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Neural Network Prediction Analysis: The Financial Distress Case

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ABSTRACT

This study aims to to test internal financial factor company to financial distress in the year 2018 using data historical 2012-2018. The independent variable taken of a set the initial of du Jardin variables in 2010. Secondary data was used in the study with 32 mining firms that listed on the Indonesia Stock Exchange in 2012-2018 with purposive the sampling method of. A prediction done by means of a utensil artificial analysis the skill of artificial neural network. The application of a method of neural network used backpropagation algorithm. Architecture neural network used 3 layers (1 for input layer, 1 for hidden layer, 1 for output layer). The activation function used a logarithm sigmoid (logsig). The value of mean square error (MSE) training a network is 0,001. The results of forecasting neural network that there is no financial distress in 2018 with accuracy of prediction reaches 84,375%. For the next researcher, it is expected to use several models and several sectors as a comparison so that it can be proven which model is the most accurate in predicting symptoms of financial distress.

Keywords: Financial Distress, Neural Network, Backpropagation Algorithm.

INTRODUCTION:

In the development of globalization, there were several adverse effects that could be felt, one of which was the global financial crisis in 2008 which resulted in a weakening of general business activities. Most countries around the world suffered a setback and financial disaster due to the outbreak of the financial crisis. The financial crisis has caused the bankruptcy of several public companies in the United States, Europe, Asia and other countries (Hidayat & Meiranto, 2014).

In the Challenges to Global Economy seminar at The Ritz Carlton Pacific Place, SCBD, Jakarta, on Thursday (09/22/2016). Sri Mulyani said "In 2008-2009 it started with Europe. At that time developed countries were quite sure that they could pass this period but the conditions changed 5 years later. As a result, commodity prices fell and Indonesia also felt the effects" (Chandra, 2016). Sri Mulyani stated that Indonesia also certainly felt the effects of this global economic crisis. Various export commodities in Indonesia to date have even experienced weakening prices which have caused Indonesia's commodity exports not too big (Chandra, 2016).

In addition, in the domestic environment, there were several impacts on the occurrence of the financial crisis, one of which was that there were several companies that were de-listed as a result of the crisis. Companies can be listed from the Indonesia Stock Exchange (IDX) because the company is in a state of financial distress or is experiencing financial difficulties (Pranowo, Achsani, H.Manurung, & Nuryartono, 2010). Sulistio (2016), states that a similar crisis occurred again in 2015, poor global economic growth, economic uncertainty, the depreciation of the rupiah against the dollar, until the central bank interest rates are still too high and the Composite Stock Price Index (IHSG) in 2015 fell up to 12.81% compared to 2014. In the midst of these conditions the Indonesia Stock Exchange (BEI) recorded a decline in value of trade reached 7.54%.

To find out whether the company is experiencing financial distress or not, it takes a prediction action. The prediction of financial distress is influenced by the micro factor of the company. Regression is a parametric forecasting while forecasting non-parametric is ANN. According to Kusumadewi (2004), ANN is one of the artificial representations of the human brain that always tries to simulate the learning process in the human brain. Artificial terms are used because neural networks are implemented using computer programs capable of completing a number of calculation processes during the learning process (Fausset, 1994).

The first study of bankruptcy carried out by Beaver (1966), used in his t-test study to evaluate five years before bankruptcy, the accounting ratio is an independent variable of research. Altman (1968), applied a new technique known as discriminant analysis and was recorded as the most common and important study in the bankruptcy field. Logit regression statistics were carried out by Ohlson (1980) for large samples that did not include the same size of the company going bankrupt and not bankrupt.

Another technique that can be used to predict bankruptcy is known as a neural network and is used by many researchers. Odom & Sharda (1990) research, comparing two statistical tools; neural network (NN) and discriminant analysis techniques to compare predictive levels of both techniques. The results show that a neural network (NN) has a better prediction rate. Similar results were obtained by Tam (1991), Leshno & Spector (1996), Terzi, Sen, & Ucoglu, (2012), which showed that Neural network results were better at producing an accuracy than statistical analytical tools.

ANN used for this research is Backpropagation Algoritm. Backpropagation is a supervised learning algorithm and is commonly used by perceptrons with multiple layers to alter the weights connected to the neurons present in the hidden layer (Kusumadewi, 2004). The results of several studies demonstrated by using computational intelligence provide better precise percentages than using statistical techniques, ie with neural network learning sepervised learning so that the preferred method of ANN - backpropagation. Artificial Neural Network (ANN) is an information processing system designed to mimic the functioning of the human brain to solve learning problems through weight change of the sinapis. Artificial neural networks can learn a direct dependence on historical data, without the need to select an appropriate model that can make data decisions.

LITERATURE REVIEW:

Financial Distress:

According to Platt & Platt (2002), financial distress is defined as the stage of decline in financial conditions that occurred prior to the occurrence of bankruptcy or liquidation. The condition of financial distress is reflected in the inability of the company or the unavailability of a fund to pay its obligations that have matured. Based on a statement from Whitaker (1999), which states that a company can be said to be in a financial distress or financial difficulties if the company has negative net profit for several years.

Financial Ratios:

Financial ratios are indexes that connect two accounting numbers and are obtained by dividing one number by another (Van Horne & Wachowicz, 2005). Meanwhile, according to Warsidi & Bambang (2011), financial ratio analysis is an instrument of achievement analysis from a company that explains various relationships and financial indicators, aimed at showing changes in financial condition or achievement of past operations and help illustrate the trend pattern change, risks and opportunities attached to the company concerned.

Neural Network:

Data analysis is used to process data. One tool is used to solve a problem in the field of grouping and pattern recognition can be used a branch of artificial intelligence which is commonly called Artificial Neural Network (ANN). The mathematical model can simulate the function of the biological neural network is the development of ANN, based on the hypothesis:

a. A simple element called a neuron is part of the information being processed.
b. The particular relationship of a neuron to another neuron can be bypassed by a signal.
c. Each relationship has a dimension called weights. The activation function is used in every neuron connected to the received input in determining the output signal.

RESEARCH METHODOLOGY:

Research Design:
The research method used in this research is quantitative research method with descriptive approach.

Sample:
The data used in this study were taken from financial reports from 32 mining sector companies listed on the Indonesia Stock Exchange during 2012 to 2018. Companies are divided into two groups (distress and non-distress). This grouping uses a statement from Whitaker (1999), which states that a company can be said to be in a financial distress or financial distress if the company has negative net profit for several years.

Independent Variable Detection:
The selected variables used in this study are based on research priorities on financial distress prediction. So the set of variables belonging to du Jardin (2010), that is perceived to be able to describe the micro enterprise condition and used in this research. Table 1 shows there are seven groups, then the researcher summarizes again into four core groups, namely the ratio of profitability, activity, liquidity-solvency, and financial structure.

Backpropagation Algorithm:
Backpropagation algorithm performs forward propagation step which is done in advance to get output error. Then the output error obtained is used to change the value of the weights in the backward (Kusumadewi, 2004). Figure 1 shows how this algorithm works simply. This Neural Network process including these sections:

Data ➡ Normalization ➡ Training ➡ Testing

Activation Function:
The activation function serves to bridge the comparison between the sum of all future weights with the input value with a certain threshold value on each neural neural neuron. According to Kusumadewi (2004), there are three of the activation functions among which provided in the MATLAB software toolbox are as follows:

a. Linier Function (Identity/ PURELIN); the output value is equal to the input value.
   $y = x$
b. Sigmoid Binary Function (LOGSIG); has an output value in the range of 0 to 1.
   $y = f(x) = \frac{1}{1+e^{-\sigma x}}$
   With the value of $f' = \sigma f(x)[1-f(x)]$
c. Sigmoid Bipolar Function (TANSIG); has an output value in the range of -1 to 1.
   $y = f(x) = \frac{1-e^{-\sigma x}}{1+e^{-\sigma x}}$

With the value of $f'(x) = \frac{\sigma}{2}[1+f(x)][1-f(x)]$

Normalization Function:
Providing formulas can display better neural network outcomes. The hyperbolic tangent function is used to reduce computing calculations that are too large, then the normalization of data into the range 0.10 to 0.99. This distance is obtained from the binary sigmoid activation adjustment (0, 1) using the following equation:

$$Yi= \frac{y_i - y_i}{y_{max} - y_{min}}(h_i - L_i) + L_i$$

Information:

Y_i = The input values is normalized by equations
y_i = Initial input value
y_{min} = Minimum input value
y_{max} = Maximum input value

Activation Function:
The fastest two indicators of Backpropagation algorithm can accelerate the learning process, namely: the rate of learning and momentum (Agarkar & Ghatol, 2010). The rate of learning is very influential on the intensity of the training process. The effectiveness and speed of attaining convergence of the training according to

Hermawan (2006), also influenced the training process. Backpropagation has a variety of learning functions for the weights that can be found in Matlab, among which used in this study are:

a.Gradient Descent with Momentum (GDM / traingdm):

The traingdm method is the same as the gradient descent, it only adds momentum that allows ANN to respond not only to its local gradient error, but also to the recent trend of change in its error (Beale, Hagan, & Demuth, 2016). There are four multiplications with momentum applied on the weight change and bias for error of more than 1.

$\Delta wjk = mc * \Delta wjk\ epoch$ before + $(1-mc) * \alpha\ \varphi\ 2jk$

$\Delta b2k = mc * \Delta b2k\ epoch$ before + $(1-mc) * \alpha\ \beta\ 2k$

$\Delta vij = mc * \Delta vij\ epoch$ before + $1-mc * \alpha\ \varphi\ 1ij$

$\Delta b\ 1j = mc * \Delta b\ 1j\ epoch$ before + $1-mc * \alpha\ \beta\ 1j$

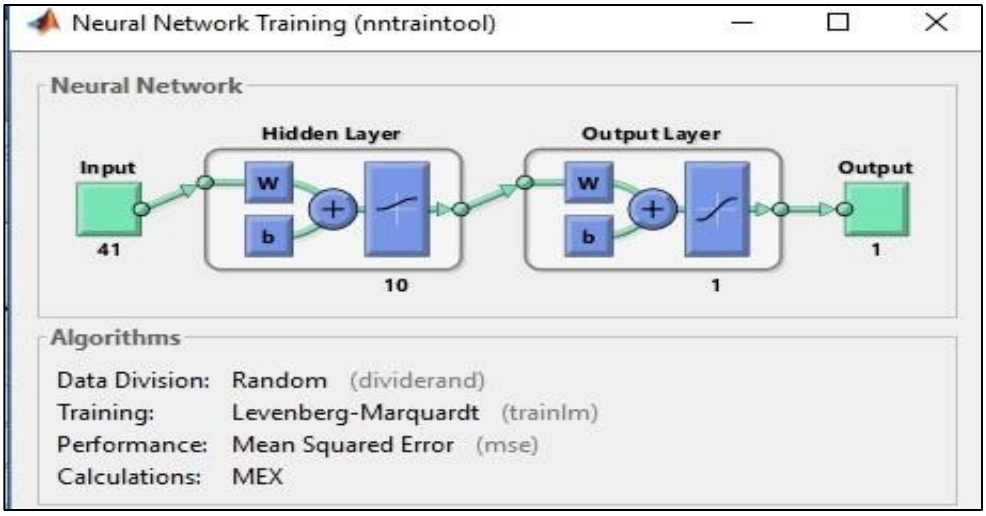
However, when the value epoch = 1 value changes its weight: $\Delta vij = \Delta vij + \alpha\ \varphi\ 1ij$

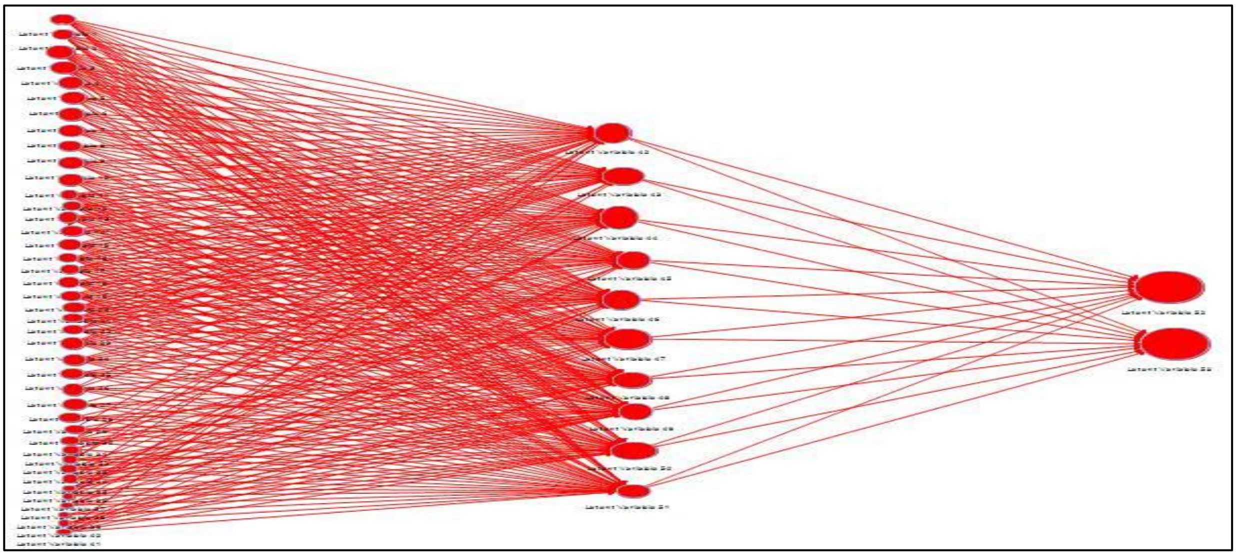
b. Levenberg-Marquardt (LM / trainlm) algorithm

One form of backpropagation function is standard numerical optimization techniques. The trainlm learning function is the fastest algorithm for large feedforward neural network training (up to hundreds of weights).

Structure of Neural Network:

In this study, a consistent Neural Network structure consisting of an input layer with 41 neurons, one hidden layer with 10 and one output layer with one neuron. These pictures below show the structural design of this study:





FINDINGS AND DISCUSSION:

RESULT:

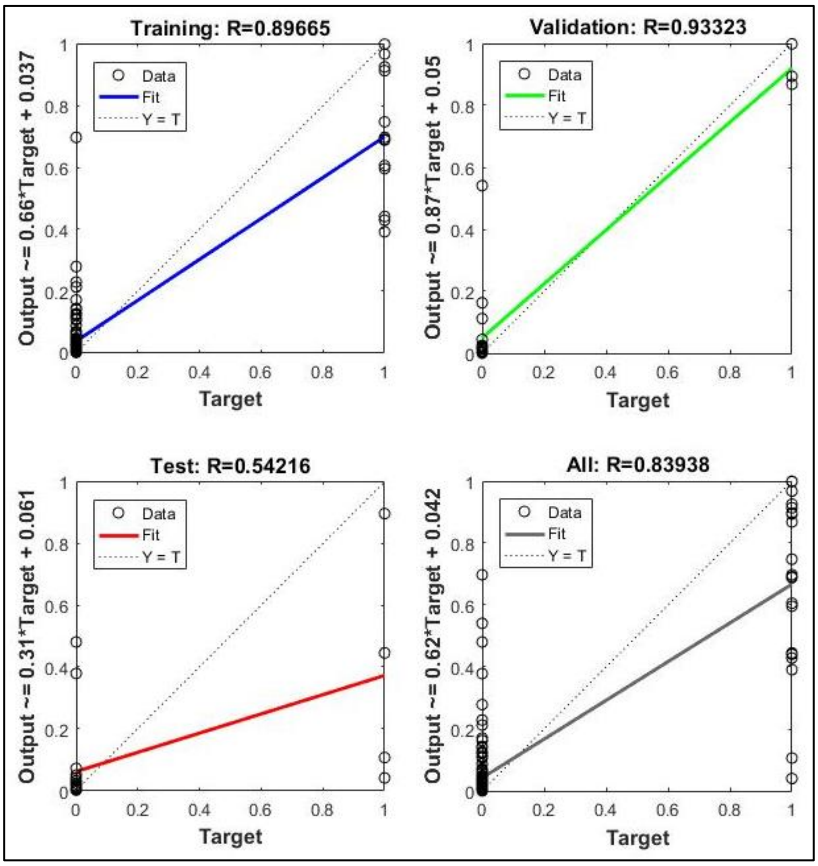
Results of Training Mining Companies in 2018

Mining Companies in 2018					
No	**Hidden Layer**	**Neuron**	**Activation Function**	**MSE**	**Epoch**
1	10	41	Logsig-Logsig	0.282	15
2	10	41	Logsig-Logsig	0.0655	6
3	10	41	Logsig-Logsig	0.0774	6
4	10	41	Logsig-Logsig	0.00837	6
5	10	41	Logsig-Logsig	0.0823	6
6	10	41	Logsig-Logsig	0.0795	6
7	10	41	Logsig-Logsig	0.001	5

The data processing in the table above shows the occurrence of the training process seven times to get the best error, as for the measurement parameters as follows:

1) Epoch (iteration) in this study uses a maximum iteration of 5000 iterations.
2) Goal in this study is 0.001.
3) Show displays the frequency of MSE changes. In this study using the default show, which is 25.
4) The function of learning using TRAINLM. This function is the fastest learning function in the backpropagation training process.
5) Activation function using logig (sigmoid logarithm)

In the table above can be seen with the number of neurons 41 and hidden layer 10 obtained the smallest Mean Square Error (MSE) is 0.001. If the error of training data is getting closer to zero then this research has a good model for forecasting.



In the picture below shows the regression of the overall learning process of 0.83938, which means that between the actual variables with ANN on the test has a good correlation. This size correlation indicates a high degree of association and that this model can affect financial distress.

Company	Correct		Non-Correct		Total	
	Number	%	Number	%	Number	%
Distress	0	0	5	15.625	5	15.625
Non-Distress	27	84.375	0	0	27	84.375
Total	**27**	**84.375**	**5**	**15.625**	**32**	**100**

Testing the data to measure the validation of whether the forecast results from the model constructed from the training data did give good results for calculating forecasting errors. The table above shows that the accuracy of this model as much as 84,375%. It shows that this model has been able to predict financial distress well. From the table above, this study is only able to predict companies that are not exposed to financial distress. This can be seen from the inability of the model to predict five companies that are suspected of experiencing financial distress.

DISCUSSION:

This study aims to determine whether the model owned by du Jardin (2010) is able to influence financial distress in mining material sector companies listed on the Indonesia Stock Exchange in 2018. Artificial neural network with backpropagation algorithms is chosen as the right method to predict this model. This study resulted that the model owned by du Jardin (2010) was able to predict financial distress in the mining material sector in 2018.

CONCLUSION:

The study of financial distress still has to be developed so as to obtain a truly precise forecasting. This study found that the model developed by du Jardin (2010), was well able to predict a condition of financial distress. The results of this study stated that in 2018, financial distress was not affected. In a study always has weaknesses. In this study there are also some weaknesses due to the limitations of research, the following weaknesses in this study: (1) The sample used in this study is only centered on one sector, namely the mining material sector. So that the results obtained cannot be generalized to other sectors. (2) The micro-enterprise measurement model is only centered on the replication of the journal du Jardin (2010). So the variables in this study have not represented all the factors to describe the state of a company. For the next researcher, it is expected to use several models and several sectors as a comparison so that it can be proven which model is the most accurate in predicting symptoms of financial distress.

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Table 1: Initial Set of Variables of du Jardin (2010)

Index	**Liquidity-Solvency**	**Index**	**Efficiency**
1	Current Assets/Current Liabilities	25	Total Sales/Shareholder Funds
2	Current Assets/Total Assets	26	Total Sales/Total Assets
3	(Current Assets-Inventory)/Tot. Assets	27	Operating Cash Flow/Total Assets
4	Quick Ratio	28	Operating Cash Flow/Total Sales
5	Current Liabilities/Total Assets	29	Gross Trading Profit/Total Sales
6	Financial Debt/Cash Flow	30	EBIT/Total Sales
7	(Cash + Mark. Sec.)/Total Sales	31	Value Added/Total Sales
8	(Cash + Mark. Sec.)/Total Assets	**Index**	**Rotation**
9	EBITDA/Total Sales	32	Current Assets/Total Sales
10	Cash/Current Liabilities	33	Net Op. Work. Capital/Total Sales
11	Cash/Total Assets	34	Accounts Receivable/Total Sales
12	Cash/Total Debt	35	Accounts Payable/Total Sales
Index	**Financial Structure**	36	Inventory/Total Sales
13	Net Op. Work. Capital/Total Assets	37	Cash/Total Sales
14	Shareholder Funds/Total Assets	**Index**	**Withdrawal**
15	Long Term Debt/Shareholder Funds	38	Change in Other Debts
16	Long Term Debt/Total Assets	39	Change in Equity Position
17	Total Debt/Shareholder Funds	**Index**	**Contribution**
18	Total Debt/Total Assets	40	Financial Expenses/Total Sales
Index	**Profitability**	41	Labor Expenses/Total Sales
19	EBITDA/Permanent Assets		
20	EBITDA/Total Assets		
21	Profit before Tax/Shareholder Funds		
22	EBIT/Total Assets		
23	Net Income/Shareholder Funds		
24	Net Income/Total Assets		
