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# Neural Network VS Genetic and Particle Swarm Optimization Algorithms in Bankruptcy

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## Abstract

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. 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 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. The results showed that the ability to explain the initial pattern has risen using GA and PSO. The evaluation of ANN performance demonstrates the superiority of the models over linear regression. 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 ANNs-PSO and ANNs-GA hybrid approach. The evidence reveals the effectiveness of the metaheuristic algorithms compared to linear ones in predicting bankruptcy. This further highlights the new breed of computational tools available to techno-savvy financial analysts and investors.

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## 1. Introduction

Bankruptcy is a bitter end for companies. It is a legal proceeding initiated when a company cannot pay outstanding debts or obligations. The event can mean a huge loss for the company's stakeholders. The distinction between bankrupt and non-bankrupt companies is one of the most critical issues for investors. Therefore, predicting bankruptcy is considered one of the most important investment factors (Ainan et al., 2024; Valizadeh Larijani and Banimahd, 2022). Consequently, investors must 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; Kumar and Bhattacharya, 2006; Mai et al., 2019; Beaver, 1966), multivariate analyses (Altman, 1968; Fulmer et al., 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 et al., 2021).

There are two aspects to the prediction time of insolvencies: key indicators and fundamental analysis (Moghaddam and Taghi- Mollayi, 2015). The difference lies in the prediction time of bankruptcy. Key indicators can show that bankruptcy is imminent. On the other hand, fundamental analysis 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 bankruptcy prediction helps improve investors' decision making. Therefore, it seems necessary to determine an appropriate model. Second, intelligent hybrid methods are 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 models are optimized based on GA and PSO algorithms. Thus, the problem raised is that the GA and PSO optimization model can 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 compare 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 (Lu 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 is 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 findings of the research and explains them in detail. Finally, section 6 provides the conclusion.

## 2. Literature review

Bankruptcy is when a company's liabilities exceed the market value of its assets (Gitman, 1996). Financial distress occurs when a company's realized rate of return on capital continuously and significantly falls short of the expected rate of return (Altman and Hotchkiss, 2010). Consequently, the two concepts of bankruptcy and financial distress differ. 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. Therefore, a company can 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 a company's conditions and financial status 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 when the company cannot provide sufficient cash flow to meet its contractual obligations. Failure to end this situation in the long term negatively impacts the company's value and the shareholders' wealth. Eventually, the conditions lead to inefficiency of financial operations and bankruptcy (Wang et al., 2021). The company's bankruptcy leads to significant business losses on a global scale. Early recognition of an unfavorable situation in the company has economic advantages. This has led scientists to develop various models for predicting bankruptcy (Dasilas and Rigani, 2024; Hosaka, 2019). Developing reliable bankruptcy prediction models is important for corporate risk assessment, helps managers avoid bankruptcies and allows shareholders to screen and select investment companies (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 various factors such as sampling, feature selection, modeling, and performance evaluation (Jamali et al., 2021). 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 Ćwięk, 2020). 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. In some ways, they are 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 the 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. Chava and Jarrow (2004) then added to the validity of Shumway's model, comparing it to scoring models. In addition, the effects of industry were also considered. Chava and Jarrow (2004) and Campbell et al. (2008) are two important combined models considering accounting and market information. 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 considers the latest market information, better reflecting 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 the company's liquidity situation.

Today, new statistical methods in finance have entered a new phase of bankruptcy prediction. For example, artificial neural networks and metaheuristic methods have increased significantly (Alibabaee 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, which are transferred from one player to the other until the player's point reaches zero. The theory states that the company can be considered 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 a company's cash balance is one of its main concerns. The imbalance between the input and output of flows means that the company is unable to manage its liquidity. This factor can lead to financial distress and bankruptcy (Mirarab-Bayegi et al., 2020).

***Credit risk theory*** 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 of 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 manage incremental earnings by reducing items such as the 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.

## 2.1 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.

## 3. 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. The data is trained in the second phase, and the model is evaluated in the third phase. SPSS, Excel and Rapidminer software were used to operationalize the phases. The study's statistical population 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 study's variables should be available in the financial statements.

The sample size based on the basis of firm-year on the above criteria is shown in Table 1.

**Table 1.** Sample selection procedures

| | **Observations** |
|---|---|
| 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: identifying and selecting relevant financial data from companies listed on TSE for ten years (2013-2023), including various financial ratios and metrics.

- Stage 2: collecting 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: GA and PSO algorithms are integrated 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.

### 3.1 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 ways to connect neurons 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 can solve 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 involves 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 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). 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 and observed values is called mean squared error (MSE) (Goodfellow et al. 2016).

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

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. An algorithm corrected the error 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 its performance is measured by comparing the predicted values of the network with the observed values (Shetty et al., 2022). Figure 1 shows a schematic diagram of a fully connected feedforward network.

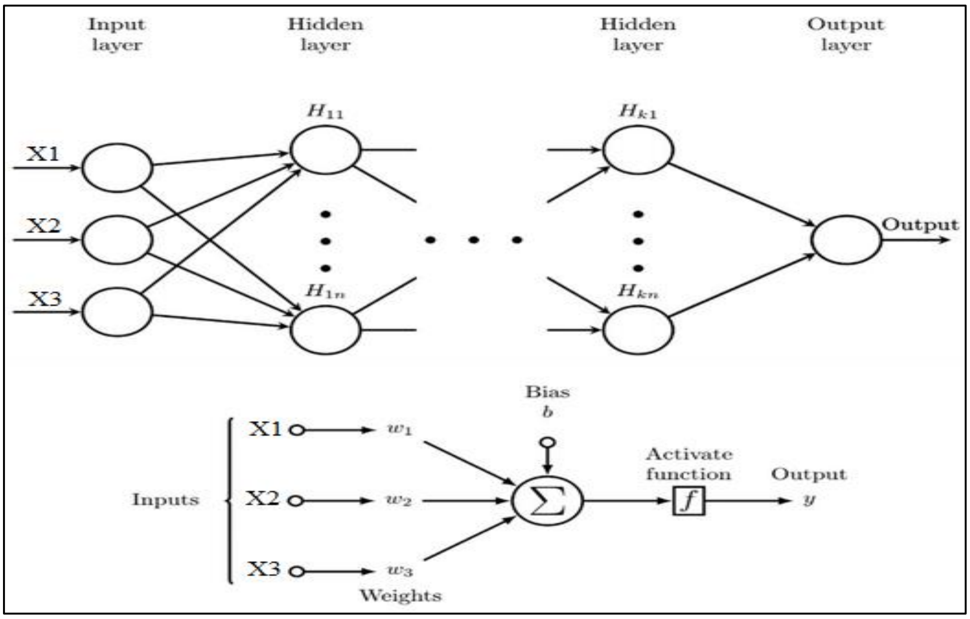



**Figure 1.** The upper figure is a fully connected feedforward artificial neural network (X1, X2, and X3 = input variables); the lower figure is a schematic of the computational unit of the network.

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.

### 3.2 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 influenced by politics, economics, psychology, *etc*. In such a situation, non-linear intelligent systems are the most suitable prediction method. 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 instrumental in selecting the best information, making logical decisions, and 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 (Parejo et al., 2012). In this research, evolutionary algorithms (EA) such as genetic algorithm and particle swarm optimization are used for optimization.

### 3.3 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 population's fitness 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 by inserting or deleting a gap. The new offspring replaces only the weakest half of the population, 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.

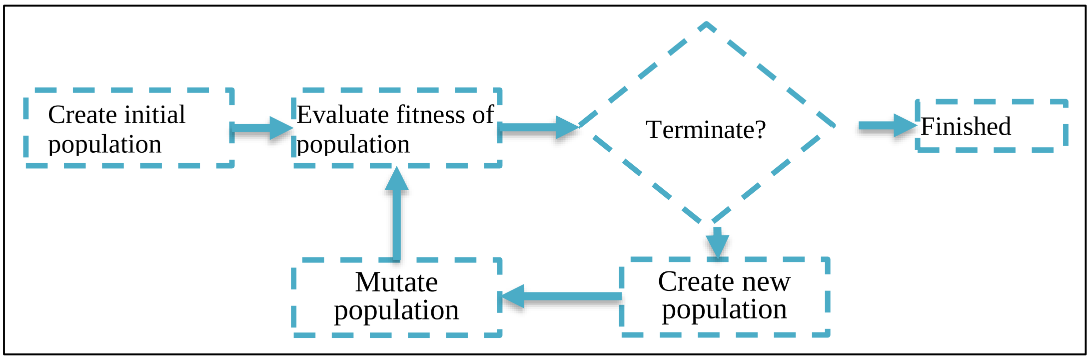



**Figure 2.** Typical genetic algorithm

### 3.4 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 it, 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 $t$. Any particle's best previous position (which gives the minimum fitness value) 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.

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

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

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.

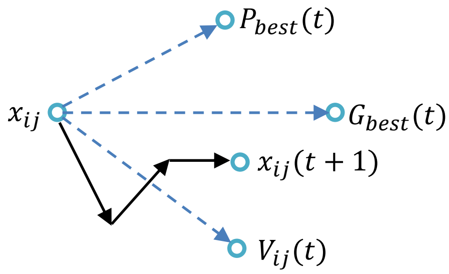



**Figure 3.** Update the diagram of the individual particles in the swarm

## 4. Research finding

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

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

Where Zeta ($\zeta$) 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 $\zeta$-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 $\zeta$ is shown in Figure 4.

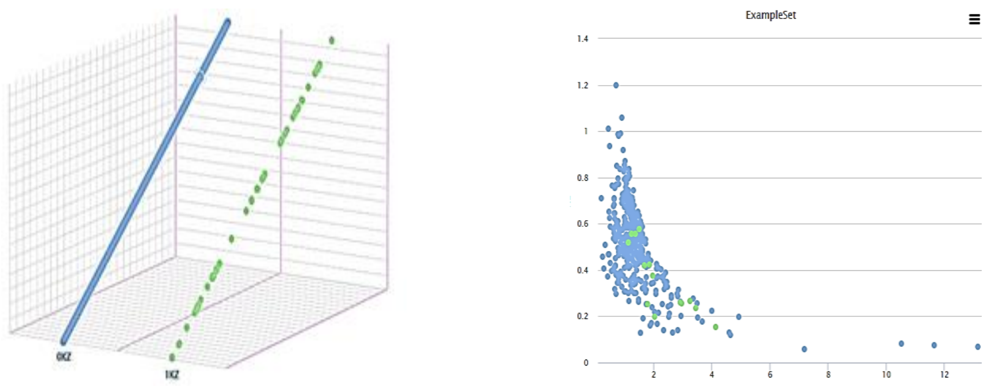



**Figure 4.** Dispersion of $\zeta$ (● healthy firms and ● bankrupt firms)

According to Table 2, Predictor variables are determined to achieve the research objectives.

Stepwise linear regression is used to clarify and select predictor variables. The aim is to determine the variable that influences 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%.

**Table 2.** Predictor variables

| | | |
|---|---|---|
| | ***Accounting measures:*** | |
| X1 | Current ratio | The ratio of current assets to current liabilities. |
| X2 | The short-term liability to assets ratio | Short-term liabilities are 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). NOPAT is net operating profit after tax; Invested Capital is Debt + capital leases + shareholder's equity; and WACC is the weighted average cost of capital. |
| X9 | The asset turnover ratio | Net sales are 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. |
| | ***Firm risk measures:*** | |
| 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. |
| | ***Corporate governance (managerial) measures:*** | |
| 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 is more than 5%. |
| | ***Macroeconomic measures:*** | |
| X20 | Inflation | Annual inflation announced by the central bank. |
| X21 | GDP | Gross Domestic Product announced by the central bank. |

Stepwise linear regression can be interpreted if the classical regression assumption is controlled. The normality of the dependent variable should be tested. This is because its normality leads to the normalization of the model's residuals. 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 suitable for entering 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-.091$X1_{i.t}$+.0128$X2_{i.t}$-.0161$X3_{i.t}$-.987$X4_{i.t}$-.501$X7_{i.t}$-.091$X8_{i.t}$-.013$X12_{i.t}$+.009$X13_{i.t}$-.005$X14_{i.t}$+.359$X15_{i.t}$+.021$X17_{i.t}$-.0192$X19_{i.t}$ Eq. (4)

**Table 4.** Multiple correlation coefficient of variables

| Variable | P-value | Improved determination coefficient $R^2$ | Multiple correlation coefficient |
|---|---|---|---|
| X1 | 0.000 | 0.412 | 0.655 |
| X2 | 0.000 | 0.562 | 0.699 |
| X3 | 0.000 | 0.546 | 0.702 |
| X4 | 0.000 | 0.591 | 0.721 |
| X7 | 0.001 | 0.501 | 0.781 |
| X8 | 0.000 | 0.601 | 0.770 |
| X12 | 0.002 | 0.623 | 0.784 |
| X13 | 0.001 | 0.599 | 0.795 |
| X14 | 0.003 | 0.600 | 0.745 |
| X15 | 0.000 | 0.669 | 0.799 |
| X17 | 0.003 | 0.544 | 0.765 |
| X19 | 0.001 | 0.619 | 0.749 |

According to Table 4, 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 subset is selected as test data, and everything is repeated. 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 with the lowest values of the two aforementioned errors whose R coefficient is closest to one is considered the best. The first criterion represents the average error between the obtained and measured results.

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

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.

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

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.

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

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

### 4.1 The best network

Training NN aims to determine the weights to obtain the best network for modeling the objective function. 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) 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 related to the labels. It trains the patterns. After training, new feature vectors whose labels are unknown are identified. Based on the previous training, it is determined which label belongs to the new feature vector. Therefore, a supervised learning model aims to predict the correct label for new feature vectors. NN structures were used in 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, ultra-learning occurs when the number of neurons is large. The modes increase network error (Charalambous, 2023; Motie Ghader et al., 2010). The modeling process of NNs in Rapidminer software is shown in Figure 5.

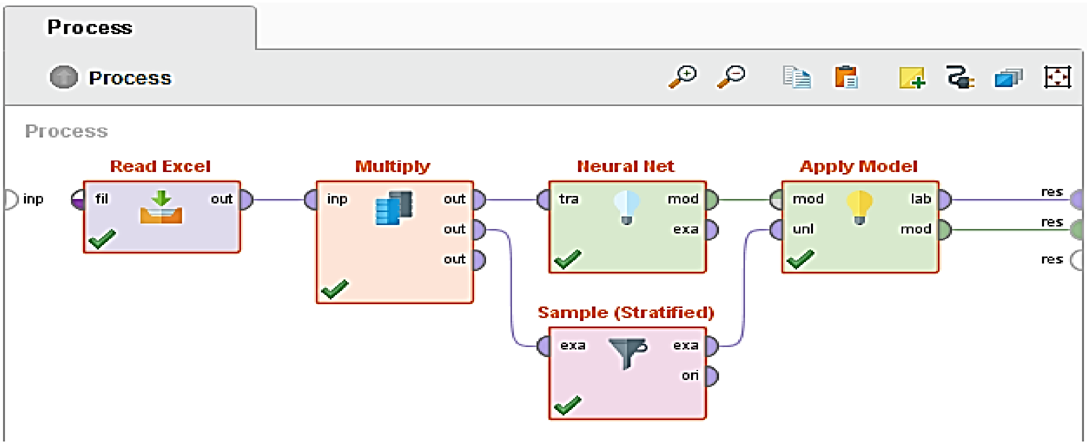



**Figure 5.** Modeling process in the software

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

**Table 6.** R, MSE, and RMSE

| Pattern | R | | MSE | | RMSE | |
|---|---|---|---|---|---|---|
| | Training | Evaluating | Training | Evaluating | Training | Evaluating |
| ANN-I | 0.800 | 0.759 | 0.097 | 0.115 | 0.314 | 0.318 |
| ANN-II | 0.861 | 0.819 | 0.043 | 0.066 | 0.215 | 0.256 |
| ANN-III | 0.842 | 0.817 | 0.066 | 0.078 | 0.261 | 0.281 |
| ANN-IV | 0.830 | 0.802 | 0.058 | 0.072 | 0.242 | 0.265 |
| ANN-V | 0.812 | 0.758 | 0.102 | 0.112 | 0.275 | 0.333 |
| ANN-VI | 0.852 | 0.822 | 0.061 | 0.065 | 0.215 | 0.255 |

Table 6 shows that the best pattern is ANN-II. In the training phase, the R, MSE and RMSE values 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 the evaluation phase indicate that all examples (feature vectors) have been trained well and are able to predict bankruptcies.

### 4.2 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 algorithm has names such as swarm, colony, group, etc. Names such as particles, chromosomes, ants and the like are assigned to each 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 patterns 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.

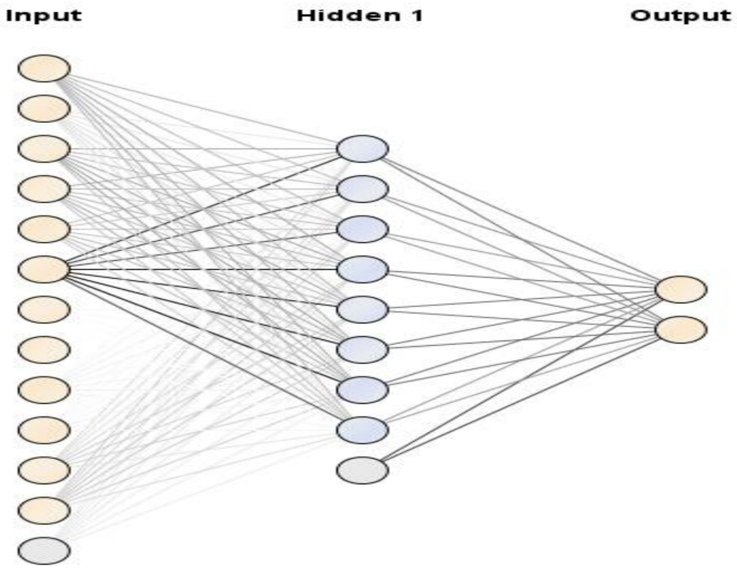



**Figure 6.** The best NN model

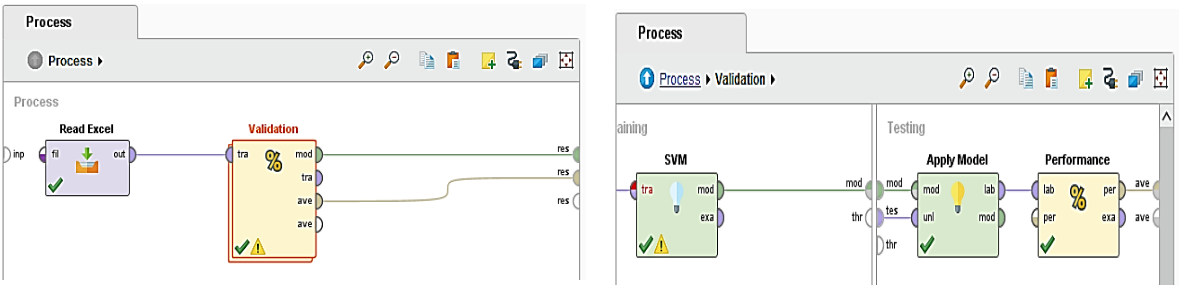
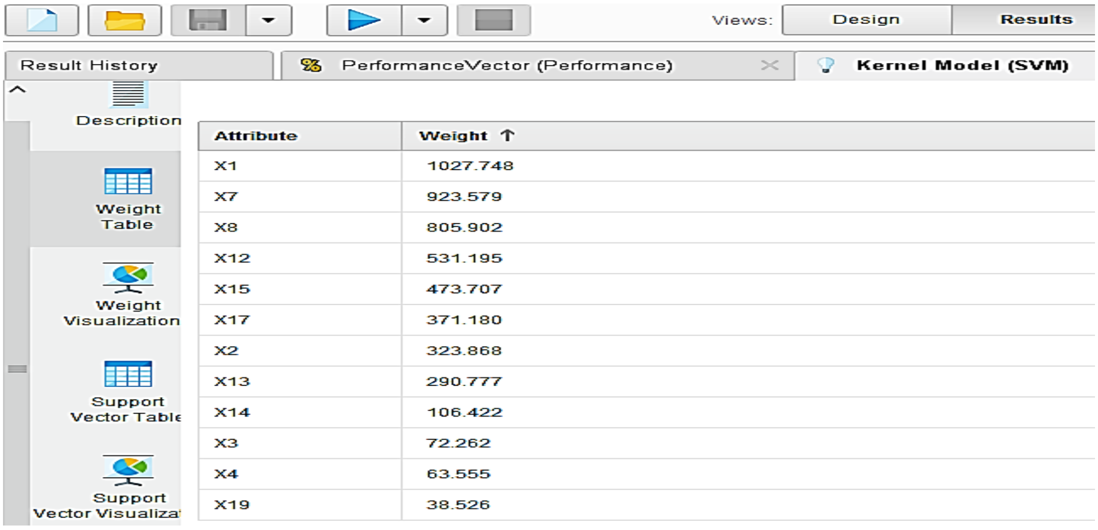



**Figure 7.** Modeling process in the software

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




| Attribute | Weight |
|---|---|
| X1 | 1027.748 |
| X7 | 923.579 |
| X8 | 805.902 |
| X12 | 531.195 |
| X15 | 473.707 |
| X17 | 371.180 |
| X2 | 323.868 |
| X13 | 290.777 |
| X14 | 106.422 |
| X3 | 72.262 |
| X4 | 63.555 |
| X19 | 38.526 |

**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 a 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 are vital for comparing the overall prediction. The confusion matrix is shown in Figure 9.

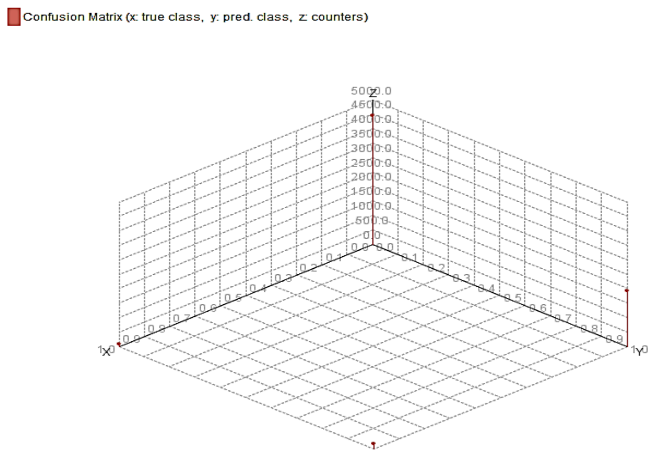



**Figure 9.** Confusion matrix

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.

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

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

| Pattern | R | | MSE | | Correlation coefficient difference b/w training and evaluating |
|---|---|---|---|---|---|
| | Training | Evaluating | Training | Evaluating | |
| LR | 0.799 | 0.767 | .0997 | 0.117 | 0.059 |
| ANNs | 0.849 | 0.828 | .0467 | 0.067 | 0.038 |
| ANNs-GA | 0.866 | 0.839 | 0.039 | 0.055 | 0.023 |
| ANNs-PSO | 0.878 | 0.861 | 0.027 | 0.046 | 0.015 |

### 4.3 Test of research hypotheses

The paired t-test is suitable to test hypotheses and determine 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 | 0.112 | 0.327 | 0.341 | 0.491 |

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

The t-test results 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 | 0.001 | ANNs |
| LR – GA | 50.214 | 0.000 | GA |
| LR - PSO | 38.229 | 0.001 | PSO |
| ANNs – GA | 11.588 | 0.000 | GA |
| ANNs – PSO | 31.334 | 0.001 | PSO |
| GA – PSO | 51.647 | 0.001 | 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 cross-validation result 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 and a lower average error. Therefore, the second hypothesis of the study is confirmed.

The cross-validation results also show that considering 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 results 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 | 0.019 | 0.048 | PSO |
| 2 | 0.027 | 0.059 | GA |
| 3 | 0.040 | 0.072 | ANNs |
| 4 | 0.124 | 0.151 | LR |

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

### 4.4. 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 for 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 identified 7 optimized variables, including X1, X7, X8, X12, X17, X4 and X19 respectively. The hybrid ANNs-PSO identified 8 optimized variables, including X1, X7, X8, X12, X15, X2, X13, and X14. It can be inferred that the ANNs-PSO is the best method for predicting bankruptcies by optimizing the variables at the lowest error level.

## 5. 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 often inappropriate, 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 using non-linear NN models can increase the model's efficiency. 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 algorithms and particle swarm algorithms as a supplement to the NN increase 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, which are significant bankruptcy predictors.

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 could explore applying 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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