# “Are Indonesian construction companies financially distressed? A prediction using artificial neural networks”


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# ARE INDONESIAN CONSTRUCTION COMPANIES FINANCIALLY DISTRESSED? A PREDICTION USING ARTIFICIAL NEURAL NETWORKS

## Abstract

Construction companies are very dependent on the projects carried out by a company. Therefore, measuring whether a company is distressed or non-distressed can be done by looking at the ratios derived from the components of the financial statements from both the balance sheet and the company's profit and loss. This study offers a new method for measuring financial distress in companies with Artificial Neural Networks (ANN). The model provided comes from several financial ratios in 17 construction companies listed on the Indonesia Stock Exchange. The model is expected to produce the best model by showing the lowest prediction error rate. The results showed that the best ANN model has 25 inputs, 20 hidden layer neurons, and 1 best model output. The model obtained will be tested directly on the sample used; the results are that 6 construction companies in Indonesia have financial distress and 11 non-distress problems. This result proves that the best model obtained can predict the level of financial distress of companies with a small error rate to produce 6 companies identified as financially distressed. This result can be a warning for companies to increase revenue by adding new projects to get out of financial distress status. Traditional financial distress models such as Altman, Zmijewski, Springate, and Fulmer, which have become researchers' guidelines for measuring financial distress, can be added to the ANN 25-20-1 model as a comparison to strengthen the research results.

**Keywords** ANN, distress, financial, model, prediction, financial statements, balance sheet

**JEL Classification** C15, C45, G32, G33, M41

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## INTRODUCTION

Construction companies are the fourth largest sector contributing to Indonesia's economic growth during 2021 by contributing 10.48% to Indonesia's Gross Domestic Product (GDP). This shows that construction companies play a relatively significant role in maintaining Indonesia's economic growth because if there are problems with construction companies, Indonesia's economic growth can also be disrupted. Currently, the financial performance of construction companies shows a relatively unfavorable condition. Revenue earned by construction companies during 2017–2021 tended to decrease. In addition, their Debt is quite large compared to the assets they own. This causes the possibility of default on construction companies to occur. Their large Debt makes construction companies have to restructure their debts to avoid default conditions, as happened to one of the construction SOEs in Indonesia.

Today, the most considerable influence on the decline in the performance of construction companies is the prolonged effects of the COVID-19 pandemic. The pandemic that has hit the whole world has significantly impacted world economic conditions. It has caused an increase in corporate financial uncertainty (Wu et al., 2022). The enactment of Large-Scale Social Restrictions in Indonesia during the pandemic has halted almost all business activities. Construction companies are one of the sectors affected by delays in their projects, which directly impact the company's financial condition. During the 2017–2021 period, construction companies in Indonesia have shown a trend of a significant decline in profits in their financial statements. Some companies even have negative earnings for several years in a row. This can be an early indication that the companies are experiencing financial distress. Muparuri and Gumbo (2022) stated that a company is said to be in financial distress if it receives losses for two consecutive years in its financial statements.

This study will create a model to predict Financial Distress by utilizing machine learning technology, namely ANN, and experimenting with various amounts of training and testing data in predicting financial distress using input variables in the form of five financial ratios, which are predictive indicators. Therefore, this study aims to find out the ANN model architecture that creates the best performance in predicting financial distress to further find out the results of financial distress predictions using the ANN model that has been formed in Heavy Constructions and Civil Engineering companies listed on the Indonesian IDX.

# 1. LITERATURE REVIEW AND HYPOTHESIS

A prediction of financial distress can be made using an Artificial Neural Network (ANN). Research related to the prediction of financial distress with ANN has been carried out in many parts of the world (Chen & Du, 2009; Lin, 2009; Altman et al., 2020; Sun & Lei, 2021; Wu et al., 2022) and has shown excellent results, namely obtaining a high degree of accuracy. Similarly, in Indonesia, the prediction of financial distress with ANN has also been carried out (Kristianto & Rikumahu, 2019; Alamsyah et al., 2021) and obtained high accuracy. Even so, only a few studies related to financial distress with ANN in Indonesia have been carried out, especially on the financial condition of construction companies.

Current financial distress has become a dire economic condition for developed and developing countries (Mishraz et al., 2021). Financial distress does not have an exact meaning, but it can be interpreted broadly as a condition that indicates a company cannot fulfill its obligations (Enumah & Chang, 2021). Financial distress causes companies to have difficulty paying their obligations and interest on their obligations due to a lack of liquidity (ElBannan, 2021). Companies can also be considered to be experiencing financial distress when their cash flow cannot cover their debts, forcing them to restructure or change their debt payment plan (Muparuri & Gumbo, 2022).

Financial distress can happen to companies of any size and type. Financial distress experienced by companies can occur due to the managerial inability to implement business strategies (Altman & Hotchkiss, 2006). Chen and Du (2009) explained that financial distress could also be caused by a lack of management knowledge related to finance, failure to determine capital plans, poor debt management, poor risk control, and failure to follow financial markets. Companies must pay close attention to financial distress because this condition will affect debt payments and company investment (Li et al., 2021). Financial distress, apart from causing significant economic losses to the company, also has a direct impact on the growth and sustainability of the company (Salehi et al., 2016).

Companies in financial distress have the chance of bankruptcy, and the company asset's liquidity level influences this in line with credit availability (Hendel, 1996). Even though they have the potential to go bankrupt, this does not mean that all companies in financial distress will go bankrupt. Companies might get through this challenging period if they take the correct precautions. Therefore, financial distress conditions must be assessed early. Seeing how significant financial distress is for companies, making predictions of financial distress is essential.

Prediction and prevention of financial distress are significant to minimize the long-term impact of the crisis (Nik et al., 2016). The prediction of finan-



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cial distress cannot be underestimated because it helps internal and external companies to see the actual conditions of the company's financial system and also plays a role in predicting bankruptcy, reducing risk levels, ensuring billing, and influencing decisions within the company (Adisa et al., 2019). Predicting financial distress has a major influence on every decision made by stakeholders (Mishraz et al., 2021). Therefore, predicting the possibility of financial distress is important for investors, shareholders, the government, and other stakeholders (Muparuri & Gumbo, 2022). It can be concluded that the prediction of financial distress is a tool to determine the company's financial condition in the decision-making process. Wu et al. (2022) explained that the results of predicting financial distress could provide an early signal of a company's financial condition that can be used by internal and external parties to make decisions to avoid losses.

Prediction of financial distress has been a research topic in the economy for a long time because it can explain the health condition of companies. Prediction of financial distress can be made using several methods. In its development, financial distress prediction models have two groups, namely the classical and alternative prediction models. The classic prediction models consist of the univariate analysis developed by Beaver (1996), the multivariate analysis by Altman (1968), and the conditional probability model by Ohlson (1980). In comparison, the alternative models consist of the decision tree developed by Frydman et al. (1985), ANN, which was first developed by Odom and Sharda (1990), and survival analysis, which was first developed by Lane et al. (1986). Research results showed that ANN has the highest level of accuracy in predicting financial distress (Mishraz et al., 2021).

ANN is a superior prediction model because it has a high accuracy, learning ability, and adaptability. Prediction of financial distress using the ANN model has been widely carried out. Chen and Du (2009) predicted financial distress using ANN for 68 companies listed on the Taiwan Stock Exchange, and the ANN produced satisfactory performance in making predictions. Salehi et al. (2016) compared several data mining techniques, including Support Vector Machines (SVM), ANN, k-Nearest Neighbor (KNN), and Naive Bayesian Classifier (NBC), with 42 companies as testing data. This study proved that ANN is superior among other data mining techniques, with an accuracy rate of 97.62%.

Mishraz et al. (2021) used 75 banks in India to compare the classic prediction models, namely logistic regression and linear discriminant analysis (LDA), with an alternative prediction model, namely ANN, and produced ANN's superiority in predicting financial distress with an accuracy rate of up to 86.66%. Sun and Lei (2021) used ANN to predict the financial distress of companies listed on the China Stock Exchange and obtained 100% accurate results. Other studies in various countries conducted by Lin (2009), Salehi et al. (2016), Marso and El Merouani (2020), and Wu et al. (2022) also obtained high accuracy results for the ANN model, which was above 80%. In Indonesia, the prediction of financial distress with ANN has also been carried out, for example, by Kristianto and Rikumahu (2019), who predicted three telecommunications companies listed on the IDX and showed that ANN is superior. Furthermore, Alamsyah et al. (2021) predicted the financial distress of 33 transportation companies listed on the IDX using ANN and obtained an accuracy of 95.6%.

Even though much research has been done in Indonesia, the prediction of financial distress using the ANN technique is scarce, especially in the context of construction companies. This study is important due to the significance of construction companies for the Indonesian economy, especially when the current phenomenon of construction companies shows unfavorable financial conditions. If not handled properly, construction companies may experience the worst condition: company bankruptcy. Based on the phenomenon raised from the debate from previous research, the hypotheses proposed in this study are:

*H1: The ANN model with the smallest Mean Square Error level is the best model for predicting the Financial Distress level in Indonesia's construction stock group.*

## 2. METHODOLOGY

The research sample is divided into two categories: the testing data sample and the training data sample. The purposive sampling criteria for the sample testing data were Heavy Construction and Civil Engineering companies listed on the Indonesia Stock Exchange and had complete data for 2017–2021. Based on these criteria, 17 companies were obtained. The training data used companies that were declared distressed and non-distressed in 2021. This study used publicly listed companies worldwide that reported financial reports in 2016–2020. Based on these criteria, 20 companies were obtained, consisting of 10 distressed companies and 10 non-distressed companies.

The descriptive statistical analysis in this study was conducted to determine differences in company financial ratios on training data. The analysis was carried out by comparing the average value of financial ratio calculation results between distressed companies and non-distressed companies. The financial ratios used were Return On Assets (ROA), Debt to Assets Ratio (DAR), Current Ratio (CR), Total Assets Turnover (TATO), and cash flow from operations to total Debt. The operation of variables is presented in Table 1.

ANN is a systematic model based on biological nerves that are developed and regulated so that the system can learn and generalize data and experience (Salehi et al., 2016). ANN consists of several components: nodes, weights, and layers (Marso & El Merouani, 2020). The ANN prediction model has three neuron nodes: input nodes, hidden layer nodes, and output nodes. The input node is related to the independent variable of the activation function, which connects the input node with the hidden layer node. Furthermore, the resulting information is processed from the hidden layer nodes to the output nodes. The output node generates a prediction model that is later compared with the expected results to adjust the parameters (Wu et al., 2022).

There are several types of ANN algorithms, but currently, the most widely used in predicting financial distress is the Multilayer Perceptron (MLP) which uses backpropagation neural network (BPNN) learning. The level of prediction accuracy depends on the number of hidden layers, so the number of hidden layers needs to be determined through continuous training and adjustments (Wu et al., 2022). Therefore, the formation of the ANN algorithm begins with data training. The MLP algorithm distinguishes the data used as follows (Fasya & Rikumahu, 2021):

1. Training data was used in the model-building process to determine the ideal weight with the BPNN method.

2. Testing data was used for the model testing process to predict the error rate after determining the final model.

In this study, the entire data training process for building ANN models used MATLAB programming software. The training process used the start

**Table 1.** Operation of variables

Source: Author's calculations.

| Category | Name | Formula | Scale |
|---|---|---|---|
| Profitability | Return On Assets | $\frac{\text{Net Income}}{\text{Total Asset}}$ | Ratio |
| Leverage | Debt to Assets Ratio | $\frac{\text{Total Liabilities}}{\text{Total Asset}}$ | Ratio |
| Liquidity | Current Ratio | $\frac{\text{Current Assets}}{\text{Current Liabilities}}$ | Ratio |
| Activity | Total Assets Turnover | $\frac{\text{Sales}}{\text{Total Assets}}$ | Ratio |
| Cash Flow | Cash flow from Operation to Total Debt | $\frac{\text{Cashflow from Operation}}{\text{Total Liabilities}}$ | Ratio |


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feature found in MATLAB software, which functions to form the ANN model. To form the best ANN model, several steps were taken (Kristianto & Rikumahu, 2019):

1. Determining the network layer.
2. Normalizing the data so that it can be matched with the value of the activation function.
3. Bias weighing and allocation, initially with random values, were adjusted during training iterations.
4. Determining the activation function.
5. Defining the optimization method.
6. Iteratively changing the learning rate, training value, and training amount to find the best-estimated performance using MSE (Mean Squared Error).

The measurement of the ANN model performance was based on the MSE value obtained and the confusion matrix. MSE was used to calculate the average error of the model, while the confusion matrix was used to measure the model's accuracy. There were 4 different prediction results, True Negative (TN), True Positive (TP), False Negative (FN), and False Positive (FP). The percentage of the number of TN and TP classifications for all data is the accuracy of the prediction model. The confusion matrix is presented in Table 2.

**Table 2.** Confusion matrix

Source: Author's calculations

| Actual Class | Prediction Class | |
|---|---|---|
| | Negative | Positive |
| Negative | TN | FP |
| Positive | FP | TN |

After the data training process was carried out and the best ANN architecture had been obtained, namely by fulfilling the error criteria, the next stage was the process of applying it to the sample test data, or it can be said that the process of predicting financial distress on the research object. The prediction was made by looking at the resulting output value. An output value close to 0 or equal to 0 meant the company was not experiencing financial distress. An output value close to 1 or equal to 1 meant the company was experiencing financial distress. The model is offered using five financial ratios as predictive indicators of financial distress, namely Return On Assets (ROA), Debt to Assets Ratio (DAR), Current Ratio (CR), Total Assets Turnover (TATO), and cash flow from operation to total Debt. The five indicators will then be input into the MATLAB software, which in this study is used to form a prediction model. Researchers then experimented on the number of hidden layers to form the best performance model, and this process was also carried out through MATLAB software. After going through a lengthy training process, a prediction model with the best performance was obtained, which will later be used to predict the financial distress of construction companies.

After obtaining the best model, it will apply it to Indonesian construction companies. Furthermore, it carries out the process of inputting the five financial ratio indicators from each construction company one by one into the ANN algorithm generated in MATLAB software. That way, the output of each company with a range of 0 to 1 is obtained, which will determine whether the company experiences financial distress. Output close to 0 means that the company does not experience financial distress, and vice versa; output close to 1 means that the company is experiencing financial distress.

## 3. RESULT

This study presented the statistical analysis results to see the differences in characteristics between distressed and non-distressed companies, which are presented in Table 3.

Table 3 shows that the average CR of non-distress companies is 2.7912, which is greater than that of non-distress companies, which is 1.4001, which means that distressed companies have a worse ability to pay off their short-term obligations compared to non-distressed companies. The ROA of non-distressed companies shows a greater average value of 0.1002 compared to that of distressed companies, which is –1.071. This means that the average non-distressed company gets profits while

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**Table 3.** Descriptive statistics of training data sample

Source: Author's calculations.

| Variable | N | Min | Max | Mean | Std. Deviation |
|---|---|---|---|---|---|
| **Non-Distress Company** | | | | | |
| Current Ratio | 50 | 0.67 | 9.42 | 2.7912 | 1.79234 |
| Return On Assets | 50 | 0.01 | 0.36 | 0.1002 | 0.07058 |
| Debt to Assets Ratio | 50 | 0.11 | 0.66 | 0.3615 | 0.16454 |
| Total Assets Turnover | 50 | 0.22 | 1.61 | 0.9297 | 0.34455 |
| Cash Flow from Operation to Total Debt | 50 | –0.04 | 19.64 | 1.7499 | 4.08524 |
| **Distress Company** | | | | | |
| Current Ratio | 50 | 0.21 | 3.97 | 1.4001 | 0.74220 |
| Return On Assets | 50 | –1.48 | 0.08 | –0.1071 | 0.21959 |
| Debt to Assets Ratio | 50 | 0.07 | 2.49 | 0.8760 | 0.54275 |
| Total Assets Turnover | 50 | 0.01 | 4.79 | 0.8852 | 1.09874 |
| Cash Flow from Operation to Total Debt | 50 | –0.10 | 0.31 | 0.0666 | 0.09404 |

the average distressed company experiences losses. The average DAR of non-distressed companies, which is 0.3615, is smaller than the average DAR for distressed companies, which is 0.8760, which means that the average distressed company has most of its assets financed by Debt which will trigger default by the company.

The average TATO of non-distressed companies, which is 0.9297, is greater than the average TATO of distressed companies, which is 0.8852, which means that distressed companies have worse asset management in earning income compared to non-distressed companies. The average cash flow from operations to total Debt of non-distressed companies, which is 1.7499, is greater than the average distressed companies, which is 0.666, which means that the ability of distressed companies to pay their debts through operating cash flow is worse than non-distressed companies.

**Table 4.** Comparison of combined MSE

Source: Author's calculations.

| Total Neuron | | MSE |
|---|---|---|
| Input Layer | Hidden Layer | |
| 25 | 10 | 0.0043625 |
| 25 | 15 | 0.0024614 |
| 25 | 20 | 0.0000772* |
| 25 | 25 | 0.0012576 |
| 25 | 30 | 0.0020627 |
| 25 | 35 | 0.0061032 |
| 25 | 40 | 0.0010285 |
| 25 | 50 | 0.0040476 |
| 25 | 55 | 0.0005868 |
| 25 | 60 | 0.0079205 |

*Note*: Input Layer 25 Hidden Layer 20 Minimum errors.

Secondly, the best ANN architecture was produced by determining the number of neurons in the hidden layer. Table 4 shows the combination of neurons in the hidden layer and produces the best ANN architecture with 20 neurons in the hidden layer. This architecture produces a Mean Squared

Source: Author's calculations.

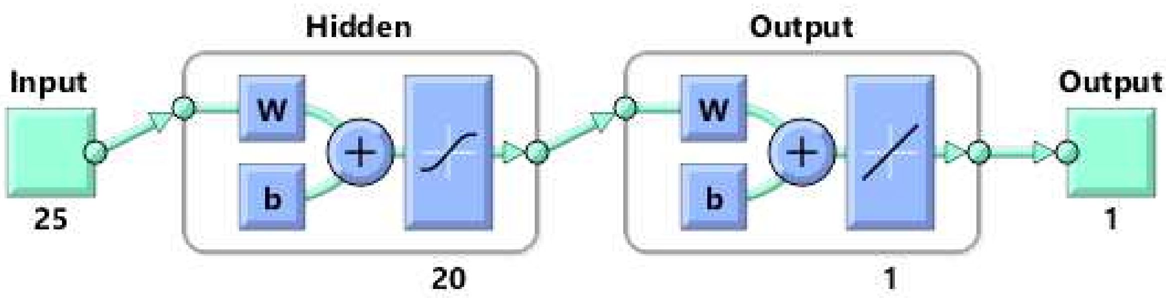


**Figure 1.** ANN architecture



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Error (MSE) value of 0.0000772 and is the smallest compared to the combination of neurons 10, 15, 25, 30, 35, 40, 50, 55, 60. Therefore, the best ANN architecture was obtained, namely 25-20-1 shown in Figure 1, and was then applied in the fourth process.

The formation of the prediction model obtained the output results shown in Table 5. It can be known that each company in the training data obtains outputs following the given target. Target output 0 indicates a group of companies that do not experience financial distress, while output 1 indicates a group of companies with financial distress. The resulting error is obtained based on the error of the output result obtained with the specified target, and it can be known that the error obtained by each company is very small.

**Table 5.** Training data output

Source: Author's calculations.

| No | Company Code | Target | Output | Error |
|---|---|---|---|---|
| 1 | AALI | 0 | 0.003 | –0.003 |
| 2 | EKAD | 0 | 0.002 | –0.002 |
| 3 | GEMS | 0 | 0.004 | –0.004 |
| 4 | JPFA | 0 | 0.223 | –0.223 |
| 5 | MBPA | 0 | –0.003 | 0.003 |
| 6 | ROTI | 0 | –0.004 | 0.004 |
| 7 | SRSN | 0 | –0.004 | 0.004 |
| 8 | TLKM | 0 | –0.004 | 0.004 |
| 9 | ULTJ | 0 | 0 | 0 |
| 11 | W | 1 | 0.828 | 0.172 |
| 12 | DO | 1 | 1.119 | –0.119 |
| 13 | WLL | 1 | 0.993 | 0.007 |
| 14 | CHK | 1 | 0.995 | 0.005 |
| 15 | REV | 1 | 0.986 | 0.014 |
| 16 | SWIR | 1 | 0.994 | 0.006 |
| 17 | SQBG | 1 | 0.994 | 0.006 |
| 18 | HXOH | 1 | 0.997 | 0.003 |
| 19 | AFI | 1 | 0.996 | 0.004 |
| 20 | I | 1 | 0.998 | 0.002 |

Based on Table 5, it can be known that the output produced shows that 10 data training companies are declared not to experience financial distress with output results close to 0 and 10 data training companies are declared to have financial distress with output results close to 1. The output results are entirely in accordance with the company's actual state. Therefore, as many as 10 TN and 10 TP classifications were obtained with 20 correctly classified data, as shown in Table 6.

**Table 6.** Confusion matrix output training data

Source: Author's calculations.

| Actual Class | Prediction Class | |
|---|---|---|
| | Negative | Positive |
| Negative | 10 | 0 |
| Positive | 0 | 10 |

Furthermore, the total number of all training data is as many as 20; therefore, to determine the accuracy of the model, a percentage calculation is carried out by dividing the total number of companies classified correctly by the entire number of training companies (20/20). This obtained an accuracy of 100% because all companies on data training have been classified appropriately. Lastly, after obtaining the best ANN architecture, namely 25-20-1, the model was then applied to predict financial distress conditions in Heavy Construction and Civil Engineering companies listed on the Indonesia Stock Exchange or the testing data.

Based on Table 4. Comparison of combined MSE found that Input Layer 25 and Hidden Layer 20 have the smallest MSE value compared to other ANN models. Therefore, from these results, the hypothesis in this study is accepted that the smallest AAN MSE model can predict with precision

**Table 7.** Results of financial distress

Source: Author's calculations.

| Company Name | Output | Prediction | Company Name | Output | Prediction |
|---|---|---|---|---|---|
| ACST | 0.6754* | Distress | PPRE | 0.1680 | Non-Distress |
| ADHI | 0.6159* | Distress | PTPP | 0.4496 | Non-Distress |
| BUKK | 0.0870 | Non-Distress | SSIA | 0.4390 | Non-Distress |
| DGIK | 0.1836 | Non-Distress | TOPS | 0.6121* | Distress |
| IDPR | 0.9136* | Distress | TOTL | 0.0714 | Non-Distress |
| JKON | 0.2680 | Non-Distress | WEGE | 0.4049 | Non-Distress |
| MTPS | 0.9305* | Distress | WIKA | 0.3124 | Non-Distress |
| NRCA | 0.2404 | Non-Distress | WSKT | 0.9004* | Distress |
| PBSA | 0.1388 | Non-Distress | | | |

as shown in Table 7. Table 7 shows the results of the prediction of financial distress of construction companies. Based on the analysis results with ANN, it is predicted that 6 construction companies will experience financial distress because the output obtained is close to 1. Meanwhile, the other 11 companies are predicted not to experience financial distress in 2022 because the output obtained is close to 0.

# 4. DISCUSSION

Construction companies are one of the sectors that support the economy in Indonesia. However, the trend that construction companies have shown over the past few years actually shows a continuous decline in performance. This is worrisome as it might lead to bankruptcy. Problems that occur in construction companies not only affect the sector but will affect other sectors directly or indirectly related to the construction sector. In addition, Indonesia's economy will also be affected if the condition of construction companies worsens. Therefore, it is necessary to predict financial distress in construction companies so that the company's financial condition can be identified early and the company's management can make the right decisions.

The process of predicting financial distress began with establishing an accurate prediction model. Descriptive statistical analysis was carried out to see differences in the financial ratios of non-distressed and distressed companies found in testing data so that the ability of the ratios to differentiate between the two groups of companies could be identified. The results of the analysis showed that there was a significant difference between the financial ratios of non-distressed companies and distressed companies. Non-distressed companies showed better financial ratios than that distressed companies. The difference between the financial ratios obtained by non-distressed and distressed companies indicated that the ratio could be used as an input parameter in testing data using ANN.

The results of testing data processing with ANN showed the best architecture, namely 25-20-1. The number 25 is the total neurons in the input layer, 20 is the total neurons in the hidden layer, and 1 is the total output layer. This architecture performed best because it had the lowest error rate with an MSE of 0.0000772 and a high accuracy rate of 100%. This architecture did not show any classification errors in testing data, meaning the model had very high accuracy. These results were in accordance with previous studies (Sun & Lei, 2021), which showed that the level of prediction accuracy of ANN was very high, so the model is highly suitable for predicting financial distress. By obtaining the best model, the process of predicting financial distress in construction companies was carried out.

Based on the prediction results with ANN, it was found that 11 construction companies obtained output close to 0, and it can be said that the company was not experiencing financial distress. Meanwhile, 6 other construction companies obtained output close to 1, meaning they were experiencing financial distress. Companies deemed to be experiencing financial distress were ACST, ADHI, IDPR, MTPS, TOPS, WSKT. This meant that these companies had a poor financial performance. Companies deemed distressed may experience liquidity problems and experience a shortage of assets or cash flow.

This will increase the likelihood that the company will fail to pay its debts. In addition, these companies may be unable to earn profits, so they continue to experience declining profits or suffer losses. This can also be caused by a decrease in the company's ability to obtain income from each asset it issues. The conditions experienced by this distressed company can lead to the worst condition, namely, experiencing business bankruptcy. Therefore, company management must make appropriate decisions in dealing with these conditions to minimize the consequences of financial distress. With this prediction, company management can find out about the company's financial health to reduce the possibility of making wrong decisions. It is possible for a company declared to be in distress and go bankrupt, but this is not necessarily the case. Therefore, company management must apply the proper strategy in its business processes to maintain financial performance and avoid existing business risks.

With proper management, it is hoped that distressed companies can survive financial distress. The condition of financial difficulties experienced


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by the company will cause huge losses to the company. Therefore, until now, theories related to the impact of financial difficulties on failures or bankruptcies experienced by companies have been widely studied (Levine, 1997; Dam, 2006; Hessels et al., 2008). A company's financial failure can be said to occur when a company suffers a very large loss or when the company has debts that are much larger than the assets it owns, which leads to bankruptcy (Hua et al., 2007).

The failure of the company does not occur in such a short time. Some researchers (Laitinen, 1991; Ooghe & Prijcker, 2008) show that the failure or bankruptcy experienced by the company occurs within 5-8 years. Beaver (1996) explains that financial ratios have some predictive ability up to 5 years before bankruptcy because of their nature that follows a year-over-year path. Financial ratios have an essential role in describing the company's financial health, so it also plays a role in maintaining the stability of the company's development and competitive position (Klieštik et al., 2020).

The ability to predict and anticipate the impact of difficulties is essential in assessing a company's financial difficulties so that the main topics studied in the study are early signs of the company's financial difficulties or the main objective is to predict financial difficulties (Sun et al., 2013; Inam et al., 2018). The current model is a traditional model, such as the classical prediction model consisting of univariate analysis developed by Beaver (1996), multivariate analysis by Altman (1968), and conditional probability models by Ohlson (1980). In comparison, alternative models include decision trees developed by Frydman et al. (1985), ANN first developed by Odom and Sharda (1990), and survival analysis first developed by Lane et al. (1986).

ANN has very high predictive accuracy when compared to other models, has better stability, has the advantage of not requiring premise assumptions, can capture non-linear relationships between two variables, and becomes a model with an excellent ability to learn and adapt to a dataset (Chen et al., 2009; Sun. W and Xu, 2016; Hoque & Rahman, 2020). Therefore, ANN can effectively overcome the shortcomings of other distress financial prediction models, such as the multivariate discriminant model, which has a concern for data quality and the fulfillment of strict classical assumptions (Kosmidou et al., 2006), logits that require more approach in the calculation process (Irimiadieguez et al., 2015; Jabeur, 2017), Support Vector Machine (SVM), which tends to be challenging to do and requires a large number of data sets in the analysis process (Zhou et al., 2016; Jiang et al., 2018). Therefore, this study has found the best AAN model with 25-20-1 to predict the level of financial distress in construction companies in Indonesia. The resulting model has the accuracy of the prediction with a small error.

# CONCLUSION

This study will build an ANN model to predict the level of financial distress of construction companies in Indonesia. The results were obtained that the hypothesis raised was proven to be the best ANN model that had the smallest Mean Squared Error (MSE) error rate to predict the level of financial distress of construction companies in Indonesia. The ANN 20-25-1 model was chosen because it has the smallest predicted MSE error rate than the simulated ANN model. The ANN 20-25-1 model was also further tested on 17 samples of construction companies in Indonesia for the category of financial distress or non-financial distress. The results obtained showed that there are six companies entering the financial distress status and 11 companies entering non-financial distress.

These results provide input to the company to pay more attention and evaluate the projects owned and whether this project is worth continuing or breaking up so as not to burden the company. Based on the observation of the ratios used in this study to form a financial distress prediction model with the help of ANN, it can be concluded that construction companies in Indonesia that are included in the financial distress group have CFTDs, TATO, and ROA below the construction industry average. Therefore, companies need to reconcile assets to save themselves from the threat of distress and be more selective in choosing subsequent projects. Investors who want to invest in construction companies can choose stocks that are non-financially distressed in this study. For future research, retesting the model offered in this study for different sectors such as food companies, manufacturing, mining, and others may be possible.

## AUTHOR CONTRIBUTIONS

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