The Accuracy of Artificial Neural Networks and Logit Models in Predicting the Companies' Financial Distress

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Abstract
In the face of the global economic crisis and the resulting uncertainty, it is crucial for investors and management to predict a company's financial distress for decision-making. Therefore, the accuracy of a prediction tool is critical for company management when implementing steps to reduce the risk of failure during an economic crisis. By taking account of the company's financial ratios, this study intends to determine which the finest financial distress prediction model is for industrial sector companies in Indonesia. This research used samples from the industrial sector on the In-donesian Stock Exchange from 2017 to 2021 and a predictor variable in the form of financial ratios to compare the accuracy of the artificial neural networks (ANN) and the logit models in predicting financial distress. The ratios in the following categories are applied for generating predictions: current ratio (CR), return on assets (ROA), debt to asset ratio (DAR), total asset turnover (TATO), and cash flow to debt ratio. The study's findings demonstrated that the Logit model beat the ANN model, with 98% accuracy, 94.20 sensitivity, and 99.30% specificity compared to the logit model's 82.50%, 84%, and 82%, respectively. It is expected that the high accuracy of this prediction model can be used to help interested parties predict the possibility of bankruptcy in the industrial sector in Indonesia. The Companies, Investors and regulators can prevent bankruptcy by knowing the best prediction method, which has an enormous impact on the Indonesian economy, and that model is Logit.

Keywords: ANN; financial distress; logit; prediction accuracy

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1. Introduction

The global economic crisis caused by the COVID-19 pandemic (Rajan, 2021) reduced the company's operational capabilities, resulting in the company experiencing business failure. Financial distress refers to the financial situation of a company before it is declared bankrupt. Therefore, early warning efforts by predicting financial distress are critical for companies, if they do not want to jeopardize the company's sustainability and harm creditors, shareholders, bondholders, and employees who will be laid off (Waqas & Md-Rus, 2018b). Early prediction of potential bankruptcy will assist companies in providing early indications of problems that occur in the company so that corrections can be made, and management can make decisions by considering company risks to reduce risks arising from financial distress (Kristanti & Isynuwardhana, 2018).

Financial difficulties can be measured using earnings per share (EPS). A corporation might be considered successful, in the opinion of Yolanda and Kristanti (2020), if its EPS value is high. The EPS number can be used to understand the company's profits; hence, if the company experiences a loss, the EPS will undoubtedly be negative (Pranita & Kristanti, 2020). When a corporation experiences negative EPS over time, it is said to be in financial difficulties (Kristanti & Syahputra, 2021)operating risk (OR. During the study period, from 2017 to 2021, the number of companies with the highest negative EPS in the Indonesian industrial sector was 18 in 2020 and decreased to 14 in 2021(Data processing results for industrial sector companies financial reports for the period 2017-2021- by author). The COVID-19 pandemic, which has spread throughout the world and reduced the company's operational capabilities, is one of the causes. As a result, the profit generated is not optimal or, in other words, it has not reached the company's target. In fact, PT Steadfast Marine Tbk., one of the industrial sector companies, had to halt its operations due to the economic crisis caused by the COVID-19 pandemic in the first quarter of 2020 (https://www.idnfinancials.com/id/news/34608/kpal-proposing-credit). As a result, an effective financial distress prediction model is necessary as an early warning system for industrial sector companies listed on the Indonesia Stock Exchange.

Various prediction models have been developed, including univariate analysis (Beaver, 1966), multiple discriminant analysis (MDA) (Altman, 1968), logit analysis (Ohlson, 1980), probit analysis (Zmijewski, 1984), and alternative prediction models comprised of decision trees, survival analysis, support vector machine (SVM), and artificial neural networks (Waqas & Md-Rus, 2018b). From the various models developed, logistic regression and artificial neural networks are the most widely used and accurate models (Geng et al., 2015; Zizi et al., 2021). Logistic regression is a binary classification regression technique using a probabilistic model by assigning a non-linear maximum likelihood function to produce a probability of company failure, making the logit model a more useful model in predicting the possibility of a company's financial distress (Muparuri & Gumbo, 2022; Waqas

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& Md-Rus, 2018a). Artificial neural networks (ANN) are a method that operates similarly to a human brain system and is implemented using a computer program with several neurons to draw conclusions (Muparuri & Gumbo, 2022). ANN is a type of machine learning that can model more complex non-linear relationships between variables, providing better prediction accuracy than other simple machine learning methods (Alamsyah et al., 2021).

The purpose of this study is to develop an effective financial distress prediction model and to estimate the ideal level for industrial sector enterprises in Indonesia utilizing financial ratios. The ANN model and logistic regression were utilized to construct a financial distress prediction model to meet the research aims. This research is expected to contribute to the literature on accurate bankruptcy prediction models for industrial sector companies in Indonesia. It is envisaged that the research findings, particularly the best prediction model, will be beneficial in making strategic decisions by regulators, investors, and corporate management.

This article is organized as follows: Section 1 explains the research background, specifically the importance of developing an optimal model in predicting financial distress; Section 2 is a literature review on the prediction of financial distress and hypothesis; Section 3 presents the sample selection, variables determined, and methodology used; Section 4 provides and explains the results ; and section 5 presents the study's discussion & conclusions, suggestions, and limitations.

2. Literature and Hypothesis

This research employs signal theory to examine company actions in describing company conditions. According to Chabachib et al. (2019). the information provided by the company regarding the condition of the company becomes a determinant for investors when making investment decisions, so companies must manage their financial reports to produce quality information. Spence (1973) first introduced signal theory in his research, which revealed that companies send signals to users of financial statements in the form of good news as a positive signal and bad news as a negative signal.

Companies with a negative signal indicate that the company is in financial distress as a result of a decline in management performance or a financial crisis. Meanwhile, a healthy company provides a positive signal indicating good financial performance (Restianti & Agustina, 2018)the retained earnings to total assets, earnings before interest and tax to total assets , return on equity, debt to assets ratio, and total assets turnover against Financial distress. The population in this study is a sub company of various industry listed in In-donesia Stock Exchange (IDX. This is critical for investors and other businesspeople because it provides information about the company's past, present, and future conditions to represent prospects (Brigham & Houston, 2012).

Financial distress occurs when a company's sales value decreases due to a failure to market its products, indicating that the company is unable to manage and maintain the performance stability (Platt & Platt, 2006). Wruck (1990) argued that the condition of a company experiencing financial distress can be described by a negative company operating cash flow so that it cannot pay off its obligations and must make improvements. Therefore, companies need to predict financial distress in order to avoid bankruptcy in the future.

According to Lee (2014), financial distress prediction is the process of estimating future financial distress based on historical data using statistical techniques or machine learning to produce a quantitative model used to identify factors that will cause a company to go bankrupt in the future. Altman (1968) developed a Z-score model after first predicting company failure using several ratios simultaneously through multiple discriminant analysis. However, financial data cannot meet the statistical conditions required for multiple discriminant analysis. As a result, an explanatory variable with a normal distribution is required, and the variance-covariance matrix must be identical for a sample of companies that do not fail and a sample of companies that do fail, and the Z-score model is only suitable for linear classification (Zizi et al., 2021).

Furthermore, several statistical models have been developed based on different distributions of explanatory ratios, such as the widely used logistic regression. Ohlson (1980) was the first American to use logistic regression to predict financial distress. Logistic regression is a probabilistic method used to deal with binary classification problems such as business failure prediction. Afterwards, logistic regression has grown in popularity and has become one of the most widely used statistical methods for predicting business failure worldwide (Shi & Li, 2019).

ANN is currently a very well-liked prediction model due to the accuracy of its results in predicting failure (Mishraz et al., 2021). The principle of ANN is to develop algorithms that replicate the functions of the human brain in information processing (Zizi et al., 2021). Odom & Sharda (1990) were the first to introduce the use of ANN in business bankruptcy prediction. In addition, several authors have since used this model to predict both business success and failure using nonlinear and nonparametric adaptive learning systems. Jeong et al. (2012)the number of hidden nodes, and the value of the decay constant. This paper suggests a new approach to fine-tune these factors to improve their accuracy. For the input variable selection, the generalized additive model (GAM conducted their research using ANN, and they found promising results in terms of predicting business failures. Moreover, the results can be regarded as one of the machine learning techniques with a high level of predictability. A predictor variable is required to forecast business insolvency. Financial ratios and corporate governance are the most commonly utilized variables as predictors of bankruptcy in the literature on financial hardship (Kristanti et al., 2016). Financial ratios such those relating to liquidity, profitability, leverage, activity, and cash flow ratios are used in this study as predictor variables.

Previous studies comparing logistic regression and ANN have found that ANN is more effective at predicting financial distress than logistic regression models (Lin et al., 2011; Mishraz et al., 2021; Nur &

Panggabean, 2020)linear discriminant analysis (LDA. There are also studies that revealed the superiority of logistic regression accuracy over ANN, as well as studies that found the accuracy of logistic regression models and ANN was better than other financial distress prediction models (Altman et al., 2020; Kristianto & Rikumahu, 2019; Muparuri & Gumbo, 2022; Zizi et al., 2021). When compared to statistical methods, machine learning techniques can provide better performance in classifying distressed or non-distressed companies (Jones et al., 2017)regulators and financial economists over the past five decades. However, much of this literature has relied on quite simplistic classifiers such as logistic regression and linear discriminant analysis (LDA. On the other hand, statistical techniques are still widely used around the world in predicting business failures, and their accuracy and performance in predicting are comparable to machine learning techniques. Each prediction model has advantages and disadvantages that depend heavily on the methodology, variables and samples used to create a predictive model (Kovacova et al., 2019). Based on differences between previous studies in the context of the accuracy of logistic regression and ANN prediction models, this research used those techniques to predict the financial distress of Indonesian industrial companies.

In addition, the main objective of this research is to recommend an early warning model that is accurate and efficient in predicting financial distress in Indonesian industrial sector companies. It is expected that the results of this research can help shareholders, investors, banking institutions, auditors, and policymakers in making decisions and formulating policies by utilizing accurate early warning information to minimize the risk of business failure. Based on the elaboration of the framework of this research, the hypothesis proposed in this research is:

H_0: Logit has more predictive strength than Artificial Neural Network (ANN).

H_1: ANN has more predictive strength than Logit.

3. Method

This research used industrial companies listed on the IDX in 2017-2021 as research objects. The purposive sampling technique (the company must have complete data during the study period in order to meet the criteria) used in this research aims at determining the research sample, so the samples obtained in this research are as many as 40 issuers engaged in the industry with a research year for 5 periods.

3.1. Variable Analysis

Based on the data collected, this research was identified as a predictive indication as shown in Table 1, both for logistic regression and ANN. Especially for ANN, the five indications will then be entered into the MATLAB software, which is employed in this study to create a prediction model. The researchers then tested with the amount of hidden layers to create the optimal performance model, which was also done using MATLAB software. Following a protracted training process, the best prediction model was created, which would eventually be used to anticipate the financial difficulties of industry companies.

Table 1. Variable Analysis.

Indicator name	Description
Distress/Not Distress	The values of 1 for the distressed company and 0 for the non-distressed company.
Current Ratio (CR)	
Return on Assets (ROA)	
Debt to Assets Ratio (DAR)	
Total Assets Turnover (TATO)	
Cash flow from Operating to Total Liabilities (CF)	

After obtaining the best model, it will apply it to Indonesian industry companies Furthermore, it performs the procedure of manually entering the five financial ratio indicators from each industry company into the ANN algorithm produced in MATLAB program. Thus, the output of each company with a range of 0 to 1 is obtained, determining if the company is in financial distress. Output close to 0 indicates that the company is not in financial distress, whereas output close to 1 indicates that the company is in financial distress. It will apply the finest model to Indonesian construction enterprises after receiving it.

3.2. Data Analysis Method

In order to find the best financial distress prediction model, this study combines two analytical techniques, namely Artificial Neural Network Backpropagation and Logistic Regression.

3.2.1. Logistic Regression model

Logistic regression, also known as the logit model, is a binomial regression model that is widely used in many fields. This model has been used many times in the past for distress prediction because of its simplicity in implementation and interpretation of results (Muparuri & Gumbo, 2021; Zhou & Gumbo, 2021; Zizi et al., 2021). The formal expression of the model is:

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$$Ln\frac{p}{1-p} = \beta_0 + \beta_1 CR + \beta_2 ROA + \beta_3 DAR + \beta_4 TATO + \beta_5 CF$$

(1)

and

$$p = \frac{n(n-1)x^2}{1 + b^{-(\beta_0+\beta_1 CR+\beta_2 ROA+\beta_3 DAR+\beta_4 TATO+\beta_5 CF)}}$$

where usually b = e

3.2.2. Artificial Neural Network Backpropagation model

There are two types of research samples: testing data samples and training data samples. Training data, which is used in the modeling process. Using the BPNN approach, this data is used to calculate the optimal weight. Testing data, which is employed in the model testing procedure. After creating the final model, this data is utilized to predict the error rate.

Purposive sampling criteria were utilized in data testing, which included industrial enterprises listed on the Indonesia Stock Exchange with complete data from 2017 to 2021 and collected 40 companies as data testing samples. Training data is used to identify companies that are distressed or non-distressed. This study employs publicly traded companies from around the world that issued financial reports between 2016 and 2020 as training data samples. Based on these parameters (Table 2), 20 companies were obtained, with 10 distressed and 10 non-distressed.

Table 2: Selection Standards for Training Data Samples

No.	Criteria	
	Distress Company	**Non-distress Company**
1.	Public companies were declared to be in financial difficulty in 2021.	Public companies did not indicate financial difficulties in 2021.
2.	Companies that issue financial reports for the 2016-2020 fiscal year	Companies that did not issue financial reports for the 2016-2020 fiscal year
3.	Having a current ratio value below 100% in the five-year period prior to being declared distressed.	Having a current ratio value above 100% in the five-year period prior to being declared distressed.
4.	Has a negative return on assets in the five-year period before being declared distressed.	Has a positive return on assets in the five-year period before being declared distressed.
5.	Having a debt-to-assets ratio above 50% in the five-year period prior to being declared distressed.	Having a debt-to-assets ratio below 50% in the five-year period prior to being declared distressed.
6.	Having a total asset turnover value of less than 45% in the five years preceding the occurrence of distress.	Having a total asset turnover value of more than 45% in the five years before the declaration of distress
7.	Has a negative cash flow value from operating to total debt in the five-year period before being declared distressed.	Has a positive cash flow value from operating to total debt in the five-year period before being declared distressed.

ANN is a type of machine learning in the form of a mathematical model similar to a biological neural network. ANN consists of artificial clusters of neurons that are interconnected and process information using a connectionist computing approach. In contrast to traditional expert systems, ANN is developed and managed so that the system can generalize data (Kristanti et al., 2023). Several steps must be taken in order to obtain the best ANN Backpropagation model (Kristianto & Rikumahu, 2019):

1. Determining the network layers, namely input, hidden and output layers.

2. Normalizing the data, so that it can be compared to the value of the activation function.

3. Weighting and bias allocation with random values are then adjusted during training iterations.

4. Determining the activation function.

5. Determining the optimization method.

6. Modifying the value of learning rate, training cost and number of trainings iteratively to find the best predictive performance using MSE.

3.3. Performance Measures

Based on research by Hsiao & Gao (2016) and Korol (2019), including the confusion matrix that served as the basis for calculating the performance of the prediction model, as shown in Table 3, the metrics used to compare the performance of the two models. True Positives (TP) are the number of observations that are correctly predicted as distress and are observed as distress; False Positive (FP) shows the number of predictions that predict distress but are non-distress; True Negative (TN) represents the number of observations that are predicted as non-distress but are non-distressed; and False Negative (FN) represents the number of observations that are predicted to be non-distress but are distressed. Accuracy is the proportion of cases that are correctly categorized; sensitivity is the proportion of cases that are correctly identified as positive; and specificity is the proportion of cases that are correctly recognized as negative. In addition to accuracy, sensitivity, and specificity, the ROC curve is used to find the best model when comparing models. The area under the ROC curve, also known as the Area Under Curve (AUC) is a measure of accuracy. The confusion matrix in Table 3 is used to assess the performance of the ANN model.

Table 3: Confusion Matrix

Actual	Prediction	
	Non distress	Distress
Non Distress	TN	FP
Distress	FN	TP

4. Results

4.1. Descriptive Statistic

According to descriptive statistics (Table 5), the average company in this industrial sector is very liquid, as evidenced by an average CR greater than one. With an average DAR of 57.55%, the ordinary corporation is likewise relatively careful with its debt. The total asset turnover of 86.22% indicates that assets' ability to develop a company is not very excellent, given that the maximum value is 510%, even though the average ROA is still positive at 1.32%.

Table 4. Descriptive statistics of testing data sample.

	N	Minimum	Maximum	Mean	Std. Deviation	Variance
CR	200	0.08	421.99	4.8825	31.72931	1006.749
ROA	200	-1.22	0.51	0.0132	0.16288	0.027
DAR	200	0.01	2.76	0.5755	0.44631	0.199
TATO	200	0.00	5.10	0.8622	0.77667	0.603
CF	200	-110.31	2.57	-0.4211	7.82652	61.254

4.2. Logistic Regression

Significant ratios in the logistic regression model are presented in Table 5. The variables CR, ROA, TATO and cash flow from operating to total liabilities had a negative effect on financial distress, meanwhile, DAR had a positive impact on financial distress. ROA and DAR had significant effect on the possibility of financial distress.

Table 5. Logit model significant term.

Significant term	Coefficient	S.E	Sig.
Current Ratio	0.021	0.313	0.947
Return On Assets	-159.734	39.668	0.000
Debt to Assets Ratio	-2.639	2.598	0.310
Total Assets Turn Over	0.755	1.013	0.456
Cash flow from operating to Total Liabilities	-1.060	2.049	0.605
Constanta	-0.490	1.866	0.793

Notes: * p<0,1, ** p<0,05, *** p<0,01***)

The table 6 shows 49 company data points that are correctly classified as being in financial distress, 1 company data point that is incorrectly classified as being in financial distress, and 147 company data points that are correctly classified as not being in financial distress, but there are 3 company data points that are incorrectly classified as non-distress companies. As a result, the logit model has an accuracy rate of 98% (196/200).

Table 6. Confusion matrix for Logit

Actual Class	Predicted Class	
	Negative	Positive
Negative	147	1
Positive	3	49

4.2. Artificial Neural Network Backpropagation

To measure ANN prediction performance, the R value (correlation coefficient) and the MSE value (mean square error) were used. If the MSE value was small and the R value between the target value and the output during training was large, the ANN model had good accuracy. Table 7 shows the best performing ANN training model with an architecture of 20 neurons.

Table 7. Comparison of MSE and R results in training model.

Total Neuron		Error (MSE)	(R %)
Input Layer	Hidden Layer		
25	10	0.0044	99.54
25	15	0.0025	99.95
25	20	0.0001	100,00*
25	25	0.0013	99.85
25	30	0.0021	99.97
25	35	0.0061	99.93
25	40	0.0010	99.99
25	50	0.0041	99.77
25	55	0.0006	99.91
25	60	0.0080	99.97

After the data training procedure is completed and the ANN architecture (which meets the error criteria) is created, the process of applying it to the sample testing data begins. This is known as the financial distress prediction process for the study item. The resulting output value is used to make predictions. An output value near to or equal to 0 indicates that the company is not in financial crisis. An output value near to or equal to 1 indicates that the company is in financial distress.

The optimal design for processing data with ANN is 25-20-1 (Table 8), where 25 is the total number of neurons in the input layer, 20 is the total number of neurons in the hidden layer, and 1 is the total number of neurons in the output layer. This design works best because it has the lowest error rate, with an MSE of 0.0001. Next, evaluate the ANN architecture's performance by examining the model's accuracy using the confusion matrix.

Table 8. Confusion matrix data testing for ANN.

Actual Classification	Predicted Classification	
	Negative	Positive
Negative	123	27
Positive	8	42

Based on the confusion matrix of the testing data (displayed in Table 10), 42 testing data were classified as suffering financial distress and 123 testing data were classified as non-distress. These findings imply that the ANN model's level of accuracy in data testing is 82,5% (165/200).

4.3. Performance analysis

The performance matrix in Table 9 provides a summary of the performance comparison between the two prediction models. According to the findings of this study, the Logit model outperforms the ANN model in terms of accuracy (98%), sensitivity (94%), and specificity (99%), with a difference of 15% accuracy, 10.50% sensitivity, and 17% specificity.

Table 9. Comparison of Logit and ANN in performance measurement results**.**

Metric	Logit Results	ANN Results	Difference
Accuracy	98.00%	82.50%	15.00%
Sensitivity	94.20%	84,00%	10,50%
Specificity	99.30%	82.00%	17.00%

5. Discussion and Conclusions

The purpose of this study is to evaluate the bankruptcy prediction model's precision in order to reduce the likelihood that industrial enterprises in Indonesia may experience financial trouble in the future. Using ANN and logistic regression analysis methodologies, performance reveals that the Logit model outperforms the ANN model. The data analysis results indicate that the null hypothesis is not true, and they come to the conclusion that the logit model outperforms the ANN model in terms of predicting financial distress in industrial companies listed on the IDX. Overall, the study's goals were met, and they can serve as the foundation for creating an ANN-based early warning prediction model, particularly for Indonesia's industrial sector.

The study's findings that the logit model has higher accuracy than the ANN model are consistent with the findings of Muparuri & Gumbo's research (2022), and Zizi et al. (2021), but inversely proportional to the findings of Mishraz et al. (2021), Nur & Panggabean (2020), who discovered that the ANN model has higher accuracy than the Logit model. Therefore, investors or company management could use the logit model to predict financial distress as an early warning syatem. In order to avoid future business failures and make it simpler for management to decide on financial strategy, the company has chosen an accurate predictive model. The model put forth in this study may help investors evaluate the financial health of a firm and choose which investments to make in order to prevent capital losses. By evaluating the risk associated with the company in order to prevent losses, the study's findings can also help creditors decide whether or not to extend credit. Likewise, regulators can use ANN to predict companies that are experiencing financial distress and make regulations for prevention before companies become bankrupt. because bankruptcy will have a heavy impact on both society and the economy of a country.

The lack of information in this study is a limitation, but the findings might be enhanced by using different variables to compare the relative effectiveness of the financial distress prediction model, a larger sample size, and better methodologies. The model with the best performance can then be obtained by combining it with additional machine learning experiments.

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