---|
| ACCURACY MEAN VALUE (%) | 91.67 | 82.5 |
| T-VALUE | 2.45786 | |
| P-VALUE | 0.02434 | |
| HYPOTHESIS TEST | $H_0$ is rejected | |

Based on table 9, there is a significant difference between the total prediction accuracy of the hybrid glowworm optimization algorithm-based neural network model and the logistic regression model because of the p-value<α at the confidence level of 95%.

**Table 10.** Results of a paired comparison test of the research model and artificial neural network in year t-1

| DESCRIPTION | HYBRID GLOWWORM OPTIMIZATION ALGORITHM-BASED NEURAL NETWORK MODEL | ARTIFICIAL NEURAL NETWORK |
|---|---|---|
| ACCURACY MEAN VALUE (%) | 91.67 | 84.17 |
| T-VALUE | -2.211 | |
| P-VALUE | 0.04014 | |
| HYPOTHESIS TEST | $H_0$ is rejected | |

Based on table 10, there is a significant difference between the total prediction accuracy of the hybrid glowworm optimization algorithm-based neural network model and the artificial neural model because of the p-value<α at the confidence level of 95%.

**Table 11.** Prediction accuracy of models employed in year t-2

| METHOD | TYPE | MEAN VALUE OF TOTAL PREDICTION ACCURACY (%) |
|---|---|---|
| HYBRID GLOWWORM OPTIMIZATION ALGORITHM-BASED NEURAL NETWORK MODEL | Artificial intelligence | 86.67 |
| ARTIFICIAL NEURAL NETWORK (NORMAL) | Artificial intelligence | 81.67 |
| LOGISTIC REGRESSION | Statistical | 79.17 |

**Table 12.** Results of a paired comparison test of the research model and logistic regression in year t-2

| DESCRIPTION | HYBRID GLOWWORM OPTIMIZATION ALGORITHM-BASED NEURAL NETWORK MODEL | LOGISTIC REGRESSION METHOD |
|---|---|---|
| MEAN VALUE (%) | 86.67 | 79.17 |
| T-VALUE | 2.3772 | |
| P-VALUE | 0.02873 | |
| HYPOTHESIS TEST | $H_0$ is rejected | |

Based on table 11 and 12, there is a significant difference between the total prediction accuracy of the hybrid glowworm optimization algorithm-based neural network model and the logistic regression model because of the p-value<α at the confidence level of 95%.

**Table 13.** Results of a paired comparison test of the research model and artificial neural network in year t-2

| DESCRIPTION | HYBRID GLOWWORM OPTIMIZATION ALGORITHM-BASED NEURAL NETWORK MODEL | ARTIFICIAL NEURAL NETWORK |
|---|---|---|
| ACCURACY MEAN VALUE (%) | 86.67 | 81.67 |
| T-VALUE | 2.3237 | |
| P-VALUE | 0.032045 | |
| HYPOTHESIS TEST | $H_0$ is rejected | |

Based on table 13, there is a significant difference between the total prediction accuracy of the hybrid glowworm optimization algorithm-based neural network model and the artificial neural model because of the p-value<α at the confidence level of 95%.

## CONCLUSION

One of the most important research issues in financial and risk management areas is predicting the financial distress of firms. Hence, many researchers, banks, corporations, managers, and investors have considered this case. We can find useful information for analysis of other firms and future predictions by predicting financial distress, findings the reasons, and overcoming the problem. Therefore, timely prediction of financial distress and firms' bankruptcy warns managers and investors about decisions they make. This prediction helps all stakeholders to minimize the financial losses caused by bankruptcy by taking predictive measures. The extant study used a hybrid neural network model based on the glowworm algorithm to predict companies' financial distress.

The results obtained from the hybrid glowworm algorithm-based neural network model indicated the high potential of this model for predicting the financial distress of companies. However, the prediction accuracy of the model will be reduced in years that are far away from the year when financial distress occurs, and this is an ordinary case. According to the comparison between the results of the hybrid glowworm algorithm-based neural network model and logistic regression model, the proposed model had a higher accuracy for predicting the financial distress of companies compared with the regression model. Therefore, the hybrid glowworm algorithm-based neural network model had significantly higher prediction accuracy in predicting financial distress rather than the logistic regression model did.

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