

# Accuracy of Financial Distress Model Prediction: The Implementation of Artificial Neural Network, Logistic Regression, and Discriminant Analysis

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## ABSTRACT

The ability to predict financial failure forms an essential topic in financial research. The various models developed to predict the occurrence of Financial Distress and serve as an early warning system for the company's stakeholders before bankruptcy occurs. Enhanced accuracy of the predictions improves the ability to mitigate its adverse effect. This study aims to build Financial Distress models using Artificial Neural Network Model, Logistic Regression, and Discriminant Analysis, based on samples taken from manufacture sectors in the Indonesia Stock Exchange in the period 2015-2018. Accuracy of the three techniques in predicting Financial Distress are compared and results indicate Artificial Neural Network Model gave a better performance than the other techniques. It is crucial to consider the choice of predictor variables that determined the success of the financial distress model.

**Keywords:** Financial Distress Model, Artificial Neural Network, Logistic Regression, Discriminant Analysis

## 1. INTRODUCTION

Assessment to measure the company's financial strength has become the domain for external parties such as investors, creditors, auditors, regulators, and other companies' stakeholders, being the ones bearing the highest risk if financial difficulties occur [1]. Such analysis is used as an early warning system to mitigate the adverse effects financial distress towards business stability and growth [2]. An accurate measurement model is needed to predict such conditions.

Various financial distress models have been developed and tested. The accuracy and predictive performance of these models depend on the set of predictors, the selection of sample data, and the classification techniques being utilized. The general predictors used for these models are financial ratios, which are further divided into financial ratios, market ratios, and macroeconomic ratios. Resulting studies show differences in the predictive power of each variable [3].

Besides the predictors, the technique used to classify sample data also determines the performance of the models. Two classification techniques presently exist, namely, statistics and machine learning. At the initial stages, research on financial distress uses statistical classification techniques. Beaver [4] developed the Univariate model for prediction of financial difficulties while Altman [5] applied the Multiple Discriminant Analysis (MDA), producing a Z-score Model. Subsequent research was carried out by Ohlson and Smijewski by developing the Logit and Probit models [6,7]. The research further evolved with the help of computer

sciences, establishing the use of artificial intelligence algorithms to identify the financial health of a company, one of which is Artificial Neural Networks (ANN) [8].

Nevertheless, an analysis of the company's financial condition based on statistical techniques is still being carried out. Among them are by directly applying the Altman formula to their country data to obtain predictions of the classification of groups of companies with financial distressed and non-financial distressed conditions [9][10]. Considering that each capital market in each country may have its uniqueness the generic application of Altman's formula to predict firm's financial conditions could provide a biased result. Alternately there are also attempts to compare the prediction performance of financial distress models between statistical techniques (MDA and Logistic regression) and Machine Learning (Decision Tree, Neural Network, and Support Vector Machine). The overall results have indicated that machine learning based on technique is superior compared to the statistical-based method [11,12]. Therefore, this study aims to develop and compare the performance of financial distress prediction models based on Multiple Discriminant Analysis, Logistic, and Artificial Neural Network techniques. We applied two models to examine the predictive performance of each method. The first model (Altman Model) used Altman variables as predictors of Financial Distress, whereas the second model (Alternative Model) used some other financial ratios estimated through the stepwise selection method.

## 2. METHOD

### 2.1. Sample

This study uses secondary data taken from the financial statements of public companies of the Indonesia Stock Exchange, whose shares registered in 2015-2018.

Companies that experience financial distress are defined as those that suffer losses amounting to 50% of capital; and or extending for three consecutive years [3].

## 2.2. Research Models

To test the prediction accuracy of the company's financial distress, the Altman Model, and an Alternative Model will be used. Predictors used in Model 1 are Altman's financial ratios. Following the methodology provided by Chung [13], the number of independent variables/ predictors in Model 2 was reduced. The process of determining the best predictor is done using stepwise discriminant analysis. So from these variables, the discriminant function is formed [14]. The analysis is done based on a limited assumption that the discriminant variable must be multivariate normal, signifying specific requirement so the results correctly obtained.

## 2.3. Prediction Techniques

Multiple Discriminant Analysis (MDA): MDA is a parametric technique used to examine of the dependence of one qualitative (classification) variable from several quantitative variables. It is the most commonly used method for financial distressed analysis. The model of discriminant analysis is as follows:

$$Z = \alpha + \beta_1 X_1 + \beta_2 X_2 + \dots + \beta_i X_i \quad (1)$$

where, Z= discriminant score,  $\alpha$  = a constant term,  $\beta_i$  = the discriminant coefficient or weight of the variable,  $X_i$  = predictor or independent variable, i = number of predictor variables; i = 1,2,3,...k.

### 2.3.1. Logistic Regression (LR):

Binary logistic regression analysis is used to explain the relationship between response variables in the form of dichotomic/binary data with independent variables in the form of interval and or categorical data. Logistic regression analysis works with non-linear relationships and uses the cumulative logistic function for bankruptcy prediction with the help of the following formula:

$$Pr(solvent) = \frac{e^z}{1+e^z} = \frac{e^{\beta_0 + \sum(\beta_j x_j)}}{1+e^{\beta_0 + \sum(\beta_j x_j)}} \quad (2)$$

Where  $\beta_j$  is the regression parameter,  $x_j$  is the independent variable, j = 1, ..., m where m is the sum of the financial ratios

### 2.3.2. Artificial Neural Network (ANN)

Artificial neural network system (ANN) is a computer algorithm that can be 'trained' to mimic neural networks in the human brain[13][14]. The results of network processing come from the collective behavior of the units and depend on how the groups interact with each other [13][15]. By processing and evaluating interactions in previously complex data sets, the neural network tries to assign the right weights to each input to enable the correct reduction of the final result. These input weights are aided by the 'genetic algorithm' optimization procedure, which simulates the predictive power of the model under a large number of scenarios and allows the best weighting scheme to survive and reproduce from one generation to the next [16].

## 2.4. Performance Comparison

The accuracy of financial distress prediction schemes in this study uses four performance metrics, namely: accuracy, precision, sensitivity, and specificity [11]. This metric is estimated based on true positive (TP), true negative (TN), false positive (FP), and false negative (FN) calculations. The formula of the four metrics is as follows:

$$accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (3)$$

$$precision = \frac{TP}{TP+FP} \quad (4)$$

$$sensitivity = \frac{TP}{TP+FN} \quad (5)$$

$$specificity = \frac{TN}{TP+FP} \quad (6)$$

## 3. RESULTS AND DISCUSSION

### 3.1. Statistics Descriptive

The data in Table 1 shows the descriptive statistics of 2 groups of companies. The mean of all financial distress company's indicators is below the non-FD company. The FD company's financial ratio shows that the company is experiencing problems with liquidity, profitability, activity, leverage, and market ratios.

**Table 1.** Descriptive statistics

Ratios	Var	Non FD		FD	
		Mean	SD	MEAN	SD
LIQUID	CASH/CL	0.604	0.84	0.211	0.436
	CR	23.852	9.257	11.523	1.381
	QUICK	1.521	1.191	0.806	0.931
	WCSALES	0.261	1.048	-0.627	4.068
	WCTA	0.218	0.211	-0.011	0.23
ACTIVE	DAYSALLES	77.066	52.576	134.372	41.655
	INVTO	6,786	7.592	6.299	9.075
PROFIT	EBITTA	0.08	0.165	-0.02	0.07
	GPM	23.397	14.605	6.795	24.656
	NPM	4.884	4.335	-33.4	14.906
	OPM	4.835	85.15	-45.385	21.778
	PROFITTE	0.104	0.1567	-0.961	7.119
	RETA	0.276	0.250	-0.513	0.732
	ROA	5.455	5.490	-3.492	5.944
	ROE	10.542	14.636	-77.772	20.4906
SOLVABLE	SALESTA	0.913	0.858	0.872	1.272
	DAR	0.452	0.211	0.707	0.363
	DER	1.117	2.031	2.812	32.308
	LTDTE	0.309	0.668	0.963	14.505
MARKET	DPR	45.949	25.473	0.501	5.728
	DYIELD	1.033	1.515	0.041	0.481
	EPS	19.361	11.763	-34.219	2.984
	PBV	2.635	8.118	2.892	12.535
	PER	28.651	11.202	-1.771	1.336

### 3.2. Multiple Discriminant Analysis (MDA)

The Distressed Financial Prediction Model developed based on the Altman variable is as follows:

$$Z = 0.089 + 0.012pbv + 0.54re/ta + 1.05wc/ta + 2.36ebit/ta + 0.42sales/ta \quad (7)$$

The function has a cutting score of 0.591 for non-FD companies and -1.309 for FD companies. Alternative Models developed based on the stepwise selection technique get the following models:

$$Z = -1.147 + 0.262quick + 0.527cash/cl + 0.318sales/ta + 1.653re/ta \quad (8)$$

The function has a cutting score of 0.704 for Non-FD companies and -1,559 for FD companies. The following table is the prediction accuracy of the Multiple Discriminant Analysis technique.

**Table 2** MDA prediction accuracy

Model	Fin.Status	Predicted		Total
		FD	NonFD	
Altman	FD	56	75	131
	NonFD	11	279	290
Alternative	FD	82	49	131
	NonFD	10	280	290

### 3.3. Logistic Regression (LR)

The Altman Model and Alternative Models are also applied to logistic regression to develop a Financial Distress prediction model, as below:

Altman Model:

$$Z = 0.31 + 0.27salesta + 7.33ebitta + 1.43wcta + 1.41reta + 0.03pbv \quad (9)$$

Alternative Model:

$$Z = 0.45 + 192reta + 0.615roa + 0.966salesta + 2.943 cash/cl + 1.517quick \quad (10)$$

The Z score obtained from the model can be transformed into a probability using the logistic transformation  $P = 1 / (1 + e^{-z})$ . The following table represents the performance of logistic regression prediction techniques.

**Table 3.** LR prediction accuracy

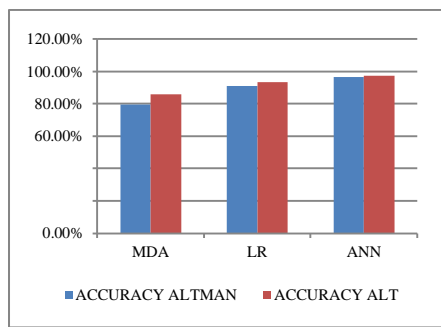
Model	Fin.Status	Predicted		Total
		FD	NonFD	
Altman	FD	107	24	131
	NonFD	13	277	290
Alternative	FD	113	18	131
	NonFD	9	281	290

### 3.4. Artificial Neural Network (ANN)

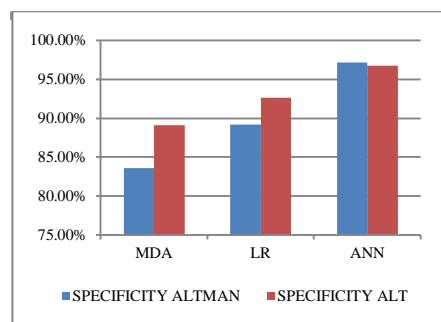
The Altman Model and Alternative Models are also applied to ANN to develop a Financial Distress prediction model, as in Table 4. At the neural network, the research sample is divided into 297 training samples and 124 testing samples, on the Altman model, 214 training samples, and 108 testing samples on Alternative Models.

**Table 4** ANN prediction accuracy

Model	Sample Type	Fin.status	Predicted		Total
			FD	NonFD	
Altman	Training	FD	85	14	94
		NonFD	8	195	203
	Testing	FD	34	3	37
		NonFD	1	86	87
Alternative Model	Training	FD	85	14	94
		NonFD	11	203	214
	Testing	FD	30	2	32
		NonFD	1	76	76



**Figure 3** Sensitivity comparison



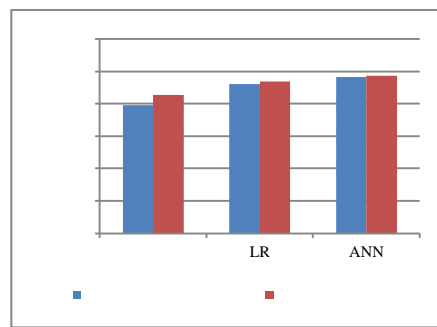
**Figure 5** Average performance of 4 metric

### 3.5. Comparative Result

In this section, we compared the results of the two methods; each method will use the Altman model and an alternative model (stepwise selection). The results of the accuracy of financial distress predictions will be displayed using performance accuracy, precision, sensitivity, and specificity at Tables 5 & Figures 1-5.

**Table 5** Comparison of prediction accuracy

Model	Tech.	Accuracy (%)	Precision (%)	Sensitivity (%)	Specificity (%)
Altman	MDA	79.57	78.81	96.21	83.58
	LR	91.21	92.03	89.17	91.98
	ANN	96.77	96.63	98.85	97.14
Alt.	MDA	85.99	85.11	96.55	98.13
	LR	93.59	93.98	98.90	92.62
	ANN	97.22	97.40	98.68	96.77



**Figure 4** Specificity comparison



#### 4. CONCLUSION

ANN prediction performance outperformed two other methods in the four metrics, accuracy, precision, sensitivity, and specificity. In the ANN technique, the selection of both Altman and Alternative models did not make a significant difference in predictive performance. ANN carries out weighting techniques on each layer to produce the best output. Each model assigns a sequence of importance to each of its predictors to provide the best prediction accuracy for both models. LR prediction performance is better than MDA, especially in three metrics, namely accuracy, precision, and specificity. The choice of predictor is very decisive on predictive techniques based on statistics. The Alternative Model provides better prediction accuracy than the Altman Model in both the LR and MDA methods. The predictors must describe the real condition of the object of research. So that alternative models are more appropriate to be applied to the firms' financial prediction models.

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