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RESEARCH PAPER

Financial Distress Prediction Using Artificial Neural Network, Partial Least Squares Regression, Support Vector Machine Hybrid Model, and Logit Model

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Abstract

Financial distress refers to the situation where a firm's cash flows are insufficient to meet contractually required payments. This has caused concern among capital owners and compelled financial analysts to employ a variety of methods to assess companies' equity and analyze the firm's financial status. Assessing and predicting financial distress in a timely and accurate manner can aid decision-makers in finding the optimal solution and preventing it. Numerous models have been developed thus far to predict and evaluate financial distress. The prediction accuracy has been improved through the use of various innovative methods. Using financial ratios and market data as independent variables and obtaining patterns for the financial forecast is one of the most important methods for evaluating the financial stability of businesses. Therefore, the primary objective of this study is to evaluate the performance of five models in this field, compare their accuracy of prediction, and ultimately select the best model to predict financial distress for a specified period in Iran. Specifically, the logit model, artificial neural network (ANN), support vector machine (SVM), partial least squares regression (PLS), and a hybrid model of SVM and PLS were chosen, analyzed, and compared. The results of the average accuracy of prediction indicate that the SVM has the highest accuracy one year before the onset of financial distress. In addition, findings from the two years preceding the failure indicate that the SVM-PLS model provides the most accurate classification of financially distressed and non-distressed firms.

Keywords: Artificial Neural Networks, Financial Distress, Hybrid Model, Logit Model, Support Vector Machine.
JEL Classification: C45, C53, C58, E17, G17.

1. Introduction

Human relations and economic relations in particular have gotten more difficult due to the development of knowledge and technology (Varahrami and Javaherdehi, 2018). The economy and business have reached a new stage in which small firms have morphed into giant global organizations. This has resulted in the rise and development of monetary and financial markets, attracting multitudes of individuals from all over the world to invest in corporate stocks (Chien et al., 2021; Farzin et al., 2021). As a result of the intensification of competition, some businesses were forced to cease operations and exit the market. Financial distress is the condition in which a company's cash flows are insufficient to satisfy contractually mandated payments. Financial distress is a preceding circumstance that drives a business into insolvency. Financial distress and business failure are typical statuses in a competitive market environment. Financial distress problems arise when companies have difficulties paying financial commitments, maintaining high payment of fixed costs, low liquidity, and uncertain revenue (Keasey and Watson, 2019). A company that is in financial difficulties is facing cash flow problems or cash shortages in its operations and is unable to generate sufficient cash to overcome current obligations. Due to the low cash flow state, companies tend to default on their debt covenants to their creditors and tend to lose significant market share. When the company is exposed to financial distress, they are more likely to go bankrupt, and this gives the company a bad reputation. Because where the business is headed for financial distress, the potential for the shareholder to get their shares back is higher and it may also deter potential shareholders from investing in the company (Kamaluddin et al., 2019). Predicting financial distress has attracted great attention from researchers due to the importance of predicting potential and current investors, stock market regulators, as well as the company itself, and this prediction can provide a signal about the company's financial performance. Research on predicting financial distress is still an essential topic in the financial field (Tang et al., 2020). The issue of financial distress and bankruptcy among companies has been discussed by researchers for years due to the importance of prediction that can show the company's performance and ability to maintain its presence in the market (Sun et al., 2020). Given the current financial market exposure, external users such as investors, lenders, investment advisors, and other stakeholders must provide early warning of companies experiencing financial difficulties. Therefore, it needs appropriate tools to identify the possibility of financial distress in the company, which enables it to address potential problems that can reduce the distressed financial position. This has caused concern among capital owners and compelled financial analysts to apply various methods to assess companies' equity and analyze the financial state of the company (Adubisi et al., 2023; Farid et al., 2022). Investors, on the other hand, were more interested in gaining further information and assurance regarding the status of a company, therefore they depended on the information offered by financial analysts. Financial ratios are one of the most important sources of data that may be used to anticipate financial distress. Ratio analysis is a simple method used in evaluating the financial strength or weakness of companies because it can explain the relationship between financial statement items. Most studies state that traditional financial ratios play an important role in determining the financial performance of companies. Researchers have been able to anticipate imminent financial difficulty by combining these ratios with multivariate models (Yu et al., 2019). Since financial distress usually produces various signals such as a gradual or sudden decrease in profits, delays in payment of obligations (interest, preferred dividends, and financial bills), and even bankruptcy, information in financial statements can be used to make diagnostic models (Liang et al., 2020). The dissatisfaction of multinational companies and the volatility of the Iranian stock market in Iran show the need for tools to evaluate the financial strength of firms. Using financial ratios and market data as independent variables and obtaining patterns for financial prediction is one of the most important methods for evaluating the financial stability of businesses. Therefore, this study majorly aims to evaluate the performance of five models in this sector, compare their prediction accuracy, and ultimately select the best model to predict financial distress for a specified period in Iran. The following questions are aimed to answer in this study: 1- What is the optimal horizon of prediction? 2- What is the most accurate prediction model? The rest of the study is organized as follows: section 2 discusses a literature review on the significance of financial ratios in the prediction of financial distress. Section 3 outlines the methodology applied; sections 4 and 5 present and discuss the main findings and the empirical results, and section 6 concludes.

2. Literature Review

Prior research has identified the issues related to variances in financial ratio values obtained from successful and failed firms (Back et al., 1996). Their results revealed poor accounting ratios and failing company profiles. Despite having distinct qualities, distressed firms are classified by their precarious financial state. According to Ardalankia et al. (2020), LIN (2021), and Myšková & Hájek (2017), financial parameters measuring profitability, liquidity, and solvency have a vital role in predicting enterprises' collapse (2017). They suggest that, in light of several studies emphasizing financial ratios as the most accurate predictor of failure, the influence of the other three factors is negligible in this regard. According to Keasey and McGuinness (1990), the profitability ratio is a key indicator of a company's failure a few years previous to its demise. It has been established that the firm's likelihood of failure is proportional to its financial leverage (debt-to-assets ratio), whereas a bigger value of liquidity, as measured by the current ratio, might reduce the chance of failure (Dirman, 2020). Moreover, the combination of low profitability and a high debt-to-assets ratio (financial leverage) raises the anticipated failure probability compared to scenarios where the two factors were evaluated independently. Similarly, Brigham and Ehrhardt (2013) stated that the majority of financial distress indicators arise from excessive debt and insufficient capital. Newton (1976) also suggests that excessive debt can render companies incapable of meeting their obligations. According to Liang and Wu (2005), to recognize financial distress promptly, it is crucial to identify cash flow scenarios in which there is insufficient cash to repay loans on time. Moreover, it is proved that the cash flow ratio and the cash flow to total debt ratio are two important factors that play a significant role in predicting financial disaster (Chen, 2011). In addition, it is crucial to determine the insolvency state of a company because numerous economic actors may be considered stakeholders of an insolvent firm (Pindado and Rodrigues, 2004). Upon detection of the company's financial distress, preventive steps can be performed with the aid of a more precise evaluation of insolvency indicators. Bellovary et al. (2007) found in another study that debt-to-net-worth is a substantial index of corporate failure that can predict financial distress up to four or five years in advance. Numerous research have confirmed the significance of financial ratios, and it is well-established that they are capable of predicting disasters. Accounting information helps detect firms that may be experiencing financial distress, according to the findings. As stated by Chen (2013), due to the complexity and dynamics of actual financial difficulties, essential sophisticated techniques can be implemented through the creation of intelligent information systems. Prior research (Maripuu and Männasoo, 2014) has examined the effects that financial distress may have on the investment performance of firms. According to López-Gutiérrez et al. (2015), the impact of financial indigence on corporate investment behavior is contingent on the company's investment opportunities. Therefore, companies with fewer investment alternatives in disadvantaged settings tend to be less eager to invest, while companies with superior investment options do not exhibit a behavioral disadvantage distinct from healthy firms in the investment sector. Manzaneque et al. (2016) have demonstrated that the effect of the ownership of the board of directors and the shares of independent shareholders on the probability of a commercial failure is comparable to that of other corporate crises in extreme scenarios preceding failure. The likelihood of financial distress is negatively connected with board size. Diversifying and improving access to information and resources is therefore possible, particularly in circumstances where ownership is concentrated and major shareholders have significant influence over the composition of the board. Finally, their findings suggested that ownership concentration had no appreciable effect on the probability of financial distress. Intriguingly, a study by Koh et al. (2015) found that while a decrease in investment and dividend improves the general health of all companies (not just those in financial distress), the life cycle has no bearing on this improvement. Further, Oliveira et al. (2017) found that suppliers of financially distressed companies would increase their debt ratio within two years of the due date, following the theory of bargaining power, which states that the increase in supplier debt will diminish the negotiable surplus. Therefore, suppliers typically increase their leverage to improve their bargaining position with a troubled consumer. There is also evidence that vendors reduce their leverage upon learning the level of debt and capital structure of their customers. It is common knowledge that each industry requires a series of financial ratios to measure its financial distress (Sayari and Mugan, 2017). Therefore, each industry must be treated differently. Also, additional research on financial ratios revealed that liquidity ratios include the most information for the majority of industries. Besides, inventory ratios and debt repayment are the most relevant ratios for determining a company’s financial distress. Additionally, Cleofas-Sánchez et al. (2016) argued that the combined models outperform the SVM model and the Logistic econometric model in predicting financial distress. Deakin (1972) and Blum (1974) utilized multiple-variable statistical techniques after Altman (1968) and applied the Z-score model to different markets, different periods, and different industries. Altman's model is perhaps one of the most well-known early studies. He developed a Z-score bankruptcy prediction model and set a point of Z-score to delineate healthy and distressed firms.

Bonabi Ghadim (2022) stated that in conditions of information asymmetry and financial distress, uncertainty about the quality of loans is reduced, and bank managers try to reduce agency costs by increasing the quality of information through conservative reporting and increasing the informing about banks' real value. Accordingly, the author investigates the effect of information asymmetry and financial distress on the relationship between accounting conservatism and loan quality portfolio in Iran's banking system. The results showed that conditional conservatism has increased the loan quality portfolio (increasing the quality of bank assets and reducing the ratio of non-current claims), and informational asymmetry and financial distress with a positive effect have modified and intensified the relationship between conditional conservatism and loan quality portfolio.

Another study by Sadehvand et al. (2022) defined financial distress as the uncertainty about the company's ability to meet its obligations and repay its debts and estimated financial distress by different models which are divided into three groups: structural models (based on the company's capital structure or market information), fundamental models (based on accounting or financial data), and hybrid models. They also underscore that predicting financial distress is still a major point of challenge for financial researchers. At first, the authors presented a hybrid model to investigate the ability of financial distress prediction models.

Then, the second version of Altman's Z model known as the Z″ model was utilized to contrast the hybrid model with accounting-based models. Their findings indicated that in the hybrid model, accounting data has significant relations with the company's financial distress probability. Also, a comparison of the hybrid model and conventional models revealed that in the group of financially distressed companies, respectively, the Z″ model with 100% accuracy, Merton's model with 85% accuracy, and the hybrid model with 90% accuracy correctly predicted the financial situation of the companies. However, the accuracy of the Z″ model, Merton's model, and the hybrid model in predicting the financial situation of the companies in the group of financially distressing companies showed 50%, 85%, and 85% accuracy, respectively. It was concluded that the hybrid and Merton models outperform predicting the financial situation of distressing companies compared to the Z″ model. Rafatnia et al. (2020) accentuated that one of the most important events in a firm's life is financial distress, propelling sectors into financial and sustainable growth problems. In their investigation, Rafatnia et al. (2020) stated that the independent variables in the background of financial distress are accounting ratios, which are estimated from financial statements, and macroeconomic variables that are mostly beyond the control of a firm or sector. They applied logistic regression and decision trees to the prediction of financial distress in Tehran Stock Exchange-listed companies. It was found that the profitability, liquidity, leverage, interest rate, cash flow, accruals, and GDP were statistically significant in distinguishing distressed from non-distressed firms across sectors. The results illustrated that the performance of a Decision Tree model was better than the other models in their investigation. As a result of the rapid advancement of computer technology, approaches such as data mining as well as machine learning are successfully used to predict economic calamities. Among the aforementioned models, the PLS, ANN, SVM, and PLS-SVM hybrid models were selected. This study adds to the recent literature in at least two ways. First, using a different set of financial ratios in the study differs this investigation from prior studies (Khademolqorani et al., 2015; Salehi and Abedini, 2009; Zarei et al., 2020), since a great majority of studies focus on the five ratios that Altman (1968) uses in his Z-Score model. Second, this study is among a few number of studies that focus on financial distress prediction in the Tehran Stock Exchange. To the best of our knowledge, no published works that predicted Iranian firms' financial distress using SVM and PLS have been found in the Iranian context so far. As such, we consider our research to be an important and timely contribution to this field. Also, the main innovation is to evaluate the performance of five models in this field, compare their accuracy of prediction, and ultimately select the best model to predict financial distress for a specified period in Iran. Specifically, the logit model, artificial neural network (ANN), support vector machine (SVM), partial least squares regression (PLS), and a hybrid model of SVM and PLS were chosen, analyzed, and compared.

3. Methodology

Our data contains annual financial statistics for all stocks of the Tehran Stock Exchange (TSE) from 2012 to 2017. Before becoming subject to Article 141 of the Corporate Trading Act, distressed company data collection is conducted over one-year and two-year terms. Article 141 of the Commercial Code applies to the dependent variable of the enterprises. The selection of the initial financial ratios for predicting financial distress was based on prior studies and Mselmi study (Mselmi et al., 2017), which are associated with the forecasting of economic disaster (Chen, 2011; Min and Lee, 2005; Sun and Li, 2012). There are a total of 41 initial financial ratios selected for prediction, which encompass nine distinct perspectives: profitability, liquidity, structure, size, management, activity and stability, cash flow, growth, and debt. Each item has multiple financial ratios to demonstrate a comprehensive picture of corporate finance. Financial ratios associated with profitability, productivity, growth, and risk qualify the impact of company actions through management competency, patent status, brands, organizational culture, and employee happiness to encompass both qualitative and quantitative indicators. Indirectly, the integration of these fundamental ratios shows the impact of qualitative elements (Mselmi et al., 2017). Stepwise regression has been applied to the selection of ratios to determine the optimal collection of predictors and increase the efficacy of models. The logit model was employed to find out the relationship between the dependent variable and 41 selected ratios. To predict financial distress, Artificial Neural Network (ANN), Support Vector Machine (SVM), Partial Least Square Regression (PLS), and a hybrid model comprising SVM and PLS were applied. After a detailed literature review and an analysis of the important financial ratios used in former research, the financial ratios are picked for one-year and two-year intervals before failure through stepwise regression. In choosing the ratios, two crucial criteria were taken into account: first, their statistically distinct averages in healthy and distressed firms, and second, the availability of information. In this study, five distinct classification techniques were used to foresee financial distress in Tehran Stock Exchange companies. After applying each of the aforementioned models to the data, R^2 is used to measure the accuracy and performance of the model, whereas, for learning machines, root-mean-square-error (RMSE) is used. Using RMSE and d-statistic, the accuracy and performance of each model are compared, and then the most robust model will be identified.

3.1 Logit Model

A dependent variable in the analysis of relationships between variables may have two levels (Dummy or Virtual). The dependent variable in this study is being distressed or not being distressed. Primarily, the logit model has been used to predict financial distress and to solve classification problems involving two classes. This model is commonly used due to its capability to overcome linear separation, and as can be seen, a nonlinear relationship exists between the likelihood of financial disaster and financial ratios (Sun and Li, 2011). Equation 1 illustrates the fundamental form of the logit model:

$$logit\ P_i = \ln\left(\frac{P_i}{1-P_i}\right) = \alpha_i + \sum_{j=1}^{k} \beta_{ij} X_{ij} \tag{1}$$

where P_i represents the likelihood of distress firm i. The parameters that need to be estimated are α_i and β_{ij}. The monetary specifications for firm i are considered in X_{ij}. Mselmi, Lahiani, & Hamza (2017) recommended reorganizing Equation 1 as follows:

$$P_i = \left[\exp(\alpha_i + \sum_{j=1}^{k} \beta_{ij} X_{ij})\right] / \left[1 + \exp(\alpha_i + \sum_{j=1}^{k} \beta_{ij} X_{ij})\right] \tag{2}$$

The logit model allows the potential of belonging to one of the two classification categories, a benefit that is present in a variety of software applications. Initially, distressed enterprises are discovered using the financial indices analyzed in Mselmi, Lahiani, & Hamza's (2017) research. Then, using the logit model and stepwise regression, the variables influencing the enterprises in financial distress are determined.

3.2 ANN Method

The ANN is a non-parametric and adaptable modeling tool. Due to its adaptive learning features, such as nonlinearity and nonparametricity, ANNs have been used to efficiently predict financial distress. Due to the varying number of nodes, the complexity of the network architecture changes depending on the intended application of this approach. However, if it is necessary to classify an imaginary set of items, a huge network is no longer required (Zhang et al., 1999). One hidden layer networks are nearly suitable for handling many issues, including classification tasks, as demonstrated. Any node in this network is regarded as a calculator receiving financial ratios. In the hidden layer, input node values are gathered and weighted during the training process.

$$P_i = \left[\exp(\alpha_i + \sum_{j=1}^{k} \beta_{ij} X_{ij})\right] / \left[1 + \exp(\alpha_i + \sum_{j=1}^{k} \beta_{ij} X_{ij})\right]_{n/2n} \tag{3}$$

The weighted inputs and their composition reflect the situation of the internal sector. Node transformation activities are performed using a suitable transfer function. Nodes on the output layer are fed by the output of the preceding layer following transformation. The output result of the previous layer is utilized to compare the company's state to the required quantity (whether non-distressed or distressed). In certain ANNs, the input and output layers are directly coupled to achieve greater flexibility. While the mean squared errors (MSE) or sum of squared errors (SSE) have been diminished to a minimum, the training phase continues to estimate the weighted connections. The five variables in Altman's model (Altman, 1968) are utilized to predict financial distress. Zhang et al. (1999) provide additional predictors, specifically the current assets to current liabilities ratio, as measures of an enterprise's capability to use liquid assets to settle short-term debts or commitments. Using a distinct set of financial parameters, this paper investigates the ability of ANNs to predict economic distress performance.

3.3 SVM Method

In MLP and RBF neural networks, there is typically an emphasis on optimizing the structure of the neural network to reduce estimate error and the number of neural network faults. In contrast, a specific type of neural network known as SVM is only concerned with lowering operational risk associated with unsatisfactory performance. The structure of an SVM network is quite similar to that of an MLP neural network, with the learning method being the primary distinction. In the early 1950s, it was claimed that the advanced SVM network could tackle two types of classification issues by constructing a linear decision rule for nonlinear input matrices. Therefore, non-distinct training data was also evaluated. Eventually, nonlinear issues are transformed into multidimensional ones using kernel functions, and a linear separation margin is obtained (Vapnik, 1995). Utilizing the mapping function, two groups of non-distressed and distressed businesses are created. By creating linear data in the input sector, the Kernel function determines the optimal mapping function. Numerous kernel functions exist, however, the radial basis function (RBF) is proposed for SVM, hence it is used in this research. Multiple predictions given by SVM classifiers have been combined to produce a unique classification (Kwak et al., 2012). For instance, a mixture of individual SVM classifiers, known as the SVM ensemble, was proposed (Sun and Li, 2012). Diverse SVM methods employing linear, polynomial, RBF, and sigmoid kernel functions were applied to various subsets. The screening procedure for classifiers is based on each nominee's individual performance. Moreover, it was proposed that the relationships between financial systems and their predictions are dynamic (Chen, 2012; Koushki et al., 2022; Osoolian et al., 2022).

3.4 PLS Method

The interrelationships between financial ratios can impede the ability of conventional statistical models to predict financial distress. Consequently, prediction models have been developed using PLS. If issues such as multi-collinearity among predictors or a greater number of predictors than observations exist, the PLS method would be useful. In PLS-based prediction, the number of weighted components is not limited to a certain value. The PLS approach can be used to extract the first hidden variable from the financial ratios. Financial ratio variation information is extracted by the first component. Additionally, the first component is related to the dependent variable. As stated previously, the dependent variable is qualitative and has two categories: non-distressed and distressed. The first component describes the dependent variable in detail. Unless the requirements are met by the regression, the second hidden variable will be extracted. If the desired precisions are not achieved, the preceding procedure is repeated (Mselmi et al., 2017). In contrast to the logit method, which solely investigates distressed organizations, this method investigates both distressed and non-distressed companies. By using the PLS, the effects of independent variables can be fitted to the dependent variable in the form of a regression model or structural model. To validate models, structural equation modeling is utilized. For the estimate of model parameters, a large sample size and the assumption of multivariate normality are necessary, however, because the PLS approach is employed for exploratory purposes, none of the above are required. Technically, the least-squares method differs from other regression methods in that, rather than considering independent variables, the main components of the analysis of independent variables are analyzed in several general factors, so that these factors explain the majority of variations in the dependent variable. One of the primary reasons for the prevalence of the least-squares method is that this technique does not require examining the normality assumption of the society or the sample size. The PLS method is ideally suited for solving coherent issues, analyzing nonlinear and complex models, and analyzing time models. This method permits the examination of the relationships between hidden variables and visible variables. When dealing with a small sample or when the distribution of variables is not normal, the approach will be utilized. Two models are examined in PLS models: external models and internal models. After testing the external model, it is necessary to present an internal model that indicates the relationship between the research’s hidden variables. Using the internal model, we may examine the payment model’s research hypotheses. However, this model should be designed for binary situations, such as being distressed or non-distressed.

3.5 PLS-SVM Method

Jayanthi et al. (2011) have demonstrated that PLS can characterize the correlations and nonlinearity between several financial ratios. In addition, SVM has demonstrated superior performance over nonlinear methods and functions. In addition, SVM can adequately account for hidden variables and their nonlinear relationships inside the internal model. The hybrid model of PLS-SVM has the potential to identify nonlinear relationships and correlated control variables. In addition, the hybrid model addresses common nonlinear approach flaws such as overfitting (Wang and Yu, 2004). Firstly, PLS is employed to extract spectrum properties. PLS also contributes to the SVM model's input. As a brief explanation of the next step, the factors affecting financial distress are identified using stepwise regression for the one-year and two-year periods preceding the occurrence of financial distress across firms. The Shapiro-Wilk (P-value) test will then be conducted on effectively selected factors at one-year and two-year intervals before the occurrence of firms' financial distress to verify their normal distribution. Next, tests of self-correlation and coordination are administered. To compare the accuracy and predictive abilities of all models, the R^2 coefficient or the RMSE criterion will be utilized in the learning machine.

3.6 Data and Sample Statistics

The reason for the selection of Tehran Stock Exchange is that the regulations demand enterprises to produce timely and accurate information. This enables access to the financial information of Exchange-admitted enterprises. Furthermore, the historical record and significance of the Tehran Stock Exchange urge the utilization of its data. In order to acquire relevant research results, the most actively traded shares listed on the Tehran Stock Exchange are picked. In fact, shares with a typical and substantial number of trading days are chosen so that the results are more trustworthy. Therefore, we can employ procedures such as the activation of shares on at least 80% of business days. The statistical sample is the same for all venture firms for which data is available from 2012 to 2017.

3.7 Variables and Measuring Variables Model

The qualitative and discrete dependent variable is distress or non-distress, and according to Article 141 of the Commercial Code, enterprises in Iran are considered financially distressed. Independent variables comprise 41 ratios in the areas of liquidity, activity, profitability, size, financial strength and stability, structure, debt, growth, and cash flow that have been utilized in models examined in prior studies. Table 1 displays the following 41 ratios:

Table 1. 41 Independent Variables in Previous Studies' Models

Variable	Meaning	Variable	Meaning
Liquidity		**Size**	
R01	Equity/ capital employed	R27	In (total assets)
R02	Financial debt/ capital employed	**Solvability and stability**	
R03	Current ratio	R28	Solvency ratio
R04	Liquidity ratio	R29	Gearing
R05	Net cash	R30	Equity / total assets
R06	Net working capital	**Structure**	
R07	Acid test ratio (quick ratio)	R31	Current assets/ total assets ratio
Management		R32	Fixed assets / total assets ratio
R08	Collection period (days)	R33	Equity/ fixed assets
R09	Credit period (days)	R34	Current liabilities/ total liabilities
R10	Financial charges / turnover	**Liabilities**	
R11	Financial debt / equity	R35	Debt / equity
R12	Repayment capacity	R36	Long term liabilities / total assets
R13	Cash flow / turnover	**Growth**	
R14	Stock turnover	R37	Turnover growth
Profitability		R38	Assets growth
R15	Operating profit margin	**Cash flow**	
R16	Profit margin	R39	Cash flow/total assets
R17	Net profit margin	R40	Cash flow/net worth
R18	Net return on shareholders' funds	R41	Cash flow / total debt
R19	Net return on total assets		
R20	Net assets turnover		
R21	EBITDA[3] margin		
R22	Net profits / total assets		
R23	Net profits / current assets		
R24	Net profits / fixed assets		
R25	Net profits / total debt		
R26	Net profits / equity		

Source: Research finding.

4. Applying Models on Variables

4.1 Stepwise Regression

In the stepwise regression method, all ratios impacting distressed companies were first included in the model (in fact, the backward modeling method was used). In the next step, following model fitting, the insignificant variables were deleted to produce a model in which all variables were significant.

4.2 Logit Model

Table 2 displays the results of the logistic regression. Only four ratios of liquidity (R04), debt (R28), debt to equity (R35), and long-term debt to total assets (R36) are significant one year prior to financial distress. Accordingly, the high liquidity and debt ratio reduced the likelihood of enterprises being in financial distress. For example, a one-unit increase in the debt ratio would reduce the likelihood of financial distress by 0.88 units. Theoretically, the ratio of long-term debt to total assets has had the greatest effect on the probability of financial distress. Additionally, the likelihood of financial distress and the ratio of debt to equity are negatively correlated.

Table 2. Estimation Results of the Logistic Regression

One year prior to failure				Two years prior to failure			
	estimated β	$\Pr(>\lvert Z\rvert)$	expected β		estimatedβ	$\Pr(>\lvert Z\rvert)$	expected β
intercept	2.4317	0.032		intercept	31.8251	0.0026	
R04	-2.829	0.0045	0.0581	R10	0.973	0.0189	2.625
R23	0.523	0.545	1.6164	R16	0.325	0.1301	1.3665
R25	-1.88	0.1655	0.1399	R17	-0.245	0.1325	0.825
R28	-0.086	0.00027	0.922	R23	-19.84	0.045	0.0000
R35	-0.125	0.00434	0.8861	R24	1.125	0.0246	2.968
R36	9.164	0.0051	8773.4	R27	-4.328	0.0016	0.012
				R33	-0.251	0.5322	0.784
				R34	2.493	0.114	12.266
				R36	2.471	0.056	11.834

Source: Research finding.

Capital gearing (the debt-to-assets ratio) increases the likelihood of a company's failure, while higher liquidity, as measured by the current ratio, decreases the probability of failure. Put differently, the interest rate on the debt is lower than the yield rate on assets developed with borrowed stock. Hennessy & Whited (2005) provide a model of dynamic exchange with an internal selection of the lever. The results show that there is no objective leverage ratio; firms may save or be leveraged strongly. Therefore, corporations' balance sheets reflect positive information by replacing debt with equity. Two years before financial distress, only 6 of 10 selected ratios were significant: financial charges to revenue (R10), repayment capacity (R12), net profit to current assets (R23), net profit to fixed assets (R24), company size (R27), and Long-term obligations to total assets (R28) (R36). The ratio of significant long-term debt to total assets remains negative. Previous research has demonstrated that a firm's repayment capacity and financial charges turnover are negatively and positively correlated, respectively, with the probability of financial distress. The probability of failure is positively proportional to the proportion of financial charges in revenue and negatively proportional to the repayment capacity. A one-unit increase in the proportion of financial charges to revenue results in a 2.71-fold increase in the probability of failure, while a one-unit increase in repayment capacity reduces the probability of distress by 0.86-fold. In addition, the findings indicate that returns on current assets and fixed asset returns are significant in predicting financial distress, but that they are also inversely related. The return on current assets reduces the probability of financial distress, while the return on fixed assets increases it. The possible failure characteristics of current assets and fixed assets are distinct.

Current assets with higher liquidity are considered low-risk investments. It can be concluded that current assets would be subject to less risk than fixed assets. Ultimately, size has a significant impact on the likelihood of financial distress, with small businesses expected to be at a greater risk. Table 3 presents the accuracy of financial estimation reports. Before paying the money, non-distressed and distressed enterprises were correctly identified with an accuracy of 94.18% and 76.15%, respectively, in one year. The prediction accuracy is enhanced for two years before payment. The proper classification accuracy for non-distressed enterprises is 96.16% and for distressed firms, it is 88.62%. It can be seen that the logit model better categorizes distressed companies. Moreover, the incorrectly classified proportion for non-distressed firms and one year before the occurrence of financial distress (~ 5.82%) is greater than that for two years (~ 3.84%).

Table 3. Confusion Matrix of Logit Model

Panel A: 1-year-ahead							
	Training data				**Testing data**		
True class	0	1	Sum	True class	0	1	Sum
0	94.46	5.54	100	0	94.18	5.82	100
1	11.35	88.65	100	1	23.88	76.15	100
Panel B: 2-year-ahead							
	Training data				Testing data		
True class	0	1	Sum	True class	0	1	Sum
0	95.85	4.15	100	0	96.16	3.84	100
1	1.39	98.61	100	1	11.38	88.62	100

Source: Research finding.

Note: 1 and 0 indicate distressed and non-distressed firms, respectively.

In addition, the percentage of financially distressed corporations that were incorrectly classified one year previous to financial distress (23.85%) is greater than the percentage that was incorrectly classified two years prior to financial distress (11.38%). Notable is the decline in the proportion of appropriately identified financially distressed corporations from training to testing.

4.3 ANN Model Results

In this study, the focus is on multilayer perceptron (MLP), a specific type of neural network (Zhang et al., 1999). We employ a neural network with 6 and 10 input nodes to investigate one- and two-year failure intervals. Due to the classification challenge involving two groups, a single node output is necessary. As shown in Table 4, the optimal neural network consists of seven hidden nodes and has a total accuracy of 91.50% one year before financial distress. Four hidden nodes are demonstrated to provide the most accurate neural network with a total accuracy of 93% for two years before the onset of financial distress.

Table 4. Average Accuracy Of One- And Two-Year-Ahead Based On Different Hidden Nodes' Number

Hidden nodes' number	Average accuracy (%) 1-year-ahead	Average accuracy (%) 2-year-ahead
2	90	92.31
3	90	91,49
4	90	**93.00**
5	90	90
6	90	90.77
7	**91.50**	90
8	90.66	90
9	90.66	92.35
13	90.66	90.66
19	90.66	90

Source: Research finding.

Note: The best accuracy of prediction is bold.

The confusion matrix of an ANN is displayed in Table 5. In the year preceding failure, the percentages of correctly classified firms based on training data are 97.12% and 88.69% for non-distressed and distressed firms, respectively. When a two-year timeframe preceding financial distress is considered, the classification of distressed firms has improved while the classification of non-distressed firms has deteriorated slightly.

Table 5. Confusion Matrix of ANNs

Panel A: 1-year-ahead							
	Training data				Testing data		
	0	1	Sum		0	1	Sum
0	97.12	2.88	100	0	94.31	5.69	100
1	11.31	88.69	100	1	18	82	100
Panel B: 2-year-ahead							
	Training data				Testing data		
	0	1	Sum		0	1	Sum
0	95.82	4.18	100	0	97.14	2.86	100
1	4.31	95.69	100	1	20	80	100

Source: Research finding.

Note: 1 and 0 indicate distressed and non-distressed firms, respectively.

Using the training sample, the proportion of distressed firms that are correctly categorized (82%) and those that are incorrectly classified (18%) are identical for the outcomes of one and two years before failure. For the year preceding financial distress, a greater proportion (~ 5.69%) of erroneously labeled as non-distressed enterprises is observed. In comparison, the incorrect classification rate for two-year terms before financial distress is 2.84%.

4.4 SVM Results

The parameters that should be optimized by utilizing the RBF kernel for the SVM are: C, the penalty parameter, and γ, the kernel function parameter. The 5-fold cross-validation is performed to detect the optimal values of the aforementioned training data parameters. It has been suggested to alter γ between 2-15 and 23, and the C between 2-5 and 213 as indicated (Min and Lee, 2005). According to Bae (2012), the pair of parameters with the highest cross-validation accuracy will be selected. It was found that optimal pairs for a year, and two years before financial distress are 2-1, 2-2, and 24, 2-4, respectively. Also, the correspondence cross-validation rates were 93.88% and 94.07%, respectively. The SVM is trained using these best parameter pairs, and the confusion matrix is presented in Table 6. One year before failure, non-distressed enterprises are predicted with more precision than distressed ones. The classification accuracy rates for non-distressed and distressed companies are 91.51% and 85.69%, respectively. On the other hand, incorrect classification rates are 8.49% and 14.23% for non-distressed and distressed firms, respectively. In addition, true classification accuracy is improved for training results. It is noteworthy to note that incorrectly classified companies have obtained lower percentages. The results are 7% and 2.78% for distressed and non-distressed firms, respectively. The test sample data and all non-distressed firms were correctly classified based on the results of the two years before failure. This indicates an improvement over the training data. For failing companies, the test data yields the same results as one year prior to failure.

Table 6. Confusion Matrix of SVM

Panel A: 1-year-ahead							
	Training sample				**Testing sample**		
	0	1	Sum		0	1	Sum
0	97.22	2.78	100	0	91.51	8.49	100
1	7.00	92.93	100	1	14.31	85.69	100
Panel B: 2-year-ahead							
	Training sample				**Testing sample**		
	0	1	Sum		0	1	Sum
0	97.22	2.78	100	0	100	0	100
1	1.54	98.46	100	1	14.23	85.77	100

Source: Research finding.

Note: 1 and 0 indicate distressed and non-distressed firms, respectively.

4.5PLS-DA Results

When the dependent variable is categorical and the task is classified, PLS-DA is recommended. In the present study, a dichotomous dependent variable PLS regression is conducted using PLS-DA. The confusion matrix for the PLS-DA approach is represented in Table 7. The results indicate that non-distressed firms can be predicted with greater precision than distressed firms. True classification rates for non-distressed and distressed firms are 88.52% and 79%, respectively. In contrast, the incorrect classification rates are 11.48% and 21% for non-distressed and distressed enterprises, respectively. Also, higher rates of accurate classification are obtained for training data. In this regard, non-distressed and distressed companies have respectively demonstrated 95.75% and 85.90%. Notable is the fact that the rates of incorrectly classified firms are lower for distressed firms (14.1%) than for non-distressed firms (21%). Intriguingly, all non-distressed firms have been correctly classified based on the test sample and results of the two years before failure. The test results of distressed enterprises are comparable to those from the year before their demise.

Table 7. Confusion Matrix of PLS-DA

Panel A: 1-year-ahead							
	Training data				Testing data		
	0	1	Sum		0	1	Sum
0	95.75	4.21	100	0	88.52	11.48	100
1	14.10	85.90	100	1	21	78	100
Panel B: 2-year-ahead							
	Training data				**Testing data**		
	0	1	Sum		0	1	Sum
0	94.37	5.63	100	0	100	0	100
1	9.88	90.12	100	1	20	80	100

Source: Research finding.

Note: 1 and 0 indicate distressed and non-distressed firms, respectively.

4.6 PLS-SVM Results

Table 8 displays the training and test results for the hybrid PLS-SVM model. The results indicate that the PLS-SVM can accurately classify 79% of distressed firms and 91.41% of firms that are not distressed. The performance of the model has improved over the past two years before failure. The classification accuracy for distressed and non-distressed firms is 97.12% and 91.39%, respectively. In addition, the misclassification rate of non-distressed companies one and two years before collapse is 8.53% and 2.88%, respectively. Moreover, the accuracy for misclassified distressed companies is 21% for one year and 8.53% for two years. PLS-SVM has successfully classified non-distressed enterprises, as was previously seen for other classification methods, where the misclassification rate is higher for the year before failure.

Table 8. Confusion Matrix of PLS-SVM

Panel A: 1-year-ahead							
	Training data				**Testing data**		
	0	1	Sum		0	1	Sum
0	97.17	2.83	100	0	91.47	8.53	100
1	8.46	91.54	100	1	21	79	100
Panel B: 2-year-ahead							
	Training data				**Testing data**		
	0	1	Sum		0	1	Sum
0	91.51	8.49	100	0	97.12	2.88	100
1	7.05	92.95	100	1	8.61	91.39	100

Source: Research finding.

Note: 1 and 0 indicate distressed and non-distressed firms, respectively.

5. Discussion

Investigations revealed that imminent financial distress in a company is more likely to motivate managers to falsify accounting records and manipulate activities (Arnis et al., 2019). It is demonstrated that the financial accounts of insolvent enterprises exhibited neither distress nor a large overstatement of revenues in the years preceding their demise (Rosner, 2003). Instead of concealing their near-financial distress, firms that are vulnerable to failure are shown to manipulate their financial reporting. Beneish et al. (2012) reveal that ROA abnormal accruals of sample firms increase by an average of 3% in the year preceding insolvency in the same scenario. In addition, it has been shown that income-increasing abnormal accruals were greater in the default year or the preceding year. According to Hsiao et al. (2010), before failure, businesses frequently alter profits by deceptive means to conceal their financial crisis and convince the public of their profitability. Moreover, to disguise the current financial catastrophe, some top executives may seek to increase book earnings or the firm's revenues through the use of overpriced assets, discretionary inventory, and discretionary receivables.

The results of the average accuracy of prediction indicate that the SVM has the highest accuracy in predicting the results one year before the onset of financial distress, 88.52%. After that, the Artificial Neural Network, the Hybrid model of PLS-SVM, the logit model, and the PLS method were the most accurate, with respective accuracy levels of 87.12%, 86.75 %, 85.81%, and 84.32%. For the two years preceding financial distress, the PLS-SVM hybrid model demonstrated the greatest accuracy (d-statistic value ~ 94.15%). In addition, SVM and logit models have demonstrated a mean precision of 91.85%, while PLS and ANN have demonstrated a precision of 88.16%. Results based on RMSE indicate that ANN, SVM, and least-squares have stable prediction accuracy across multiple periods. The SVM model outperforms other models for results one year before failure, except the ANN and logit models, which perform similarly and poorer than the

SVM and PLS. The PLS-SVM hybrid model has a reduced RMSE and outperforms the SVM, logit, PLS, and ANN models when considering the results of the two years preceding failure. A comparison of the General Model's performance is tabulated in Table 9:

Table 9. General Model's Performance Comparison

	Logit model		**ANN**		**SVM**		**PLS**		**Hybrid model**	
	N-1	N-2	N-1	N-2	N-1	N-2	N-1	N-2	N-1	N-2
d-statistic	85.81	91.85	87.12	88.16	88.52	91.85	84.32	89	86.75	94.15
RMSE	1.95	1.88	1.95	1.88	1.85	1.82	2.85	2.04	1.89	1.74

Source: Research finding.

A model with a lower RMSE and a higher d-statistic value is deemed more effective at explaining and classifying financial distress when compared to other models. SVM is the superior model for predicting financial distress one year in advance. In addition, findings from the two years preceding the failure indicate that the SVM-PLS model provides the most accurate classification of financially distressed and non-distressed companies.

In the reviewed literature, the authors used statistical techniques have achieve an overall predictive accuracy of 84%. In the case of the authors used machine learning models, their overall accuracy was 88%, and the authors used theoretical models the accuracy was obtained as 85% (Aghaei et al., 2013; Bonabi Ghadim, 2022; Khademolqorani et al., 2015; Mselmi et al., 2017; Rafatnia et al., 2020; Sadehvand et al., 2022; Tarighi et al., 2022). In general, the results of the studies that were performed on the value of data of financial cases of financial distress prediction show that accounting data can predict financial distress in companies (Khademolqorani et al., 2015; Muller et al., 2012). Also. The results obtained from the current study indicate the accounting data has a high predicting power and is also a reliable proxy for predicting financial distress for the companies listed in TSE. Additionally, the finding of the research is the confirmer of this point that two years before the financial distress, we can predict the financial distress in the TSE listed companies. The results regarding the accuracy of the models are indicative of this point that with the distant time of occurrence of the financial distress, the ability of the models' prediction increases, and this matter can be a result of the importance of the barometers of the prediction of the financial distress in longer periods (the calculated variables according to the accounting data). On the other hand, the results show financially distressed companies may have lower financial reporting quality in one year preceding being announced as financially distressed because they try to mislead other stakeholders about the corporate actual performance to attract more investors and lenders. Future studies can investigate the ability of the models with longer temporal periods (three- or five-year periods for example).

6. Conclusion

In the year preceding the financial distress, SVM demonstrated the highest average accuracy with 88.52%, followed by the Artificial Neural Network, the Hybrid model of PLS-SVM, the logit model, and the PLS method with 87.12%, 86.75 %, 85.81%, and 84.32%, respectively. Also, In the two years before financial distress, the Hybrid model of PLS-SVM demonstrated the highest average accuracy (d-statistic) of 94.15%, followed by the SVM and logit models with a mean accuracy of 91.85%, the PLS model with an accuracy of 80%, and the ANN with an accuracy of 88.16%. Due to the RMSE criterion, the accuracy of ANN, SVM, and least squares does not fluctuate over time and remains constant. The SVM model outperformed other models one year before the onset of financial distress. The ANN model and the logit model perform similarly to SVM and PLS, or worse. The PLS-SVM hybrid model has a lower RMSE and is superior to the SVM, logit model, PLS, and ANN in the two years preceding financial distress. A model with a lower RMSE and a higher d-statistic value is deemed more effective at explaining and classifying financial distress when comparing model performance. SVM and SVM-PLS have demonstrated the best performance for one-year and two-year terms before the financial distress, respectively. The SVM-PLS is also superior to the aforementioned models for classifying financially distressed and non-distressed firms.

Conflict of interest

The authors declare no conflict of interest.

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