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Selection of Effective Financial Ratios for Predicting Financial Distress and Predicting Financial Distress Using Artificial Neural Network and Logistic Regression Models(Case Study: Iranian Companies Listed in Iran Capital Market)[1]

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Research Paper

Abstract

The aim of the present study is to identify financial ratios effective in predicting financial distress using stepwise selection regression and LASSO regression models, and then to predict financial distress of companies listed on Iran's capital market using a multilayer artificial neural network model and a logistic model. This study is applied in terms of objective and, methodologically, quantitative, retrospective, descriptive, and correlational. The statistical population includes all companies active in Iran's capital market for 7 years from 2016 to 2023, which 148 companies were selected as the sample after screening. The initial filtered independent variables included 19 financial ratios in four groups: liquidity, profitability, leverage, and activity. For data analysis, stationarity, Chow, and Hausman tests were first applied, followed by a panel data regression model with fixed effects; for selection of financial ratios, stepwise regression and LASSO methods were used, both identifying four key variables. In the next step, logistic regression and artificial neural network models were employed to predict financial distress. Results showed that the neural network, with an accuracy of 92.6%, outperformed the logistic regression, which had 89.48% accuracy.

Keywords: Artificial Neural Network, Financial Distress, LASSO Regression, Logistic Regression, Stepwise Regression.

JEL Classification: G33, C45, C25, G17.

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Introduction [1]

Over the past 50 years, a large number of scientific and applied studies have focused on predicting bankruptcy (Altman, 1968; Beaver, 1966; Ohlson, 1980; OECD, 2010). The study of financial distress will always be important and refers to a situation in which the cash flow of companies are insufficient to pay the company's obligations and repay the company's debts, it means, cash outflows exceed cash inflows, and if this situation continues, it may lead to bankruptcy (Kordestani et al; 2011). This phenomenon is considered one of the most important challenges facing economic enterprises and has widespread negative effects on the company's stakeholders, including lenders, employees, investors, customers, and even the broader economic system. Therefore, accurate and in time prediction of financial distress is important to various stakeholders and can be an effective tool for reducing risk, preventing losses, and making timely decisions.

In recent years, especially after the global recession of 2009, this subject has attracted the attention of researchers(Mselmi et al; 2017). Financial institutions always need to anticipate financial crises to assess the financial health of companies and individuals. Predicting financial problems has become very important in recent years (Sethi & Mahadik, 2024). Several models have been used to predict financial difficulties. Altman (1968) created a z-score model, and Balasubramanian et al. (2019) defined a conditional logit model for Indian companies, using financial and non-financial characteristics to predict the accuracy of corporate financial rigidity. In the same context, Sehgal et al. (2021) examined the accuracy of the prediction of distress: they compared the logit model to an artificial neural network and machine learning algorithm in India's industrial sector. A combination of the Altman Z model and a multi-level artificial neural network was proposed by Wu et al. (2022) to predict the stock market using Chinese market data.

Traditional methods of predicting financial distress such as the Z-Altman scoring model (1968) and the Ohlson model (1980) are mainly based on regression and statistical analysis, and despite their simplicity and high interpretability, they suffer from limitations such as inability to model nonlinear and complex relationships. In recent years, with advances in the field of artificial intelligence and machine learning, methods such as artificial neural networks and hybrid models have been introduced as a suitable alternative to traditional methods. Using the ability to identify complex patterns and nonlinear relationships, these models have been able to significantly increase predictive accuracy (Barboza et al; 2017). In

1. This article is an extract from a PHD dissertation.

contrast, challenges such as the need to adjust multiple parameters, low interpretability, and computational complexity are also among the limitations of these approaches.

Despite numerous studies in the field of predicting financial distress, most of the studies, focused on the detection of financial ratios or probed limited comparison between several models. In the meantime, the simultaneous use of statistical variable selection techniques such as step-by-step regression and lasso regression, along with the comparison of the performance of classic predictive models (such as logistics) and new methods (such as artificial neural networks), has been less considered. Also, most of the studies developed in mature markets and in the developing markets like Iran, comparative studies in this field remains limited.

Although the findings of previous researchs can be very beneficial for many companies and investors, but in these studies, the method of selecting the variables examined is often based on the history of literature and without innovation, while in this study, variables are selected from the perspective of the unique variable selection method and by two methods of lasso regression and step-by-step. In most studies, the study of financial patterns has been conducted using traditional AI approaches (such as multiple differential analysis) and has not been analyzed using new AI approaches; however, due to the negative effects of financial distress on companies, the use of new methods that can predict the occurrence of financial distress is of particular importance; so in recent years, researchers in the field of artificial intelligence have developed a kind of hybrid model that has performed better than AI methods. The multilayer perceptron neural network hybrid pattern is a new and innovative hybrid pattern in financial and accounting researchs. In this regard, some studies have also predicted financial distress and bankruptcy of companies using financial ratios in Tehran Stock Exchange, but these studies have often modeled on foreign studies; if any pattern of predicting financial distress, although effective in different economies, cannot necessarily have proper accuracy and must be localized according to the economic situation of each country.

Accordinggly, this study, with the aim of improving the accuracy of financial distress forecasting in companies listed on the Iranian capital market, first identifies the effective financial ratios in predicting financial distress using two statistical methods of variable selection (step-by-step regression and lasso regression). Then, by using selected variables, two models of Statistical Classification (logistic regression) and intelligent (Multilayered Artificial Perceptron Neural Network) are designed and implemented to predict financial distress, and finally, the performance and accuracy of models are compared. Thus, this research, while responding to the gaps in the literature, can provide scientific and practical tools suitable for managers, financial analysts, investors and regulatory bodies.

The future sections of the study, which will be presented below, are structured as follows. First, a summary of the background of internal and external research is mentioned in the second part, the research methodology in the third part, the analysis and findings of the analysis in the fourth part and the conclusion, future proposals and limitations of the research in the fifth part are presented.

Literature Review

Several studies have been conducted in the past on corporate bankruptcy forecasts; Beaver (1966), Altman(1968), Deakin (1972), Blum (1974), Ohlson(1980) and Zmijewski (1984) have published the most notable studies. Bankruptcy forecasting is one of the essential variables needed to predict and estimate possible financial failure. Many stakeholders in a company have serious concerns about the exact timing of the company's financial problems. This applied importance has led to a large amount of researchs to predict the financial crisis of companies (Zhou et al; 2015).

Financial ratios are used as one of the most important tools for analyzing the financial situation of companies and to predict financial distress. Examining these ratios allows analysts and investors to assess the company's financial weaknesses and strengths and identify the risk of bankruptcy (Lee et al; 2020). Numerous studies have shown that companies usually show signs of disruption in their financial ratios years before bankruptcy.

Financial ratios are typically classified into four main categories: liquidity ratios, capital structure ratios, profitability ratios, and activity ratios (Ross et al; 2022).

Among these categories, cash ratios such as current ratio, instant ratio and cash ratio show the company's ability to pay short-term debts. Capital structure ratios such as total debt to shareholder equity ratio and interest coverage ratio also examine the company's reliance on external financial resources and its ability to manage debts. Debt coverage ratios are also among the key ratios in examining the company's ability to repay debts based on operating cash flow (Brigham and Houston, 2021).

Studies conducted by John (2021), Fachrudin (2021) and Zhiyong et al. (2021) emphasize that operating cash flow is one of the most important indicators of financial distress forecasting. Strong cash flow is a sign of the financial health of the company and its ability to manage financial obligations.

Overall, given the alarming function of financial ratios, these tools can be used as key elements in the design of financial distress prediction models and play an important role in financial and managerial decisions, and in this study, 19 financial ratios have been examined to predict financial distress.

Zizi et al. (2021) in the Moroccan economic environment determined the critical factors of the financial crisis and created the best forecast models for two years. Compared to small-scale healthy companies, their models classified the financial crisis of companies, and stateted that the first type errors are less than the second type errors.

Gepp and Kumar (2015) semiparametrically examined the Cox survival analysis model and nonparametric decision trees in order to predict the financial crisis, and their results were compared. They found that the survival analysis and decision tree models had strong predictive accuracy, which supported further researchs and justified their use. On the other hand, Xie et al. (2011) built multivariate audit analysis models and backup vector machines, using Chinese listed companies and found that the predictive power of backup vector machine models was better than multivariate audit analysis models.

Beaver (1966) used financial ratios to predict financial problems by using single-variable analysis. Financial metrics that assess profitability, liquidity and the ability to pay debts play an important role in predicting financial problems, like Altman (1968), who later developed the famous model of multivariate differentiation analysis. Based on the unique characteristics of each business, multivariate differentiation analysis places them in one of the different categories. Several studies have shown that profitability ratios help predict when financial problems arise in companies, for example, research by Altman et al. (2017), Beaver (1966), Hill et al. (1996), Ohlson(1980), Shumway (2001), and Xu et al. (2014) emphasized this. Therefore, according to results of research, there is a negative relationship between financial problems and profitability. On the other hand, the company's cash assets usually help pay off debts. One of the definitions of liquidity is the speed and efficiency of the company in converting assets into cash in order to fulfill its short-and long-term financial obligations (Brealey et al; 2011).

Previous research by Campbell et al. (2008), Chiaramonte and Casu (2017), Ijaz et al. (2013), Manab et al. (2015) and Zmijewski (1984) has shown that high levels of liquidity reduce the likelihood of financial problems.

The step-by-step regression model is a systematic method for selecting independent variables in multiple regression that uses three main approaches: forward, backward and hybrid (James et al; 2021).

Logical logistic regression lasso can be used to combine feature selection and classifier training. The advantage of this regression is to optimize the set of features for a specific model, and thus improve the performance of the model. In addition, the combination of feature selection and coefficient estimation reduces the computational load. Because there is no need for any explicit feature selection algorithm. Due to the simplicity of the model, the coefficients of the model are simply interpretable and offer more knowledge.

Basically, determining whether there is a financial problem is a binary decision in anticipating financial problems. Most statistical and AI techniques calculate the likelihood of financial problems; if this probability exceeds the threshold, financial problems are predicted (Bae, 2012). Adisa et al. (2019) proposed a hybrid model for bankruptcy forecasting that combines key component analysis (PCA) and artificial neural network analysis (ANN). It turned out that the PCA-ANN model, compared to other models, performed better.

Inam et al. (2019) used multiple audit analysis, logistic regression and artificial neural network to assess the likelihood of bankruptcy in non-financial companies of the Pakistani sector. They found that the neural network model performed better in predicting bankruptcy.

Balasubramanian et al. (2019) predicted financial distress in Indian listed companies using a conditional logit regression model. Such a model included not only financial indicators, but also non-financial indicators. The accuracy of predicting models based on financial variables was between 85.19% and 86.11%. However, when the financial and non-financial variables were considered together, the predictive accuracy improved significantly to 89.81% and 91.67%.

The majority of the researchs used the Altman Z model and paid little attention to the accuracy parameter of the model. This clearly shows a gap in research. Therefore, the aim of this study is developing a model by useing two models including logistic regression and artificial neural network to predict financial distress in companies listed in Iran capital market.

More advanced models of bankruptcy forecasting have been presented in recent research (Ohlson, 1980; Barboza et al; 2017; Tsai, 2009). In this technique, various financial ratios are also used to assess the risk of bankruptcy. In contrast, a financial distress prediction model that can sound the right warnings helps companies predict when they may file for bankruptcy and guides investors in search of investment opportunities. Accordingly, this study evaluates the issue of financial distress with two models of predicting distress. Since the artificial neural network used in our research is based on technological advances, it does not impose any specific limitations on predictive variables and it is one of the most common methods of predicting financial distress. However, the research that compares artificial neural network with statistical modeling of logistic regression, using the financial ratios derived from step-by-step regression and lasso is unique.

Artificial neural networks are computational models inspired by the biological nervous system that are used to learn complex patterns from data (Goodfellow et al; 2016). These models consist of sequential input, latent, and output layers, each layer comprising learnable neurons and weights (Bishop, 2006).

Ra'i and Fallahpour (2004) used artificial neural networks to predict financial distress in Iranian manufacturing companies and presented a comprehensive review of financial distress prediction models and artificial neural networks. The results of the models based on data of 80 companies showed that the artificial neural network model is significantly more accurate in predicting financial distress than the multiple discriminant analysis model.

Khodakarimi and Piri (2017) conducted a study on predicting financial distress based on a combined model of accounting and market information using a logistic regression approach and concluded that logistic regression is a suitable method for examining and estimating the model using accounting and market information to predict financial distress. For this purpose, thirteen variables, including eight accounting variables and five market variables, were used to determine financial distress. According to the results of the study, a combination of accounting and market information has the ability to predict the distress of companies and, considering the continuity of companies' activities, it can improve the quality of decision-making of shareholders and stakeholders.

Ashtab et al. (2017) conducted a study comparing the accuracy of financial crisis prediction models and their impact on earnings management tools and showed that machine learning models are more reliable tools for predicting financial crises compared to statistical models.

Dabbagh and Sheikhbigloo (2019) showed that the artificial neural network performs better than the Fulmer model and the accounts receivable to sales ratio was identified as the most effective ratio.

In a study by Sadehvand et al. (2022), a hybrid model using a multinomial logit model was presented, which in some cases performed better than the Altman and Merton models in predicting financial distress.

Azizi and Jokar (2022) investigated the effect of working capital information on financial distress prediction based on a combination of artificial neural networks and the cumulative particle motion algorithm. The main objective of the study was to investigate the effect of working capital information on financial distress prediction based on a combination of artificial neural networks and the cumulative particle motion optimization algorithm. The results of comparing the two models showed that the development of the research model reduces the neural network training error with the cumulative particle motion algorithm by 0.0641.

Aminimehr and Hekmat (2023) presented a deep learning model in a study while looking at the evolution of the financial distress prediction literature. The results of this study show that the convolutional neural network model performs better than previous distress prediction models, including logistic regression and support vector machines, at a confidence level of 95%.

Mehrani et al. (2020) investigated the prediction of financial distress of companies using an artificial immune system. In this study, various algorithms including wavelet neural network, artificial immune system, logistic regression and a combined algorithm of wavelet neural network and artificial immune system have been used. The results show that the combined algorithm has a higher ability to predict financial distress and can be used as a useful tool for financial decision-making.

Soleimani et al. (2023) presented a comprehensive model for predicting financial crises in banks using structural equations and artificial neural networks.

Finally, Hajazian et al. (2024) compared the rough set theory with neural and fuzzy network models and showed that the rough set model has a higher performance than other models in predicting financial distress with an accuracy of 98.7%.

Research Hypotheses

This study examines the following hypotheses:

Main Hypotheses:

H1. Financial ratios affect the prediction of financial distress among firms listed on Iranian capital market.

H2. Artificial neural networks provide higher prediction accuracy and precision for financial distress compared to logistic regression.

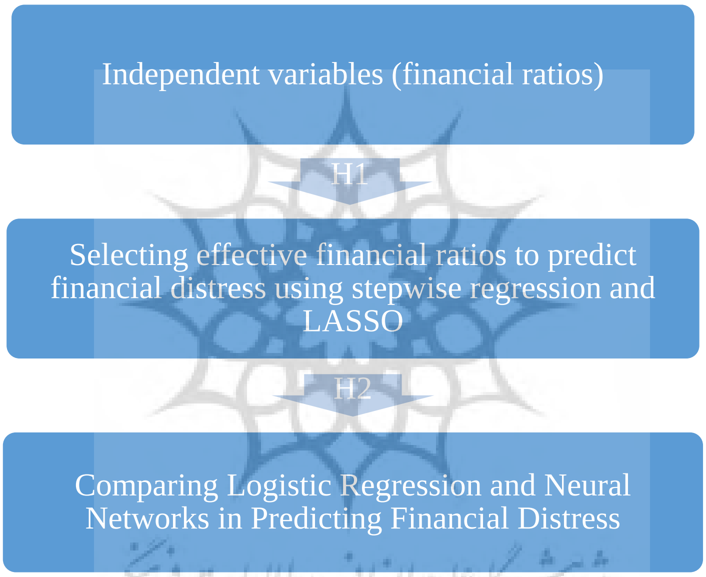

Figure 1. Conceptual Research Model

This study was conducted in three thematic, spatial, and temporal domains as follows:

- Subject area: This research examines the financial ratios that affect the prediction of financial distress and is classified in the field of finance and economic.
- Location area: Companies listed on Tehran Stock Exchange and the Iranian OTC (Fara Bourse).

- Time frame: 7 years from 2016 to 2023.

The statistical population includes all companies active in the Iranian capital market. Sampling was carried out using the systematic exclusion method and based on the following criteria:

- Admission to Tehran Stock Exchange or Fara bourse (OTC) before 2016 and continuous activity until 2023;
- Availability of annual financial statement data (balance sheet, profit and loss, cash flow and explanatory notes);
- Fiscal year-end ending on March 29 and no change in fiscal year;
- Exclusion of financial companies (investment, banking, insurance, leasing, holdings) and agricultural and livestock companies due to different reporting standards.

As a result, 148 companies were selected as the final sample.

Research Model and Variables

The model used in this study is as follows (Sethi and Mahadik, 2024) (Osoulian et al; 2024):

$$FD_{t+1} = \alpha_0 + \beta_1 R_{1it} + \beta_2 R_{2it} + \beta_3 R_{3it} + \beta_4 R_{4it} + \beta_5 R_{5it} + \beta_6 R_{6it} + \beta_7 R_{7it} + \beta_8 R_{8it} + \beta_9 R_{9it} + \beta_{10} R_{10it} + \beta_{11} R_{11it} + \beta_{12} R_{12it} + \beta_{13} R_{13it} + \beta_{14} R_{14it} + \beta_{15} R_{15it} + \beta_{16} R_{16it} + \beta_{17} R_{17it} + \beta_{18} R_{18it} + \beta_{19} R_{19it} + e_{it}$$

Dependent variable: Financial distress

Most studies rely on Article 141 of the Iranian Commercial Code to define distress, which relates to legal bankruptcy proceedings. In contrast, financial distress in this study reflects declining profitability, inability to service interest payments, increased financing costs and weakened cash flows (Kordestani, 2011).

Accordingly, firms are classified as financially distressed if they meet at least one of the following five criteria (based on Mansourfar et al; 2015; Mehrani et al; 2019):

1. Three consecutive years of net losses.
2. A reduction of more than 40 percent in cash dividends per share compared to the prior year.
3. EBIT below 80 percent of interest expenses for two consecutive years.
4. Negative stock returns accompanied by negative sales growth.
5. Book value per share below par value for three consecutive years.

Based on these criteria, 128 firm-years were distressed and 908 firm-years were non-distressed.

Independent Variables – Financial Ratios

Nineteen financial ratios were selected based on their documented forecasting power in prior empirical studies (Jabeur, 2017; Kliestik et al;

2020; Mslemi et al; 2017; Zizi et al; 2020; Zizi et al; 2021). These ratios fall within four categories: liquidity, leverage, profitability and activity.

Independent research variables are listed in Table 1 with their operational definitions (Zizi et al; 2021):

Table 1. Research Variables and Operational Definitions

Symbol	Variable	Operational definition
Liquidity		
R_1	Current ratio	Current assets divided by current liabilities
R_2	Quick ratio	Cash assets divided by current liabilities
R_3	Working Capital to Total Assets Ratio	Working Capital divided by Total Assets
R_4	Cash Ratio	(Cash and Cash Equivalents + Short-Term Investments) divided by Current Liabilities
Debt Repayment and Capital Structure		
R_5	Total Debt to Equity Ratio	Total Liabilities divided by Shareholders’ Equity
R_6	Interest Coverage Ratio	Earnings Before Interest and Taxes (EBIT) divided by Interest Expense
R_7	Debt Coverage Ratio	(Net Operating Income + Depreciation + Non-Cash Expenses) divided by Current Liabilities
R_8	Equity Ratio	Long-Term Debt divided by Shareholders’ Equity
R_9	Equity-to-Total-Assets Ratio	Shareholders’ Equity divided by Total Assets
R_{10}	Total Debt Ratio	Total Liabilities to Total Assets Ratio
Profitability		
R_{11}	Net Profit Margin	Net Profit divided by Sales
R_{12}	Operating Profit Margin	Operating Profit divided by Sales
R_{13}	Interest to Sales Ratio	Interest Expense divided by Sales
R_{14}	Return on Assets (ROA)	Net Profit divided by Total Assets
R_{15}	Return on Equity (ROE)	Net Profit divided by Shareholders’ Equity
R_{16}	Gross Profit Margin	Gross Profit divided by Sales
Efficiency Ratio		
R_{17}	Asset Turnover Ratio	Sales divided by the Average Total Assets (beginning and ending of the period)
R_{18}	Inventory Turnover Period (Days Inventory Outstanding)	(Average Inventory ÷ Cost of Goods Sold) × 365
R_{19}	Accounts Receivable Collection Period (Days Sales Outstanding – DSO)	(Accounts Receivable ÷ Credit Sales) × 365

Data Analysis Methods and Hypothesis Testing

For conducting appropriate statistical analysis, both descriptive and inferential statistics were employed. Descriptive statistics were used to summarize and describe the data. Additionally, aspects such as the normality of variable distributions, reliability of variables, correlations between variables, and multicollinearity were examined.

For inferential analyses and testing the research hypotheses, regression models for pooled (combined) data were. These data consisted of observations from different companies over multiple years and were treated as company–year panel data. EViews 12 and R were used for analysis and hypothesis testing.

In each fitted model, various statistical tests were conducted, which are described in detail below. Decisions regarding the different test statistics were based on comparing the obtained values with critical values and also by comparing the p-values of the statistics with a 5% significance level (95% confidence level).

Research Findings

Descriptive Statistics

The research variables were examined using central tendency measures (mean and median), dispersion measures (maximum, minimum, and standard deviation), and distribution shape measures (skewness and kurtosis). The results are reported in Table 2. Descriptive statistics provide an overall view of the distribution of observations for each variable and can be useful for assessing the generalizability of the results to other populations.

Table 2. Descriptive Statistics

Varaiables	Average	Median	Max	Min	Standard deviation	Skewness	Kurtosis
FD	0.122	0.000	1.000	0.000	0.327	2.309	6.332
R1	1.503	1.319	13.455	0.179	0.976	4.137	35.777
R2	0.961	0.825	11.382	0.082	0.755	5.015	50.556
R3	0.103	0.118	5.715	-1.657	0.264	8.907	204.775
R4	0.202	0.080	5.851	0.001	0.426	6.516	62.161
R5	2.007	1.271	105.993	-63.434	5.554	4.477	163.689
R6	-110.843	-2.861	155.458	-60711	1924.075	-30.829	970.506
R7	39.450	5.322	24407.67	0.334	766.896	31.626	1005.338

Variables	Average	Median	Max	Min	Standard deviation	Skewness	Kurtosis
R8	0.198	0.078	13.558	-27.904	1.158	-10.972	372.805
R9	41.630	41.741	92.600	-119.890	22.501	-1.179	8.911
R10	0.583	0.570	3.939	0.066	0.263	3.747	40.542
R11	17.140	14.672	492.329	-342.483	37.814	1.857	68.362
R12	18.230	17.458	153.234	-279.635	26.641	-3.812	40.412
R13	42.738	2.475	5533.098	0.000	298.228	14.403	237.283
R14	13.541	11.223	76.492	-69.989	15.141	0.248	5.307
R15	26.775	30.648	276.775	-1735.992	84.241	-14.996	286.318
R16	19.486	17.013	492.329	-342.483	38.762	1.655	61.805
R17	0.949	0.805	5.681	0.025	0.598	1.821	9.329
R18	163.815	128.038	2375.841	0.170	182.127	5.934	54.658
R19	181.238	115.390	5570.673	0.000	327.785	10.924	154.046

Source: Research Findings

Inferential Statistics and Hypothesis Testing

In the inferential statistics section, the first step involved examining the stationarity of the variables, followed by an analysis of the correlations between variables. Finally, econometric techniques were applied to test the research hypotheses.

Testing the Stationarity of Variables

Non-stationary variables can lead to spurious regression, distorting the interpretation of results. Therefore, it is essential that all research variables are stationary at the same order. To examine this assumption, the Levin, Lin & Chu (LLC) test was employed.

The hypotheses for this test are as follows:

- Null hypothesis (H_0): The variable is non-stationary.
- Alternative hypothesis (H_1): The variable is stationary.

According to these hypotheses, if the significance level of the test statistic is greater than 0.05, the null hypothesis is accepted; otherwise, the alternative hypothesis is supported. The results of the stationarity test at the variable level are reported in Table 3.

Table 3. Stationarity of variables

Variables	Symbol	Statistic	Significance Level	Result
Financial Distress	FD	-2.826	0.0024	stationary process
Current ratio	R_1	-20.974	0.000	stationary process
Quick ratio	R_2	-13.966	0.000	stationary process
Working Capital to Total Assets Ratio	R_3	-46.862	0.000	stationary process
Cash Ratio	R_4	-136.83	0.000	stationary process
Total Debt to Equity Ratio	R_5	-21.877	0.000	stationary process
Interest Coverage Ratio	R_6	-231.963	0.000	stationary process
Debt Coverage Ratio	R_7	-813.348	0.000	stationary process
Equity Ratio	R8	-79.533	0.000	stationary process
Equity-to-Total-Assets Ratio	R9	-41.614	0.000	stationary process
Total Debt Ratio	R10	-49.344	0.000	stationary process
Net Profit Margin	R11	-27.887	0.000	stationary process
Operating Profit Margin	R12	-17.762	0.000	stationary process
Interest to Sales Ratio	R13	-1047.43	0.000	stationary process
Return on Assets (ROA)	R14	-21.427	0.000	stationary process
Return on Equity (ROE)	R15	-52.772	0.000	stationary process
Gross Profit Margin	R16	-12.011	0.000	stationary process
Asset Turnover Ratio	R17	-48.130	0.000	stationary process
Inventory Turnover Period (Days Inventory Outstanding)	R18	-41.199	0.000	stationary process
Accounts Receivable Collection Period (Days Sales Outstanding – DSO)	R19	-40.753	0.000	stationary process

Source: Research findings

The results of the stationarity test indicate that all variables are stationary, as the significance levels of the test statistics for these variables are less than 0.05.

Although all variables are stationary, in order to avoid spurious regression and to ensure that the final results can be relied upon with confidence, it is necessary to examine the existence of a long-run relationship among the research variables prior to model estimation by applying a cointegration test. In fact, if the variables are found to be cointegrated, spurious regression will not arise.

Accordingly, the Kao cointegration test was employed, and the results of this test are reported in Table 4.

Table 4. Kao Cointegration Test

Test result	Significance level (p-value)	t-statistic	Null Hypothesis (H_0)
The null hypothesis is rejected	0.000	-21.4692	No cointegration exists among the variables

Source: Research findings

The results of this test indicate that cointegration exists among the variables, as the significance level is less than 0.05, which implies rejection of the null hypothesis. Therefore, given that cointegration among the variables is confirmed, it can be concluded that a long-run equilibrium relationship exists among the variables.

Diagnostic Tests

First, diagnostic tests must be conducted to select the most appropriate econometric model. The results of these diagnostic tests for the model are presented in Table 5. To perform these tests, the following model was employed:

Table 5. Diagnostic Tests for the Model

Test Result	Significance Level (p-value)	Test Statistic	Type of Test
The fixed effects (panel data) model is appropriate.	0.000	666.99737	Chow Test
The fixed effects model is appropriate.	0.000	7.364239	Hausman Test

Source: Research Findings

Based on the results of the diagnostic tests, it was determined that the fixed effects regression is the most appropriate estimation method for the model. According to the model selection tests, the fixed effects panel data model was accepted, and the estimation results of this model are reported in Table 6.

Table 6. Fix Effect

$$FD_{t+1} = \alpha_0 + \beta_1 R_{1it} + \beta_2 R_{2it} + \beta_3 R_{3it} + \beta_4 R_{4it} + \beta_5 R_{5it} + \beta_6 R_{6it} + \beta_7 R_{7it} + \beta_8 R_{8it} + \beta_9 R_{9it} + \beta_{10} R_{10it} + \beta_{11} R_{11it} + \beta_{12} R_{12it} + \beta_{13} R_{13it} + \beta_{14} R_{14it} + \beta_{15} R_{15it} + \beta_{16} R_{16it} + \beta_{17} R_{17it} + \beta_{18} R_{18it} + \beta_{19} R_{19it} + e_{it}$$

Variable	Symbol	Coefficient	Standard Error	t Statistic	Significance Level
Fixed	α	0.2272	0.05787	3.9275	0.00010
Current ratio	R1	0.0452	0.03583	1.2620	0.20730
Quick ratio	R2	-0.0263	0.04620	-0.5712	0.56800
Working Capital to Total Assets Ratio	R3	-0.0902	0.03774	-2.3925	0.01690
Cash Ratio	R4	-0.0517	0.04157	-1.2444	0.21370
Total Debt to Equity Ratio	R5	-0.0015	0.00159	-0.9857	0.32450
Interest Coverage Ratio	R6	0.0000	0.00000	0.5839	0.55940
Debt Coverage Ratio	R7	0.0000	0.00001	0.3058	0.75980
Equity Ratio	R8	-0.0132	0.00679	-1.9570	0.05070
Equity-to-Total-Assets Ratio	R9	-0.0035	0.00052	-6.9166	0.00000
Total Debt Ratio	R10	0.1194	0.05628	2.1222	0.03410
Net Profit Margin	R11	0.0037	0.00436	0.8534	0.39370
Operating Profit Margin	R12	-0.0010	0.00078	-1.3261	0.18520
Interest to Sales Ratio	R13	-0.0000	0.00003	-0.4382	0.66130
Return on Assets (ROA)	R14	0.0017	0.00110	1.5762	0.11530
Return on Equity (ROE)	R15	-0.0002	0.00010	-2.0759	0.03820
Gross Profit Margin	R16	-0.0036	0.00443	-0.8202	0.41230
Asset Turnover Ratio	R17	-0.0440	0.01898	-2.3202	0.02060
Inventory Turnover Period (Days Inventory Outstanding)	R18	0.0000	0.00007	0.7932	0.42780
Accounts Receivable Collection Period (Days Sales Outstanding – DSO)	R19	0.0000	0.00005	-0.0667	0.94680
Significance Level of F-Statistic	7.3642		F-Statistic		0.0000

$$FD_{t+1} = \alpha_0 + \beta_1 R_{1it} + \beta_2 R_{2it} + \beta_3 R_{3it} + \beta_4 R_{4it} + \beta_5 R_{5it} + \beta_6 R_{6it} + \beta_7 R_{7it} + \beta_8 R_{8it} + \beta_9 R_{9it} + \beta_{10} R_{10it} + \beta_{11} R_{11it} + \beta_{12} R_{12it} + \beta_{13} R_{13it} + \beta_{14} R_{14it} + \beta_{15} R_{15it} + \beta_{16} R_{16it} + \beta_{17} R_{17it} + \beta_{18} R_{18it} + \beta_{19} R_{19it} + e_{it}$$

Variable	Symbol	Coefficient	Standard Error	t Statistic	Significance Level
Adjusted R^2	0.5918		Coefficient of Determination (R^2)		0.5115

Source: Research Findings

Since the p-values of the t-statistics for some research variables are less than 0.10, these variables have a statistically significant effect on the prediction of financial distress at the 10% significance level (90% confidence level). The variables in this category include the working capital to total assets ratio, equity ratio, equity-to-total-assets ratio, total debt ratio, return on equity, and asset turnover ratio. Based on the model estimation results, these variables are statistically significant at the 90% confidence level and have a significant effect on the dependent variable.

The goodness of fit of each statistical model is evaluated using the coefficient of determination (R^2) and the F-statistic. The coefficient of determination of the estimated model is 0.591, indicating that the model explains 59% of the variation in the dependent variable. Moreover, the F-statistic and its associated p-value, which is less than 0.05, confirm the overall statistical significance of the estimated model.

Finally, given that the adjusted R^2 is 0.511 and close to the R^2 value, the inclusion of appropriate explanatory variables in the model is confirmed. These statistics indicate that the model exhibits a good overall fit; therefore, the interpretation of the findings and the estimated coefficients can be conducted with confidence.

The summary of the hypothesis testing results is presented in Table 7.

Table 7. Hypothesis Testing Results

Result	Hypothesis
Confirmed	The working capital to total assets ratio, equity ratio, equity-to-total-assets ratio, total debt ratio, return on equity, and asset turnover ratio have a significant effect on the prediction of financial distress.

Source: Research Findings

Based on these results, the research hypothesis, that financial ratios have an effect on the prediction of financial distress, is accepted.

Identification of Indepen dent Variables Using Stepwise Logistic Regression and LASSO Techniques

In applied studies, a large number of variables can lead to higher variance in the predictive performance of models and reduce their accuracy. Eliminating insignificant variables prevents poor model fit. Therefore, to identify the best-specified model, it is necessary to select variables that adequately explain the endogenous (output) variable.

In empirical research, using selection techniques based on likelihood ratio tests or Wald statistics is often difficult or sometimes impractical. For this reason, it is preferable to use numerical selection techniques, such as stepwise logistic regression or cross-validation-based ranking methods, to obtain the most appropriate variables that effectively explain the endogenous variable (Zizi et al; 2021).

In this study, two techniques were employed to reduce the number of variables:

1. Stepwise Logistic Regression Selection
2. LASSO Logistic Regression Selection

1. Stepwise Logistic Regression Selection

The main principle of the stepwise method is the minimization of one of the following two criteria:

Akaike Information Criterion (AIC)

$AIC=-2\ln(L)+2(K+1)$

Bayesian Information Criterion (BIC)

$BIC=-2\ln(L)+(K+1)\ln(n)$

L = Likelihood of the logistic model

K = Number of variables in the model

N = Number of observations

In this study, the AIC model was used for selecting independent variables because, due to its lower model complexity, it allows the inclusion of a larger number of variables.

2. LASSO Logistic Regression Selection

Selecting the optimal model is one of the most important issues in regression analysis. The aim of model selection methods in regression is to identify important explanatory variables and neglectable variables, thereby simplifying the relationship between the response variable and explanatory variables.

Considering the limitations of classical variable selection methods, such as stepwise selection, penalized regression methods can be employed. One such method is LASSO regression, which assumes that the errors follow a normal distribution. For statistical analysis of datasets with outliers, a Student's t-distribution can be used for the errors instead of the normal distribution.

Least Absolute Shrinkage and Selection Operator (LASSO) is a method for reducing coefficient multicollinearity and has been extended to many statistical models, including generalized linear models, M-estimators, and proportional hazard models.

The LASSO method provides the advantage of parsimonious and consistent variable selection, offering a better-defined and more interpretable model by selecting a limited subset of variables. Therefore, the selected subset of variables will be used for prediction.

To select the best explanatory variables for the endogenous variable and to determine the optimal penalty coefficient, cross-validation was employed. The LASSO estimator for the logistic regression model is thus defined as follows:

$$\hat{\beta}(\lambda) = \underset{\beta}{\operatorname{argmin.}} \left(n^{-1} \sum_{i=1}^{n} \rho(\beta)(Xi\,, Yi) \right) + \lambda \|\beta\| 1$$

To select the best explanatory variables for the endogenous variable and to determine the optimal penalty coefficient, cross-validation was employed.

Stepwise Regression Results

In this section, the research variables were reduced using the stepwise regression method, identifying the key variables that significantly influence the prediction of financial distress. The results are reported in Table 8.

Table 8. Reduction of Independent Variables Using Stepwise Regression

$FD_{t+1} = \alpha_0 + \beta_3 R_{3it} + \beta_9 R_{9it} + \beta_{15} R_{15it} + \beta_{17} R_{17it} + e_{it}$					
Variable Name	Variable Symbol	Coefficient	Standard Error	t-Statistic	Significance Level (p-value)
Constant Coefficient	α	0.336217	0.027889	12.05565	0.0000
Working Capital to Total Assets	R_3	-0.089270	0.037330	-2.391357	0.0170
Equity-to-Total-Assets Ratio	R_9	-0.003787	0.000504	-7.506017	0.0000

$FD_{t+1} = \alpha_0 + \beta_3 R_{3it} + \beta_9 R_{9it} + \beta_{15} R_{15it} + \beta_{17} R_{17it} + e_{it}$					
Variable Name	Variable Symbol	Coefficient	Standard Error	t-Statistic	Significance Level (p-value)
Return on Equity	R_{15}	-0.000181	9.40E-05	-1.930008	0.0539
Asset Turnover Ratio	R_{17}	-0.042460	0.018406	-2.306869	0.0213
Significance Level of F-Statistic	8.412831		F-Statistic		8.412831
Adjusted R²	0.591535		Coefficient of Determination (R²)		0.591535

Source: Research Findings

As inferred from the results, by removing 15 independent variables and retaining 4 variables, the coefficient of determination (R^2) remained at 0.59, indicating the correct elimination of variables. Moreover, all retained variables were statistically significant at the 90% confidence level.

LASSO Regression Results

In this section, the research variables were reduced using the LASSO regression method with the help of R software, identifying the key variables that significantly influence the prediction of financial distress. The results are reported in Table 9.

Table 9. Reduction of Independent Variables Using LASSO Regression

$FD_{t+1} = \alpha_0 + \beta_3 R_{3it} + \beta_9 R_{9it} + \beta_{15} R_{15it} + \beta_{17} R_{18it} + e_{it}$					
Variable Name	Variable Symbol	Coefficient	Standard Error	t-Statistic	Significance Level (p-value)
Constant Coefficient	α	0.28326	0.023387	12.1118	0.0000
Working Capital to Total Assets	R_3	-0.10308	0.037018	-2.78476	0.0055
Equity-to-Total-Assets Ratio	R_9	-0.00364	0.000505	-7.20575	0.0000

$FD_{t+1} = \alpha_0 + \beta_3 R_{3it} + \beta_9 R_{9it} + \beta_{15} R_{15it} + \beta_{17} R_{18it} + e_{it}$					
Variable Name	Variable Symbol	Coefficient	Standard Error	t-Statistic	Significance Level (p-value)
Return on Equity	R_{15}	-0.00021	9.42e-05	-2.22529	0.0263
Asset Turnover Ratio	R_{18}	5.18e-05	5.75e-05	0.90041	0.3681
Significance Level of F-Statistic	0.000000		F-Statistic		8.340611
Adjusted R^2	0.518778		Coefficient of Determination (R^2)		0.589450

Source: Research Findings

As inferred from the results, by removing 15 independent variables and retaining 4 variables, the coefficient of determination (R^2) remained at 0.589, indicating the correct elimination of variables. Moreover, three out of the four retained variables were statistically significant at the 95% confidence level.

Among the two methods presented, stepwise regression demonstrated a higher R^2 and greater predictive accuracy.

Logistic Regression and Neural Network Analysis

The research variables, which were reduced using the stepwise and LASSO methods, along with all original research variables, were tested using two logistic regression approaches to predict financial distress. The overall process of conducting logistic regression and artificial neural network (ANN) analysis is summarized in the Table 10.

Table 10. Steps for Conducting Logistic Regression and Artificial Neural Network Analysis

Steps for Artificial Neural Network (ANN) Analysis	Steps for Logistic Regression Analysis
1. Install and load the necessary packages in the software.	1. Install and load the necessary packages.
2. Load and preprocess the data.	2. Load and preprocess the data.
3. Split the data into training (70%) and testing (30%) sets.	3.Split the data into training (70%) and testing (30%) sets.
4. Build and train a multilayer perceptron (MLP) neural network model.	4. Build and train the logistic regression model.
5. Evaluate the model	5. Evaluate the model
6.Analyze the results	6.Analyze the results.

Source: Research Findings

The training data are used to build the model and extract rules, while the testing (control) data are employed to validate the model’s accuracy.

Logistic Regression Results

The classification of samples into two groups, training and testing, was carried out, with 70% assigned to the training group and 30% to the testing group. All activities in this section were performed using R software through custom coding.

Table 11. Accuracy and Precision Assessment of Logistic Regression

Method	Number of Variables	Accuracy	Precision	F1-Score
Logistic Regression	19 variables	89.77	32.03	68.33
	5variables	89.48	27.34	68.63

Source: Research Findings

As the research results indicate, the accuracy and precision of the logistic regression model with 19 variables do not differ significantly from those of the 5-variable model, and the removal of variables did not have a meaningful impact on the model’s performance. The extracted 5-variable logistic regression model is as follows:

$$FD_{t+1} = 0.941 - 4.72R_{3it} - 0.0308*R_{9it} - 0.0112*R_{15it} + 0.21*R_{17it} + 0.0013*R_{18it} + e_{it}$$

In the above model, R3 represents Working Capital to Total Assets, R9 represents Equity-to-Total-Assets Ratio, R15 represents Return on Equity, R17 represents Asset Turnover Ratio, and R18 represents Inventory Turnover Period.

Artificial Neural Network (ANN)

Perceptron neural networks, particularly multilayer perceptrons (MLPs), are among the most widely used and practical neural networks. These networks can perform a nonlinear mapping with desired accuracy by appropriately selecting the number of layers and neurons per layer, which often does not need to be large.

A typical multilayer perceptron network consists of a input layer, one or more hidden layers, and an output layer. Artificial neural networks are considered intelligent dynamic systems (Hajazian et al; 2024). In perceptron networks, nodes (neurons) are arranged in sequential layers, and connections are unidirectional. When an input pattern is fed into the network, the first layer calculates the output values and passes them to the next layer. Each subsequent layer receives these values as inputs, computes its outputs, and transmits them to the next layer. This process continues layer by layer until the final output is obtained.

The number of hidden layers and neurons within them is usually determined through a trial-and-error method. The input values of each neuron are multiplied by their corresponding weights, and the weighted inputs are summed with a value called the bias. The resulting value is then passed through a nonlinear function, known as the activation (transfer) function, which produces the neuron's output. Multilayer perceptrons can generate the desired output by learning from examples. The learning process is carried out by comparing the model outputs with the actual outputs, known as target values.

The multilayer perceptron ANN consists of two main stages: model training and model testing. The training dataset is used to train the model, while the testing dataset is used to evaluate the model's performance. It is important to note that the data for each group in the datasets are randomly selected in each run by the software.

The architecture of the artificial neural network in this study consists of an input layer (including the independent variables selected based on the stepwise and LASSO logistic regression models), a hidden layer with a sigmoid activation function, and one output layer. The overall schematic of the process is illustrated in Figure 2.

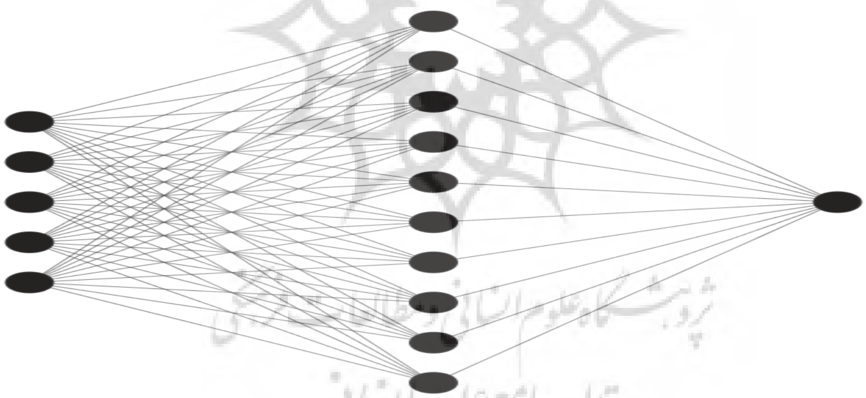

Figure 2. Schematic of the Neural Network Process

The first layer on the left represents the independent input variables of the model, which are fed into the hidden middle layer and result in the predicted output layer. The neurons in the hidden layer are determined through trial-and-error and iterative optimization over time.

The results of the neural network are presented in Table 12.

Table 12. Accuracy and Precision Assessment of Logistic Regression

Method	Number of Variables	Accuracy	Precision	F1-Score
Artificial Neural Network (ANN)	19 variables	89.07	50	50
	5 variables	92.6	47.06	58.18

Source: Research Findings

As observed, the removal of variables in this model did not have a significant impact on accuracy and precision. In the 5-variable model, there was a slight increase in accuracy and a decrease in precision.

The results obtained from the confusion matrix, which is used as a criterion to evaluate data mining models, for the two models are presented below. In the table, 0 indicates no financial distress, and 1 indicates financial distress.

Table 13. Confusion Matrix Results

		Logistic Regression Analysis		Artificial Neural Network Analysis	
		Predicted Data (Number/Percentage)		Predicted Data (Number/Percentage)	
		0	1	0	1
Actual Data (Number/Percentage)	0	(85.5)266	(3.5)11	(85.9)267	(1.9)6
	1	(8)25	(2.9)9	(5.5)17	(6.8)21

Source: Research Findings

The confusion matrix shows the number (and percentage) of observations for which the predicted outcomes matched the actual outcomes.

For logistic regression analysis:

- 266 observations (85.5%) did not experience financial distress in reality and were correctly predicted as non-distressed.
- 11 observations (3.5%), which were not distressed in reality, were incorrectly predicted as distressed.
- 25 observations (8%) were actually distressed but were incorrectly predicted as non-distressed.
- 9 observations (2.9%) were actually distressed and were correctly predicted as distressed.

For artificial neural network (ANN) analysis:

- 267 observations (85.9%) did not experience financial distress in reality and were correctly predicted as non-distressed.

- 6 observations (1.9%), which were not distressed in reality, were incorrectly predicted as distressed.
- 17 observations (5.5%) were actually distressed but were incorrectly predicted as non-distressed.
- 21 observations (6.8%) were actually distressed and were correctly predicted as distressed.

By comparing these results, it can be inferred that the second research hypothesis is confirmed, indicating that the neural network method demonstrates better performance in terms of accuracy and precision compared to the logistic regression method.

Discussion and Conclusion

In the present study, descriptive statistics of the key variables were first examined. This section included the analysis of statistical characteristics such as central tendency, dispersion, and distribution, which helped in gaining a better understanding of the data structure.

Subsequently, to ensure the validity of the results, preliminary tests such as unit root tests, cointegration, and correlation analysis were carefully conducted. These tests allowed for the verification of the necessary conditions for subsequent analyses and ensured the reliability of the results.

Next, using econometric techniques and performing Chow and Hausman tests, the most appropriate method for estimating the statistical models was selected. This process enabled a more precise analysis of the data and allowed the research hypotheses to be thoroughly tested. The results obtained from the hypothesis tests were presented comprehensively and systematically.

To simplify the model and avoid unnecessary complexity, the number of influential independent variables was reduced using stepwise and LASSO regression methods. Finally, to determine the most effective method for predicting financial distress, the multilayer perceptron neural networks and logistic regression were compared. The results indicate that the main research hypotheses are confirmed, as summarized in Table 14.

Table 14. Examination of Research Hypotheses

Hypothesis	Description	Result
Hypothesis1	Financial ratios significantly affect the prediction of financial distress in listed companies.	Confirmed
Hypothesis2	Neural network–based methods provide higher accuracy and precision in predicting financial distress compared to logistic regression models.	Confirmed

Source: Research Findings

The results of the first research hypothesis indicated that financial ratios significantly affect the prediction of financial distress, which is consistent with the findings of Beaver (1966), Altman (1980), Zhou et al. (2015), Altman et al. (2017), Lee et al. (2020), John (2021), Fachrudin (2021), and Li et al. (2021).

The results of the second research hypothesis showed that machine learning–based models, particularly the artificial neural network (perceptron), provide a more reliable tool for predicting financial crises compared to statistical models, especially logistic regression. This conclusion aligns with the findings of Tsai (2009), Barboza et al. (2017), Inam et al. (2019), Ashtab et al. (2017), Aminimehr and Hekmat (2023), and Mehrani et al. (2020).

Recommendations for Future Research

The findings of this study can assist auditors in evaluating the going-concern status of companies, and stakeholders should carefully consider the independent auditor’s opinion before conducting any analysis. Based on the results, it is recommended that researchers employ modern methods such as artificial neural networks for predicting financial distress in their analyses.

For capital market analysts and investors, it is advisable to avoid investing in companies that are financially distressed.

The comparison of neural network models in predicting financial distress and analyzing their efficiency across different industries has received limited attention. Future studies are recommended to examine these models across various industries. Additionally, the impact of macroeconomic variables on corporate financial distress using neural network models should be considered in future research.

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