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Use of Artificial Neural Network in Predicting Financial Distress in Banking Companies in Indonesia

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ABSTRACT

A situation known as financial distress occurs when the company's finances are in poor or experiencing a decline before bankruptcy occurs. To test and predict transport, you can use an Artificial Neural Network. The purpose aims to predict Banks that are listed on the Indonesian stock exchange are experiencing financial difficulties using predictive indicators, namely the current ratio, return on equity, and BOPO. Based on the research results of the summary model in neural network testing, the Artificial Neural Network backpropagation algorithm was applied to obtain 3-2-2 architecture results. Based on the results of the three tests, the percent incorrect prediction value was obtained, which had the lowest error rate, namely in the first test, namely 11.7% or a model correctness level of 88.3% in determining the neural network. The highest influence on financial distress is the Current Ratio variable, with an importance value of 0.521. Based on three tests, it is stated that the prediction model using the artificial neural network algorithm backpropagation indicators CR, ROE, and BOPO can predict financial distress. CR is the most dominant influencer in financial distress. The outcome of this research have implications for banking companies that need to pay attention to or maintain liquidity levels because this proportion shows how much money the organization has plus assets that can turn into money in the short term.

Keywords: Financial Distress; Current Ratio; Return On Equity; BOPO; Artificial Neural Network

JEL Clasification: G0, G3, O3

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SDGs: Quality Education (4); Decent Work and Economic Growth (8); Peace, Justice and Strong Institutions (16)

INTRODUCTION

Economic activities in banking cannot be separated from the role of banking. Therefore, banking plays a crucial role in supporting the Indonesian economy. Banking plays an essential role in helping the government finance infrastructure projects and economic development, and banking can also help people overcome financial problems. Economic conditions, domestic and foreign, greatly influence banking conditions because, based on income, around 80% of business funding comes from the banking sector. Therefore, banking companies must show sound financial performance and be healthy. Companies in banking need to be able to keep their financial condition so that they remain healthy. If the economic condition is unhealthy or experiencing a decline, the company can be said to be in financial distress.

Financial Distress is a condition where the organization's funds are in an undesirable condition or experiencing a decline before bankruptcy or liquidation occurs [1]. Meanwhile, according to (Fahmi Hernadianto, Yusmaniarti, and Fraternesi, 2020), The company's inability to meet its obligations is the first sign of financial trouble short-term obligations, including liquidity and solvency.

A company needs to assess its financial condition to get a clearer picture of its current condition and to identify appropriate actions to overcome problems such as economic distress. Financial difficulties can occur due to increasing debt every year, and even some companies experiencing a financial crisis show poor financial performance, which can result in bankruptcy [2].

The sooner a company knows its financial condition, the better it will be because it can identify the appropriate actions to overcome the problem. One way that can be done to test and predict transport is by using an Artificial Neural Network (ANN). ANN is an information processing system with the same performance characteristics as biological neural networks. Computer scientists have discovered that neural networks have great potential for solving problems. Haykin (2009) states that an artificial neural network (ANN) is designed to resemble the human brain and carry out specific tasks. This network is usually implemented using electronic components or simulated in computer applications. Artificial intelligence neural networks are powerful tools for modeling problems where the explicit form of relationships between variables is not known with certainty. Neural Networks can model linear and non-linear relationships. The ANN model is an alternative that has attracted much attention from researchers because several options have attracted attention for several reasons. NN does not require assumptions on data that are often difficult to fulfill.

Several studies have tested financial distress using ANN. [3] using the ratios of company value, liquidity, leverage, and profitability, the research results show that These four ratios provide significant differences between and are suitable for input parameters declared distressed and non-distressed companies. Using ANN to predict research with 20 neurons as the input layer, 5 neurons as the hidden layer, and 1 neuron as the output layer with the best accuracy results, namely 87% [4], Using company value, liquidity, leverage, and profitability to predict conditions of financial difficulty result in an accuracy of 80% [5]. This research shows the best financial distress prediction model with an AUC of 92.5 percent and the highest accuracy of 92.7%, which is included in the very good classification. Furthermore [6], The results of this research show that the shareholder's equity ratio, current ratio, and return on assets are very good to use as input parameters that differentiate between bankrupt and non-bankrupt companies. The ANN training model produces the best training performance with a model architecture of 15 neurons in the input layer and 30 neurons in the hidden layer, with one hidden layer. Meanwhile, according to [7], the results of their research stated that these ratios were very suitable for making predictions because they showed significant differences between companies that were declared to be experiencing financial distress and those reported to be experiencing financial distress and were used as training data for the prediction process.

Previous studies show different banking performance results, so the author is interested in comparing financial and non-financial distress. Based on the problems explained above, this research aims to determine and predict financial distress through the use of intelligence neural networks in banking companies in Indonesia.

LITERATURE REVIEW

Financial Distress

Companies must always check the company's financial condition so that financial distress does not occur and bankruptcy can be avoided. If left unchecked, financial difficulties will result in company bankruptcy. Financial distress shows a situation of financial difficulty experienced by a company because its cash flow is insufficient to meet its obligations [8]. Financial distress as financial difficulty is a stage before the bankruptcy of a company (Francis Hutabarat, 2021:27). Monetary Misery is a phase of financial decline that begins with the company's inability to pay company debt, especially short-term debt, which ultimately leads to bankruptcy [9]. A company can be in financial distress or in a problematic condition if the company experiences negative net profit for several years [10].

Current Ratio

The current Ratio is a ratio that determines capacity of the company to pay off short-term obligations or debts that are due immediately when they are fully collected. This ratio reveals the company's cash balance has plus assets that can be paid off in one year when compared to the number of debts that will be due in the near future (not more than one year) on a specific date, as stated on the asset report. Divide current assets by liabilities to get the current ratio [11]. According to (Kashmere, 2018) [12], The company's ability to pay short-term obligations or debts that are due immediately upon collection is measured by the current ratio in full. Simply put, how much cash is available to pay for short-term obligations from current assets owed soon?

Return On Equity

Return on Equity in a company makes the company's financial managers strive to achieve the best performance in utilizing the company's capital and assets [13]. Return On Equity is a ratio used to measure a company's level of return in generating profits by utilizing the company's equity. ROE is a tool for calculating net profit after tax on one's capital. According to [14], the rate of return on equity compares net profit and equity.[15] (Husnan and Pudjiastuti, 2012), “ROE shows the capacity of own cash-flow to produce benefits for investors.

Operating Costs Operating Income

Operating costs to operational income (BOPO) is the ratio of operating expenses to operational income (BOPO) formulated as a comparison of operational costs to operational income in the same period [16]. The Ratio of Operational Costs to Operational Income is the ratio used to calculate how much a bank can control the amount of operational costs relative to the inflow of operational income in each bank. Operating costs operational income

(BOPO) is an productivity proportion used to quantify bank the executives' capacity to control functional expenses towards operational income. The operational expenses is more effective the lower this ratio incurred by the bank concerned, so the possibility of a bank being in trouble is smaller [17].

Artificial Neural Networks

The term "Artificial Neural Network" refers to a system in which many processors are distributed in parallel and consisting of basic handling units, where every unit tends to store experienced knowledge and can be reused (Haykin, 1999, p2). An artificial neural network, usually called an artificial neural network, is an architectural computing system whose operation is a system for processing information that stimulates an artificial intelligence system with the same characteristics as the workings of the human biological nervous system. [18]. Artificial Neural Networks are mathematical models derived from the organization and function of biological neurons [19]. ANN is a method of grouping and separating data whose working principle is the same as that of neural networks in humans. The essential component of the paradigm is the new information processing system structure. Artificial Neural Networks are formed to take care of issues like example acknowledgment or grouping through learning [20].

RESEARCH METHODOLOGY

This research uses a comparative research method with a quantitative approach. Secondary data will be used in the form of financial reports of banking companies listed between the years 2018 and 2022 on the Indonesia Stock Exchange, and data will also be used in the form of articles, literature studies, journals, and sites on the internet related to the research topic. A total of 36 companies were sampled, or 180 observations. The descriptive analysis method uses analytical tools, such as the artificial neural network method using IBM SPSS 22 software, with the backpropagation method in predicting financial distress. This research uses the activation function to determine the relationship between input and output from an artificial neural network. The activation function measures nonlinearity, which is the main focus in applying ANN (Zhang et al., 1998). This study's operational variables are as follows:.

Table 1. Operational Variables

Variable	Variable definition	Indicators	Prediction Model
Financial distress	Financial distress shows the situation of financial difficulties experienced by the company because the cash flow it has is insufficient to meet the company's obligations. (Altman, et al., 2019)	Current ratio (CR) Return On Equity (ROE) Operating expenses operating income (BOPO)	Artificial intelligence neural networks (ANN) using: 1. Partition dataset 2. Model Summary 3. Parameter Estimates 4. Independent Variable Importance 5. Receiver Operating Characteristic (ROC) curve

RESULTS AND DISCUSSION

Descriptive Analysis

The use of descriptive statistical analysis explain all the variables used descriptively. Descriptive statistical analysis aims to collect, process, analyze, and obtain the required information. This information includes minimum, maximum, average (mean), and standard deviation values.

Table 2. Overall Descriptive Statistics Test Results for Banking

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
CR_X1	180	-286.64	79.55	.6087	23.80186
ROE_X2	180	-273.52	21.08	1.3996	23.77112
BOPO_X3	180	-210.85	287.00	87.0137	45.24402

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Valid N (listwise)	180				

Source: processed data (test results), 2024

From the results above, it can be seen that during 2018-2022, the Current Ratio variable as a whole data has a value mean of 0.6087 and a deviation from the mean of 23.80186, as well as the Return On Equity variable has a mean value of 1.3996 and a standard deviation of 23. .77112, this result states that if the standard deviation value is greater than the mean value, then the distribution of data from the Current Ratio and Return On Equity variables is uneven due to the distinction between one data and another data is more significant than the average value or there are several outliers. [21], Outliers are data that look very different (extreme) from a variable. Meanwhile, BOPO has a mean value of 87.0137 and a standard deviation 45.24402. Suppose you compare the standard deviation value with the mean value. The standard deviation value is smaller than the mean BOPO value. In that case, the data distribution from the banking BOPO variable is even.

Artificial Neural Network Testing

The next stage is data partitioning or data division. After normalizing the data, the normalized data will be tested using the artificial neural network method using IBM SPSS 22 software. From the entire data, the partitioned dataset is divided into two, namely training samples and testing samples. The testing in this research was carried out three times with differences in data proportions. Researchers carried out tests with the first data proportion of the ANN architecture with a data proportion of 90%:10%, the second test with the ANN architecture with a data proportion of 80:20, and the third test with the ANN architecture with a data proportion of 70:30.

From testing the model by applying the artificial neural network backpropagation algorithm, the results were 3-2-2 architecture. From the results of the artificial neural network architecture, it can be seen that there are 3 input parameter variables, namely CR, ROE, and BOPO, and there is 1 bias in the input layer. Bias is the uncertainty value in a model in a layer. There is only one hidden layer with 2 neurons plus 1 bias in the hidden layer. Meanwhile, in the output layer, there are 2 outputs, which present Financial distress = 1 for positive banking, indicating financial distress, and Financial distress = 0 for negative banking, indicating financial distress.

Model Summary

The summary model in neural network testing provides information regarding the proportion of prediction errors caused by neural network training and testing. The following are the results of testing data through 3 tests. The first test (90:10) can be seen in Tables 3 and 4, the second in Tables 5 and 6, and the third in Tables 7 and 8.

Table 3. First Test (90:10)

Case Processing Summary

		N	Percent
Samples	Training	159	88.3%
	Testing	21	11.7%
Valid		180	100.0%
Excluded		0	
Total		180	

Source: processed data (test results), 2024

Table 4. Model summary of first test (90:10)

Model Summary

Training	Sum of Squares Error		142,003
	Average Overall Relative Error		,899
	Relative Error for Scale Dependents	FinancialDistress_0000	,906
		FinancialDistress_1000	,891
	Stopping Rule Used		1 consecutive step(s) with no decrease in error
	Training Time		0:00:00.07

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Model Summary

Testing	Sum of Squares Error		,051
	Average Overall Relative Error		,176
	Relative Error for Scale Dependents	FinancialDistress_0000	,263
		FinancialDistress_1000	,090

a. Error computations are based on the testing sample.
Source: processed data (test results), 2024

Table 5. First test (80:200)

Case Processing Summary

		N	Percent
Samples	Training	148	82.2%
	Testing	32	17.8%
Valid		180	100.0%
Excluded		0	
Total		180	

Source: processed data (test results), 2024

Table 6. Model summary of second test (80:20)

Model Summary

Training	Sum of Squares Error		86,175
	Average Overall Relative Error		,586
	Relative Error for Scale Dependents	FinancialDistress_0000	,537
		FinancialDistress_1000	,636
	Stopping Rule Used		1 consecutive step(s) with no decrease in error
	Training Time		0:00:00.09
Testing	Sum of Squares Error		.116
	Average Overall Relative Error		,329
	Relative Error for Scale Dependents	FinancialDistress_0000	,451
		FinancialDistress_1000	,207

a. Error computations are based on the testing sample.
Source: processed data (test results), 2024

Table 7. Third Test (70:30)

Case Processing Summary

		N	Percent
Samples	Training	127	70.6%
	Testing	53	29.4%
Valid		180	100.0%
Excluded		0	
Total		180	

Source: processed data (test results), 2024

Table 8. Third test summary model (70:30)

Model Summary

Training	Sum of Squares Error		8,945
	Average Overall Relative Error		.071
	Relative Error for Scale Dependents	FinancialDistress_0000	.071
		FinancialDistress_1000	.071

Model Summary

Testing	Stopping Rule Used		Relative change in training error criterion (.0001) achieved
	Training Time		0:00:00.03
	Sum of Squares Error		5173.211
	Average Overall Relative Error		,898
	Relative Error for Scale Dependents	FinancialDistress_0000	,898
		FinancialDistress_1000	,899

Source: processed data (test results), 2024

Based on the results of the percent incorrect prediction value from the three tests, it is known that the error rate is the lowest, namely in the first test, 11.7%. This means that, from a prediction error rate of 11.7%, the first test model has a model correctness rate of 88.3% when determining the neural network. Furthermore, the highest error rate in the third test was 29.4%, meaning the model's correctness level in determining the neural network was 70.6%. The test recapitulation results can be seen in Table 9 below.

Table 9. Recapitulation of Percentage Incorrect Prediction

Testing	Percent Incorrect Prediction
Testing I	11.7%
Testing II	17.8%
Testing II	29.4%

Source: processed data (test results), 2024

Parameter Estimates

Parameter estimates show the prediction value obtained from weighting (synaptic weight) using the sigmoid activation function in the artificial neural network backpropagation algorithm. Strictly increasing functions exhibit a high balance between linear and non-linear properties. Testing Parameter Estimates 90:10, Testing Parameter Estimates 80:20, and Testing Parameter Estimates 70:30 can be seen in the following table.

Table 10. Tests Parameter Estimates 90:10

Parameter Estimates

Predictors		Predicted			
		Hidden Layer 1		Output Layer	
		H(1:1)	H(1:2)	FinancialDistress_0000	FinancialDistress_1000
Input Layers	(Biased)	-.031	-.417		
	CR_X1	,433	,222		
	ROE_X2	,351	-.007		
	BOPO_X3	-.081	,040		
Hidden Layer 1	(Biased)			,208	,236
	H(1:1)			,345	,477
	H(1:2)			,369	,361

Source: processed data (test results), 2024

Table 11. Testing Parameter Estimates 80:20

Parameter Estimates

Predictors		Predicted			
		Hidden Layer 1		Output Layer	
		H(1:1)	H(1:2)	FinancialDistress_0000	FinancialDistress_1000
Input Layers	(Biased)	,044	-.505		
	CR_X1	,054	-.048		
	ROE_X2	,082	-.353		
	BOPO_X3	.211	,170		

Parameter Estimates

Predictors		Predicted			
		Hidden Layer 1		Output Layer	
		H(1:1)	H(1:2)	FinancialDistress_0000	FinancialDistress_1000
Hidden Layer 1	(Biased)			-.686	-.500
	H(1:1)			1,123	,753
	H(1:2)			-1,442	-1.103

Source: processed data (test results), 2024

Table 12. Parameter Test Estimates 70:30

Parameter Estimates

Predictors		Predicted			
		Hidden Layer 1		Output Layer	
		H(1:1)	H(1:2)	FinancialDistress_0000	FinancialDistress_1000
Input Layers	(Biased)	-.424	-1,706		
	CR_X1	.041	.102		
	ROE_X2	,444	-.418		
	BOPO_X3	-.050	,314		
Hidden Layer 1	(Biased)			-1,093	-1,081
	H(1:1)			1,603	1,605
	H(1:2)			-1,901	-1,890

Source: processed data (test results), 2024

Based on the table above, you can find the bias and weights that connect the input layer with the hidden layer and the hidden layer with the output layer. Each unit in the output layer is influenced by a combination of many parameters from the previous layer that use non-linear functions. However, it is not easy to know the influence of the weight of each unit in each layer, which has an impact on the output layer and the influence of the blend. The output and input in the ANN backpropagation algorithm try not to have balanced correspondence because this is not the same as linear models where the parameters and weights can be assessed (Candes & Fine, 2000). Then, a bias is connected to each neuron in the input and hidden layers.

Independent Variable Importance

Independent Variable Importance to analyze sensitivity where this can make sense of how much influence it has the neural network's design. Based on the percentage of incorrect predictions made by artificial neural networks, In the first test, 90:10, the one with the highest influence on financial distress is the Current Ratio variable with an importance value of 0.521. It states that CR contributes to determining indications of financial distress if it is a percentage of 52.1% of the total variables that make up the monetary misery forecast model. The second significant value for ROE is 0.431, which states that ROE contributes 43.1% of all the the model's components, or variables. Meanwhile, BOPO, the variable with the slightest influence on financial distress, is 0.048, meaning BOPO contributes 4.8% of all the variables that make up the model.

Receiver Operating Characteristic (ROC) curve

Testing was carried out on Parameter Estimates 90:30, Parameter Estimates 80:20, and P Parameter Estimates 70:30, with the recapitulation results of the area under the curve being as follows.

Table 13. Recapitulation Of Areas Under The Curve

Testing	AUC	
	Non-Financial Distress	Financial Distress
Testing I	0.548	0.506
Testing II	0.548	0.506
Testing II	0.548	0.684

Source: processed data (test results), 2024

Based on the three tests above, the prediction model using the artificial neural network backpropagation algorithm is classified as poor, with an AUC value between 0.54 and 1. However, the highest value was obtained in the third test, where the AUC value was 0.684, more significant than in the first and second tests with the same AUC value of 0.506.

CONCLUSIONS AND RECOMMENDATIONS

Based on research results, this model summary in neural network testing provides information regarding the proportion of prediction errors caused by neural network training and testing. From testing the model by applying the artificial neural network backpropagation algorithm, the results were 3-2-2 architecture. From the results of the artificial neural network architecture, it can be seen that there are 3 input parameter variables, namely CR, ROE, and BOPO, and there is 1 bias in the input layer. Based on the results of the percent incorrect prediction value from the three tests, it is known that the error rate is the lowest, namely in the first test, 11.7%. This means that from a prediction error rate of 11.7%, the first test model has a model correctness rate of 88.3% in determining the neural network.

Based on the percentage of incorrect predictions made by artificial neural networks, in the first 90:10 test, the one with the highest influence on financial difficulty was the Current Ratio variable, which had an importance value of 0.521. The second significant value for ROE is 0.431, which states that ROE contributes 43.1% of all the variables that make up the model. Meanwhile, BOPO, the variable with the slightest influence on financial distress, is 0.048, meaning BOPO contributes 4.8% of all the variables that make up the model. Based on three tests, it is stated that the prediction model using the artificial neural network backpropagation algorithm with CR, ROE, and BOPO indicators is classified as poor for predicting financial distress where the AUC value is between 0.54 and 1. However, the highest value was obtained in the third test, where The AUC value of 0.684 is greater than the first and second tests, which have the same AUC value of 0.506.

The results of this research imply that to test and predict whether a company is experiencing financial distress, companies using CR, ROE, and BOPO indicators can use the artificial neural network method. This method can predict financial conditions, with estimates made so companies can overcome economic problems. It is recommended that other variables be used to predict finances for future research so that a better prediction model can be obtained using an artificial neural network backpropagation algorithm.

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