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

**Sinta Dewi**
Telkom University, Indonesia
*ppsintadewi@student.telkomuniversity.ac.id*

**Abstract**
**Purpose:** This study aims to predict financial distress in transportation and logistics companies before, during, and after the Covid-19 pandemic.
**Research Methodology:** The research subjects were 23 companies, and the study utilized an artificial neural network model. This study uses financial ratios, including the debt-to-asset ratio (DAR), Current Ratio (CR), and Return on Assets (ROA) as input variables in the artificial neural network architecture. The objectives of this study are to calculate the three ratios used as test data, determine the differences in financial ratios between companies reported as financially distressed and those not experiencing financial distress in the training data, identify the artificial neural network model architecture that produces good performance on the training data sample for use in testing predictions, and predict financial distress using an artificial neural network on transportation and logistics companies listed on the Indonesia Stock Exchange, which are part of the research sample. The research sample consisted of 20 transportation and logistics companies listed on the Indonesia Stock Exchange from 2015 to 2019.
**Results:** The results reveal that companies reported as financially distressed have lower average values for the three ratios compared to 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 one 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 predicted to experience financial distress.
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## 1. Introduction
A company is an operating organization that aims to gain profits 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 (Restiani & Indiyati, 2024; Rinayuhani, Arisandi, & Sutrisno, 2024). A company must perform well in carrying out its goals. Company performance is the overall success of a company in

achieving planned strategic goals through the translation of its mission, vision, core values, core beliefs, and strategy (Mulyadi, 2007).

In its business journey, every company will face 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. When the pandemic hit, the situation changed significantly. Many companies face sharp declines in revenue, operational restrictions, and increased health and safety costs. During the pandemic, many companies have 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.

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 contained in financial statements (Putri and Dharma, 2016). In a company, precisely in terms of the resources utilized, the level of effectiveness can be measured using a ratio, the ratio is the activity ratio (Matthew & Onwuzor, 2023). Total asset turnover proxies the activity ratio because sales created from all assets used with the capabilities of a company 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

The research problem is that there are 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. The following year, there was an increase in the ROA of 19 companies.

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. This helps analysts and decision-makers better understand changes in actual economic production, regardless of possible price changes. 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. This can contribute positively to a company's income in this sector. However, this hypothesis requires further investigation.

According to Sinaga and Hidayat (2020), transportation is a parameter for measuring the rate of economic growth and can also facilitate the mobility of people from one area to another. The development of transportation is currently increasingly complex, with various types of transportation offered to the public; trains are still one of the choices for Indonesian people. However, a warehouse can be said to be 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 (Makinde & Abati, 2024).

Previous research has stated that several ratios have proven to be accurate in predicting financial distress conditions. According to Mafiroh and Triyono (2016), 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 highlight the interest in predicting the possibility of financial distress in transportation and logistics companies in Indonesia. This study

expands on previous research by combining approaches from several previous studies. The difference is that 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. Then, the author 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 is 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 how the results of the three ratio calculations (Current Ratio, Return On Assets, and Debt to Assets Ratio) are 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 of time. Financial performance is important because it is used to assess the conditions of a company. The performance of a company can be measured through a 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. This ratio aims to determine the company's position in relation to obligations to the other parties. In practice, if there is a large risk of loss, it indicates that the company has a high leverage ratio, but the company has the opportunity to generate high profits (returns). Conversely, if there is a small risk of loss, this indicates that the company has a low leverage ratio, but the company has the opportunity to

generate low profits (returns), according to Kasmir (2015). Thus, financial managers must control their level of 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. Conversely, if the ratio is high, then 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 it feared that the company would 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 it is billed. According to Munawir (2004), 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, then the company has a weak financial position, which will result in financial risk of bankruptcy (Bans-Akutey & Ebem, 2022; Hossain, Khatun, & Shanjabin, 2023).

The Current Ratio (CR) formula was used in this study. According to Sudana (2015), this ratio is used to pay for current liabilities using the current assets owned. The higher the current ratio, the greater the company's ability to pay its various bills; however, this ratio should be considered a rough measure because it does not consider the liquidity of each component of current assets, according to Horne and Wachowicz (2012). where is the formula for Current Ratio.

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

### 2.1 3 Preferabilities

According to Harahap (2018), the profitability ratio is the 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. The results of measuring the profitability ratio can be used to evaluate management performance, whether management has worked effectively or not. If they succeed in achieving the predetermined target, they are said to have succeeded in achieving the target for a certain period 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.

The profitability ratio used in this study is return on assets (ROA). This ratio shows how many assets contribute to creating net profits. 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 and results of operations and their elements, which aim to evaluate and predict the financial condition of a company or business entity and evaluate the results that have been 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 that 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 experienced before the company goes bankrupt or liquidation. 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 for a company in which it cannot fulfill its obligations; if this condition occurs, the company will go bankrupt. Financial distress can be defined from many perspectives, namely, from an economic, financial, working capital, inability to pay, and sales growth perspective (Nursal et al., 2023). Companies that fail to run their business because they cannot finance business continuity can experience financial distress. Every company can experience financial distress because the factors causing financial distress can come from internal or external sources. According to Utami (2015), there are two reasons for a company to fail financially.

### 2.4 Artificial Neural Network

One of the techniques that can be used in pattern recognition and its application for prediction is an Artificial Neural Network system. Neural Networks are soft computing or data-mining methods that are widely used for classification and prediction. Artificial Neural Networks (ANN) were first developed by McCulloch and Pitts in 1943 and have now been widely developed into various forms of ANN (Musliyanto and Defit, 2015).

An Artificial Neural Network is an artificial network based on the structure of the brain's nerves. The brain has the principle of learning from experience. The actual functioning of the brain has not been fully revealed, although its function as an extraordinary processor is known. The main element of the brain is the cells, similar to other parts of the body. Brain cells have the ability to remember, think, and apply their experiences (Kustono & Hatmojo, 2006).

Backpropagation is an Artificial Neural Network method that uses a supervised learning process (Setiawan, 2011). The purpose of this backpropagation method is to achieve a balance between the network's ability to recognize patterns used during the training process and its ability to provide the correct response to input patterns that are different from the training input patterns. There are several types of ANN algorithms, but the most commonly used in financial distress prediction is the Multilayer Perceptron (MLP), or an algorithm that uses backpropagation neural network (BPNN) learning (Paule-Vianez et al., 2020). Multilayer perceptron is an ANN that has neurons arranged in layers, namely, one input layer, various multiple layers, and one output layer (Salehi et al., 2016).

### 2.5 Previous Research

Research by Susilawati (2019). The study included four cement companies for the period 2012-2018. The samples were collected using purposive sampling techniques with predetermined criteria. This study used the Altman Z-Score model with the Multiple Discriminant Analysis (MDA) method on five types of financial ratios equipped with cut-off points. (X1) Working capital/total assets, (X2) retained earnings/total assets, (X3) earnings before interest and taxs/total assets, (X4) market value of equity/total liabilities, and (X5) sales/total assets. Descriptive statistics were used in the research approach. The results of the analysis 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. and PT Semen Indonesia, Tbk is in the grey area. PT Holcim Indonesia Tbk. has the worst conditions.

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 is still 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 analysis. 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% INRU shares.

Financial Distress Prediction Using Artificial Neural Networks (ANN) in Banking Companies Listed on the Indonesia Stock Exchange (IDX) for 2017-2021 Period was studied by Awalia and Kristanti (2023). The analysis technique used was an Artificial Neural Network. 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. The ANN architecture used for the prediction cycle of 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 results of 87%.

Bankruptcy Prediction Using Artificial Neural Network was studied by Yoga et al. (2018). 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 were learned during the training process. The weights of the redundant features are suppressed so that they become very small. The training process for model formation requires a long time. This is because the ANN Perceptron must perform a number of 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 to correctly identify distress. In particular, ESG significantly reduces the likelihood of misclassifying troubled/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 Methods
### 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, namely, 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.

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. So that a total sample of 460 research report data 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 samples. This study selects public companies in the world that are not experiencing financial distress in 2019 and this study selects public companies in the world that are 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 are as follows:

1. Non-distress Companies
   a. Public companies declared that they were not experiencing financial distress by 2024.
   b. Companies that publish audited financial statements in 2019-2023.
   c. Public companies listed on the stock exchange in 2019-2023.
   d. Financial ratios were used as research variables for the financial distress prediction process.
      i. Current ratio above 100% in 2019-2023.
      ii. Positive return on assets in 2019-2023.
      iii. Debt-to-assets ratio below 50% in 2019-2023.

2. Distressed Companies
   a. Public companies are declared to be experiencing financial distress in 2024.
   b. Companies that publish audited financial statements in 2019-2023.
   c. Public companies listed on the stock exchange in 2019-2023.
   d. Financial ratios were used as research variables for the financial distress prediction process.
      i. Current ratio below 100% in the five-year period in the year or 2019-2023 before being declared distressed.
      ii. Negative return on assets in the five-year period or 2019-2023 before being declared distressed.
      iii. Debt-to-assets ratio above 50% in the five-year period or 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 both in the short and long term. This study uses the debt-to-asset 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 debt. 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 it falls due. This study used the Current Ratio (CR). According to Murhadi (2013), the current ratio measures a company's ability to pay current liabilities using current assets owned. 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 activities, asset use, 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 creating a net profit. The formula for ROA is as follows:

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

### 3.3 Research Stages

The research begins by identifying and formulating the problem to be studied. After identifying and formulating the problem, the next step is to determine the purpose of the research. Then, we conducted a literature review by starting with the search 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 data and training data.

The next stage is to conduct a descriptive statistical analysis of the results of the calculation of financial ratios for the training data sample. Descriptive statistical analysis was carried out 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 conducting descriptive statistical analysis, and testing 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 of three-time conditions, namely before the pandemic, during the pandemic, 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 are 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 companies 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*

Measurements in descriptive statistics are used to describe the center, spread, and distribution, which acts 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, researchers used descriptive statistical methods to identify the differences between the two groups of companies. Financial ratios were used to carry out descriptive statistical analysis. The ratios used are the current ratio, return on assets, and debt-to-asset ratio. This analysis compares the average value of the calculation results of companies that do not face financial distress and those that face financial distress.

*3.5.3 Prediction Model Using Artificial Neural Network*

**1. Training Data**

Predicting predictions 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 been carried out.

**2. Backpropagation Algorithm**

There are three layers in an artificial neural network. The first layer was used to input information into the hidden layer. The second layer, the hidden layer, functions for the learning phase that is connected to the weights (numerical values) to obtain the appropriate output. The third layer, the output layer, produces outputs for 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 uses a binary sigmoid activity function because the output interval value starts from 0 to 1. A value of 0 means that the company is not experiencing financial distress, whereas a value of 1 means that the company is experiencing financial distress. 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):

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

F$i$ = Total input neurons in an artificial neural network

1. Activation process

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

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

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

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

b. Calculate the output value obtained from the neurons in the output layer.

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

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

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

1. Weight update process

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

a. Calculate the error gradient for the neurons in the output layer.

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

Calculate the weight correction:

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

Update the weights in the output layer.

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

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 |
| $\delta_k$ | = error gradient of neuron k on the output layer |
| $\Delta w_{jk}$ | = weight correction |
| $\eta$ | = 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 |

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

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

Calculate the weight correction:

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

To calculate the number of hidden layer neurons,

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

Description:
$\delta$ = gradient error on neuron j in the hidden layer
$y_j$ = output value of neuron j in the output layer
$\Delta wij$ = weight correction
$x_i$ = input value of neuron i
$\eta$ = learning rate
$w_{ij}$ = weight from neuron i in the input layer to neuron j in the hidden layer

## 3. 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. Open the artificial Neural Network programming software and then search for the command window 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 has been 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 do not experience financial distress, and a value of 1 for companies that experience financial distress.

2. The input and target values are 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 artificial neural network programming.

3. Next, create a network by clicking the new button on the data manager window and then adjust the network according to the needs of the network. The network is then successfully created, and double-clicking the network displays the network display form.



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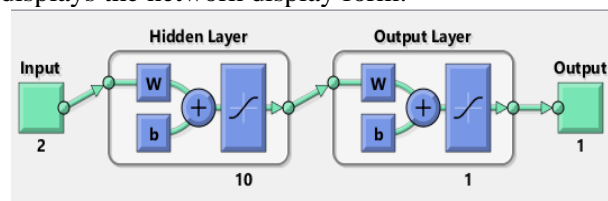Source: Researcher processing (2023)

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 needs. The trained network then clicks to perform training on the network. After the training process was complete, a learning dialog display appeared.
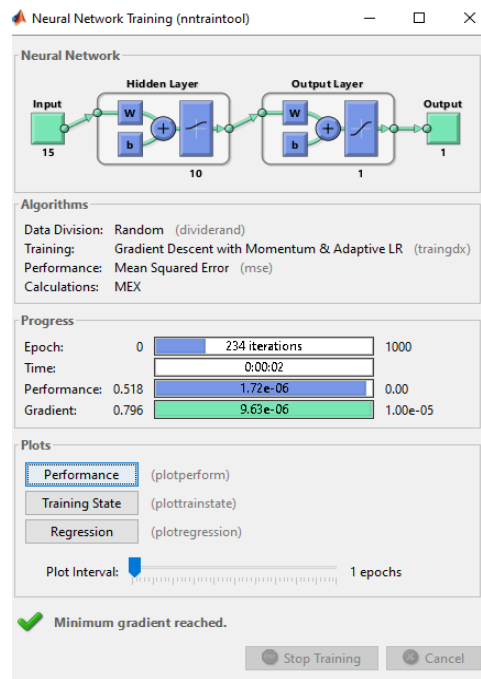
Figure 2. Training Data Method Dialog Display
Source: Researcher processing (2023)

5. Subsequently, to obtain the total weight calculation results in the training data process, we selected View/Edit Weights in the network display. The output value and error value 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 testing data sample. To use the network from the training data, exports were selected at the beginning of the nntool display. This command will create all artificial neural network architectures from the training data that have been processed in the artificial neural network programming workspace.

*To obtain the best artificial neural network backpropagation model, several steps must be taken (Kristianto & Rikumahu, 2019).*
1. Determination of the network layer. Kristianto and Rikumahu (2019) used a back-propagation neural network with input, hidden, and output layers.
2. Normalize the data such that it can be matched with the activation function value.
3. Weighting and bias allocation, initially with random values, were adjusted during training iterations.
4. Determination of activation function.
5. Determination of the optimization method.
6. The learning rate value, training value, and number of training iterations are changed to find the best estimated performance using the Mean Squared Error (MSE).

## 4. Data Application
*After conducting training 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. The procedure for operating the testing data sample is as follows:*
1. Establish the artificial neural network research results on training data that have been successfully exported to the artificial neural network programming workspace.

2. The input values for each company were entered as testing data one by one.
3. The next step is to predict the output class of the testing data using the sim () function. The resulting output values are
   a. If the resulting output value obtains a predicted result 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, then the company is experiencing financial distress.

## 4. Result and Discussion
### 4.1 Descriptive Statistical Analysis
To conduct descriptive statistical analysis for 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, namely the group of companies that do not experience financial distress and the group of companies that experience financial distress. The sample used for descriptive statistical analysis was training data. The results of the descriptive statistical analysis are presented 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 (2024)

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, namely 4.3661, compared to companies that are stated to be experiencing financial distress, namely 0.8083. This indicates that companies that do not experience financial distress have better liquidity. Thus, the ability to meet short-term obligations is higher than that of companies that experience 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 by analyzing financial reports to calculate the 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. 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 ratio. 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 needed for the artificial neural network model. The multilayer perceptron architecture of the artificial neural network consists of three layers: the input, hidden, and output layers. 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 distress. There are 60 input parameters in the input layer for 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. To clarify 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 simply 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 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 (2024)

Table 3 shows that the total number of neurons that produce small error value results are 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 neurons in the hidden layer, and 1 neuron 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.
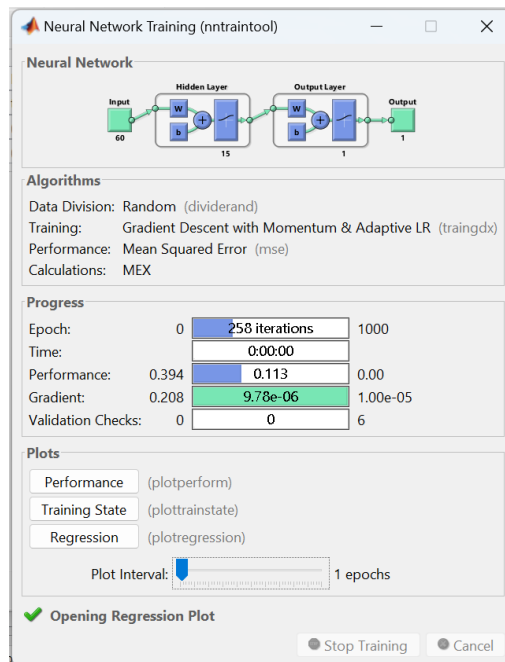
Figure 3. Training Data Results using 15 hidden layers
Source: Researcher processing (2024)

The following is explained in Fig. 3.
1. The artificial neural network training process ended after 258 epochs, with the smallest error results obtained. This means that the data training process was complete after 258 iterations.
2. The MSE and error obtained were 0.125004.
3. The gradient of similarity between the 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 the 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 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 (2024)

Table 4 shows that the artificial neural network training model that produces good performance is the artificial neural network model with an architecture using 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 the training output results is quite 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 is a non-distress company and a target value of 1 is 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 (2024)

*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 (2024)

## 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. The financial ratios used are the current ratio, return on assets, and debt-to-assets ratio in 2019-20123. The calculation results are used to predict whether transportation and logistics companies will experience financial distress in 2024 or in the future using artificial neural networks. The results of this ratio calculation were used as a sample of the testing data.

### 4.3.2 Results of Descriptive Statistical Analysis of Training Data Samples
From the results of the descriptive statistical analysis of the training data sample, it can be concluded 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. 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, which is 25.2%, compared to distress companies that reach 90.9%. These results show that the performance of non-distressed companies is better than that of distressed companies. Therefore, this training data sample could 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 can be seen in Table 7, which is 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 do 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, 2024)

The ratio value of transportation and logistics companies that are predicted to experience financial distress can be seen in Table 8, which is 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 do 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

From the results of the study on the analysis of financial distress prediction of transportation and logistics companies in Indonesia using artificial neural networks, it can be concluded 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 companies that experience financial distress. This ratio calculation data is used as a training data sample for 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 neurons in the hidden layer, and one neuron in the output layer. With this configuration, the model achieved the best performance with the lowest Mean Squared Error (MSE) of 0.113 and correlation coefficient (R) of 50%. This shows that the model has fairly good predictive ability for identifying company financial distress.

The results of financial distress prediction using artificial neural networks on sample testing data from transportation and logistics companies show that 12 out of 23 companies are predicted to experience financial distress in 2024. The output results are 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 provide 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 and to 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. This research can be used by transportation and logistics companies that are predicted not to experience financial distress to monitor the company's condition and improve performance. For companies predicted to experience financial distress, it is advisable to 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 action. The use of a financial distress prediction model can help formulate a more effective strategy.

3. For investors and prospective investors, it is advisable to understand financial distress and bankruptcy as a consideration for making investment decisions in a company, especially those who will invest in transportation and logistics companies in Indonesia. This research can inform investors and prospective investors about the prediction of the condition and performance of a company using artificial neural networks.

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