

Neural Network VS Genetic and Particle Swarm Optimization Algorithms in Bankruptcy

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ABSTRACT

Purpose: The goal of the study is to estimate an artificial neural network (ANN) model for bankruptcy prediction and optimize processes using the Particle Swarm (PSO) and Genetic (GA) algorithms.

Design/methodology/approach: 21 variables that were related to the likelihood of bankruptcy were chosen for the study. Neural networks (NNs) choose the optimal network with the least amount of error in training and evaluating patterns in the second phase. The neural network's weights and biases were optimized in the final stage by combining GA and PSO with the neural network.

Findings and contribution: The results showed that the initial pattern's ability to be explained has risen with the use of GA and PSO. The superiority of the models over linear regression is demonstrated by the evaluation of ANN performance. Finally, four variables—current ratio, sales to current assets ratio, economic value added, and gross profit margin ratio—that may reliably predict bankruptcy were found using the hybrid approach of ANNs-PSO and ANNs-GA. The evidence brings out the effectiveness of the metaheuristic algorithms as compared to linear ones on predicting bankruptcy. This goes on to further highlight the new breed of computational tools to available as techno-savvy financial analysts as well as investors.

Keywords: Bankruptcy, Artificial neural networks, Genetic algorithm, Particle Swarm algorithm

JEL codes: M4, G.

1. INTRODUCTION

Bankruptcy is a bitter end for companies. It is a legal proceeding that is initiated when a company is unable to pay outstanding debts or obligations. The event can mean a huge loss for the company's stakeholders. For investors, the distinction between bankrupt and non-bankrupt companies is one of the most important issues. Therefore, predicting bankruptcy is considered one of the most important investment factors (Ainan *et al.*, 2024; Larijani and Banimahd, 2022). Consequently, it is crucial for investors to distinguish favorable from unfavorable investment opportunities. Alternatively, the research can help investors to predict bankruptcies more accurately.

One way that can help to properly utilize investment opportunities and prevent the waste of resources is to predict the financial crisis and ultimately bankruptcy. Companies can be warned of the financial crisis through appropriate warnings. Consequently, companies can take appropriate measures after receiving the warnings. Investors should also differentiate between favorable and unfavorable investment opportunities and invest their resources in the desired opportunities (Khani and Guruli, 2015).

Bankruptcy does not show itself quickly. It is hidden in a mass of financial and non-financial information. For example, some researchers have used financial ratios (Alam *et al.*, 2021; Kuldeep, 2019; Mai *et al.*, 2018; Beaver, 1966), multivariate analyses (Altman, 1968; Fulmer, 1984), multi-discriminant analyses (Deakin, 1972 and Shirata, 1998), logistic regression (Ohlson, 1980), neural networks (Letkovský *et al.*, 2024; Wallace, 2004), genetics and vector machines (Shin *et al.*, 2005) as financial factors on predicting bankruptcy. On the other hand, some researchers have used qualitative factors

such as the company's problems in the market, financing, human power, and extra-organizational to predict bankruptcy (Vaghfi, 2019; Zarin, 2020).

There are two aspects to the prediction time of insolvencies: key indicators and fundamental analysis (Moghaddam and Taghi-Mollaeei, 2015). The difference lies in the prediction time of bankruptcy. Key indicators can show that bankruptcy is imminent. Fundamental analysis, on the other hand, predicts the probability of bankruptcy in the next two to five years (Ashori, 2012).

The need for this research can be explained for several reasons. First, an accurate prediction of bankruptcy helps to improve investors' decision making. Therefore, it seems necessary to determine an appropriate model. Second, the use of intelligent hybrid methods is more efficient than traditional methods in terms of cost and time. Thirdly, metaheuristic algorithms are able to make more accurate predictions.

This study addresses this gap by proposing a bankruptcy prediction model leveraging intelligent hybrid methods such as ANNs techniques. Then the optimization of the models is performed based on GA and PSO Algorithms. Thus, the problem raised that the optimization model of GA and PSO is able to optimize the initial bankruptcy prediction model.

The research contributes to the literature on bankruptcy in several ways. First, to the best of our knowledge, the study is the first to make a comparative assessment of the accuracy of linear regression (LR) and ANN methods in bankruptcy prediction. Second, previous research on bankruptcy has used only one pattern to optimize ANNs (Rui, 2010; Zeng *et al.* 2015; Azayite and Achchab, 2018). The research improves the accuracy of bankruptcy prediction by adding the genetic model. Third, the influence weight of predictor variables in neural networks was determined. This issue can help analysts to identify the most effective factors in predicting bankruptcy.

The rest of the research organized as follows. Section 2 discusses the study's theoretical background. Section 3 presents the research hypotheses. Section 4 contains the

research methodology, i.e., the database used and the methods applied for further analysis. Section 5 discusses the finding of the research is explained in detail. Finally, section 6 provides the conclusion.

2. LITERATURE REVIEW

Bankruptcy is a situation in which a company's liabilities exceed the market value of its assets (Gitman, 1996). When a company's realized rate of return on capital continuously and significantly falls short of the expected rate of return, financial distress occurs (Altman and Hotchkiss, 2005). Consequently, the two concepts of bankruptcy and financial distress are not the same. Bankruptcy is a legal situation that occurs for a company. In financial distress, however, the company continues its activities as there is no legal prohibition. Financial distress is a step before bankruptcy. It is therefore possible for a company to be in financial distress for a long time. However, as there is no legal prohibition, it continues its activities.

Appropriate tools and models to assess the conditions and financial status of a company can help with the investment decision. Predicting financial distress and bankruptcy is one of the most important tools (Zainol *et al.*, 2024; Kou *et al.*, 2019). The large number of companies that have run into financial distress and consequently had to file for bankruptcy has drawn the attention of researchers and market participants to this topic and has led to the development of predictive models. Predicting the financial status of the investee company will be able to protect investors. In particular, predicting the financial distress and bankruptcy of some companies after the financial crisis of 2007 and the economic recession in Europe in 2009 (Ogachi *et al.*, 2020) and more recently the period of COVID-19 has become the main subject of many researches.

Financial distress is a situation in which the company cannot provide sufficient cash flow to meet its contractual obligations. Failure to end this situation in the long term has a negative impact on value of the company and the shareholders' wealth. Eventually the conditions lead to inefficiency of financial operations and bankruptcy (Wang *et al.*, 2021). The bankruptcy of the company leads to significant business losses

on the global scale. Early recognition of an unfavorable situation in the company therefore has economic advantages. This has led scientists to develop various models for predicting bankruptcy (Dasilas and Rigani, 2024; Hosaka, 2019). The development of reliable bankruptcy prediction models is important for corporate risk assessment and helps managers to avoid bankruptcies and shareholders to screen and select companies for investment (Fagerland *et al.* 2008). As the number of models increases, one of the challenges for researchers is to evaluate and select the best model (Mousavi and Ouenniche, 2018). The performance of bankruptcy models depends on primary data-based research and a variety of factors such as sampling, feature selection, modeling, and performance evaluation (Jamali *et al.* 2022). In feature selection, researchers use different types of market information, i.e. accounting, market and microeconomic variables in distress and bankruptcy prediction models. Bankruptcy prediction models can be divided into three general categories (Jaki and Cwięk, 2021). Scoring models obtain their data from the market. Based on financial reports, the model uses profitability, financial leverage, liquidity, solvency and activity ratios to predict the probability of bankruptcy.

Accounting-based models: Beaver (1966) believes that financial ratios such as cash flow to total assets, net income to total assets, and total assets plus total liabilities to total assets are good predictors of bankruptcy in separate univariate models. Altman (1968) introduced the z-score model. Ohlson (1980) developed the o-score model based on balance sheet ratios. The index was used as an indicator of bankruptcy to perform a logistic regression. Altman *et al.* (1977) developed the z-score by introducing the ZETA model. The ZETA model consists of seven variables that reflect different characteristics of the company. The model performs better than the z-score in predicting bankruptcy.

The quality of forecasting models based on accounting data is criticized with regard to the source of information. The accounting data is historical data taken from the company's financial statements. They are in some ways inconsistent with new and updated company information. Therefore, accounting-based models may be inadequate for predicting bankruptcy.

Market-based models: Merton (1974) was the first to introduce the market-based models. He assumes that a company is considered bankrupt if it cannot pay its financial debt. In other words, if the company's debts exceed its assets, it is exposed to bankruptcy. As a result, the Merton model uses market information instead of accounting information. Although market-based models can be more accurate than accounting-based models, they have the limitations of pattern assumptions and the need to return the asset value and fluctuations.

Combined models: The models take into account both accounting information and market information together. Shumway (2001) was the first to propose this model. He proposed the discrete-time risk model, which explicitly takes time into account. Structural explanatory models based on both accounting and market ignore the passage of time, so the estimates are biased. Shumway's model represented a major advance in the field of bankruptcy prediction because it takes time into account. Then Chava and Jarrow (2004) added to the validity of Shumway's model compared to scoring models. In addition, the effects of industry were also considered. Two important combined models are Chava and Jarrow (2004) and Campbell *et al.* (2008), which consider both accounting and market information together. Campbell *et al.* (2008) made two contributions in their research. First, the development of explanatory variables in the model. The market value of the share is better than the book value. The market value takes into account the latest market information, which better reflects the company's position. In addition, the company's intangible assets are valued more accurately. Based on this argument, Campbell *et al.* (2008) replaced the ratios of net income/market value of total assets and liabilities/market value of total assets with the ratios of net income/total assets and total liabilities/total assets. Second, they included the ratio of cash and short-term assets/the market value total assets as an explanatory variable in the model, reflecting that reflects the liquidity situation of the company.

Today, new statistical methods in the finance have entered a new phase of bankruptcy prediction. For example, the use of artificial neural networks and metaheuristic methods has increased significantly (Alibabae and Kan-Mohammadi,

2022; Marso and Merouani, 2020; Goletsis *et al*, 2009). The models also fall into the group of combined models. Some theories related to bankruptcy are mentioned below.

Gambler's Ruin Theory: Two players start the game with certain initial points and the points are transferred from one to the other until one player's point reaches zero. The theory states that the company can be considered as a gambler who repeatedly plays at a certain loss. The gambler continues to gamble until his net worth falls below zero, i.e. until he is in financial distress (Rocha and Stern, 2004).

Cash Management Theory: The short-term management of the company's cash balance is one of the main concerns of any company. The imbalance between input and output of flows means that the company is unable to manage its liquidity. This factor can lead to financial distress and eventually bankruptcy (Mirarab-Bayegi *et al*, 2020).

Credit risk theory: It is the risk that a borrower will not be able to meet its obligations for any reason. Bhattacharya *et al*. (2020) express credit risk as the non-fulfillment the debt commitment at the time of the parties' agreement. The models and their risk forecasts are based on the contingency theory of financial management.

Earnings behavior: Companies are likely to engage in incremental earnings management by reducing items such as cost of goods sold. If managers are optimistic that the firm's performance will improve in future periods, they will manipulate earnings (Graham *et al*, 2005). This can happen even if they are aware that their actions will be reversed in the future. Peasnell *et al*. (2000) are the opinion that earnings manipulation is practiced in bankrupt companies with the aim of showing the increase in current earnings and hiding the manager's poor performance.

3. HYPOTHESES

The following hypotheses were formulated to answer the research problem.

H1: Bankruptcy prediction based on the artificial neural networks (ANNs) model is more accurate than the linear regression (LR) method.

H2: Bankruptcy prediction based on a hybrid model of artificial neural networks (ANNs), genetic algorithm and particle swarm optimization (PSO) is more accurate than the linear regression method (LR).

H3: Bankruptcy prediction based on a hybrid model of artificial neural networks (ANNs), genetic algorithm and particle swarm optimization (PSO) is more accurate than the artificial neural networks (ANNs) method.

4. RESEARCH METHODOLOGY

The main objective of the research is to explain the bankruptcy prediction model using an intelligent hybrid method of neural networks and metaheuristic algorithms (genetic and particle swarm optimization). The research was conducted in three general phases. In the first phase, the data is selected and cleaned. In the second phase, the data is trained, and in the third phase, the model is evaluated. SPSS, Excel and Rapidminer software were used to operationalize the phases. The statistical population of the study is the companies listed on the Tehran Stock Exchange (TSE) for the years 2013 to 2023, including 1791 firm-years. Banks, financial institutions, foreign companies, investment and insurance companies were not included in the study due to the specific regulatory framework for financial reporting. In addition, observations on companies that did not meet the following criteria were removed from the population:

- (1) The companies should have been registered with the TSE before 2013 and should not cancel the registration before 2023.
- (2) The data required to define the variables of the study should be available in the financial statements.

The sample size based on the bases of firm-year on the above criteria is shown in [Table 1](#).

Table 1. Sample selection procedures

	observations
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Firms listed on TSE from 2013 to 2023 [11years×560firms]	5170
Less: Firm-years with insufficient information	(3863)
Less: Financial, foreign and insurance firms [11years×44firms]	(484)
Final sample	1791

The research follows a systematic and structured approach to evaluate the effectiveness of hybrid models combining Artificial Neural Networks (ANNs) with Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) for bankruptcy prediction. The methodology consists of the following sequential stages:

Data Collection:

- Stage 1: Identification and selection of relevant financial data from companies listed on TSE for the period of ten years (2013-2023) and includes various financial ratios and metrics.
- Stage 2: Collection of annual financial statements and reports from reliable sources to ensure data accuracy and completeness.

Data Preprocessing:

- Stage 3: Cleaning and preprocessing the collected data to handle missing values, outliers, and inconsistencies. Standardization of financial ratios is performed to ensure uniformity.
- Stage 4: Splitting the dataset into training and testing subsets, ensuring a representative sample for model validation.

Model Development:

- Stage 5: Designing the ANN model architecture, including the number of layers, neurons per layer, activation functions, and learning rate. Selection of appropriate hyper-parameters through cross-validation.
- Stage 6: Integration of GA and PSO algorithms with the ANN model to optimize the weights and biases. GA is employed for initial parameter optimization, followed by fine-tuning using PSO to achieve the best performance.

Model Training and Evaluation:

- Stage 7: Training the hybrid ANN-GA and ANN-PSO models on the training dataset. Monitoring the training process to prevent overfitting and ensure convergence.

- Stage 8: Evaluating the trained models on the testing dataset using performance metrics such as accuracy, precision, recall, and F1-score. Comparing the results with traditional linear regression models to assess the improvement.

Analysis and Interpretation:

- Stage 9: Analyzing the results to identify the most significant financial ratios contributing to bankruptcy prediction. Performing sensitivity analysis to understand the impact of each variable.

- Stage 10: Interpreting the findings in the context of existing literature and theories. Highlighting the advantages of using hybrid models over traditional methods.

Validation and Robustness Checks:

- Stage 11: Conducting robustness checks to validate the stability and reliability of the hybrid models. Testing the models on different subsets of data and alternative time periods.

- Stage 12: Comparing the performance of the hybrid models with other advanced computational techniques to further validate their effectiveness.

4.1. Artificial neural networks

McCulloch and Pitts (1943) introduced artificial neural networks (ANNs). ANNs consist of a large number of artificial neurons. An artificial neuron is a simple electronic pattern of a biological neuron. The number of neurons used in an ANN depends on the nature of the work to be performed. There are many different ways to connect neurons together to form a neural network. The most common method is the feed-forward method. The neurons of each layer send their output as a feed to the next layer, and the process continues until the final output. A NN with a maximum of two hidden layers and a sufficient number of neurons is capable of solving the most complex problems (Ghaderi *et al*, 2018). However, the number of hidden layers and the neurons that compose them is usually determined by trial and error depending on the complexity of the problem. The function of ANNs involve several actions. First, each input variable belongs to a user-defined weight in the interval from zero to one. Then this weight is multiplied by the input value. The sum of these values reaches the neurons in

the hidden layer and is added to a value called the bias value. Then an activation function (step, linear and/or sigmoid) acts on the neuron. The value is reweighted and passed on to the next neuron (in the next hidden layer or output layer). In this way, the values obtained from all neurons in the hidden layer are collected. At this stage, one training period is completed. The predicted values obtained are compared with the observed values. The difference between the predicted values and the observed values is called mean squared error (MSE) (Goodfellow *et al.* 2016).

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2 \quad \text{Eq. (1)}$$

Where n is the number of data points; Y_i the observed values, \hat{Y}_i predicted values and $(Y_i - \hat{Y}_i)^2$ the squares of the errors. The error is corrected by an algorithm after propagation on the return path. The values of the weights are changed and a new training period begins. This process is repeated until the termination criterion of the network (i.e. the specified training period or the desired error rate) is met. Thus, the network is trained and the performance of the network is measured by comparing the predicted values of the network and the observed values (Shetty *et al.*, 2022). Figure 1 shows a schematic diagram of a fully connected feedforward network.

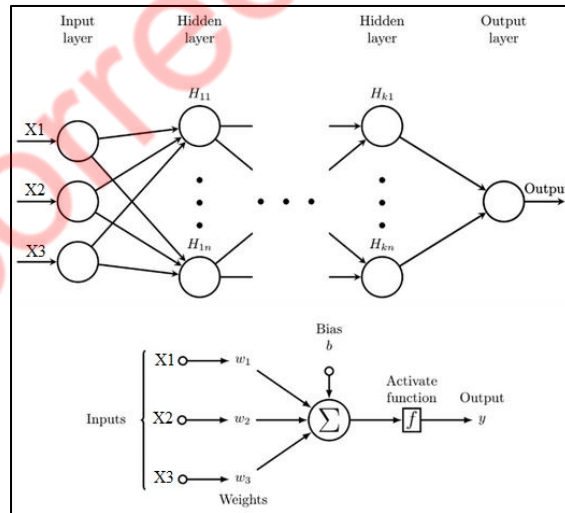


Figure 1. Upper figure: fully connected feedforward artificial neural network (X1, X2, and X3 = input variables); lower figure: schematic of the computational unit of the network.

A feedforward network is said to be fully connected if each neuron in a given layer receives the outputs of the neurons in the previous layers.

4.2. Combined intelligent methods

Many predictions in finance do not follow a simple linear pattern. Rather, they are based on a non-linear and chaotic system that is influenced by political, economic, psychological, *etc.* Factors, in such a situation, non-linear intelligent systems are the most suitable method for predictions. Nowadays, much attention is paid to artificial intelligence (AI) to predict such cases as bankruptcy. Foroughi and Yadegari (2010) see the most important application of AI systems in finance as the prediction of variables. ANNs and metaheuristic algorithms are among the most important combined intelligent methods. They are particularly useful in selecting the best information and making logical decisions as well as making predictions in complex and non-linear situations (Motie Ghader et al., 2010).

Optimization refers to achieving the best result under a certain condition. The term metaheuristic is a higher level procedure to find, generate or select a heuristic that can provide a sufficiently good solution to an optimization problem (Moscato, 2012). In this research, evolutionary algorithms (EA) such as genetic algorithm and particle swarm optimization are used for optimization.

4.3. Genetic algorithm

The algorithm is a metaheuristic inspired by the process of natural selection and belongs to the larger class of evolutionary algorithms. The algorithm consists of five steps, namely initialization of the population (coding), fitness function (evaluation), selection, reproduction (crossover) and convergence (mutation). During the initialization step, a population of alignments is generated that is as diverse as possible, either randomly or, for example, through dynamic programming. The fitness of the population is evaluated by scoring each alignment with a specific objective function. A new population is then created using operators such as crossover and mutation. Crossovers create a child alignment by combining two parent alignments and are important to promote

the exchange of high value regions. The children can then be mutated, for example by inserting or deleting a gap. Only the weakest half of the population is replaced by the new offspring, while the other half is carried over into the next generation. The process ends when an empirical criterion is reached, i.e. after a certain number of generations or when no more improvement is observed (Thompson, 2016). Figure 2 shows a schematic version of the genetic algorithm.

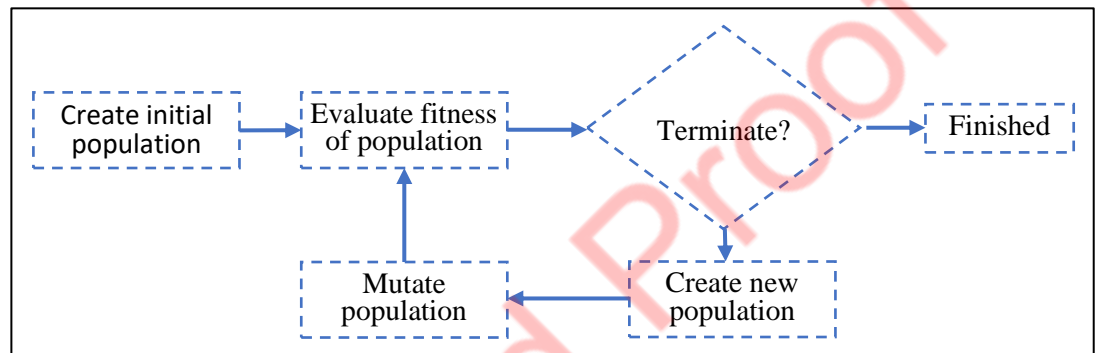


Figure 2. Typical genetic algorithm

4.4. Particle swarm optimization

The algorithm is inspired by the strategy that flocks of birds follow in their search for optimal food sources and avoid predators by “exchanging information” and thus gaining an evolutionary advantage. In a flock, a bird behaves according to its limited intelligence as well as the intelligence of the group. Each bird observes the behavior of its neighbors and adapts its own behavior accordingly. If one bird discovers a good path to food, the other birds will follow this path, no matter where they are in the flock (Qin *et al.*, 2024; Zahra *et al.*, 2017).

The optimization problem is a position $x_{ij}(t)$ and a velocity $V_{ij}(t)$ at time t . The best previous position (which gives the minimum fitness value) of any particle is recorded and called the personal best (P_{best}). Another best value achieved by any particle in the neighborhood of this particle is called global best (G_{best}). Each particle updates its P_{best} and G_{best} positions with a random weighted acceleration at any given time (Kumar *et al.*, 2013). The process is illustrated in Figure 3.

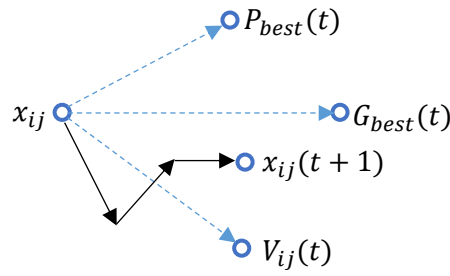


Figure 3. Update diagram of the individual particles in the swarm

Equation 2 provides the mathematical expression for the updated position and velocity of each particle iteration t and in the search space j .

$$V_{ij}t + 1 = w \times V_{ij}t + C_1 \times r_1 \times P_{best_{ij}} - x_{ij}t + C_2 \times r_2 \times G_{best_{ij}} - x_{ij}t \quad \text{Eq. (2)}$$

Where w is the inertia factor used as the control parameter for the swarm velocity, r_1 and r_2 are the random numbers between zero and one, C_1 and C_2 are the cognitive and social parameters, i.e. acceleration constants.

5. RESEARCH FINDING

The dependent variable of the study is bankruptcy, which results from the following formula.

$$\zeta = 1.2A + 1.4B + 3.3C + 0.6D + 1.0E \quad \text{Eq. (3)}$$

Where Zeta (ζ) is Altman's Z-score; A is the working capital/total assets ratio; B is the earnings/total assets ratio; C is the EBIT/total assets ratio; D is the market value of equity/total liabilities ratio and E is the total sales/total assets ratio. If the ζ -value of a company is less than 1.8, it is described as bankrupt. The range between 1.8 and 3 is the grey zone and more than 3 is the safe zone. The spread of ζ is shown in Figure 4.

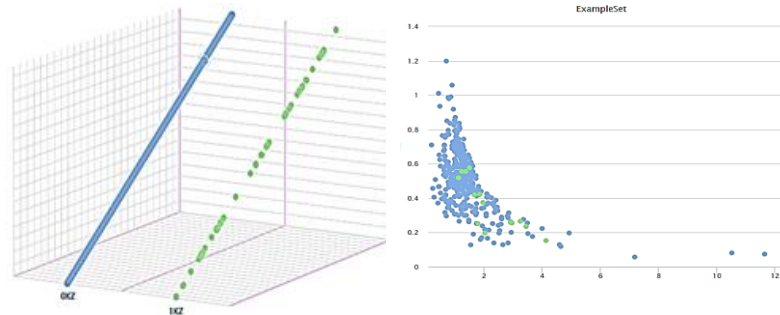


Figure 4. Dispersion of ζ (• healthy firms and • bankrupt firms)

Predictor variables are determined to achieve the objectives of the research.

Table 2. Predictor variables

<u>Accounting measures:</u>		
X1	Current ratio	The ratio of current assets to current liabilities.
X2	The short-term liability to assets ratio	Short-term liabilities divided by assets.
X3	Basic Earning Power	The ratio of EBIT divided by total assets.
X4	The operating cash ratio	The ratio of operating cash divided by total assets.
X5	Market-to-book ratio	Share price divided by net book value per share.
X6	The accounts receivable to assets ratio	The ratio of accounts receivable divided by total assets.
X7	The sales to current assets ratio	The ratio of net sales divided by current assets
X8	Economic value added (EVA)	EVA= NOPAT – (Invested Capital × WACC). Where, NOPAT is net operating profit after tax; Invested Capital is Debt + capital leases + shareholder' equity; and WACC is weighted average cost of capital.
X9	The asset turnover ratio	Net sales divided by average total assets.
X10	The retained earnings to total assets ratio	The ratio of retained earnings divided by total assets
X11	The retained earnings to shareholder's equity ratio	The ratio of retained earnings divided by shareholder's equity
X12	The gross profit margin ratio	[(Net revenue – direct expenses)/net revenue]×100%
X13	The long-term debt to equity ratio	Long-term debt divided by shareholders' equity.
X14	Net profit margin	The ratio of net income to sales.
X15	Cost of goods ratio	The ratio of cost of goods sold to sales.
<u>Firm risk measures:</u>		
X16	Systematic risk	Systematic risk measures the degree to which a particular investment's return changes relative to changes in return. $\beta = Cov(R_m, R_i) / \delta^2 R_m$
X17	Financial risk	The ratio of liabilities to assets.
<i>Corporate governance (managerial) measures:</i>		

X18	Non-executive directors	The ratio of non-executive directors to all members of the board.
X19	Institutional ownership	The total number of shares owned by shareholders more than 5%.
<u>Macroeconomic measures:</u>		
X20	Inflation	Annual inflation announced by the central bank.
X21	GDP	Gross Domestic Product announced by the central bank.

Stepwise linear regression is used to clarify and select predictor variables. The aim is to determine the variable that has an influence on the prediction of bankruptcy. To include independent variables in the stepwise linear regression model, the variable that has the highest correlation with the dependent variable is selected first. Then the second variable is included in the analysis, which causes the largest increase in the coefficient value after separating the previous variable. In this way, the variables are entered into the model one after the other until the error rate is less than 5%.

Stepwise linear regression can be interpreted if the classical assumption of regression is controlled. The normality of the dependent variable should be tested. This is because its normality leads to the normalization of the residuals of the model. The Kolmogorov-Smirnov test was used to test normality. The normality of the sample is confirmed if the P-value is greater than 5%. A P-value of 0.065 was confirmed here. The independence of the residuals is a further regression assumption. The interpretation of the regression results is incorrect if the error values are correlated with each other. The Durbin-Watson statistic is suitable for testing the independence of the residuals. The calculated value is 1.721. The assumption of a correlation between the residuals is rejected if the Durbin-Watson statistic is between 1.5-2.5. The result shows that the residuals are independent of each other. In other words, there is no autocorrelation between the errors. Then the t-test is used to select the variables whose significance level is less than 5% by calculating the coefficient of determination as suitable for enter to the model. Table 3 shows the status of the variables.

Table 3. General status of the variables

variable	result	variable	result	variable	result
X1	accept	X8	accept	X15	accept
X2	accept	X9	reject	X16	reject

X3	accept	X10	reject	X17	accept
X4	accept	X11	reject	X18	reject
X5	reject	X12	accept	X19	accept
X6	reject	X13	accept	X20	reject
X7	accept	X14	accept	X21	reject

The linear model can be presented as [equation 4](#).

$$\zeta = .191 - .091X1_{i,t} + .0128X2_{i,t} - .0161X3_{i,t} - .987X4_{i,t} - .501X7_{i,t} - .091X8_{i,t} - .013X12_{i,t} + .009X13_{i,t} - .005X14_{i,t} + .359X15_{i,t} + .021X17_{i,t} - .0192X19_{i,t} \quad \text{Eq. (4)}$$

Table 4. Multiple correlation coefficient of variables

variable	P-value	Improved determination coefficient R ²	Multiple correlation coefficient
X1	.000	.412	.655
X2	.000	.562	.699
X3	.000	.546	.702
X4	.000	.591	.721
X7	.001	.501	.781
X8	.000	.601	.770
X12	.002	.623	.784
X13	.001	.599	.795
X14	.003	.600	.745
X15	.000	.669	.799
X17	.003	.544	.765
X19	.001	.619	.749

The 10-fold cross-validation was applied to test the generalizability of the prediction. The method is completely reliable and sufficient to predict the actual error rate (Ellis and Mookim, 2013). In the method, the data set is shuffled. Then the data set is divided into 10 subsamples. In the first iteration, nine samples are used as training data and the rest as test data. The model is trained with the training data and evaluated with the test data. The evaluation results or the error rate are retained and the model is discarded. In the next iteration, a different subset is selected as test data and everything is repeated again. The iteration is repeated k times until all data is considered. Finally, the total error rate is the average of all individual evaluation results.

Criteria were used to evaluate the efficiency of networks with different structures and to determine the best one. (1) Mean Square Error (MSE); (2) Root Mean Square of

Errors (RMSE); and (3) the correlation coefficient (R). The network that has the lowest values of the two aforementioned errors whose R coefficient is closest to one is considered the best network. The first criterion represents the average error between the result obtained and the actual measured values.

$$MSE = \frac{\sum_{i=1}^N (O_i - T_i)}{N} \quad \text{Eq. (5)}$$

Where T_i and O_i are the estimated and actual values respectively and N are the available data pairs. The second criterion indicates the average error between the actual and predicted data. The criterion is calculated from [equation 6](#).

$$RMSE = \sqrt{\frac{\sum_{i=1}^N (O_i - T_i)^2}{N}} \quad \text{Eq. (6)}$$

The third criterion is the correlation coefficient between the values predicted by the NN and the output data of the numerical modeling. The criterion is calculated from [equation 7](#).

$$R = \frac{\sum_{i=1}^N (O_i - \bar{O}_i)(T_i - \bar{T}_i)}{\sqrt{\sum_{i=1}^N (O_i - \bar{O}_i)^2 - \sum_{i=1}^N (T_i - \bar{T}_i)^2}} \quad \text{Eq. (7)}$$

Where \bar{T}_i and \bar{O}_i are the average of estimated and actual values respectively.

5.1. The best network

The purpose of training NN is to determine the weights to obtain the best network for modeling the objective function. In general, supervised learning is one of the best types of learning ([Foroughi and Yadegari, 2010](#)). In supervised learning, the training data consists of inputs (feature vectors) that are paired with correct outputs (labels). Therefore, the feature vectors assume the correct output labels. During training, the algorithm searches for patterns in the feature vectors that are related to the labels. It trains the patterns. After training, new feature vectors are identified whose labels are unknown. will be identified. On the basis of the previous training, it is determined which label belongs to the new feature vector. The aim of a supervised learning model therefore is to predict the correct label for new feature vectors. NN structures were used as [Table 5](#).

Table 5. Different neural network structures

Pattern	No. of hidden layers	No. of first layer neurons	No. of second layer neurons	No. of output layers
ANN-I	1	10	6	2
ANN-II	1	12	8	2
ANN-III	1	14	10	2
ANN-IV	2	10	6	2
ANN-V	2	12	8	2
ANN-VI	2	14	10	2

The number of neurons in the hidden layers is determined by trial-and-error and does not follow a specific rule. The network is not able to train if the number of neurons is too low. In addition, the phenomenon of ultra-learning occurs when the number of neurons is large. The modes lead to an increase in network error (Charalambous, 2023; Motie Ghader *et al.*, 2010). The modeling process of NNs in Rapidminer software is shown in Figure 5.

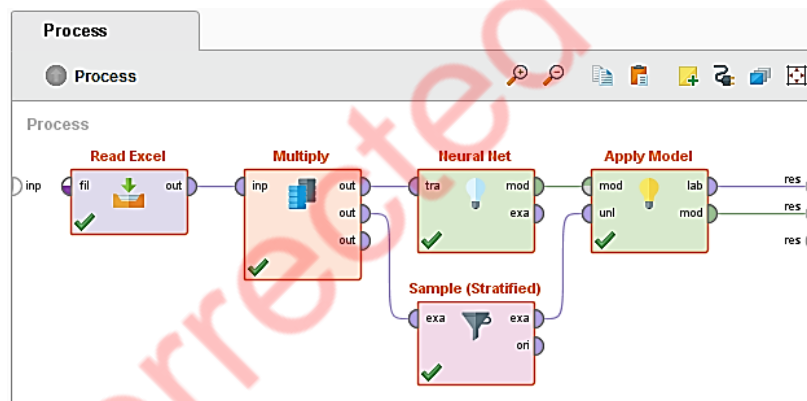


Figure 5. Modeling process in the software

Table 6 shows the values of R, MSE, and RMSE for different artificial network structures.

Table 6. R, MSE, and RMSE

Pattern	R		MSE		RMSE	
	Training	evaluating	Training	evaluating	Training	evaluating
ANN-I	.800	.759	.0971	.1155	.3141	.3187
ANN-II	.861	.819	.0436	.0666	.2152	.2560
ANN-III	.842	.817	.0666	.0781	.2613	.2812

ANN-IV	.830	.802	.0582	.0721	.2424	.2651
ANN-V	.812	.758	.1021	.1127	.2752	.3333
ANN-VI	.852	.822	.0610	.0652	.2151	.2550

Table 6 shows that the best pattern is ANN-II. In the training phase, the values of R, MSE and RMSE are 0.861; 0.0436 and 0.2152, respectively. The values in the evaluation phase are 0.819; 0.0666 and 0.2560. The process is shown in Figure 6. The values of evaluation phase indicate that all examples (feature vectors) have been trained well and are able to predict bankruptcies.

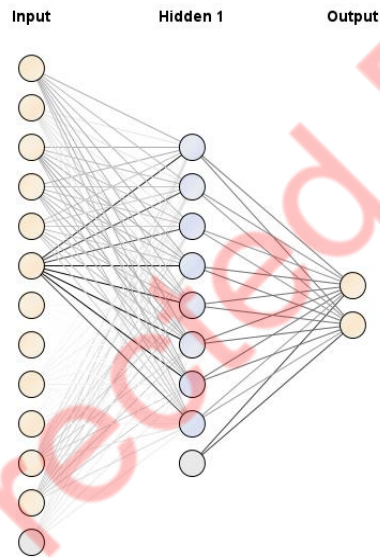


Figure 6. The best NN model

5.2. Genetic and particle swarm optimization algorithms

Metaheuristic algorithms use a relatively similar mechanism to find the optimal solution. In most algorithms, the search begins by generating a set of random solutions within the allowable range of the decision variables. The set of solutions in each of the algorithms has names such as swarm, colony, group, etc. Names such as particles, chromosome, ants and the like are assigned to each individual solution. Then a set of new solutions with operators is generated. The process continues until the stopping criterion is reached (Sharifzadeh and Amjady, 2014). The performance of the two algorithms used in

the research is based on swarm. Therefore, the combination of the two algorithms with the NN shows different performance due to their nature. The purpose of combining algorithms with NN is to optimize the weights and biases of the NN. Algorithms are swarm-oriented in nature. Therefore, the problem should be defined in such a way that it can be optimized as a swarm. In the problem definition phase, the chromosomes or particles should be such that the weights and biases are optimized. Therefore, the number of genes of each chromosome should be equal to the number of weights and biases. The program is executed 10 times to perform the necessary validation. In each execution, a combination of the input pattern was determined to optimize the factors affecting the bankruptcy. Finally, the best solutions (variables) were compared based on the values of R and MSE. The modeling process of PSO in software is shown in Figure 7.

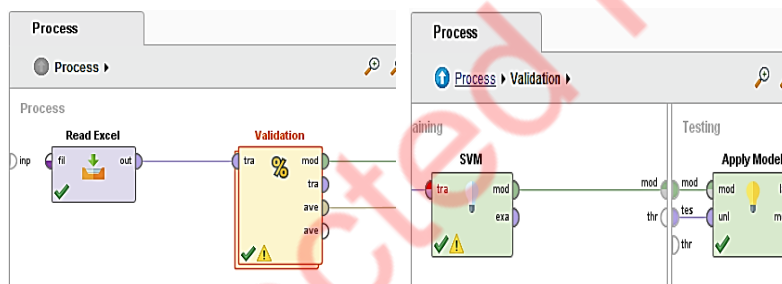


Figure 7. Modeling process in the software

For data classification, the nonlinear Support Vector Machine (SVM) based on the Gaussian Kernel was used in the optimization model. The method is suitable both for searching for the best parameters of the SVM and for selecting the best feature. The results of the Kernel test can be found in Figure 8.

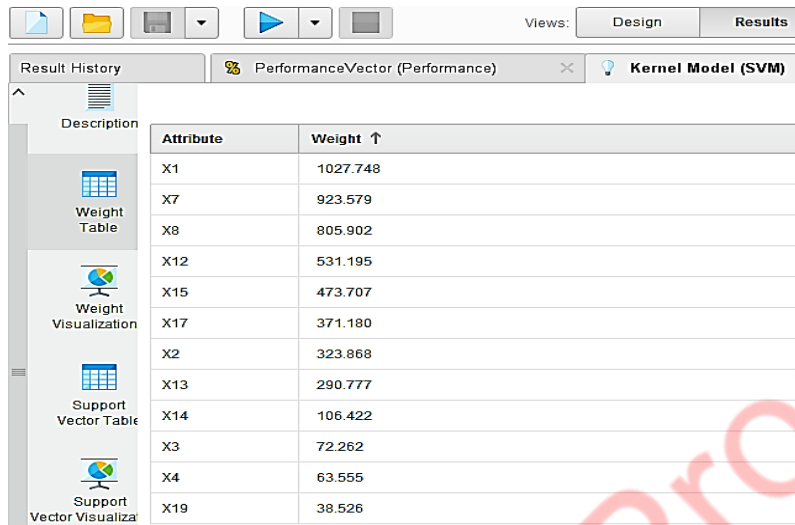


Figure 8. The Kernel model result

The results of the Kernel model show that features (variables) with a higher weight have a higher accuracy. This means that they have more influence on the bankruptcy model. The features are listed in Figure 8. The performance of the algorithms can be illustrated using confusion matrix. The error in predicting healthy firms can be neglected, but not for bankrupt firms. In other words, the expectation is to predict bankrupt firms without leaving even one bankrupt firm. The confusion matrix is useful when the accuracy and precision in predicting one feature is very important for comparing the overall prediction. The confusion matrix is shown in Figure 9.

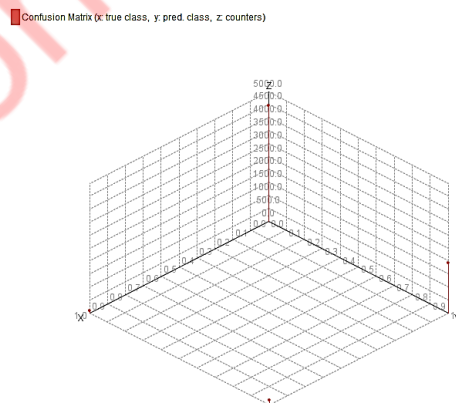


Figure 9. Confusion matrix

Table 7 shows the error value indices of the research models. Compared with other patterns, the combination of ANNs and PSO (ANNs-PSO) can reduce the MSE error and increase the correlation coefficient. On the other hand, linear regression (LR) has the highest rate and the lowest correlation.

Table 7. Comparative values of R and MSE indices of the research models error

Pattern	R		MSE		Correlation coefficient difference b/w training and evaluating
	Training	evaluating	Training	evaluating	
LR	.799	.767	.0997	.1174	.0591
ANNs	.849	.828	.04673	.06725	.0383
ANNs-GA	.866	.839	.03999	.05548	.0234
ANNs-PSO	.878	.861	.02751	.04611	.0152

The results in Table 7 show that the ANNs-PSO pattern is almost able to handle new data. Therefore, the efficiency of the pattern towards the prediction of bankruptcy is proven.

5.3. Test of research hypotheses

The paired t-test is suitable to test hypotheses and determine out the existence of significant differences between the patterns. Prior to this, the normality of the MSE indices is tested using the Shapiro-Wilk test according to Table 8.

Table 8. Results of the Shapiro-Wilk

MSE index	LR	ANNs	ANNs-GA	ANNs-PSO
Shapiro-Wilk P-value	.112	.327	.341	.491

A P-value of more than 5% in the Shapiro-Wilk test means that the MSE indices are normal.

The results of the t-test in Table 9 show a significant difference in all performance criteria between a pair of predictor patterns. The 10-fold cross-validation is used to compare the predictive accuracy of the patterns. Cross-validation is typically used in applied machine learning to compare and select a pattern for a particular predictive modeling problem.

Table 9. t-test results

Paired patterns	t statistic	P-value	10-fold cross-validation (more accuracy)
LR – ANNs	43.651	.001	ANNs
LR – GA	50.214	.000	GA
LR - PSO	38.229	.001	PSO
ANNs – GA	11.588	.000	GA
ANNs – PSO	31.334	.001	PSO
GA – PSO	51.647	.001	PSO

The result of the t-test for the LR and ANNs patterns shows that the MSE value of the two patterns has a significant difference at the 5% error level. The result of the cross-validation confirms that the ANNs pattern can have higher optimization accuracy with lower error. Therefore, the first hypothesis of the study is confirmed.

The results of Table 9 show that the MSE value of the LR pattern has a significant difference with the GA and PSO patterns at the 5% error level. The result indicates that the two patterns are different and the hybrid pattern of ANNs, GA and PSO may have a higher optimization accuracy with a lower average error. Therefore, the second hypothesis of the study is confirmed.

The cross-validation results also show that consider the hybrid patterns of ANNs, GA and PSO have a lower average error than the ANNs pattern. Therefore, the third hypothesis of the study is confirmed.

The result of ranking the patterns based on the higher accuracy in predicting bankruptcies are shown in Table 10.

Table 10. The ranking of patterns in predicting bankruptcy

Rank	MSE training error	MSE evaluating error	Result test (more accuracy)
1	.0198	.0485	PSO
2	.0276	.0591	GA
3	.0401	.0722	ANNs
4	.1244	.1511	LR

The PSO pattern has fewer training and evaluation errors compared to the others and takes first place.

5.4. Key variables for bankruptcy prediction

Table 11 shows the importance of the predictor variables in ANNs, GA and PSO, based on the ratio of the accuracy of the variables to the overall accuracy of the variables.

Table 11. Key variables on predicting bankruptcy

variable	(ANNs) ¹	(GA) ²	(PSO) ³	(2-1)	(3-1)	selection
X1	17.41%	18.62%	19.01%	+ 1.21%	+ 1.6%	◀ Best
X2	4.68%	3.57%	5.08%	- 1.11%	+ .4%	
X3	4.25%	1.08%	2.88%	- 3.17%	- 1.37%	
X4	3.53%	5.10%	1.39%	+ 1.57%	- 2.14%	
X7	15%	18.01%	17.24%	+ 3.01%	+ 2.24%	◀ Best
X8	14.73%	14.89%	15.93%	+ .127%	+ .136%	◀ Best
X12	12.31%	12.51%	13.44%	+ .109%	+ .117%	◀ Best
X13	5.45%	4%	5.68%	- 1.45%	+ .23%	
X14	3.51%	2.71%	3.91%	- .8%	+ .4%	
X15	11.39%	9.90%	12.21%	- 1.49%	+ .82%	
X17	5.88%	6.05%	.223%	+ .17%	- 5.66%	
X19	1.86%	3.56%	1%	+ 1.7%	- .86%	
Total	100%	100%	100%	-	-	-

The ANNs confirmed the predictive power of 12 variables, including X1, X7, X8, X12, X15, X17, X2, X13, X14, X3, X4, and X19 respectively. The combined model is used for optimization. The optimization is performed when the MSE error leads to an increase in accuracy. The hybrid ANNs-GA led to the identification of 7 optimized variables, including X1, X7, X8, X12, X17, X4 and X19 respectively. The hybrid ANNs-PSO led to the identification of 8 optimized variables, including X1, X7, X8, X12, X15, X2, X13, and X14 respectively. It can be inferred that the ANNs-PSO is the best method for predicting bankruptcies by optimizing the variables at the lowest error level.

6. CONCLUSION

The study's exploration of predictive modeling techniques for financial risk assessment offers valuable insights into the limitations of linear statistical analysis and the potential of non-linear approaches, particularly ANNs combined with metaheuristic optimization algorithms like GA and PSO. An important limitation of linear models is the lack of a direct indicator that best represents the data in a linear condition. Therefore, linear statistical analysis is inappropriate in many cases, which is the nature of social sciences. With linear patterns, the basic pattern must be established in advance. The basic pattern makes the problem easier to solve. But it requires a lot of guesswork. In addition, the pattern depends on various assumptions, such as the absence of multiple linear correlations and the normal distribution of the residuals.

It can be concluded that the use of non-linear NN models can increase the efficiency of the model. On the other hand, the evaluation of the performance of the hybrid models of ANNs, GA algorithm and particle swarm showed the superiority of the models compared to the linear regression model and the NN. In general, it can be stated that metaheuristic algorithms such as genetic algorithm and particle swarm algorithm as a supplement to the NN increase the prediction accuracy. The increase in accuracy can lead to different results. The study also identifies four key financial ratios—current ratio, sales to current assets ratio, economic value added, and gross profit margin ratio—as significant predictors of bankruptcy.

One key lesson from the study is the importance of leveraging advanced modeling techniques to overcome the limitations of traditional linear approaches. The success of hybrid models combining ANNs with metaheuristic algorithms highlights the value of integrating diverse methodologies to enhance prediction accuracy and robustness. While the study demonstrates the effectiveness of hybrid modeling approaches, it is not without limitations. One notable limitation is the reliance on historical financial data, which may not fully capture the dynamic nature of financial markets. Additionally, the study's focus on bankruptcy prediction may limit its applicability to other financial risk domains. Therefore, future

research in this area could explore the application of hybrid modeling techniques to other financial risk scenarios beyond bankruptcy prediction. Additionally, investigating the impact of incorporating alternative data sources such as sentiment analysis and social media data could further enhance predictive accuracy and broaden the scope of financial risk assessment.

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