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Prediction of financial distress in transportation and logistics companies before, during and after the Covid-19 pandemic listed on the Indonesia Stock Exchange

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Abstract
Purpose: This study aims to predict financial distress in transportation and logistics companies before, during, and after the Covid-19 pandemic.
Research Methodology: A total of 23 transportation and logistics companies were selected as the research sample using purposive sampling method. Secondary data from audited financial statements for 2019–2023 were analyzed. Three financial ratios—Current Ratio (CR), Return on Assets (ROA), and Debt-to-Asset Ratio (DAR)—were used as input variables. An Artificial Neural Network (ANN) with a multilayer perceptron backpropagation algorithm was employed to train and test the prediction models. The best architecture was identified by comparing the model performance across variations in hidden neurons.
Results: The results reveal that companies reported as financially distressed have lower average values for the three ratios than companies not experiencing financial distress, making them suitable input variables. The best artificial neural network architecture in this study included an input layer with 60 neurons, a hidden layer with 15 neurons, and an output layer with a single neuron. This architecture achieved a training performance mean square error (MSE) of 0.125004 and an R-value of 50.00%. The study's findings suggest that 12 companies are likely to experience financial distress.
Conclusions: Financial ratios are effective indicators of distress, and ANN models can predict potential bankruptcy with a reasonable accuracy.
Limitations: This study is limited to three financial ratios and a single sector, which may not fully capture the broader determinants of financial distress.
Contribution: This study contributes to the financial distress prediction literature by applying ANN to transportation and logistics firms in Indonesia and offers practical tools for stakeholders to anticipate risks and design preventive strategies.

Keywords: *Artificial Neural Network, Financial Distress, Financial Ratio*

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1. Introduction

A company is an operating organization that aims to gain profit by selling products (goods or services) to its customers (Hery, 2015). The company's goal is a statement of the desire that will be used by the company's management to achieve certain results for activities carried out within a certain time dimension (Fuertes et al., 2020). Companies must perform well in achieving their goals. Company performance is the overall success of a company in achieving its planned strategic goals by translating its mission, vision, core values, core beliefs, and strategy (Akter, 2021).

In their business journey, every company faces various problems that can hinder its progress. Before the pandemic, companies faced financial distress related to factors such as market competition, economic fluctuations, and debt management (Kanoujiya, Rastogi, Abraham, & Bhimavarapu, 2023). However, the situation changed significantly when the pandemic hit. Many companies faced sharp declines in revenue, operational restrictions, and increased health and safety costs. During the pandemic, many companies had to adapt their business models to survive. Some companies are still facing an ongoing decline in demand, while others have to manage increasing debt burdens due to loans taken out during the pandemic (Chiu, Kokkinis, & Miglionico, 2022).

Financial performance reflects the economic results that can be achieved by a company in a certain period of time through company activities to realize profits effectively and efficiently, which can be measured by analyzing financial data in financial statements (Amiram, Bozanic, & Rouen, 2015). In a company, precisely in terms of the resources utilized, the level of effectiveness can be measured using a ratio, which is the activity ratio (Matthew & Onwuzor, 2023). Total asset turnover proxies the activity ratio because sales created from all assets used with a company's capabilities are assessed from this proxy. Below is the Return on Assets (ROA) value for 2019-2022 which describes the conditions before the Covid-19 pandemic crisis and during the Covid-19 pandemic (Widyawati & Ningtyas, 2022).

The research problem is that there were nine transportation and logistics companies with negative Return on Assets (ROA) conditions before the pandemic; in 2019, as many as 19 companies in the transportation and logistics sector experienced a decrease in Return on Assets (ROA) during the Covid-19 pandemic, namely in 2020, the decrease in Return on Assets (ROA) in some companies during the Covid-19 pandemic can reflect the negative impact of the crisis on their financial performance (Widowati & Nugroho, 2022). The following year, the ROA of 19 companies increased.

Economic growth measured at constant prices provides an overview of changes in output or the real value of goods and services without being affected by price fluctuations (Babafemi, 2015). This helps analysts and decision-makers better understand changes in actual economic production, regardless of possible price changes (Howdon, Hinde, Lomas, & Franklin, 2022). Based on the figure above, the high growth experienced by the transportation and warehousing sectors indicates a positive indicator of financial health, one of the factors being the increase in shipping volume and logistics activities (Woo, Kwon, & Yuen, 2021). This can contribute positively to a company's income in the sector. However, this hypothesis requires further investigation (Ibrahim, Hussainey, Nawaz, Ntim, & Elamer, 2022).

According to Yang, Lu, Chen, and Li (2022), transportation is a parameter for measuring the rate of economic growth and can facilitate the mobility of people from one area to another. Transportation development is increasingly complex, with various types of transportation offered to the public; trains are still one of the choices for Indonesian people (Lanori & Supriyanto, 2023). However, a warehouse can be considered effective and efficient in various respects, such as the storage of materials and products. A poor warehousing system can cause expired goods and loss of goods, which can ultimately reduce a company's income (Ghapar et al., 2023).

Previous research has shown that several ratios are accurate in predicting financial distress. According to Asyha, Astuti, Subandi, Syarifudin, and Makbuloh (2023), the debt-to-asset ratio and total asset turnover have been proven to affect financial distress. According to Sumani (2020), return on assets and the debt-to-assets ratio can also be used to predict a company's financial distress. Yudawisastra and Febrian (2019) stated that the current ratio and return on assets have an effect on financial distress. Thus, the current ratio influences financial distress (Kusa & Danladi, 2023; Tharu & Shrestha, 2019).

This is based on the phenomena that have been described and highlights the interest in predicting the possibility of financial distress in transportation and logistics companies in Indonesia. This study expands on previous research by combining the approaches of several previous studies. This study examines conditions in three different situations: before, during, and after the pandemic, in addition to the use of different data samples, namely transportation and logistics companies in Indonesia, allowing researchers to examine trends and patterns of companies' financial behavior more comprehensively. The author then conducted a study entitled "Prediction of Financial Distress in Transportation and Logistics Companies Before, During,, and After the Covid-19 Pandemic Listed on the Indonesia Stock Exchange".

1.1 Formulation of the problem

Based on the background described above, Financial Distress as a dependent variable will be partially or simultaneously influenced by independent variables. Thus, the following problem was formulated:

1. What are the results of the three ratio calculations (current ratio, return on assets, and debt-to-assets ratio) in transportation and logistics companies listed on the Indonesia Stock Exchange before, during, and after the pandemic?
2. How can the results of the analysis of the calculation of the three ratios (Current Ratio, Return On Assets, and Debt to Assets Ratio) between groups of companies declared distressed and non-distressed in the training data sample be identified?
3. What is the architecture of the artificial neural network model that creates good performance on the training data sample to be used in the testing data to predict financial distress in transportation and logistics companies listed on the Indonesia Stock Exchange before, during, and after the pandemic?
4. What are the results of predicting financial distress using the artificial neural network method on the testing data of transportation and logistics companies listed on the Indonesia Stock Exchange before, during, and after the pandemic?

1.2 Research purposes

In accordance with the previous problem formulation, the objectives of this study were as follows:

1. To determine the results of the three ratio calculations (Current Ratio, Return On Assets, and Debt to Assets Ratio) for transportation and logistics companies listed on the Indonesia Stock Exchange before, during, and after the pandemic.
2. To determine how to identify the results of the analysis of the calculation of the three ratios (Current Ratio, Return On Assets, and Debt to Assets Ratio) between groups of companies declared distressed and non-distressed in the training data sample.
3. To determine how the architecture of the artificial neural network model performs well on the training data sample to be used in the testing data to predict financial distress in transportation and logistics companies listed on the Indonesia Stock Exchange before, during, and after the pandemic.
4. To determine how the results of financial distress predictions use the method on the testing data of transportation and logistics companies listed on the Indonesian Stock Exchange.

2. Literature review

2.1 Company Performance

A company's financial performance describes the activities carried out to achieve business goals over a certain period (Barauskaite & Streimikiene, 2021). Financial performance is important because it is used to assess a company's condition. A company's performance can be measured through financial ratio analysis by comparing one report item with another financial report item. Three types of financial ratios are used in this study:

2.1.1 Leverage

Leverage is a ratio that describes a company's ability to meet all its obligations, both short- and long-term obligations. This ratio aims to determine a company's position in relation to its obligations to other parties. In practice, a large risk of loss indicates that the company has a high leverage ratio, but the company has the opportunity to generate high profits (returns). Conversely, a small risk of loss indicates that the company has a low leverage ratio, but the company has the opportunity to generate low profits (returns). Thus, financial managers must control their leverage to avoid difficulties in paying debts.

This study uses the debt-to-asset ratio (DAR) formula. According to Kasmir (2015), a company can easily obtain additional loan capital if its debt usage is low because it is considered capable of paying off its debts using its assets, which indicates that the ratio is low (Yenni, Arifin, Gunawan, Pakpahan, & Siregar, 2021). Conversely, if the ratio is high, the company is financed by debt. If the debt-to-asset ratio is high, this will reduce the company's ability to obtain additional loans from creditors because they fear that the company will not be able to pay off its debts with the total assets it owns. Here, is the debt-to-asset ratio formula.

$$Debt\ Ratio = \frac{Total\ Liabiities}{Total\ Assets}$$

2.1.2 Liquidities

Liquidity is a ratio that describes a company's ability to meet its financial liabilities that must be met immediately. This ratio aims to determine the position of a company's liabilities when billed. A company that meets its liabilities on time, namely when billed, means that the company has a strong financial position. However, if the company has difficulty paying its obligations when billed, it has a weak financial position, which will result in the financial risk of bankruptcy (Bans-Akutey & Ebem, 2022; Hossain, Khatun, & Shanjabin, 2023).

The Current Ratio (CR) formula was used in this study. Ratio is used to pay for current liabilities using current assets owned. The higher the current ratio, the greater the company's ability to pay its bills. However, this ratio should be considered a rough measure because it does not consider the liquidity of each component of the current assets. where is the formula for the Current Ratio.

$$Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilites}$$

2.1 3 Preferabilities

The profitability ratio is a company's ability to gain profit through all existing capabilities and sources, such as sales activities, cash, capital, number of employees, and number of branches (Rashid, 2021). The results of measuring the profitability ratio can be used to evaluate management performance and whether management has worked effectively. If they succeed in achieving the predetermined target, they are said to have succeeded in achieving the target for one or several periods. However, on the other hand, if they fail or fail to achieve the predetermined target, this will be a lesson for management for the next period (Evangelatos, Bamias, Kitas, Kollias, & Sfikakis, 2022).

The profitability ratio used in this study is the return on assets (ROA). This ratio shows how many assets contribute to creating net profits (Puspitasari, Sudiyatno, Hartoto, & Widati, 2021). The higher the return on assets, the higher the net profit generated from each rupture of funds invested in total assets. Here, is the formula for return on assets:

$$Return\ On\ Assets = \frac{Net\ Income}{Total\ Assets}$$

2.2 Financial Report Analysis

Financial statement analysis is a process of reviewing financial statements and studying relationships and tendencies or trends to determine the financial position, results of operations, and their elements. It aims to evaluate and predict the financial condition of a company or business entity and evaluate the results achieved by the company or business entity in the past and present. Financial statement analysis also means breaking down financial statement accounts into smaller units of information and seeing their significant or meaningful relationships with one another, both between quantitative and non-quantitative data, with the aim of understanding the financial condition more deeply, which is very important in the process of producing the right decisions, according to Harahap (2018). Financial statement analysis is a financial statement analysis technique used to determine the relationship between certain items in the balance sheet or profit and loss, both individually and simultaneously (Kekeocha, Anoke, Chukwuemeka-Onuzulike, & Ngozi, 2023).

2.3 Financial Distress and Corporate Bankruptcy

Financial distress is a condition in which a company experiences a decline in profit, which can result in losses and lead to bankruptcy. According to Platt and Platt (2008), financial distress is a process of declining the financial position of a company before the company goes bankrupt or liquidates. The high costs incurred by the company to develop and maintain the business cause the company require additional funds. These funds are obtained from external factors; if the company does not pay off the funds given by external parties (debt), it causes high debt and results in bankruptcy.

According to Putri and Kristanti (2020), financial distress is a condition in which a company cannot fulfill its obligations; if this condition occurs, the company will go bankrupt. Financial distress can be defined from many perspectives, namely, economic, financial, working capital, inability to pay, and sales growth (Nursal et al., 2023). Companies that fail to run their businesses because they cannot finance business continuity can experience financial distress. Every company can experience financial distress because the factors causing financial distress can originate from internal or external sources. According to Utami (2015), there are two reasons for a company's financial failure.

2.5 Previous Research

The study included four cement companies for the period 2012-2018. The samples were collected using purposive sampling techniques with pre-determined criteria. This study used the Altman Z-Score model with the Multiple Discriminant Analysis (MDA) method on five types of financial ratios equipped with cutoff points. (X1) Working capital/total assets, (X2) retained earnings/total assets, (X3) earnings before interest and taxes/total assets, (X4) market value of equity/total liabilities, and (X5) sales/total assets. Descriptive statistics were used in this study. The analysis results show that the four cement companies experienced a decline in their financial performance. Z-Score prediction PT. Indocement Tunggal Prakasa, Tbk. did not go bankrupt. PT. Semen Baturaja Persero Tbk. PT Semen Indonesia, Tbk., is in the grey area. PT Holcim Indonesia Tbk. has the worst condition.

Bhunia and Sarkar (Bagchi) showed a strong discriminant function built with seven ratios found to be significant in distinguishing strength; the classification results showed a high level of prediction accuracy between 86% and 96% for each of the five years before failure, indicating that even though more sophisticated and popular statistical tools are used recently, MDA remains a very reliable and powerful statistical tool.

Bankruptcy Prediction Using the Altman Z-Score Method (Case Study of PT Toba Pulp Lestari, Tbk) was studied by Miskiyah, Elisa, et al (2022). The object studied was PT Toba Pulp Lestari, Tbk., during the period 2010-2019. The Altman Z-score method was used for the analyses. The results of the study explain that the company's financial condition is in the bankrupt category because the calculation criteria value from 2010 to 2019 is at a Z value <1.81, but in this condition, the company continues to operate because it received a loan from Pinnacel Company Limited of 90.45% of INRU shares.

Awalia and Kristanti (2023) studied financial distress prediction using Artificial Neural Networks (ANN) in Banking Companies Listed on the Indonesia Stock Exchange (IDX) for the 2017-2021 Period was studied by Awalia and Kristanti (2023). An Artificial Neural Network was used for the analysis. The results of this study confirmed that the four ratios were suitable for use as input parameters because they provided a significant contrast between the associations stated as distress and non-distress states. The ANN architecture used for the prediction cycle in this study consisted of 20 neurons as the input layer, five neurons as the hidden layer, and one neuron as the output layer, with the best accuracy of 87%.

Yoga et al. (2018) studied bankruptcy prediction using artificial neural networks. An Artificial Neural Network was used for this analysis. The results of this study indicate that the ANN Perceptron can handle redundant data features because identical weights are learned during the training process. The weights of the redundant features are suppressed to become very small. The training process for model formation requires a long duration. This is because the ANN Perceptron must perform several iterations to update the weights to make relatively correct predictions for all training data.

The study entitled The role of Environmental, Social, and Governance (ESG) in predicting bank financial distress was studied by Citterio and King (2023). The analysis technique used was the power of Environmental, Social, and Governance (ESG). The results of this study show that ESG improves the predictive ability of our model in correctly identifying distress. In particular, ESG significantly reduces the likelihood of misclassifying troubled or defaulting banks as healthy banks. Our model, which we estimate using six alternative approaches, including traditional statistical techniques, machine learning approaches, and ensemble methods, has practical implications for banking sector supervisors, as well as the literature on default prediction.

3. Research methodology

3.1 Population and Sample

The population used as the object of the study is transportation and logistics companies listed on the Indonesian Stock Exchange. The population of transportation and logistics sector companies listed on the Indonesia Stock Exchange consisted of 36 transportation and logistics companies. The sample in this study totals twenty-three transportation and logistics companies listed on the Indonesia Stock Exchange. The sampling technique used in this study was non-probability sampling, specifically purposive sampling.

The criteria and purposive sampling techniques used in this study were as follows:

a. Stocks on the Indonesia Stock Exchange (IDX) in the transportation and logistics sectors.
b. Companies listed on the Indonesia Stock Exchange no later than December 31, 2018, were included.

The stages of the research sample selection based on the above criteria are described in the following table.

Table 1. Research Sample Selection

No	Sample Criteria	Amount
1	Companies on the Indonesia Stock Exchange (IDX) in the Transportation and Logistics sector	36
2	Reduced by companies listed on the Indonesia Stock Exchange after December 31, 2018	(13)
	Total Companies that meet the sample criteria	**23**
3	Multiplied by the number of financial reports in the research period	20
	Total Sample	**460**

From the results of the table above, 23 companies were obtained that met the criteria and were used as samples in this study, multiplied by the number of financial report data during the research period, namely, 20 report data within five years of research from 2019 to 2023. Therefore, a total sample of 460 research reports was obtained.

The data recorded in the financial statements of companies that are not experiencing financial distress and are experiencing financial distress are called training data. This study selects public companies worldwide that were not experiencing financial distress in 2019, and selects public companies worldwide that were declared to be experiencing financial distress, obtained from companies that went bankrupt in 2019, as training data. The criteria selected for the sample in the training data were as follows:

1. Non-distress Companies
   a. Public companies declared that they were not experiencing financial distress in 2023.
   b. Companies that published audited financial statements in 2019-2023.
   c. Public companies listed on the stock exchange between 2019-2023.
   d. Financial ratios were used as research variables in the financial distress prediction process.

i. The current ratio was above 100% in 2019-2023.
ii. Positive return on assets from to 2019-2023.
iii. The debt-to-assets ratio was below 50% in 2019-2023.

2. Distressed Companies
a. Public companies are declared to have experienced financial distress in 2023.
b. Companies that published audited financial statements in 2019-2023.
c. Public companies listed on the stock exchange between 2019-2023.
d. Financial ratios were used as research variables in the financial distress prediction process.
   i. A current ratio below 100% in the five-year period of 2019-2023 before being declared distressed.
   ii. Negative return on assets in the five-year period of 2019-2023 before being declared distressed.
   iii. A debt-to-assets ratio above 50% in the five-year period of 2019-2023 before being declared distressed.

3.2 Operational Variables

1. Leverage

Leverage is a ratio that describes a company's ability to meet its obligations in the short and long term. This study uses the debt-to-assets ratio (DAR). According to Sudana (2015), the debt-to-asset ratio is the main source of debt, where a company's assets are used to guarantee its debts. Here, is the debt-to-asset ratio formula.

$$Debt\ Ratio = \frac{Total\ Liabiities}{Total\ Assets}$$

2. Likuiditas

Liquidity describes a company's ability to meet its obligations when they are due. This study used the Current Ratio (CR). According to Murhadi (2013), the current ratio measures a company's ability to pay its current liabilities using its current assets. The Current Ratio is calculated as follows:

$$Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilites}$$

3. Profitabilitas

Profitability is the ratio that describes a company's ability to generate profits from sales, asset, and capital use. This study uses the return on assets (ROA). According to Hery (2015), this ratio shows the number of assets that contribute to the creation of net profit. The ROA is calculated as follows:

$$Return\ On\ Assets = \frac{Net\ Income}{Total\ Assets}$$

3.3 Research Stages

This study began by identifying and formulating the problem to be studied. After identifying and formulating the problem, the next step was to determine the purpose of the research. We then conducted a literature review by searching for information, theories, references, and other supporting data through literature reviews and digging up information about the research object. Then search for data on the financial statements of retail companies recorded in 2015-2019 which are sourced from the company's official website and the official website of the Indonesia Stock Exchange which are used for testing data samples, and training data samples are taken from non-distress and distress companies taken from the company's official website, www.annualreports.com, sec.report, www.investing.com, www.macrotrends.net, and the official website of the Indonesia Stock Exchange. After the financial report data are obtained, the next step is to calculate the financial ratios, namely the current ratio, return on assets, and debt to assets ratio in the company, which are the testing and training data.

The next stage was to conduct a descriptive statistical analysis of the results of the calculation of financial ratios for the training data sample. A descriptive statistical analysis was conducted to determine the difference in the financial ratios of non-distressed and distressed companies. The main purpose of conducting descriptive statistical analysis is to determine the difference in financial ratios between non-distress and distress.

3.4 Data collection
The data used in this study is secondary data, which comes from published financial reports for quarterly periods each year, starting from 2019 (quarter 1) to 2023 (quarter 4) which are taken from the website www.idx.co.id.

3.5 Data analysis technique
In this study, the author manages data starting by calculating financial ratios, then conducts descriptive statistical analysis, and tests the artificial neural network model to predict the company's financial distress, starting with testing training data and then using testing data. Financial distress is estimated using financial data from three time periods: before, during, and after the pandemic. The estimated duration and prediction period are the entire sample period, namely–2019-2023.

3.5.1 Calculating Financial Ratios
The financial ratios used in this study were the input values. The three financial ratios used are the current ratio, representing the liquidity ratio; the return on assets ratio, representing the productivity ratio; and the debt-to-asset ratio, representing the solvency ratio. Financial ratios for the period 2019-2023. There are 23 company samples from the transportation and logistics sector listed on the Indonesia Stock Exchange as a data testing sample. The formula for the financial ratio is as follows.

a. $Debt\ Ratio = \frac{Total\ Liabiities}{Total\ Assets}$
b. $Current\ Ratio = \frac{Current\ Assets}{Current\ Liabilites}$
c. $Return\ On\ Asset = \frac{Net\ Income}{Total\ Assets}$

3.5.2 Descriptive Statistical Analysis
Descriptive statistics are used to describe the center, spread, and distribution, which act as a preliminary tool to describe data (Cooper & Schindler, 2013). The descriptive statistical analysis in this study aims to explain and summarize data on the financial ratios of companies that do not experience financial distress, compared to companies that experience financial distress. In this analysis, the researchers used descriptive statistical methods to identify the differences between the two groups of companies. Financial ratios were used to conduct a descriptive statistical analysis. The ratios used were the current ratio, return on assets, and debt-to-asset ratio. This analysis compares the average values of the calculation results for companies that do not face financial distress and those that do.

3.5.3 Prediction Model Using Artificial Neural Network

a) Training Data

Predicting financial distress using artificial neural network models requires training data before conducting a financial distress prediction test. In terms of data mining, artificial neural networks are used as models to make predictions and complete procedures faster to accurately predict the results of certain data tests that have not yet been carried out.

b) Backpropagation Algorithm

An artificial neural network has three layers. The first layer was used to input information into the hidden layer. The second layer, the hidden layer, functions in the learning phase, which is connected to the weights (numerical values) to obtain the appropriate output. The third layer, the output layer, produces outputs for the activities in the input and hidden layers.

The following are the stages of the procedure for training the Multilayer Perceptron Backpropagation algorithm to assess the weights on the hidden and output layers, which will later be determined as the activity function used for the entire layer (citation) (Kristianto & Rikumahu, 2019). This study used a binary sigmoid activity function because the output interval value started from 0 to 1. A value of 0 indicates that the company is not experiencing financial distress, whereas a value of 1 indicates that the company is experiencing financial distress. The initialization of the overall weight can use a range of random numbers, namely, in the range [-0.5,0.5], or it can also use a uniform distribution with a small range (citation):

$$(-\frac{24}{Fi} + \frac{24}{Fi})$$

Fi = Total input neurons in an artificial neural network

c) Activation process

In this process, activation is performed by the network activation process, and the desired input and output values are applied to it.

1. Formula for calculating the input value obtained in the hidden layer:

$$v_j(p) = \Sigma_{i=1}^{n} x_i(p).w_{ij}(p)$$

$$y_j(p) = \frac{1}{1 + e^{-v_j(p)}}$$

2. The output value obtained from the neurons in the output layer was calculated.

$$v_k(p) = \Sigma_{j=1}^{m} x_j(p).w_{jk}(p)$$

$$y_k(p) = \frac{1}{1 + e^{-v_k(p)}}$$

Description:
i = neuron index in the input layer
j = neuron index in the hidden layer
k = neuron index in the output layer
n = number of inputs on neuron j in the hidden layer
m = indicates the number of inputs on neuron k in the output layer
x = input value
w = vector weight
p = iteration value

d) Weight update process

The next step is a weight update, in which the weight updates the error conditions sent back by an artificial neural network. The error was propagated back in accordance with the output value.

1. The error gradient for the neurons in the output layer is calculated as follows:

$$e_k(p) = y_{dk}(p) - y_k(p)$$

$$\delta_k(p) = y_{dk}(p) \times [1 - y_k(p)] \times e_k(p)$$

The weight correction was calculated as follows:

$$\Delta w_{jk}(p) = \eta \times y_j(p) \times \delta_k(p)$$

The weights in the output layer are updated.

$$w_{jk}(p+1) = w_{jk}(p) + \Delta w_{jk}(p)$$

Description:
e = error signal
y_{dk} = target output value on neuron k
y_k = actual output value produced by neuron k on the output layer
δ_k = error gradient of neuron k on the output layer
Δw_{jk} = weight correction
η = learning rate
y_j = output value of neuron j on the output layer

w_{jk} = weight from neuron j on the hidden layer to neuron k on the output layer

2. The error gradient for the neurons in the hidden layer was then calculated.

$$\delta_j(p) = y_j(p) \times [1 - y_j(p)] \times \Sigma_{k=1}^{1} \delta_k(p).w_{jk}(p)$$

The weight correction was calculated as follows:

$$\Delta w_{ij}(p) = \eta \times x_i(p) \times \delta_j(p)$$

To calculate the number of hidden layer neurons,

$$w_{ij}(p+1) = w_{ij}(p) + \Delta w_{ij}(p)$$

Description:
δ = gradient error on neuron j in the hidden layer
y_j = output value of neuron j in the output layer
Δwij = weight correction
x_i = input value of neuron i
η = learning rate
w_{ij} = weight from neuron i in the input layer to neuron j in the hidden layer

3.5.4 Iteration process

The last step is the iteration process, in which step increases by one for iteration p, then returns to step 2, and then repeats the process until the error criteria are reached.In this study, the training process on training data for artificial nearal networks uses artificial neural network programming software that has the nntool feature. Nntool is an artificial neural network programming tool that models artificial neural networks. The procedures for training the data using nntool are as follows.

1. The artificial Neural Network programming software is opened, and the command window is searched for by typing nntool or by clicking the start button on the artificial neural network programming, then clicking Toolboxes and searching for a neural network. Subsequently, the Neural Network/Data Manager (nntool) display appears. The input value in this study is the financial ratio that was calculated using the training data sample, namely 30 sample companies, and for the target entered according to the predetermined company criteria, a value of 0 for companies that did not experience financial distress, and a value of 1 for companies that experienced financial distress.
2. The input and target values were then entered into the artificial neural network toolbox. Then, click import on the data manager, after which the Import to Network/Data Manager display appears. Next, we selected the variables to be imported according to imports as an option in the artificial neural network programming.
3. Next, a network is created by clicking the new button on the data manager window, and then the network is adjusted according to the needs of the network. The network was then successfully created, and double-clicking the network displayed the network display form.

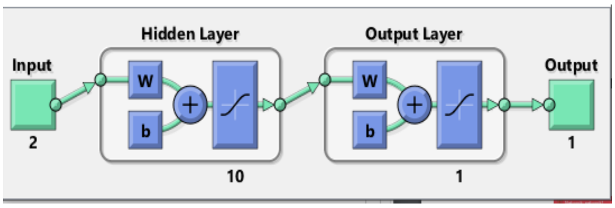

Figure 1. Network View
Source: Researcher processing (2023)

4. After the network display that has been created appears, click on the train and enter the input and target values that have been created in the training information and determine the training parameters according to their requirements. The trained network is then clicked to perform training on the network. After the training process was complete, a learning dialog display was presented.

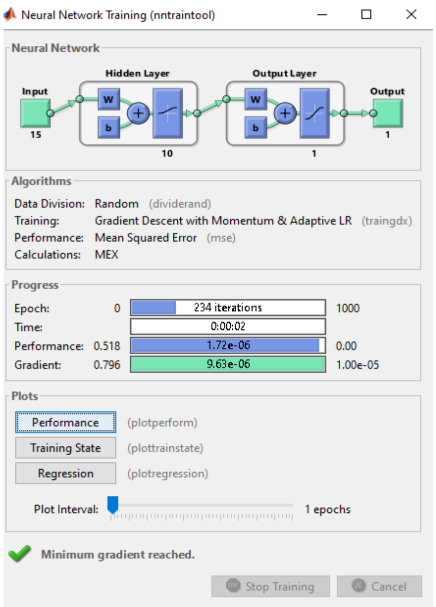

Figure 2. Training Data Method Dialog Display
Source: Researcher processing (2023)

5. Subsequently, to obtain the total weight calculation results in the training data process, we selected the View/Edit Weights option in the network display. The output and error values of the training results can be displayed on the initial display in the nnTool window.
6. If the error value produced is sufficient, the trained network can be used to process the predictions on the test data sample. To use the network from the training data, exports were selected at the beginning of the nntool's display. This command creates all artificial neural network architectures from the training data that have been processed in the artificial neural network programming workspace.

Several steps must be taken to obtain the best artificial neural network backpropagation model (Kristianto & Rikumahu, 2019).

1. Determination of the network layer: Kristianto and Rikumahu (2019) used a backpropagation neural network with input, hidden, and output layers.
2. The data were normalized to match the activation function value.
3. The weighting and bias allocation, initially with random values, were adjusted during the training iterations.
4. Determination of the activation function.
5. Determination of the optimization method:
6. The learning rate value, training value, and number of training iterations were changed to determine the best estimated performance using the Mean Squared Error (MSE).

3.5.5 Data Application

After training the model on the training data and producing the desired error weights and criteria, the next stage is to conduct the operating process on the testing data sample to predict whether the company is experiencing financial distress. The testing data sample is the predetermined financial ratio of 23 transportation and logistics sector companies listed on the Indonesia Stock Exchange (IDX). The procedure for operating the test data samples is as follows:

1. The artificial neural network research results were established on training data that had been successfully exported to the artificial neural network programming workspace.
2. The input values for each company were entered as testing data.
3. The next step was to predict the output class of the testing data using the sim () function. The resulting output values are
   a. If the resulting output value is close to 0 or equal to 0, the company will not experience financial distress.

b. If the resulting output value obtains a predicted result close to 1 or equal to one, the company is experiencing financial distress.

4. Result and discussion

4.1 Descriptive Statistical Analysis

To conduct a descriptive statistical analysis of training data samples on the artificial neural network model, the financial ratios of companies reported as non-distress and reported as distress. This analysis is conducted by comparing the average results of financial ratio calculations, namely the current ratio, return on assets, and the debt-to-assets ratio, between two groups of companies: the group of companies that do not experience financial distress and the group of companies that experience financial distress. The training data were used for the descriptive statistical analysis. The results of the descriptive statistical analysis are shown in Table 2.

Table 2. Descriptive Statistics of Training Data Sample

Variables	N	*Min*	*Max*	*Mean*	*Std. Deviation*
Sample Company Training Data (in decimal)					
Current Ratio	600	0,0214	51,1928	2,5872	4.8531
Return On Assets	600	(0,2331)	30,5175	0,2917	2,1801
Debt To Assets Ratio	600	0,0084	3,0332	0,5807	0,4444
Non-Distress Companies (in decimal)					
Current Ratio	300	0,2710	51,1929	4,3661	6,2848
Return On Assets	300	0,0009	30,5175	0,5601	3,0601
Debt To Assets Ratio	300	0,0084	0,6881	0,2523	0,1130
Distress Company (in decimal)					
Current Ratio	300	0,0213	18,9089	0,8083	1,1562
Return On Assets	300	(0,2331)	0,6877	0,0232	(0,0010)
Debt To Assets Ratio	300	0,4615	3,0332	0,9092	0,4080

Source: Researcher processing (2023)

Based on Table 2, it can be seen that the average value of the current ratio in companies that do not experience financial distress is greater (4.3661) than that of companies that are stated to be experiencing financial distress (0.8083). This indicates that companies that do not experience financial distress have better liquidity than those that do. Thus, the ability to meet short-term obligations is higher than that of companies experiencing financial distress.

4.2 Research Results

4.2.2 Financial Ratio Calculation

The initial stage in predicting financial distress in transportation and logistics companies listed on the Indonesia Stock Exchange is to analyze financial reports to calculate financial ratios. The results of calculating financial ratios from the testing data sample are used as input parameters in the artificial neural network to predict financial distress approaching bankruptcy, as follows: In addition, the calculation of financial ratios is carried out on training data samples, which are then processed in descriptive statistical analysis and used as input parameters in the data training process for prediction using artificial neural networks.

The financial ratios used are the current ratio, return on assets, and debt-to-assets ratios. After calculating the financial ratios, PT Samudera Indonesia TBK. (SMDR) obtained an average current ratio of 162%, which means that every Rp100 of short-term debt is supported by Rp162 in current assets. In addition, the average return on assets during the same period was 3.31%, indicating that every Rp100 owned assets generated a profit of Rp3. The average debt-to-assets ratio for the same period was 50%, which means that for every Rp100 of assets owned, Rp50 was financed by debt, and the rest was financed by equity (Figure 55 %).

4.2.3 Prediction Using Artificial Neural Network Training Data Using Backpropagation Training Algorithm

Before conducting the financial distress analysis, training data were required for the artificial neural network model. The multilayer perceptron architecture of the artificial neural network consists of three layers: input, hidden, and output. The data training process used company samples from the training data with a total of 30 companies, which were divided into 15 companies that did not experience distress and 15 companies that experienced it. There are 60 input parameters in the input layer for the training data, consisting of the current ratio 2019 Q1 to Current ratio 2023 Q4, Return on assets 2019 Q1 to Return on assets 2023 Q4 and Debt to assets ratio 2019 Q1 to Debt to assets ratio 2023 Q4..

To produce the smallest error rate, researchers conducted several experiments on total neuron variations with numbers 1, 5, 10, 15, 20, 30, 40, 50, and 60 neurons. For further details on the process and results of using the hidden layers, see Appendix 8. The use of too many hidden layers reduces the generalization performance of the neural network (Paquet, 1997). Therefore, the researchers changed the total number of neurons in the hidden layer without changing the network settings and training parameters. The error values obtained from the training data generated from all variations of the total number of neurons in the hidden layer are listed in Table 3.

Table 3. Training Error Values on Total Variation of Hidden Layer Neurons

Total *Neuron*		**Nilai *error* (MSE)**
Input Layer	***Hidden Layer***	
60	1	0.163741
60	5	0.131905
60	10	0.136559
60	**15**	**0.125004**
60	20	0.125118
60	30	0.126955
60	40	0.127528
60	50	0.133471
60	60	0.125072

Source: Researcher processing (2023)

Table 3 shows the total number of neurons that produced small error values in the training data with 15 hidden layers. Therefore, the artificial neural network architecture used to carry out financial distress prediction is 60-15-1, with specification 60 being the total number of neurons in the input layer, 15 in the hidden layer, and 1 in the output layer. The results of the data training process using 15 neurons in all variations of the total neurons are shown in the following Figure.

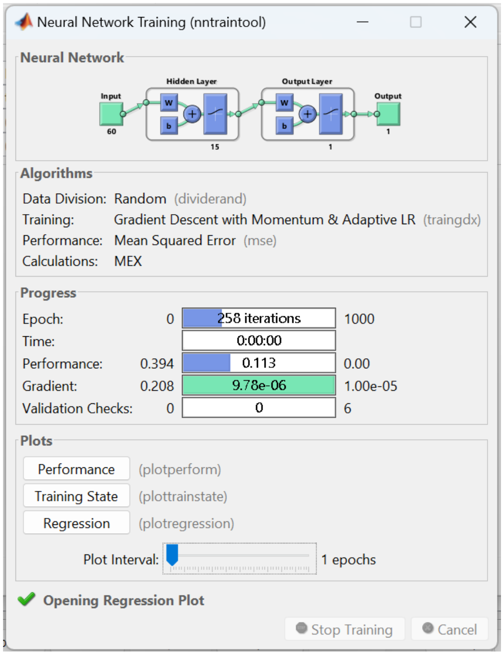

Figure 3. Training Data Results using 15 hidden layers
Source: Researcher processing (2023)

The process is illustrated in Fig. 3.

1. The artificial neural network training process ended after 258 epochs, with the smallest error. This indicates that the data training process was completed after 258 iterations.
2. The MSE and error obtained were 0.125004, respectively.
3. The gradient of similarity between iterations was 9.78e-06 or 0.00000978.

4.2.4 Performance Measurement of Artificial Neural Network Backpropagation Training Model Prediction

The correlation coefficient (R) and mean square error (MSE) were used to measure prediction performance. The smaller the MSE value and the greater the R value between the target and output values during the training process, the better the accuracy of the network model (Kristianto and Rikumahu, 2019). Table 4 shows the differences in the MSE and R values for each variation in the total number of neurons in the hidden layer.

Table 4. Comparison of MSE and R Values on Training Models

Training Function	**Activation Function**		**Total Neurons in Hidden Layer**	**MSE**	**R(%)**
	Hidden Layer	***Output Layer***			
TRAINGDX	LOGSIG	TANSIG	1	0. 1637	34.50
TRAINGDX	LOGSIG	TANSIG	5	0. 1319	47.24
TRAINGDX	LOGSIG	TANSIG	10	0. 1366	45.38
TRAINGDX	**LOGSIG**	**TANSIG**	**15**	**0. 1250**	**50.00**
TRAINGDX	LOGSIG	TANSIG	20	0. 1251	49.95
TRAINGDX	LOGSIG	TANSIG	30	0. 1270	49.22
TRAINGDX	LOGSIG	TANSIG	40	0. 1275	48.99
TRAINGDX	LOGSIG	TANSIG	50	0. 1335	46.61
TRAINGDX	LOGSIG	TANSIG	60	0. 1251	49.97

Source: Researcher processing (2023)

Table 4 shows that the artificial neural network training model that produces good performance is the artificial neural network model with an architecture that uses 15 neurons in the hidden layer. The model can be said to be very good for predicting company financial distress, with an R value of 50.00% and the smallest MSE of 0.1250.

As previously explained, the R-value obtained from the artificial neural network training model was 50%. This shows that the correlation between the target value and training output results was good. Table 5 shows a comparison of the target value with the results of the training output value in each company used as a training data sample, where a target value of 0 indicates a non-distress company and a target value of 1 indicates a distress company.

Table 5. Comparison of Target and Output Values on Training Data Samples

No.	Company	Issuer Code	Target	*Output*	*Error*
1.	Akasha Wira International Tbk	ADES	0	0,500001855	-0,50000186
2.	Aneka Tambang Tbk.	ANTM	0	0,500003777	-0,50000378
3.	Baramulti Suksessarana Tbk.	BRRS	0	0,500002616	-0,50000262
4.	Borneo Olah Sarana Sukses Tbk	BOSS	1	0,999831206	0,000168794
5.	Bumi Resources Tbk	BUMI	1	0,999330196	7,93857E-05
6.	Bakrie Sumatera Plantations Tbk	UNSP	1	0,999983455	1,65452E-05
7.	Chitose Internasional Tbk	CINT	0	0,500006216	-0,50000622
8.	Cowel Development Tbk	COWL	1	0,999445627	0,000554373
9.	Ebit		1	0,99733329	0,00266671
10.	Ekadharma International Tbk	EKAD	0	0,500000267	-0,50000027
11.	Eterindo Wahanatama Tbk.	ETWA	1	0,999973015	2,69845E-05
12.	Express, Inc.		1	0,998512337	0,001487663
13.	FKS Food Sejahtera Tbk	AISA	1	0,999803899	0,000196101
14.	Indosat Tbk	ISAT	1	0,999700502	0,000299498
15.	Grand Kartech Tbk	KRAH	1	0,998857693	0,001142307
16.	Indo Tambangraya Megah Tbk	ITMG	0	0,500001789	-0,50000179
17.	Industri Jamu & Farmasi Sido Muncul Tbk	SIDO	0	0,500000685	-0,50000069
18.	Kalbe Farma Tbk	KLBF	0	0,500000469	-0,50000047
19.	Krakatau Steel Persero Tbk	KRAS	1	0,999834304	0,000165696
20.	Modernland Realty Ltd Tbk	MDLN	1	0,999330196	0,000669804
21.	Multipolar Tbk	MLPL	1	0,994855849	0,005144151
22.	Pakuwon Jati Tbk	PWON	0	0,500008588	-0,50000859
23.	Prima Alloy Steel Universal Tbk	PRAS	1	0,998805506	0,001194494
24.	Selamat Sempurna Tbk	SMSM	0	0,500000425	-0,50000042
25.	Siantar Top Tbk	STTP	0	0,500000422	-0,50000042
26.	Surya Citra Media Tbk	SCMA	0	0,500000797	-0,5000008
27.	Tambang Batubara Bukit Asam Tbk	PTBA	0	0,500005784	-0,50000578
28.	United Tractors Tbk	UNTR	0	0,500054503	-0,5000545
29.	Vale Indonesia Tbk	INCO	0	0,500000444	-0,50000044
30.	Visi Media Asia Tbk	VIVA	1	0,999954786	4,52141E-05

Source: Researcher processing (2023)

4.2.5 Predicting Company Financial Distress Using Artificial Neural Network Model

The financial distress prediction process is carried out on sample data testing companies, which are transportation and logistics companies listed on the Indonesia Stock Exchange from to 2019-2023. Table 6 shows the output results of the Artificial Neural Network model for transportation and logistics companies listed on the Indonesia Stock Exchange from to 2019-2023.

Table 6. Artificial Neural Network Model Output Results for Transportation and Logistics Companies Listed on the Indonesia Stock Exchange in 2019-2023

No.	Company Name	Stock Code	*Output*	Prediction

1.	AirAsia Indonesia Tbk.	CMPP	0.9999	*Distress*
2.	Adi Sarana Armada Tbk.	ASSA	0.9943	*Distress*
3.	Batavia Prosperindo Trans Tbk	BPTR	0.9989	*Distress*
4.	Berlian Laju Tanker Tbk	BLTA	0. 8385	*Distress*
5.	Blue Bird Tbk.	BIRD	0.5	*Non Distress*
6.	Dewata Freightinternational Tbk.	DEAL	0.9999	*Distress*
7.	Eka Sari Lorena Transport Tbk.	LRNA	0. 502	*Non Distress*
8.	Express Transindo Utama Tbk.	TAXI	0. 9992	*Distress*
9.	Guna Timur Raya Tbk.	TRUK	0.5	*Non Distress*
10.	Garuda Indonesia (Persero) Tbk.	GIAA	1	*Distress*
11.	Indomobil Multi Jasa Tbk.	IMJS	0. 9999	*Distress*
12.	Jaya Trishindo Tbk.	HELI	0.9743	*Distress*
13.	Mineral Sumberdaya Mandiri Tbk.	AKSI	0. 5003	*Non Distress*
14.	Mitra International Resources Tbk.	MIRA	0. 5008	*Non Distress*
15.	Mitra Investindo Tbk.	MITI	0. 8145	*Distress*
16.	Pelayaran Nelly Dwi Putri Tbk.	NELY	0. 5	*Non Distress*
17.	Samudera Indonesia Tbk.	SMDR	0. 5007	*Non Distress*
18.	Satria Antaran Prima Tbk.	SAPX	0. 5	*Non Distress*
19.	Sidomulyo Selaras Tbk.	SDMU	0. 9999	*Distress*
20.	Steady Safe Tbk.	SAFE	1.0000	*Distress*
21	Temas Tbk.	TMAS	0.5333	*Non Distress*
22	Trimuda Nuansa Citra Tbk.	TNCA	0,5	*Non Distress*
23	WEHA Transportasi Indonesia Tbk.	WEHA	0,5098	*Non Distress*

Source: Researcher processing (2023)

4.3 Discussion of Research Results

4.3.1 Results of Calculation of Financial Ratios of Transportation and Logistics Companies as Testing Data

The prediction process uses financial ratios as input parameters, and artificial neural networks are used by transportation and logistics companies to predict bankruptcy. The financial ratios used are the current ratio, return on assets, and debt-to-assets ratio for 2019-20123. The calculation results were used to predict whether transportation and logistics companies would experience financial distress in 2023 or in the future using artificial neural networks. The results of this ratio calculation were used as a sample of the test data.

4.3.2 Results of Descriptive Statistical Analysis of Training Data Samples

The results of the descriptive statistical analysis of the training data sample indicate that it is suitable for use in the data training process. This is because of the significant differences shown by the average results of the three financial ratios between the groups of companies that declared non-distress and distress cases. The average current ratio for non-distressed companies is greater, at 436.6%, compared to distressed companies, which only reach 80.8%. The average return on assets for non-distress companies is also higher, at 23.7%, compared to distress companies, which is only 10.8%. In addition, the average debt-to-assets ratio results in non-distress companies showing a lower and better value (25.2 %) compared to distress companies (90.9 %). These results show that the performance of non-distressed companies is better than that of distressed companies. Therefore, this training data sample can be effectively used for the data training process in the artificial neural network model.

4.3.3 Financial Distress Prediction Results in Transportation and Logistics Companies

For more details, the ratio values of transportation and logistics companies that are not predicted to experience financial distress are presented in Table 7, which are expressed in percentage form. The column containing red numbers shows that the financial ratio does not match the criteria of the training data sample of companies that did not experience financial distress.

Table 7. Financial Ratios of Transportation and Logistics Companies That Are Not Predicted to Experience Financial Distress

No	Company name	Issuer Code	Year		
			CR	ROA	DAR
1	Blue Bird Tbk.	BIRD	291%	11%	24%
2	Eka Sari Lorena Transport Tbk.	LRNA	117%	12%	28%
3	Guna Timur Raya Tbk.	TRUK	118%	13%	25%
4	Mineral Sumberdaya Mandiri Tbk.	AKSI	291%	40%	55%
5	Mitra International Resources Tbk.	MIRA	121%	8%	33%
6	Pelayaran Nelly Dwi Putri Tbk.	NELY	475%	12%	13%
7	Samudera Indonesia Tbk	SMDR	162%	22%	50%
8	Satria Antaran Prima Tbk.	SAPX	313%	62%	35%
9	Temas Tbk.	TMAS	116%	23%	57%
10	Trimuda Nuansa Citra Tbk.	TNCA	577%	35%	18%
11	WEHA Transportasi Indonesia	WEHA	93%	14%	45%

Source: Processed data (Indonesian Stock Exchange, 2023)

The ratio of transportation and logistics companies predicted to experience financial distress is presented in Table 8, expressed in percentage form. The column containing red numbers shows that the financial ratio does not match the criteria of the training data sample of companies that did not experience financial distress.

Table 8. Financial Ratios of Transportation and Logistics Companies Predicted to Experience Financial Distress

No	Company name	Issuer Code	Year		
			CR	ROA	DAR
1	AirAsia Indonesia Tbk.	CMPP	13%	24%	170%
2	Adi Sarana Armada Tbk.	ASSA	80%	17%	69%
3	Batavia Prosperindo Trans Tbk	BPTR	46%	8%	64%
4	Berlian Laju Tanker Tbk	BLTA	105%	8%	52%
5	Dewata Freightinternational Tbk	DEAL	73%	10%	96%
6	Express Transindo Utama Tbk.	TAXI	374%	2%	123%
7	Garuda Indonesia (Persero) Tbk.	GIAA	29%	11%	120%
8	Indomobil Multi Jasa Tbk.	IMJS	83%	4%	85%
9	Jaya Trishindo Tbk.	HELI	90%	14%	57%
10	Mitra Investindo Tbk.	MITI	208%	6%	53%
11	Sidomulyo Selaras Tbk.	SDMU	69%	12%	85%
12	Steady Safe Tbk.	SAFE	12%	17	120%

5. Conclusion

5.1 Conclusion

The results of the study on the analysis of financial distress prediction of transportation and logistics companies in Indonesia using artificial neural networks show that based on descriptive statistical analysis, the calculated values of the current ratio, return on assets, and debt to assets ratio show differences between companies that do not experience financial distress and those that do. Companies that do not experience financial distress have better ratio performance than those that do. This ratio calculation data is used as a training data sample for the prediction of input parameters using artificial neural networks and shows that better ratio performance is significantly related to healthier financial conditions.

Based on the data training process for prediction using artificial neural networks, the most optimal artificial neural network architecture for prediction using company financial distress data consists of 60 neurons in the input layer, 15 in the hidden layer, and one in the output layer. With this configuration, the model achieved the best performance with the lowest Mean Squared Error (MSE) of 0.113 and a correlation coefficient (R) of 50%. This shows that the model has a fairly good predictive ability for identifying financial distress in companies.

The results of financial distress prediction using artificial neural networks on sample testing data from transportation and logistics companies show that 12 of the 23 companies are predicted to experience financial distress in 2023. The output results were close to or equal to 1. The companies predicted to experience financial distress are AirAsia Indonesia Tbk. (CMPP) and Adi Sarana Armada Tbk. (ASSA), and Batavia Prosperindo Trans TBK. (BPTR), Berlian Laju Tanker Tbk (BLTA), Dewata Freightinternational Tbk (DEAL), Express Transindo Utama Tbk (TAXI), Garuda Indonesia (Persero) Tbk (GIAA), Indomobil Multi Jasa Tbk (IMJS), Jaya Trishindo Tbk (HELI), Mitra Investindo Tbk (MITI), Sidomulyo Selaras Tbk (SDMU), Steady Safe Tbk (SAFE).

5.2 Suggestion

Based on the results of the present study, the researcher would like to make the following suggestions. Based on the research conducted by the researcher, suggestions for other practical users are as follows.

1. For companies, it is necessary to ensure that net profits remain positive, avoid losses to maintain future funding, and avoid financial distress. Predicting financial distress, such as by using an artificial neural network model, can help companies anticipate bankruptcy and take appropriate action. Transportation and logistics companies that are predicted not to experience financial distress can use this research to monitor their condition and improve their performance. Companies predicted to experience financial distress should implement the right business strategy, increase sales, and manage finances efficiently and effectively. Reducing debt levels is also important for preventing future financial distress.
2. For internal members of a company, it is advisable to understand the company's financial condition, including income statements, cash flow, and balance sheets, to detect early signs of financial distress and take immediate corrective actions. The use of a financial distress prediction model can help formulate more effective strategies.
3. For investors and prospective investors, it is advisable to understand financial distress and bankruptcy when making investment decisions in a company, especially those who will invest in transportation and logistics companies in Indonesia. This study can inform current and prospective investors about the prediction of the condition and performance of a company using artificial neural networks.

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