Prediction of Financial Distress in Vietnam Using Multi-Layer Perceptron Artificial Neural Network

Oanh T.K Nguyen[1], Dinh V. Nguyen[*,1], Truong Cong Doan[1], Anh H. L. Nguyen[1], Anh T. M. Ta[1]

[1] *International School, Vietnam National University, Hanoi, Vietnam*
[*] *The corresponding author's email address: dinhnv@vnuis.edu.vn*

ABSTRACT

Research purpose: *This study attempts to use artificial neural networks to predict financial distress measured by EBIT lower than interest expenses for two consecutive years of the listed firms in Vietnam, which has no study conducted before*

Research motivation: *Although research on financial distress prediction has a long history, prediction methods have been updated along with information technology's advancement to improve the accuracy of the predictive model. This study is designed to enhance the predictive power of the financial distress model for listed firms on the Vietnam Stock Exchange.*

Research design, approach, and method: *The multi-layer perceptron artificial neural network (MLP-ANN) was employed to analyze data collected data from 509 companies with a total of 6617 observations. Financial ratios are collected on the Hanoi Stock Exchange and Ho Chi Minh Stock Exchange for the period 2007-2019 by using the FiinPro Platform.*

Main findings: *The result of the empirical analysis shows that the model can correctly classify up to 93.9% of the company's financial position into financial distress and financial health. In addition, the average classification result by sector shows that the manufacturing sector has the highest percent correct classification with 94.7%, followed by the service sector with 94.2%, and the trade sector presents the lowest correct classification among the 3 industries with 90.6%. Moreover, the model is suitable and can be applied to make early forecasts to avoid the risks of financial distress in Vietnam.*

Practical/managerial implications: *The model is suitable and can be applied to make early forecasts of financial distress in Vietnam.*

Keywords: *Financial distress prediction, Multi-layer perceptron artificial neural network*

The original version of the chapter has been revised. The authors name has been corrected in chapter 22. A correction to this chapter can be found at https://doi.org/10.2991/978-94-6463-348-1_45

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I. INTRODUCTION

Financial corporate distress is a topical and devastating concern of large corporations. Knowing the likelihood of distress helps investors make informed investment decisions and adjust their investment strategies to reduce investment-related losses (Muparuri & Gumbo, 2022a). Also, a reliable financial crisis prediction will help business managers initiate remedial measures to avoid a pre-crisis recession and investors can grasp the profit situation of listed companies, and their investment strategies are adjusted to reduce expected investment-related losses (Geng, Bose, & Chen, 2015).

Although research on financial distress prediction has a long history, prediction methods have been updated along with information technology's advancement to improve the accuracy of the predictive model. Recent studies have employed artificial intelligence such as decision trees, support vector machines, and artificial neural networks instead of traditional methods (e.g. regressions, or logit models) (e.g. Aydin, Sahin, Deveci, & Pamucar, 2022; Doğan, Koçak, & Atan, 2022; Huang & Yen, 2019).

Although financial distress has been popular predicted by employing Altman's model in various studies (ElBannan, 2021; García & Herrero, 2021; Nguyen, Alphonse, & Nguyen, 2022; Sun, Li, Huang, & He, 2014; Wu, Ma, & Olson, 2022), financial distress is considered when companies' earnings before interest and taxes (EBIT) are lower than their interest expenses for two consecutive years (Muparuri & Gumbo, 2022a; Pham Vo Ninh, Do Thanh, & Vo Hong, 2018; Pindado, Rodrigues, & de la Torre, 2008). Prior studies conducted in Vietnam mainly focused on traditional methods and Altman's model, thus this study attempts to use artificial neural networks to predict financial distress measured by EBIT lower than interest expenses for two consecutive years of the listed firms in Vietnam, which has no study conducted before.

Prior literature has been devoted In this study, the MLP-ANN model is employed to forecast corporate financial distress. Additionally, the prediction ability of the model is also tested for the manufacturing, services, and commerce sectors. This model uses financial collected data from 509 Vietnamese listed companies with 6617 observations. Financial ratios were collected on the Ho Chi Minh Stock Exchange and Ha Noi Stock Exchange from 2007 to 2019 by using the FiinPro Platform. Our findings show that the prediction model can correctly classify up to 93.9% of the company's financial status as healthy and financial distress. In addition, the findings also show that the predictive model achieves its highest accuracy of 94.7% for the manufacturing sector, followed by the service sector with a classification accuracy of 94.2% while the model holds the lowest classification accuracy of 90.6% for the trade sector.

The paper is organized into 6 sections. After the introduction, Section 2 provides a reviews of the literature on financial distress, followed by the prediction model in Section 3. The research methods are presented in section 4 before the presentation of the results and discussions in Section 5 The study closes with conclusions and future research in Section 6.

2. LITERATURE REVIEW

2.1 Financial distress and its measurement

Habib, Costa, Huang, Sun, and Bhuiyan (2018) pointed out that four general terms that describe corporate financial distress are insolvency, failure, default, and bankruptcy. When a company is inability to cover its current obligations, possibly because of liquidity issues, it is defined as insolvency. When the corporate revenue is insufficient to pay expenses or the actual rate of return on investments, after considering risk factors, is much lower than the returns produced from comparable assets is identified as failure. Default can have both a legal and technological concept. Technical default occurs when a business disregards a requirement in a contract. A legal default on a debt is more likely to occur if periodic installments are not made. Bankruptcy, which demands a formal declaration in most nations, is a sign of the company's financial crisis. To differentiate between "default", "insolvency" and "bankruptcy". Geng et al. (2015) summarized that "insolvency" which occurs when a debtor is unable to pay his or her debts was a legal term; when a debtor has not paid a debt which he or she was required to have paid called "default"; a legal finding that imposed court supervision over the financial affairs of those firms that were insolvent or were in default is the meaning of "bankruptcy". Overall, default is an event, insolvency is a state of being and bankruptcy is a legal process.

When the amount of debt, particularly short-term debt is high and the short-term debt cannot effectively be covered by the net operating cash flow of enterprises for a long time, along with limited refinancing ability, private businesses are more likely to default from a micro viewpoint (Wang, Ran, Huang, & Li, 2022). For Jabeur and Fahmi (2018), before a company is declared bankrupt, it faces progressively more serious financial challenges, such as debt default, temporary insolvency, a lack of liquidity, etc.

Pham Vo Ninh et al. (2018) and Sun et al. (2014) summarized previous studies and stated that financial distress occurs because of a decrease in the firm's business operations, illiquid assets, and high fixed costs lead to the inability to meet its financial obligations of the firm. The degrees of financial distress including extreme financial distress and mild financial distress might result in business failure or bankruptcy, and may only be a temporary cash flow issue, respectively. Being a sign of financial distress, the final state in which companies stop doing their business because of that financial distress is bankruptcy.

Jiang, Lyu, Yuan, Wang, and Ding (2022) pointed out that financial distress is defined and measured differently across studies. A company is considered financially distressed when it cannot meet the interest payment on debt financial obligations, its cash flows are limited, getting into liquidation or asset seizures because of failure to pay the debt that leads to bankruptcy (Gilson, John, & Lang, 1990; Muparuri & Gumbo, 2022b; Outecheva, 2007; Sun, Li, Fujita, Fu, & Ai, 2020; Sun et al., 2014).

Some articles also provide criteria to define financial distress in more detail. Hernandez Tinoco and Wilson (2013) pointed out that when a company's earnings before interest, taxes, depreciation, and amortization (EBITDA) are determined to be less than its financial expenses and its market value has experienced negative growth for two years in a row, that company is said to be in financial distress. Sun, Fujita, Chen, and Li (2016) and Geng et al. (2015) stated that when a company is marked for special treatment, denoted ST, on the Chinese Stock Exchange, it will be determined to be in a state of financial distress, which indicates negative cumulative earnings over two consecutive years or net asset value (NAV) per share below par book value (Jiang et al., 2022).

Sun et al. (2014) offer suggestions for future research that researchers need to consider a metric that can classify businesses in difficulty into several levels, such as mild, moderate, and bankrupt because financial distress is a dynamic, ongoing process that is brought on by ongoing business operations that are abnormal for an extended period of time (from months to years or even longer). As a result, several measurement methods have also been developed in order to forecast corporate financial distress at various levels.

Financial ratio have been commonly used as a measurement of financial distress. Altman (1968) used 22 ratios extracted form financial statement in his Z-score model, which is divided into 5 categories. Although there are several other financial indicators being used with huge amount of variables; Ben Jabeur and Fahmi (2018) used 33 variables, Climent, Momparler, and Carmona (2019) used 26 variables developed from 38 ratios, Liu, Wu, and Li (2019) used 16 variables), Altman's Z-score model and its later developed variants are a commonly used tool in the financial sector and especially in studies on financial distress prediction. Wu et al. (2022) directly applied five of Altman's independent variables as they argued that the model's explanatory power and predictive accuracy are not based solely on the increasing of financial factors. ElBannan (2021) measure distress by along with 2 other models.

Beside using Altman's variables, other variables also used in case of predicting financial distress. In addition to using macroeconomic variables (short-term Treasury bills in one year, inflation), Pham Vo Ninh et al. (2018) also used market variables (market value of equity, equity volatility, leverage ratio, and stock price) to get around the shortcomings of an accounting-based distress prediction model. Stronger inferences may be made by researchers if they take into consideration both accounting- and market-based indicators and assess which metric is relatively superior to the other. (Habib et al., 2018).

Aydin et al. (2022) said that failures are assessed based on the criteria for two or more years in a row. Companies are categorized as successful or unsuccessful based on this standard. Muparuri and Gumbo (2022b) also used the same definition as a measurement of their study. Pham Vo Ninh et al. (2018) adopted the approach developed in Pindado et al. (2008). According to this method, a company is considered financially distressed if it satisfies both of the following criteria: (1) its earnings before interest, taxes, depreciation, and amortization (EBITDA) are lower than its financial expenses for two years in a row; and (2) a decline in its market value occurs between two consecutive periods. In their prediction model employed in Vietnam by Pham Vo Ninh et al. (2018). They utilized the ratio of earnings before interest, tax, and depreciation (EBITDA) and interest payments. When the EBITDA ratio is less than 1, according to that approach, the company enters a state of financial crisis. (Wu et al., 2022).

2.2 Prior studies on financial distress prediction

2.2.1 Traditional statistical methods

Reviewing on financial distress prediction modeling method, Sun et al. (2014) summarized its research progress as follows: from single variable analysis to multivariate prediction; from traditional statistical methods to machine learning methods based on artificial intelligence; from pure single classifier methods to hybrid single classifier methods and classifier ensemble methods.

A study by Beaver (1966) was one of the first to use financial ratios to predict bankruptcy by analyzing for 5 years before the firm's failure. The most famous model that was able to distinguish bankruptcy firms from non-bankruptcy firms was developed by Altman (1968). Altman improved Beaver's method by applying multiple discriminant analyses (MDA) using five multiple variables (Wu et al., 2022). According to Sun et al. (2014), Altman (1968) firstly used the MDA for FDP that belongs to multivariate prediction. He developed the well-known Z-score model, which is a multivariate linear discriminant function using five financial ratios and discovered that its predictive power one year before bankruptcy was much higher than the single variable discriminant model.

Z score model is still widely used and applied as a measurement of financial distress such as Wu et al. (2022) used this for China market (ElBannan, 2021; García & Herrero, 2021); or adapted to either test its accuracy or predict the bankruptcy risk in many countries: Awwad and Razia (2021) in Palestinian, Diakomihalis (2012) in Greece, Praveena, Kandasamy, and Sengodan (2012) and Sarbapriya and Mahavidyalaya (2023) in India; Radivojac, Krčmar, and Mekinjić (2021) in Republic of Srpska; Hasan, Hadi, and Alhuda (2021) in Iraqi. Odibi, Basit, and Hassan (2015) used Altman a-score model to predict in Malaysia. Cındık and Armutlulu (2021) the Altman Z score model's efficiency and modified it for Turkish enterprises.

Most studies in Vietnam applied traditional statistical methods in the case of predicting financial distress. D. A. Tran (2022) examined the Altman Z-score (1968) models' accuracy for each year.

The results reveal that the original model accurately classifies 75.79% of the tested firms in the year preceding their delisting. Thanh Tung and Phung (2019) used the Altman Z-score model to estimate the bankruptcy risk of a variety of interdisciplinary firms, using binary logistic regression to assess the impact of non-financial and financial aspects on enterprise bankruptcy risk. The findings pointed out that both non-financial and financial factors influence firm bankruptcy risk.

The Logit linear probability model employs the logistic function to convert the dependent variable of financial distress likelihood into a completely continuous variable that can then be analyzed using linear regression (Sun et al., 2014). Vu Thi Loan (2019) sought to determine whether market information, such as stock price volatility, may anticipate a firm's failure in the future by employing Logit regression and the Support Vector Machine (SVM) research technique to produce a prediction one to three years in advance. The results demonstrated that combining accounting ratios with market characteristics such as price volatility and Price-to-Earnings ratio can improve the ex-ante model's classification abilities.

Xuan (2015) adopted the logistic regression model to examine the effects of financial variables on financial distress in Vietnamese enterprises from 2009 to 2012. The findings suggested that financial ratios can be used to provide an early warning of financial difficulties because they are highly connected with the likelihood of business financial trouble. Using the quantile regression method, Phan, Hoang, and Tran (2022) the influence of cash flow on the financial distress of private listed enterprises on the Vietnamese stock market from 2010 to 2020. This study discovered a negative correlation between cash flow from operating operations and cash flow from financial activities with financial distress.

2.2.2 Artificial neural networks

Artificial neural networks (ANN) are systems of computational intelligence that mimic the capacity and behavior of the human brain (Fadlalla & Lin, 2001). Neural networks excel in learning the relationship between input-output from a given dataset without any prior knowledge or assumptions about the statistical distribution of data (Kamruzzaman, Begg, & Sarker, 2006; Paule-Vianez, Gutiérrez-Fernández, & Coca-Pérez, 2019; Sun et al., 2014).

ANN models combined of three components: nodes, weights, and layers (Marso & El Merouani, 2020; Pregowska & Osial, 2021). Nodes are the digital neurons that comprise an artificial neural network. Each node has a unique attribute known as weight. The greater the weight, the more crucial it is in causing a company's distress (Muparuri & Gumbo, 2022b). In order to express the relative relevance of the inputs and outputs from the ANN "black box" or hidden layer, the ANN undertakes the task of calculating the weights connecting the input and output layers. The weights can be compared to the beta coefficients in regression models, which demonstrate the influences of independent variables on dependent variables (Aryadoust & Baghaei, 2016).

Wu et al. (2022) noted that the input node deals with observations or independent variables from the data. The output node deals with dependent variables that are compared to expected results to alter parameters. The hidden layer is essentially an intermediate layer between the network's input and output layers. The number of hidden layers varies depending on the problem. Some situations require a single hidden layer, while others require numerous hidden layers (Uzair & Jamil, 2020).

Neural network applications in finance, which were almost nonexistent before 1988, exploded from 1993 to 1995 (Fadlalla & Lin, 2001). Numerous real-world issues can be successfully solved using neural networks, such as bankruptcy prediction, credit scoring, stock market analysis future price estimation, and many others (Kamruzzaman et al., 2006).

Various types of neural networks are developed and applied widely. Lee and Choi (2013) presented a multi-industry research of bankruptcy employing back-propagation neural network (BNN) against MDA technique using a bankruptcy sample in Korea (229 enterprises, including 91 bankrupt companies). Meanwhile, Aydin et al. (2022) also classified failure based on data of companies doing business in different sectors by using ANN and decision trees (DTs). Data of one and three years before bankrupt of manufacturing sectors are collected in the research of Marso and El Merouani (2020) in Poland. They used cuckoo search feedforward neural network compared with backpropagation feedforward neural network (BPNN) and logistic regression (LR) and in order to investigate its efficiency. A study by Wu et al. (2022) presented a stock market forecasting model combining a multi-layer perceptron artificial neural network (MLP-ANN) with the traditional Altman Z-Score model to provide early warning signals of a company's deteriorating financial situation.

ANN is also applied by many researchers to combine or compare with other methods in predicting financial distress. Some studies shows that ANN outperformed others (e.g. (Aydin et al., 2022; Wu et al., 2022) , some shows the opposite (e.g. (Muparuri & Gumbo, 2022a; K. L. Tran, Le, Nguyen, & Nguyen, 2022a), while others show the combined model present the greater result (e.g. Wu et al. (2022)).

Aydin et al. (2022) classified failure based on data of companies doing business in different sectors by using artificial neural networks (ANN) and decision trees (DTs) and concluded that ANN model provides a higher rate of accurate classification.

In Vietnam, K. L. Tran, Le, Nguyen, and Nguyen (2022b) compared the predictive power of several methods including logistic regression, support vector machine, decision tree, random forest, artificial neural network, and extreme gradient boosting by interpreting the prediction results on the dataset of listed companies in Vietnam from 2010 to 2021. The extreme gradient boosting and random forest models outperformed the other models, according to the results.

Wu et al. (2022) compared artificial neural network (MLP-ANN) with the traditional Altman Z-Score model and introduced new hybrid enterprise crisis warning model combining Z-score and MLP-ANN models using China data. The results of empirical analysis show that the average correct classification rate of the new hybrid neural network model (99.40%) is higher than that of the Altman Z-score model (86.54%) and of the pure neural network method (98.26%).

Study by Muparuri and Gumbo (2022b) presented that the Logit model outperformed the ANN with an overall accuracy of 92.21% versus 85.8% for the ANN in predicting corporate distress in Zimbabwe.

ANN can produce results with an incomplete dataset in the case of unbalanced panel data (Muparuri & Gumbo, 2022b). Under some conditions, the ANN model's early warning effect outperforms both parametric and non-parametric models. It is free of sample distribution constraints and addresses the shortcomings of traditional quantitative prediction algorithms (Wu et al., 2022). For the reasons listed below, Lam (2004) believes neural networks are a good tool for projecting financial success. For starters, neural networks are numerical in nature, making them ideal for processing numerical data such as financial data and economic indicators. Second, no data distribution assumptions are required for input data in neural networks. Third, neural networks are an incremental mining method that allows new data to be fed into a trained neural network to update the previous training result. Fourth, neural networks are estimators that do not require a model.

Table 1. Compare of corporate FDF literature using ANN

Literature	Classifier	Sample size	Result
Wu et al. (2022)	Pure MLP-ANN Hybrid ANN and Z-score	China data from 2016 to 2020	Pure MLP-ANN: *98.26% accuracy.* Hybrid ANN and Z-score: *99.4% accuracy.*
Muparuri and Gumbo (2022b)	Logit vs ANN	Zimbabwe Data from 2014 to 2021	Logit result: *92.21% accuracy.* ANN result: *85.8% accuracy.*
Marso and El Merouani (2020)	Logit regression (LR) Backpropagation feedforward neural network (BPNN). Cuckoo Search Feedforward neurol networks (CSFNN).	Poland	LR: t-1: 82.15% accuracy t-3: 73.27% accuracy BPNN: *t-1: 88.33% accuracy* *t-3: 81.05% accuracy* CSFNN: *t-1: 90.30% accuracy* *t-3: 82.79% accuracy*
Aydin et al. (2022)	ANN Decision trees (DTs)	Turkey Data from 2015.2016.2017	ANN: Manufacturing sectors: *93.1% accuracy* Service sectors: *94.44% accuracy* Trade sectors: *89.47% accuracy* Decision trees (DTs): Manufacturing sectors: *84.03% accuracy*

			Service sectors: *87.93% accuracy* Trade sectors: *95.24% accuracy*
Lee and Choi (2013)	Back-propagation neural network (BNN) MDA	Korea Data from January 1, 2000 to December 31 2009	BNN: *81.43% accuracy for total sample* MDA: *74.82% accuracy for total sample*

3. PREDICTION MODEL

3.1 Independent variables

In this study, a combination of 13 index data including development capacity, profitability, solvency, operating capacity, market variable, capital structure that affect financial distress is used as independent variables. The different ratio categories used in the prediction model are shown in Table 2.

Table 2. Independent variable

Clarification	Index	Explanation/Computation	Source
Development capacity	$\frac{NP(t)}{NP(t-1)}$	Net profit of this year/net profit of last year	Liu et al. (2019)
Profitability	$\frac{NP}{S}$	Net profit/sale revenue	
Development capacity	$\frac{TA(t)}{TA(t-1)}$	Total assets of this year/total assets of last year	
Solvency	$\frac{TL}{TA}$	Total liabilities/total assets	
Solvency	$\frac{EBIT}{IE}$	Earnings before interest and taxes/interest expense	

Solvency	$\frac{NOCF}{CL}$	Net operating cash flow/current liability	
Solvency	$\frac{WC}{TA}$	Working capital/total assets	Wu et al. (2022)
Profitability	$\frac{RE}{TA}$	Retained earnings/total assets	
Operating capacity	$\frac{EBIT}{TA}$	Earnings before interest and taxes/total assets	
Development Capacity/Profitability	$\frac{S}{TA}$	Sales/total assets	
Capital structure	$\frac{MVE}{TL}$	The market value of equity/total liability	
Market variable	Market capitalization	Market capitalization	Pham Vo Ninh et al. (2018)
Market variable	Leverage	total liabilities /(total market value of equity + total liabilities)	

3.2 Dependent variables

We based on the definition of financial distress developed by Pindado et al. (2008) and Pham Vo Ninh et al. (2018) to determine the dependent variables. Companies which meet the criteria that their earnings before interest and taxes (EBIT) are lower than their interest expenses for two consecutive years are consider to be financial distress (code as number 0). Otherwise, the company in that year will consider to be financial healthy (code as number 1). For example, we have data for year n and (n+1) of a company A (where n runs from 2006 to 2018). If earnings before interest and taxes (EBIT) are lower than their interest expenses for both years n and (n+1), then in year (n+1) company A will be classified to be in financial distress (coded as 0). If the above conditions are not satisfied, then in year (n+1) company A will be classified to be financially healthy (code as number 1).

4. RESEARCH METHODS

4.1 Sample, data collection, and data pre-processing

We collected financial ratios of 769 listed companies (10766 observations) on Ha Noi Stock Exchange and Ho Chi Minh Stock Exchange for the period 2006-2019 via the FiinPro Platform[1]. The listed firms with at least 6 years of missing data were removed from the sample, and the year 2006 was remove from the sample, leaving a final sample of 509 companies with 6617 observations from 2007-2019.

4.2 Data analysis with MLP-ANN

The ANN models are built by using SPSS software. Figure 1 presents the data analysis process. After cleaning and solving the issue of missing data, the data of 509 companies with 6617 observations from 2007-2019 were loaded in SPSS, which is followed by setting input and output variables. Then, the observation samples are randomly split into training samples and testing samples in a ratio of 7:3. To develop the neural network model, 70% of the observations were utilized for training, and the remaining 30% were used for testing and evaluating the model's predictive power (see Table 3). The hidden layer and output layer's active functions were then set before the MPL-ANN model was run. The result was then examined.

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[1] http://fiinpro.com/: FiinPro is Vietnam's first rich and comprehensive financial database system, co-developed by FiinGroup and QUICK Corp (part of Japan's Nikkei group). The FiinPro system combines basic and detailed transaction data from the Vietnam stock market, as well as complete data on over 3000 public firms with total revenue accounting for almost 70% of Vietnam's GDP; this includes corporate profiles, financial information, industry data, and macro data. Furthermore, FiinPro offers important analysis tools such as Stock Analysis, Stock Screening, Excel Data Extraction, and many more designed to help analysts, fund managers, investment specialists, researchers, and financial advisers.

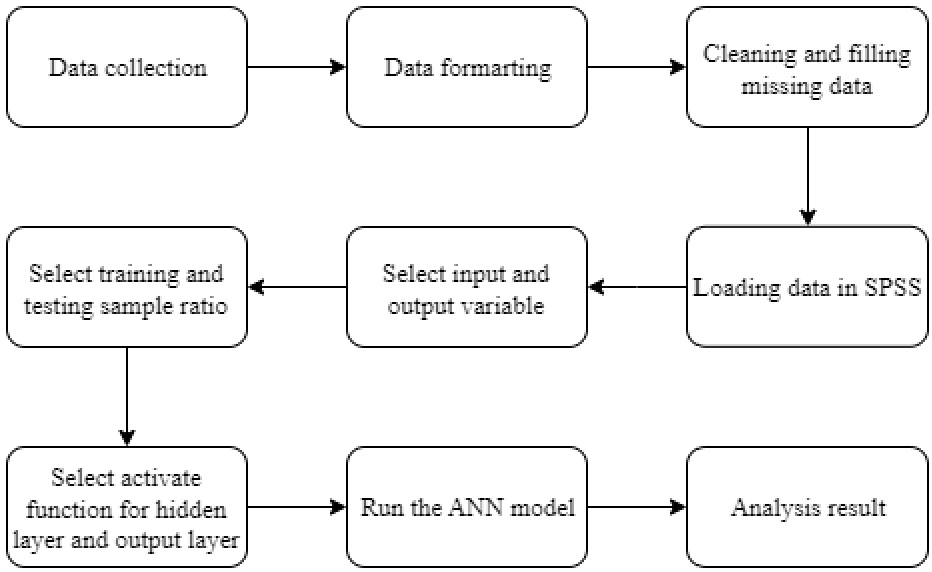

Figure 1. Data analysis framework

Table 3 shows the case processing summary: 6617 observation samples are randomly split into 4611 training samples and 2006 testing samples in a ratio of 7:3. The training samples were used to develop the model and the testing sample were used to test the accuracy of the model.

Table 3. Distribution table of training and testing sample of total observation

		N	Percent
Sample	Training	4611	69.7%
	Testing	2006	30.3%
Total		6617	100%

Figure 2 shows the network diagram. It represents the input layer, hidden layer, output layer. The lines linking the nodes together represent the weights.

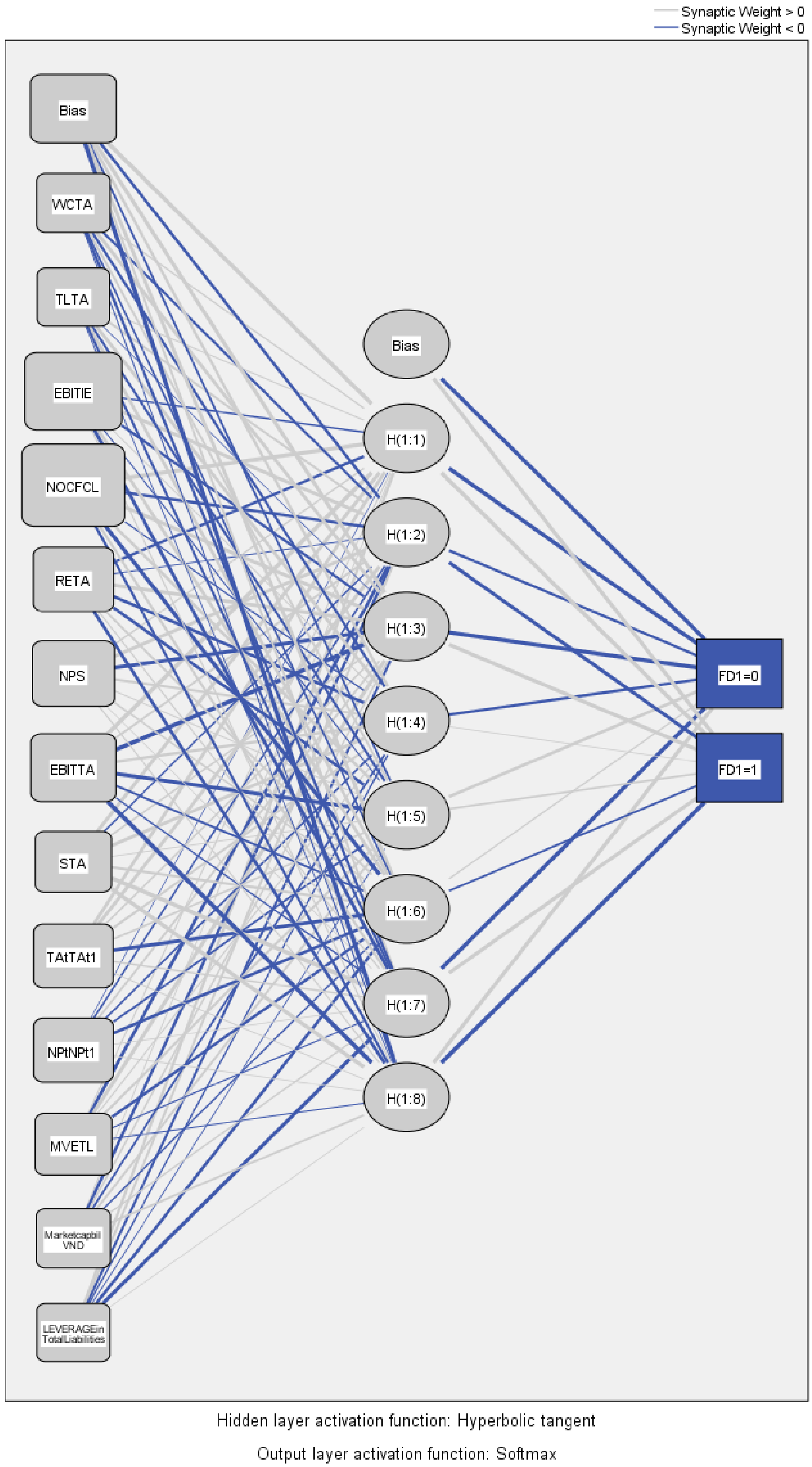

Figure 2. Network Diagram

Table 4 presents the weight of each node of the model, which basically present our model. The weight indicated the impact of independent variables on dependent variables.

Table 4. Independent Variables and Their Weight of model

Parameter Estimates

Predictor		Predicted									
		Hidden Layer 1								Output Layer	
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	H(1:8)	[FD1=0]	[FD1=1]
Input Layer	(Bias)	.940	-.385	.553	.355	-.207	.452	.239	-1.018		
	WCTA	.107	-.274	.430	-.307	.246	-.171	-.315	-.062		
	TLTA	.071	.257	-.005	.414	-.262	.406	-.262	-.016		
	EBITIE	-.147	.454	-.312	.054	-.063	.408	-.438	.087		
	NOCFCL	.622	-.373	.500	-.102	.386	-.590	.303	-.292		
	RETA	-.328	-.035	.495	-.395	-.399	.222	.096	-.410		
	NPS	.118	.436	-.547	.274	.037	.161	.006	.081		
	EBITTA	.969	.255	-1.201	.372	-.563	-.230	-.113	-1.383		
	STA	.477	-.139	.160	.424	.031	.287	1.030	.601		
	TAtTAt1	.428	.444	.165	.261	.190	-.490	.151	.028		
	NPtNPt1	-.004	-.166	.217	-.177	-.202	-.389	.009	.014		
	MVETL	.078	-.413	.524	.084	.281	-.373	-.079	-.046		
	MarketcapbilVND	.034	-.374	.152	-.193	.260	-.128	.134	.219		
	LEVERAGEinTotalLiabilities	.353	.261	-.273	-.128	-.025	-.385	-.519	.009		
Hidden Layer 1	(Bias)									-.638	.589
	H(1:1)									-.721	.807
	H(1:2)									-.309	-.484
	H(1:3)									-.815	.581
	H(1:4)									-.318	.012
	H(1:5)									.401	.190
	H(1:6)									.103	-.203
	H(1:7)									-.745	.552
	H(1:8)									.576	-1.319

4.3 Model evaluation

We evaluate the model by analyzing the accuracy in the classification of the model and adapting Receiver Operating Characteristic (ROC) and area under the ROC curve (AUROC). ROC is a statistic that shows a curve of the sensitivity against the specificity of a binary classifier. A successful classifier should have an AUROC above the diagonal line and as close to the axis as feasible, with a value close to 1 (Muparuri & Gumbo, 2022b).

5. RESULT AND DISCUSSION

5.1 Findings on total sample

Table 5 summarizes prediction result using total sample. Among the training samples, 188 observations are financial distress are classified correctly as financial distress; 168 observations in financial distress situation were misjudged as healthy, the correct rate was 52.8%; 96 of the 5255 healthy sample were misjudged as financial distress, and the correct rate was 97.7%. Overall, ANN used the training sample to come up with a model with an accuracy rate of 94.3%.

Among testing samples, 95 of the 160 observations in financial distress were misjudged as healthy samples, the correct rate was 40.6%; 1799 observations in healthy situation were correctly classified as healthy, and the correct rate was 97.5%. Overall, the testing sample shows that the model can predict with an accuracy rate of 92.9%. The average correct classification rate of both training and testing sample is 93.9%.

Table 5. Classification results using total sample in MLP-ANN model

Sample		Predicted		
		0	1	Percent Correct
Training	0	188	168	52.8%
	1	96	4159	97.7%
	Overall Percent	6.2%	93.8%	94.3%
Testing	0	65	95	40.6%
	1	47	1799	97.5%
	Overall Percent	5.6%	94.4%	92.9%
Total	0	253	263	49.0%
	1	143	5958	97.7%
	Overall Percent	6.0%	94.0%	93.9%

Figure 3 presents ROC curves for 2 values of the dependent variable. The area under the curves based on both training and testing samples was closed to 0,9 (show in Table 6), indicating a good classification accuracy rate.

Table 6. Area under the Curve using total sample in MLP-ANN model

		Area
FD 1	0	.875
	1	.875

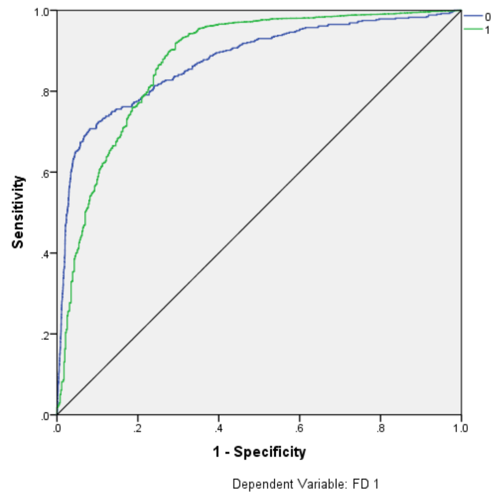

Figure 3.ROC curves for the dependent variable using total sample

. Note: 0- financial distress, 1- financial healthy

Table 7 and Figure 4 show the variable importance of the MLP-ANN model for total observations. The ratio of net operating cash flow to current liability ranks the first place in term of importance, and the ratio of total liabilities/ total assets play the least importance role of the model.

Table 7. Variable importance for total sample

Independent Variable Importance	Importance	Normalized Importance
NOCF/CL	.212	100.0%
EBIT/IE	.177	83.2%
EBIT/TA	.102	47.9%
NP/S	.083	38.9%
RE/TA	.073	34.2%

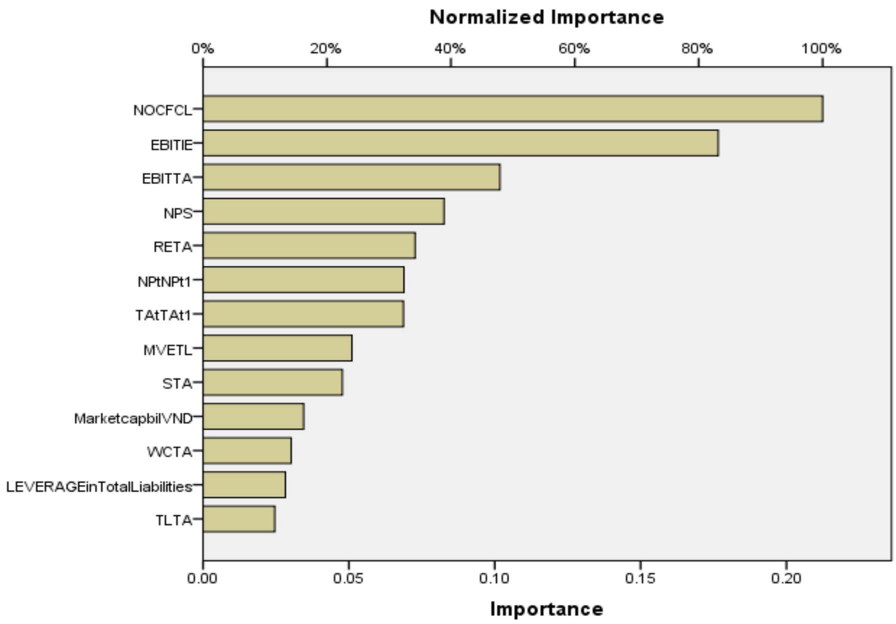

Figure 4.Variable importance using total sample in MLP-ANN model

5.2 Findings by sectors

In this part, models have been checked with the goal of comparing the correct classification rates by sectors including: manufacturing (201 companies), service (88 companies), and trade (75 companies). Observations when classified distribution of training and testing sample in each sector are divided into training and test samples in the ratio 7:3. Table 8 show the cases summary by sector.

Table 8. Distribution of training and testing sample summary by sector

		Manufacturing	**Service**	**Trade**
Sample	Training	1834 (70.2%)	788 (68.9%)	681 (69.8%)
	Testing	779 (29.8%)	356 (31.1%)	294 (30.2%)
Total		2613 (100%)	1144 (100%)	975 (100%)

Table 9 summarizes prediction result by sector. In the case of manufacturing, among the training samples, 32 observations is financial distress are classified correctly as financial distress; 74 observation in financial distress situation were misjudged as healthy, the correct rate was 30.2%; 11 of the 1728 healthy sample were misjudged as financial distress, and the correct rate was 99.4%. Overall, ANN used the training sample to come up with a model with an accuracy rate of 95.4%.

Among testing samples, 47 of the 57 observations in financial distress were misjudged as healthy samples, the correct rate was 17.5%; 716 observations in healthy situation were correctly classified as healthy, and the correct rate was 99.2%. Overall, the testing sample shows that the model can predict with an accuracy rate of 93.2%. The average correct classification rate of both training and testing sample is 94.7%.

Overall, the average classification result in the manufacturing sector has the highest percent correct classification (94.7%), followed by the service sector with 94.2%, and the trade sector presents the lowest correct classification among the 3 industries with 90.6%.

Table 9. Classification result by sector

			Predicted							
Sample			Manufacturing			Service			Trade	
		0	1	Percent Correct	0	1	Percent Correct	0	1	Percent Correct
Training	0	32	74	30.2%	49	37	57.0%	47	47	50.0%
	1	11	1717	99.4%	12	690	98.3%	20	567	96.6%
	Overall Percent	2.3%	97.7%	95.4%	7.7%	92.3%	93.8%	9.8%	90.2%	90.2%
Testing	0	10	47	17.5%	27	14	65.9%	15	14	51.7%
	1	6	716	99.2%	3	312	99.0%	11	254	95.8%
	Overall Percent	2.1%	97.9%	93.2%	8.4%	91.6%	95.2%	8.8%	91.2%	91.5%
Total	0	42	121	25.8%	76	51	59.8%	62	61	50.4%
	1	17	2433	99.3%	15	1002	95.5%	31	821	96.4%
	Overall Percent	6.2%	93.8%	**94.7%**	11.1%	88.9%	**94.2%**	12.6%	87.4%	**90.6%**

Table 10 shows AUROC. The results indicated that service and trade models present excellent classification, the manufacturing sector presents good classification.

Table 10. Area under the ROC curve by sector

Area Under the Curve

		Manufacturing	Service	Trade
FD	0	0.84	0.922	0.926
	1	0.84	0.922	0.926

5.3 Discussion

Although the model using pure MLP-ANN developed by Wu et al. (2022) provide higher correct classification rate (98,26% compare to 93,9%), our model can provides higher correct classification rate for distressed companies (49% compare to 0,34%). We assume that because the sample of that study is much larger than our sample (17,206 observations vs 6617 observations), so the overall correct classification rate of the study by (2022) is higher.

Using the same neural network method in predicting financial distress, our model provides higher accuracy rate compare to the model developed by (Lee & Choi, 2013; Marso & El Merouani, 2020; Muparuri & Gumbo, 2022a).

Most research in Vietnam employed established approaches to forecast financial distress. They constructed the model using the traditional method, which concentrated on the relationship between variables rather than the prediction element of the model (Pham Vo Ninh et al., 2018; Vo, Pham, Ho, & McAleer, 2019; Yen & Hiep, 2014). In comparison to the old method, ANN constructs the model quickly while also providing the percentage correct classification of the model, highlighting the prediction component.

For the adopted of machine learning method for predicting financial distress in Vietnam, K. L. Tran et al. (2022a) used 25 financial ratios, the model using ANN an accuracy of 91.68%. Our model only uses 13 ratios and provides a higher rate of average classification accuracy (93,9%).

When comparing the result by sector, it is concluded that the ANN model for the manufacturing sector provides the highest rate of accurate classification of financial distress companies (94,7%).

Our model also provides higher correct classification for manufacturing sector and trade sector compared to the model developed by Aydin et al. (2022).

6. CONCLUSION AND FUTURE RESEARCH

In this study, we conduct a model in predicting the financial distress of listed firms in Vietnam for the period of 2007-2019 using the machine learning approach, multilayer perceptron artificial neural networks. Based to the findings, the model successfully classified the total sample of listed companies on the Vietnam Stock Exchange into two financial scenarios: financial distress and financial healthy, with a classification accuracy of 93.9%. The ratio of Net Operating cash flow to Current Liability and Earnings before Interest and Taxes to Interest Expense play an important role in forecasting the company's financial distress situation. Additionally, we also divided the data into 3 sectors and the result shows that manufacturing industry achieves the highest classification (94,7%), followed by the service sector with 94,2%, and the trade sector presents the lowest correct classification among the 3 sectors with 90,6%.

The proposed model's limitation is that it is reliant on financial ratios. Future studies may enhance the number and variety of elements, including governance structure, market variables, and macroeconomic variables. Additionally, we could employ other prediction techniques to compare the classification accuracy of the model, then select the most accurate model of prediction in the context of Vietnam. s

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