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Analysis of Financial Distress Predictions Using Altman, Zavgren, Fulmer, Ohlson, Taffler, and Ca-Score Models as Early Warning Systems in Manufacturing Companies

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ABSTRACT

This research aims to analyze the application of the Altman, Zavgren, Fulmer, Ohlson, Taffler, and CA-Score models as early warning systems, as well as the differences in the ability of the accuracy level of the six early warning system models to predict financial distress and which of the six prediction models is most accurate and is most accurate in predicting financial distress. The sampling technique in this research was with purposive sampling criteria. The analysis technique is to use financial distress prediction models. The results showed that the highest and most reliable method for forecasting financial trouble in this research was the CA-Score model which had an accuracy rate of 97.14% and error type II of 2.86%. compared to Altman, Zavgren, Ohlson, Taffler, and CA-Score models. Then, followed by the Ohlson model whose accuracy rate is 94.29% and error type II of 5.71%.

ABSTRAK

Penelitian ini bertujuan untuk menganalisis penerapan model Altman, Zavgren, Fulmer, Ohlson, Taffler, dan CA-Score sebagai early warning system, serta adanya perbedaan kemampuan tingkat akurasi dari keenam model early warning system dalam memprediksi financial distress dan manakah diantara enam model prediksi yang mempunyai tingkat akurasi tertinggi dan paling akurat dalam memprediksi financial distress. Teknik menentukan sampel pada penelitian ini dengan kriteria purposive sampling. Teknik analisis ialah menggunakan model-model prediksi financial distress. Hasil penelitian menunjukkan kalau model tertinggi dan sangat akurat dalam memprediksi financial distress untuk studi penelitian ini adalah model CA-Score yang tingkat akurasi sebesar 97,14% dan tipe error II sebesar 2,86%. dibandingkan model Altman, Zavgren, Ohlson, Taffler, dan CA-Score. Kemudian, diikuti model Ohlson dengan tingkat akurasi sebesar 94,29% dan tipe error II sebesar 5,71%.

1. Introduction

Each business group must improve operational efficiency in the era of global business competition to achieve its goals. To compete in the free market (AEC), the food and beverage industry is classified as very competitive. This development gave rise to competition between companies. For a company to be competitive, the company must also pay attention to its own financial management (Nurdyastuti & Iskandar, 2019). Financial management is carried out to evaluate the condition of the firm's anticipation of the occurrence of financial distress (financial difficulties) that could end in bankruptcy. This is given the no small phenomenon of financial distress experienced by companies in Indonesia, one of which is listed in the IDX.

This has been demonstrated in companies registered in the IDX such as the company Tri Banyan Tirta Tbk (ALTO), PT Berlina Tbc (BRNA), PT Panasia Indo Resources (HDTX), PT Hero Supermarket (HERO), PT Langgeng Makmur Industries (LMPI) and PT Asia Pasific Investama (MYTX) that have experienced a decline in revenue for five years in a row. Therefore, a company must be able to control and evaluate a company under various circumstances. This is evidenced in the company PT. Tri Banyan Tirta Tbk (ALTO) PT. Berlina Tbk (BRNA), PT. Panasia Indo Resources Tbk (HDTX), PT Hero Supermarket Tbk (HERO), PT. Langgeng Makmur Industri Tbk (LMPI) and PT. Asia Pacific Investama Tbk (MYTX) which experienced a decline in revenue for five consecutive years. Therefore, companies must be able to control and evaluate companies in certain circumstances.

One of the tools used by the company in evaluating the condition of the firm is the annual finance report. Comparing the financial statements in the previous period with this period, the company can see a better picture of the company's current condition. According to Brimantyo et al., (2013) analyzing and predicting financial conditions is very important for assessing the success of a company, not only for shareholders and creditors but for the company itself. To predict impending bankruptcy, this approach is very important. Analyzing a company's financial statements will reveal the level of its financial health. If the company enters a period of financial distress and is not immediately handled will lead to bankruptcy.

However, in 2017 PT. Sorini Agro Asia Corporindo Tbk (SOBI) which operates in the basic & chemical industry sector and PT. Taisho Pharmaceutical Indonesia Tbk (SQBB), which operates in the pharmaceutical subsector delisting from IDX due to experiencing financial distress. Then in 2018, PT. Dwi Aneka Jaya Kemasindo Tbk (DAJK) which operates in the basic & chemical industry sector delisting from IDX due to experiencing financial distress (financial difficulties) and unable to pay large debt bills so the company was declared bankrupt. DAJK was declared bankrupt by the Central Jakarta Commercial Court on November 23th, 2017. This was because the court accepted the request to cancel the peace agreement by PT Bank Mandiri Tbk (BMRI) as DAJK's creditor (Sugianto, 2018). Further, followed in the year 2018 also PT. Jaya Pari Steel Tbk (JPRS) moved the basic industry sector & chemical delisting due to financial distress (financial difficulties), so the company decided to make a merger with PT Gunawan Dianjaya Steel Tbk (GDST). It points out that manufacturing companies also need special attention regarding financial distress issues.

Financial distress defined when the company is in financial trouble and fails to fulfill its obligations to creditors (Edi & Tania, 2018). Circumstances financial distress can be divided into two groups namely solvency (solvency) and insolvency. Financial problems can be detected by several systems that can provide an early warning system that must be developed to be able to predict case of financial difficulties (financial distress) before bankruptcy happens. Research about financial distress and corporate bankruptcy has mushroomed since the classic study by Beaver (1966) and Altman (1968). Analysis of financial distress has a variety of prediction models that can be used to anticipate a company's financial trouble. Model analysis is an analysis that is often known and used because apart from being an easy measurement method, the level of accuracy in determining predictions is also quite accurate. This analysis model is made and adjusted through consideration of financial ratios in identifying the final result of the prediction itself. However, these models have their advantages and disadvantages in determining the model. So, by doing a comparison of this analysis model, it can be seen the differences of these anticipating financial hardship in manufacturing enterprises using models.

Previous research has compared or analyzed the financial distress prediction model using several models, as done by Komarudin et al., (2019) showing that the Altman model itself has the best prediction rate. Similar research by Pangkey et al., (2018) found that Altman's approach (Z-Score) is consistently more accurate than other analytical models. Widiasmara & Rahayu (2019) compare the Ohlson, Taffler, and Springate models. The taffler models produce the highest level of accuracy. Masdiantini & Warasniasih (2020) yield the result that the taffler, Fulmer, and Zmijewski models all have results with a 100% degree of accuracy. The study Elvama et al., (2021) showed that the Ohlson model is the best in predicting a company's financial distress. However, the results of study Wahidah (2021), show that the most accurate models in forecasting financial distress are the Ohlson and CA-Score models, with a 100% accuracy rate and a 0% error rate. Nenengsih (2018) in his research results cited that CA-Score is the best predictor of delisting.

This research refers to research conducted by Masdiantini & Warasniasih (2020) and Hantono (2019) with several differences. In this study, researchers used six analytical models with the use of other analytical models such as Zavgren, Ohlson, and CA-Score in manufacturing companies. This study aims to analyze predictions of financial distress by using the Altman, Zavgren, Fulmer, Ohlson, Taffler, and CA-Score models, and to find the prediction model with the highest degree of precision and the most accurate of the six prediction models for financial distress in Manufacturing firms for the 2017-2021 Period.

According to what has been stated above, the researcher feels that it is very important to be able to research on how to apply the Altman, Zavgren, Fulmer, Ohlson, Taffler, and CA-Score models as early warning system in predicting financial distress in Manufacturing Companies, and there are differences in the degree of precision of the six models early warning system in predicting financial distress and which of the six prediction models possesses the highest degree of precision and is most adept at identifying financial trouble.

The objectives of this research are: (1) to analyze the application of the Altman, Zavgren, Fulmer, Ohlson, Taffler, and CA-Score models as an early warning system in predicting financial distress in Manufacturing firms for the 2017-2021 period; (2) to determine the difference in the ability of the accuracy level of the six models early warning system in predicting financial distress in Manufacturing firms for the 2017-2021 period; (3) to find out which of the six prediction models has the highest and most accurate the degree of precision in identifying financial trouble in Manufacturing firms for the 2017-2021 Period.

2. Literature Review

2.1. Signal Theory

Signal theory is one of the theories that will be applied in this study. Michael Spence developed the signal balance theory in 1973. Based on Spence (1973), the signal theory is a signal sent by management in response to relevant information collected by investors and is known as signal theory. Understanding signaling theory requires determining how a company is required to send "signals" to the benefit of users of financial statements. It would be very interesting for investors or other shareholders if management always publishes personal information about its interests, especially if the information is a positive signal (Susilawati, 2019).

The connection between this research and signal theory is when analyzing predictions of financial distress implemented and providing predictive results that can be used to describe the companies analyzed that did not experience financial distress, then the company sends a positive signal for each user's financial statements. Conversely, if the prediction analysis findings show that the company being analyzed is experiencing financial distress, then the company sends a negative signal to each user of financial statements (Kusumaningtyas, 2017).

2.2. Stakeholder Theory

According to Freeman & McVea (2001), stakeholders namely each group of people or individuals can influence the achievement of organizational goals of a company. Theory stakeholder defines which group is responsible for the corporation (Freeman, 1984). Theory stakeholder states that the company must be able to provide benefits to the stakeholder besides operating for its benefit. In this theory, it is also explained that a company is not only an entity that carries out its operational activities for personal gain but must be able to provide benefits to every stakeholder (such as investors, creditors, customers, suppliers, government, community, and other parties).

Management is required to present its financial reports transparently, because information from financial accounts can be used to determine whether the firm is in good or bad condition (financial distress) (Komarudin et al., 2019). Companies in financial distress are more likely to get an early warning because companies experience a lack of cash flow to meet their current obligations or run their business, so they may end up at risk of bankruptcy. According to this theory, company executives are only responsible for improving company performance and increasing company value in the eyes of the stakeholders to avoid causing financial distress.

2.3. Financial Distress

There is no one specific meaning for all definitions of financial distress since Beaver (1966) conducted a study on his research subject. As a result, every economist has a different definition of financial distress. According to Anggarini & Ardiyanto (2010), financial distress is a financial situation in which the firm's finance are not in a healthy condition or are in crisis. Before bankruptcy or liquidation occurs, a company is in financial trouble. Edi & Tania (2018) stated financial distress refers to a scenario where a company is defined as being in financial difficulty and failing to fulfill its liability to creditors. The firms can be said until condition financial distress if they are no longer able to bear the obligation must be remunerated in running their firms. This situation is a consequence of the company's inability to recompense bills on time.

2.4. Altman Model

According to Al-Sulaiti & Almwajeh (2007), Edward Altman is a professor and economist at New York's Stern School of Business and who introduced the Altman model in 1968. Initially, Altman only introduced this model based on the company's manufacturing sector, after that modifications were made for various company sectors. In 1968, the first time Altman implemented Multiple Discriminant Analysis which has a rate of accuracy of 72% in the prior two years company experienced financial distress. Similar to logistic regression, a statistical method that is widely used to form formulas in which an is the dependent variable qualitative variable. The output of the MDA method is a linear analogy that can tell the two apart conditions of the a dependent variable.

Various studies that were repeated by Altman showed that the accuracy of the model was estimated at 80 to 90% with predictive conditions of financial distress at the time one year before the firms for bankruptcy. Altman conducted research by assessing current financial ratios and creating a model capable of predicting whether a company might go bankrupt or not. This model can determine whether high chances of the firms failing exist or not. The following is the equation of the Altman model:

$$\mathbf{Z= 0{,}717X_1 + 0{,}847X_2 + 3{,}107X_3 + 0{,}420X_4 + 0{,}998X_5} \quad \text{............} \quad (1)$$

Information:
X_1: Working Capital / Total Assets
X_2: Retairned Earning / Total Assets
X_3 : Earnings Before Interest and Taxes / Total Assets
X_4 : Book Value of Equity / Book Value of Debt
X_5 : Sales / Total Assets

The Altman Z-score model classifies the values cut off <1.23 then the company is expected to encounter financial difficulty. If 1.23 - 2.90 then it will be classified as a grey area (prone areas) experiencing financial distress, whereas > 2.90 is classified as a good company or will not experience financial distress.

2.5. Zavgren Model

In the 1980s logit translation (Logit Analysis) apart from multiple discriminant analyses used to build research study methodologies that were relatively new in calculating the potential for financial trouble (Financial distress). Christine V. Zavgren is the developer of the first logit analysis, which surveyed 45 insolvent and non-bankrupt companies, considering industries similar in asset size. As a result, Zavgren made an estimation model for 5 years to see probability and level of precision the models. The model in year 1 can be used because the model in year 1 has significant results (greater percentage rate of 99%) in differentiating between bankrupt and non-bankrupt companies for 5 years. Zavgren (1985) defines a formula used in calculating a company's likelihood of going bankrupt, namely:

$$\boxed{P_i = \frac{1}{1 + e^y}}$$

Description: e = 2.718282

If the Y value has been obtained, then proceed to determine the probability of bankruptcy using the logit model. P_i is a bankruptcy probability formula for the company. The power of y is the multivariate part in which there is only one constant and several independent variable coefficients.

$$\mathbf{Y = 0{,}23883 - 0{,}108X_1 - 1{,}583X_2 - 10{,}78X_3 + 3{,}074X_4 - 0{,}486X_5 - 4{,}35X_6 + 0{,}11X_7} \;\ldots\ldots\ldots (2)$$

Information:
X_1 = Inventory/Sales
X_2 = Receivable/Inventory
X_3 = Cash/Total Assets
X_4 = Current Asset/Current Liabilities
X_5 = Net Income/(Total Assets-Current Liabilities)
X_6 = Long Term Liabilities/(Total Assets-Current Liabilities)
X_7 = Sales/(Working Capital+Fixed Asset)

The Zavgren model classifies that if the probability value results in a value of 1, the company is classified as suffering financial distress. If the probability scale produces a value below 1, then the company is classified as good.

2.6. Fulmer Model

Fulmer's model is a model made by Fulmer in 1984. Fulmer's bankruptcy model H-score with multistep discriminant analysis (Stepwise Multiple Discriminant). Fulmer evaluated 40 finance ratios used in a sample of 60 companies, including 30 unsuccessful companies and 30 successful companies (Parquinda & Azizah, 2019). Here is the Fulmer model equation:

$$\mathbf{H= 5.528X_1 + 0.212X_2 + 0.073X_3 + 1.270X_4 - 0.120X_5 + 2.335X_6 + 0.575X_7 + 1.083X_8 + 0.894X_9 - 6.075} \;\ldots\ldots\ldots (3)$$

Information:
X_1 : Retairned Earning/Total Asset
X_2 : Sales/Total Asset
X_3 : EBT/Total Equity
X_4 : Cash Flow From Operation/Total Debt
X_5 : Debt/Total Equity
X_6 : Current Liabilities/Total Asset
X_7 : Log Fix Asset
X_8 : Working Capital/Total Debt
X_9 : Log (EBIT)/Interest Expenses

The Fulmer H-Score model classifies scores cut off <0 then the company is expected to encounter financial difficulty. If > 0, the firms predicted not to experience financial distress.

2.7. Ohlson Model

One of the prediction models is the Ohlson models created by James A. Ohlson in 1980. At the beginning of his findings, Ohlson (1980) suspected the method of Multiple Discriminant Analysis made by Altman (1968). As a comparison, Ohlson (1980) O-Score use logistic regression on the formula. The model's outcomes development shows the percentage level of bankruptcy prediction with Model 1 showing a figure of 96.12%, Model 2 of 95.55%, and Model 3 of 92.84%. So the model used in predicting financial distress for the ohlson model is model 1. The following is the equation of the Ohlson model:

$$\mathbf{O = -1{,}32 - 0{,}407X_1 + 6{,}03X_2 - 1{,}43X_3 + 0{,}0757X_4 - 2{,}37X_5 - 1{,}83X_6 + 0{,}285X_7 - 1{,}72X_8 - 0{,}521X_9} \quad \text{........ (4)}$$

Information:
X_1 = Log (Total Assets/GNP Price-Level Index)
X_2 = Total Liabilities/Total Assets
X_3 = Working Capital/Total Assets
X_4 = Current Liabilities/Current Assets
X_5 = Nilai 1 Jika Total Liabilities > Total Assets ; Nilai 0 Jika Sebaliknya
X_6 = Net Income/Total Assets
X_7 = Cash Flow From Operations/Total Liabilities
X_8 = Nilai 1 Bila Net Income Negatif ; Nilai 0 Bila Sebaliknya
X_9 = (NIt – NIt-1) / (NIt + NIt-1)

The Ohlson O-Score model classifies values cut off <0.38, it is anticipated that the firms won't go through financial difficulty. If > 0.38 then the company is expected to encounter financial difficulty.

2.8. Taffler Model

R.J. Taffler published the Taffler model in 1977, then Taffler developed this model in 1983. Taffler (1983) sparked a model for predicting bankruptcy intended for manufacturing companies quoted on the Stock Exchange of London Period 1969-1976. The results found that 4 variable scales were used in the research study and the taffler also used the MDA analysis method with an accurate prediction rate of 100% for the non-bankrupt company category and 95.70% for bankrupt companies (Widiasmara & Rahayu, 2019). The following is a formula for the Taffler model:

$$\mathbf{T = 3{,}20 + 12{,}18X_1 + 2{,}50X_2 - 10{,}68X_3 + 0{,}0289X_4} \text{........ (5)}$$

Information:
X_1 = Earnings Before Taxes/Current Liabilities
X_2 = Current Assets/Current Liabilities
X_3 = Current Liabilities/Total Assets
X_4 = Earnings After Tax/Total Assets

The Taffler model classifies values cut off <0.38, it is predicted that the company will in no way suffer financial distress. If > 0.38 then the firm is predicted to suffer financial distress

2.9. Model CA-Score

Developed under leadership of Jean Legault University of Quebec-Montreal, the CA-Score model analyzes the failure rate of Canadian companies using discriminatory analysis. The predicted accuracy percentage for this approach is 83%. The following is the equation of the CA-Score model:

$$\mathbf{CA\text{-}Score = 4{,}591X_1 + 4{,}508X_2 + 0{,}3936X_3 - 2{,}7616} \text{ .... (6)}$$

Information:
X_1 = Shareholder Investment (1) / Assets (1)

X_2 = EBT + Financial Expenses(1) / Assets (1)
X_3 = Sales (2) / Assets (2)
(1) = Display of the previous period
(2) = Display of the previous two periods

The CA-Score value is divided into two groups, namely if the CA-Score scale is <-0.3 then the firms is predicted not to suffer financial distress. Vice versa, if the CA-Score is > -0.3, then the firms are predicted to suffer financial distress.

The framework for this study is founded on the background, previous research, and the theoretical basis used. The Altman, Zavgren, Fulmer, Ohlson, Taffler, and CA-Score models are used to calculate financial financial statements ratios of manufacturing firms for the 2017-2021 period. This predictive analysis can provide information to a company so that it can be used in making quick decisions in anticipating or planning situations in that the company will face financial distress, and able to assist investors in making investment decisions on entities that are expected to experience financial distress. The following framework can be used to describe predictive analytics of financial distress:

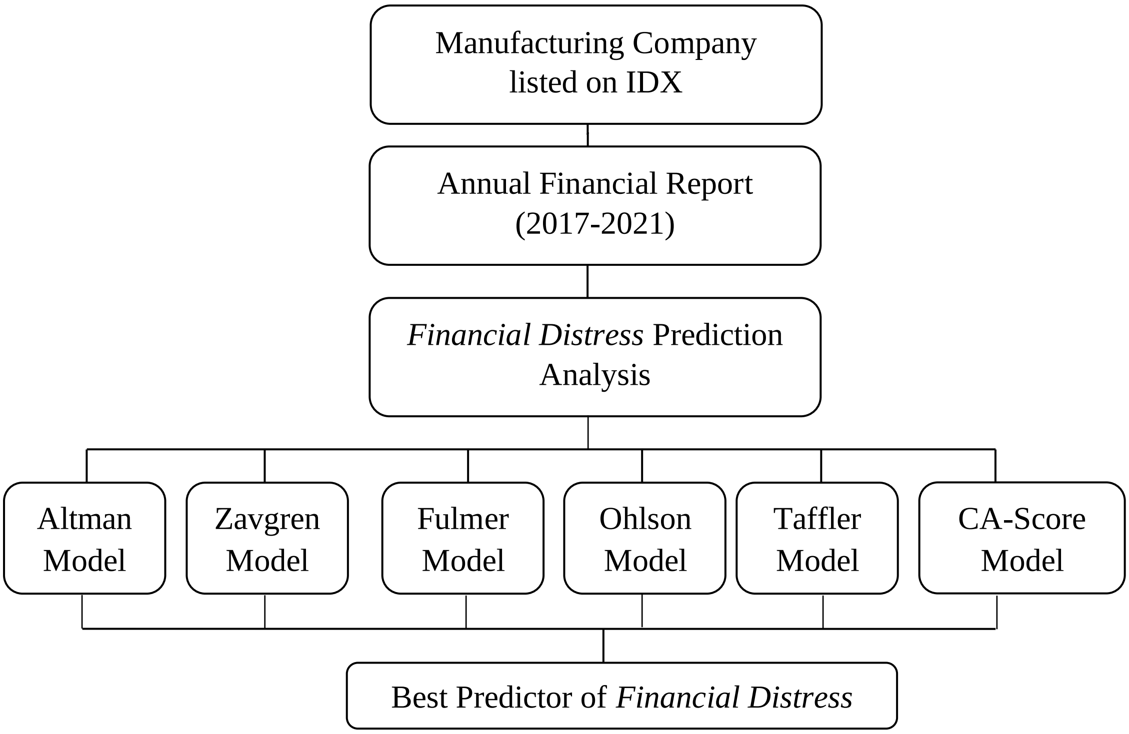

Figure 1. Framework of Mind

3. Research Methods

This kind of research is quantitative research. The research secondary data are used where researchers take the financial reports of manufacturing firms sourced from the Indonesian Stock Exchange's web page www.idx.co.id as well as the website of each company. Data analysis techniques in this study use financial distress prediction models. The Population in this research are manufacturing firms indexed on the IDX 2017-2021. This can be seen in the research phenomenon where some companies have experienced a decline in revenue for five consecutive years from 2017-2021 so that companies could be affected by financial distress conditions. The sample selection method in this research uses criteria purposive sampling. Purposive sampling is a strategy that determines samples that pay attention to certain factors (Sugiyono, 2019) .

Criteria purposive sampling in research, namely: companies listed on the IDX are manufacturing companies; the company has published complete and accessible financial reports for the period 2017-2021; financial statement items used to calculate the ratios in the independent variables (Altman Models, Zavgren, Fulmer, Ohlson, Taffler, and CA-Score); companies that have suffered losses for 2 years; as well as using the rupiah currency in presenting financial reports. According to the criteria purposive sampling research, the total number of samples used in this research was 35 firms.

4. Results and Discussion

4.1 Altman Models

Table 1. Altman Models Calculation Results

No	Company Code	2017	2018	2019	2020	2021	Average	Information
1	AISA	-10,747*	-3,702*	0,827*	2,757^	-0,451*	-2,263	D
2	AKKU	0,725*	0,907*	0,248*	1,317^	0,198*	0,679	D
3	ALTO	0,211*	0,179*	0,293*	0,265*	0,311*	0,252	D
4	AMFG	1,510^	1,124*	0,882*	0,718*	1,358^	1,119	D
5	APLI	1,588^	1,131*	1,708^	1,332^	1,724^	1,496	GA
6	BAJA	1,226*	1,104*	1,077*	1,784^	3,021	1,642	GA
7	BATA	2,784^	3,015	2,901	0,716*	1,486^	2,180	GA
8	BIMA	0,128*	0,100*	0,061*	-1,124*	-1,180*	-0,403	D
9	BRNA	0,855*	0,723*	0,560*	0,458*	0,291*	0,577	D
10	BTEK	0,637*	0,462*	0,368*	-0,021*	-0,018*	0,286	D
11	CPRO	-1,155*	0,360*	0,046*	1,998^	1,260^	0,501	D
12	ETWA	-0,680*	-1,191*	-1,156*	-0,501*	-0,995*	-0,905	D
13	GDST	1,893^	1,302^	1,321^	0,916*	0,958*	1,278	GA
14	HDTX	-0,503*	-3,293*	-4,325*	-5,062*	-5,739*	-3,784	D
15	HERO	2,485^	1,897^	2,434^	0,891*	-0,083*	1,525	GA
16	IKAI	-3,490*	-0,050*	0,098*	-0,026*	0,074*	-0,679	D
17	IMAS	0,706*	0,542*	0,507*	0,378*	0,439*	0,514	D
18	INAF	1,273^	1,365^	1,383^	1,236^	1,652^	1,382	GA
19	INCF	1,049*	1,822^	1,468^	1,011*	1,102*	1,290	GA
20	KICI	1,653^	1,262^	1,139*	1,160*	1,965^	1,436	GA
21	LION	1,903^	2,097^	2,001^	1,850^	1,618^	1,894	GA
22	LMPI	0,753*	0,790*	0,595*	0,510*	0,726*	0,675	D
23	LMSH	3,638	3,734	2,486^	2,276^	3,139	3,054	S
24	MBTO	1,478^	0,459*	0,309*	-0,198*	-0,124*	0,385	D
25	MRAT	2,164^	1,970^	1,874^	1,611^	1,584^	1,841	GA
26	MYTX	-0,397*	-0,258*	-0,456*	-0,526*	-0,470*	-0,422	D
27	PICO	1,784^	1,496^	0,913*	0,177*	0,238*	0,922	D
28	PRAS	0,503*	0,610*	0,202*	0,424*	0,357*	0,419	D
29	PSDN	3,035	2,523^	2,034^	1,366^	0,893*	1,970	GA
30	RICY	1,628^	1,872^	1,754^	0,993*	1,312^	1,512	GA
31	RMBA	1,622^	1,514^	1,408^	0,324*	0,679*	1,109	D
32	SMCB	0,569*	0,390*	0,903*	0,898*	1,093*	0,770	D
33	TIRT	0,924*	1,095*	0,400*	-4,442*	-3,838*	-1,172	D
34	WSBP	1,290^	1,345^	1,212*	-1,446*	-2,039*	0,072	D
35	YPAS	1,149*	1,442^	1,914^	1,778^	1,725^	1,602	GA

Information:

*	The company is predictable in condition distress (<1,23)
^	The company is predictable in condition grey area (1,23 – 2,90)
	The company is predicted to be in healthy condition (>2.90)
D	Distress
GA	Grey Area
S	Healthy

Based on the findings of financial ratios using the Altman models, there are 21 sample firms that which it is anticipated suffer financial distress time to come, 13 sample companies in the stategrey region (it is unable to predicted if firms is in good health or suffer financial distress) and the remaining 1 sample company is predicted to be healthy or not in financial difficulties.

4.2 Zavgren Model

Table 2. Zavgren Model Calculation Results

No	Company Code	2017	2018	2019	2020	2021	Average	Information
1	AISA	-18,364	-24,309	-47,722	-10,742	-6,003	-21,428	S
2	AKKU	13,058*	20,858*	4,131*	-43,273	12,494*	1,454	D
3	ALTO	2,435*	-0,416	0,387	-0,261	-0,187	0,392	S
4	AMFG	11,572*	4,469*	2,426*	0,247	3,089*	4,361	D
5	APLI	7,751*	-1,686	4,384*	3,717*	2,367*	3,306	D
6	BAJA	9,034*	11,277*	8,225*	-46,716	10,625*	-1,511	S
7	BATA	21,034*	25,000*	28,145*	10,190*	13,539*	19,582	D
8	BIMA	-266,269	-67,283	5,009*	-1,276	-5,553	-67,075	S
9	BRNA	0,389	0,405	-0,233	-2,147	-2,631	-0,844	S
10	BTEK	0,005	12,248*	9,016*	-0,682	-4,013	3,315	D
11	CPRO	-1,880	-7,202	-2,561	-1,755	2,293*	-2,221	S
12	ETWA	-26,619	-24,982	-101,325	-60,299	-66,061	-55,857	S
13	GDST	10,921*	4,182*	5,789*	5,152*	3,267*	5,862*	D
14	HDTX	-7,349	-4,842	-5,769	-8,883	-12,952	-7,959	S
15	HERO	10,871*	10,797*	9,682*	4,743*	-0,585	7,102	D
16	IKAI	51,924*	-15,079	3,065*	0,538	-9,919	6,106	D
17	IMAS	-2,426	-1,674	-3,089	-5,452	-4,348	-3,398	S
18	INAF	2,632*	1,206*	1,646*	-12,086	-2,204	-1,761	S
19	INCF	4,073*	-13,094	-15,473	-7,063	-6,905	-7,692	S
20	KICI	56,128*	46,866*	58,130*	59,131*	37,261*	51,503	D
21	LION	17,965*	19,465*	34,001*	41,164*	19,286*	26,376	D
22	LMPI	8,161*	8,173*	8,872*	8,637*	8,258*	8,420	D
23	LMSH	29,262*	38,487*	25,289*	23,723*	32,538*	29,860	D
24	MBTO	0,514	2,759*	-0,617	2,460*	5,039*	2,031	D
25	MRAT	20,654*	19,087*	16,865*	12,092*	13,441*	16,428	D
26	MYTX	-5,793	-6,645	-5,875	-7,662	-8,656	-6,926	S
27	PICO	8,171*	5,778*	-1,820	-0,035	-1,220	2,175	D
28	PRAS	4,004*	12,160*	2,190*	11,012*	7,231*	7,319	D
29	PSDN	6,725*	4,252*	-0,789	-1,717	-4,745	0,745	S
30	RICY	6,769*	6,177*	6,651*	5,539*	12,719*	7,571	D
31	RMBA	16,074*	12,787*	13,127*	13,621*	11,565*	13,435	D
32	SMCB	-6,982	-4,404	-2,559	-64,729	-6,360	-17,007	S
33	TIRT	2,267*	1,764*	-0,685	131,554	-79,280*	11,124	D
34	WSBP	-20,793	2,592*	5,027*	-6,405	-5,994	-5,115	S
35	YPAS	2,873*	2,476*	3,228*	7,025*	7,772*	4,675	D

Information:

*	The company is predictable in condition distress (>1)
	The firms is predicted being in good health (<1)
D	Distress
S	Healthy

According to the results of the calculating the financial ratios of the Zavgren model and calculating the probability value, there are 20 sample firms which it is anticipated suffer financial distress time to come, and the remaining 15 sample companies are predictions state that healthy or not to experience financial distress.

4.3 Fulmer Model

Table 3. Fulmer Model Calculation Results

No	Company Code	2017	2018	2019	2020	2021	Average	Information
1	AISA	2,384	-3,439*	0,165	2,889	0,902	0,580	S
2	AKKU	6,852	7,697	5,695	12,091	2,117	6,890	S
3	ALTO	9,395	8,682	9,288	5,885	8,396	8,329	S
4	AMFG	15,257	13,532	13,188	13,589	15,111	14,135	S
5	APLI	12,306	11,382	11,849	10,710	12,804	11,810	S
6	BAJA	9,118	8,621	7,988	11,167	12,619	9,903	S
7	BATA	18,666	18,702	18,460	16,430	15,574	17,566	S
8	BIMA	-2,064*	-1,638*	4,483	4,841	1,486	1,422	S
9	BRNA	10,237	10,215	10,492	9,899	10,117	10,192	S

No	Company Code	2017	2018	2019	2020	2021	Average	Information
10	BTEK	10,988	10,215	7,229	10,631	8,429	9,498	S
11	CPRO	7,993	5,504	3,929	17,285	9,008	8,744	S
12	ETWA	7,637	6,623	6,846	8,665	6,310	7,216	S
13	GDST	12,459	11,931	11,252	7,981	9,682	10,661	S
14	HDTX	7,536	-6,095*	-12,602*	-18,003*	-16,694*	-9,172	D
15	HERO	17,466	17,760	14,017	11,803	9,402	14,090	S
16	IKAI	3,026	9,460	8,183	7,966	7,070	7,141	S
17	IMAS	12,190	11,858	11,617	11,605	12,063	11,866	S
18	INAF	9,223	10,493	10,525	10,499	10,517	10,251	S
19	INCF	9,754	10,510	10,087	8,945	9,263	9,712	S
20	KICI	11,570	8,029	10,604	9,908	13,399	10,702	S
21	LION	15,691	15,139	14,845	15,575	15,183	15,287	S
22	LMPI	7,413	10,077	8,724	8,396	7,711	8,464	S
23	LMSH	18,691	17,426	18,301	17,005	16,712	17,627	S
24	MBTO	10,984	11,623	9,147	10,177	8,658	10,118	S
25	MRAT	13,099	13,227	13,092	12,580	12,549	12,909	S
26	MYTX	7,166	6,352	6,410	-7,207*	7,929	4,130	S
27	PICO	16,216	15,327	13,054	12,391	12,262	13,850	S
28	PRAS	10,497	10,992	7,760	9,430	8,038	9,343	S
29	PSDN	12,010	11,129	10,547	9,438	7,168	10,058	S
30	RICY	11,718	11,801	10,880	8,751	9,218	10,473	S
31	RMBA	11,288	10,533	10,135	10,292	7,775	10,004	S
32	SMCB	10,476	9,245	12,034	12,808	13,508	11,614	S
33	TIRT	6,751	7,963	7,192	5,548	-2,250*	5,041	S
34	WSBP	13,362	14,599	14,057	9,961	6,666	11,729	S
35	YPAS	8,736	8,631	10,796	11,140	9,289	9,718	S

Information:

*	The company is predictable in condition distress (<0)
	The firms is predicted being in good health (>0)
D	Distress
S	Healthy

Based on the findings of calculating financial ratios from the Fulmer model, there are as many as 1 sample firms which it is anticipated suffer financial distress time to come, and the remaining 34 sample companies' predictions state that healthy or not to experience financial distress.

4.4 Ohlson Model

Table 4. Ohlson Model Calculation Results

No	Company Code	2017	2018	2019	2020	2021	Average	Information
1	AISA	20,660*	20,776*	9,706*	4,923*	6,939*	12,601	D
2	AKKU	3,644*	2,692*	4,606*	3,438*	3,062*	3,489	D
3	ALTO	4,281*	5,284*	5,568*	4,828*	5,155*	5,023	D
4	AMFG	4,979*	5,866*	2,662*	3,620*	11,912*	5,808	D
5	APLI	4,780*	1,593*	8,222*	9,228*	3,896*	5,544	D
6	BAJA	10,999*	6,279*	9,502*	6,916*	6,008*	7,941	D
7	BATA	3,833*	3,484*	3,995*	2,429*	3,699*	3,488	D
8	BIMA	12,915*	12,977*	8,255*	5,860*	7,970*	9,595	D
9	BRNA	2,995*	4,648*	3,662*	4,702*	4,575*	4,116	D
10	BTEK	2,284*	2,015*	-16,749	3,646*	5,078*	-0,745	S
11	CPRO	7,175*	11,936*	8,564*	8,148*	4,041*	7,973	D
12	ETWA	5,906*	10,761*	13,924*	18,260*	2,394*	10,249	D
13	GDST	3,510*	2,195*	7,316*	1,903*	4,432*	3,871	D
14	HDTX	6,497*	8,296*	8,733*	9,084*	22,856*	11,093	D
15	HERO	-2,552	1,917*	3,528*	3,760*	5,983*	2,527	D

No	Company Code	2017	2018	2019	2020	2021	Average	Information
16	IKAI	12,716*	1,269*	-169,250	3,188*	3,337*	-29,748	S
17	IMAS	4,547*	7,218*	5,176*	2,621*	3,718*	4,656	D
18	INAF	4,283*	4,886*	7,584*	7,700*	3,981*	5,687	D
19	INCF	7,810*	7,147*	40,634*	4,743*	8,135*	13,694	D
20	KICI	3,936*	4,457*	2,880*	4,754*	3,786*	3,963	D
21	LION	4,645*	5,845*	4,720*	0,927*	2,939*	3,815	D
22	LMPI	2,375*	4,170*	4,756*	5,017*	5,572*	4,378	D
23	LMSH	3,514*	4,285*	1,291*	3,094*	13,305*	5,098	D
24	MBTO	1,231*	3,661*	6,416*	3,023*	3,980*	3,662	D
25	MRAT	2,518*	1,846*	5,131*	1,840*	5,842*	3,436	D
26	MYTX	6,535*	6,877*	6,335*	7,321*	4,877*	6,389	D
27	PICO	5,800*	6,581*	7,716*	4,934*	6,664*	6,339	D
28	PRAS	4,017*	2,963*	3,503*	7,134*	5,570*	4,637	D
29	PSDN	21,290*	-0,335	6,284*	6,097*	7,162*	8,100	D
30	RICY	6,402*	6,517*	6,565*	3,618*	5,079*	5,636	D
31	RMBA	0,991*	2,060*	2,857*	2,051*	4,937*	2,579	D
32	SMCB	3,381*	4,501*	9,316*	5,091*	4,174*	5,293	D
33	TIRT	8,628*	5,354*	6,709*	13,242*	18,413*	10,469	D
34	WSBP	3,745*	4,046*	4,246*	5,155*	8,4148	5,121	D
35	YPAS	4,881*	5,475*	8,642*	5,452*	-11,040	2,682	D

Information:

*	The company is predictable in condition distress (>0,38)
	The firms is predicted being in good health (<0.38)
D	Distress
S	Healthy

Based on the findings of measuring the financial ratios of the Ohlson model, there are 33 sample firms which it is anticipated suffer financial distress future, and the remaining 2 sample companies are predictions state that healthy or not to experience financial distress.

4.5 Taffler Model

Table 5. Calculation results of the Taffler Model

No	Company Code	2017	2018	2019	2020	2021	Average	Information
1	AISA	-34,009	-27,067	12,073*	15,066*	0,642*	-6,659	S
2	AKKU	6,520*	7,837*	-4,670	1,306*	1,038*	2,406	D
3	ALTO	-0,574	0,478*	2,798*	2,559*	2,579*	1,568	D
4	AMFG	7,302	4,252*	2,075*	-0,377	5,287*	3,708	D
5	APLI	6,163	0,235*	7,185*	4,607*	5,699*	4,778	D
6	BAJA	-3,446	-5,644	-4,142	-2,272	14,006*	-0,300	S
7	BATA	10,687	13,967*	12,091*	-7,798	-0,207	5,748	D
8	BIMA	-3,132	-3,094	5,336*	-6,026	-3,297	-2,043	S
9	BRNA	-1,785	1,766*	-1,100	-2,579	-2,746	-1,289	S
10	BTEK	3,055*	9,550*	3,809*	-19,719	-2,017	-1,064	S
11	CPRO	-12,377	6,542*	-5,904	-4,078	15,571*	-0,049	S
12	ETWA	-5,019	-7,037	-7,478	3,973*	-3,856	-3,884	S
13	GDST	5,902*	-1,906	1,060*	-1,047	-1,782	0,445	D
14	HDTX	-6,669	-19,115	-6,188	-6,286	-6,696	-8,991	S
15	HERO	1,943*	-4,121	1,650*	-5,637	-3,204	-1,874	S
16	IKAI	-11,632	7,143*	-1,988	-2,771	0,181*	-1,813	S
17	IMAS	0,041*	-0,283	0,259*	-0,422	-0,562	-0,194	S
18	INAF	-1,206	-0,677	4,770*	1,638*	1,129*	1,131	D
19	INCF	-2,273	-1,406	-1,034	3,660*	2,337*	0,257	D
20	KICI	31,015*	16,530*	17,223*	23,009*	27,896*	23,135	D
21	LION	10,568*	11,714*	15,418*	16,2358	8,756*	12,538	D
22	LMPI	1,385*	-0,381	-1,375	-1,694	-0,390	-0,491	S

No	Company Code	2017	2018	2019	2020	2021	Average	Information
23	LMSH	22,703*	18,815*	0,386*	6,1338	16,879*	12,983	D
24	MBTO	3,377*	-4,548	-2,506	-6,282	-4,647	-2,921	S
25	MRAT	9,745*	8,596*	7,760*	5,372*	4,972*	7,289	D
26	MYTX	-3,010	-2,345	-2,434	-1,692	-1,724	-2,241	S
27	PICO	3,033*	1,672*	-1,652	-3,699	-4,006	-0,930	S
28	PRAS	1,277*	3,517*	-1,859	7,904*	6,308*	3,429	D
29	PSDN	2,892*	-0,507	-0,060	-1,128	-3,549	-0,470	S
30	RICY	-0,268	-0,285	-0,651	-0,985	5,177*	0,598	D
31	RMBA	3,407*	2,781*	4,203*	-3,104	3,912*	2,240	D
32	SMCB	0,066*	-2,563	5,964*	6,490*	8,021*	3,596	D
33	TIRT	-0,259	-1,798	-2,548	-18,954	-11,348	-6,981	S
34	WSBP	3,432*	3,807*	5,233*	-10,996	-13,110	-2,327	S
35	YPAS	-1,509	-0,784	3,848*	5,378*	2,718*	1,930	D

Information:

*	The company is predictable in condition distress (>0,38)
	The firms is predicted being in good health (<0.38)
D	Distress
S	Healthy

According to the results of the calculating the financial ratios of the Taffler models, there are 16 sample firms to which it is anticipated suffer financial distress time to come, and the remaining 19 sample companies are predictions state that healthy or not to experience financial distress.

4.6 CA-Score Model

Table 6. Calculation Results of the CA-Score Model

No	Company Code	2017	2018	2019	2020	2021	Average	Information
1	AISA	-4,699*	-1,093*	2,742*	1,695*	1,940*	0,117	D
2	AKKU	0,198*	-0,009	-0,688*	0,396*	0,568*	0,093	D
3	ALTO	-2,067*	-1,940*	-1,807*	-1,783*	-1,759*	-1,871	D
4	AMFG	-2,191*	-2,328*	-2,489*	-2,680*	-2,229*	-2,384	D
5	APLI	-0,183	-1,016*	-0,966*	-0,949*	-0,525*	-0,728	D
6	BAJA	-1,533*	-1,927*	-1,313*	-0,952*	-0,396*	-1,224	D
7	BATA	-1,733*	-1,714*	-2,061*	-3,422*	-2,632*	-2,312	D
8	BIMA	5,148*	4,828*	4,191*	-0,488*	-0,411*	2,653	D
9	BRNA	-2,862*	-2,439*	-2,700*	-2,865*	-2,932*	-2,759	D
10	BTEK	-2,121*	-2,135*	-2,281*	-2,726*	-2,223*	-2,297	D
11	CPRO	-1,375*	1,530*	0,862*	1,655*	2,969*	1,128	D
12	ETWA	-1,657*	-1,607*	-1,561*	-0,841*	-0,687*	-1,270	D
13	GDST	0,563*	-0,201	0,884*	-0,069	0,107*	0,257	D
14	HDTX	-1,572*	-0,973*	10,922*	16,484*	18,244*	8,621	D
15	HERO	-2,061*	-2,679*	-1,943*	-2,554*	-2,467*	-2,341	D
16	IKAI	3,271*	7,093*	0,201*	0,410*	0,652*	2,326	D
17	IMAS	-2,324*	-2,389*	-2,450*	-2,567*	-2,532*	-2,452	D
18	INAF	-1,501*	-1,429*	-1,325*	-1,240*	-1,521*	-1,403	D
19	INCF	-0,596*	-0,977*	-0,950*	-0,652*	-0,710*	-0,777	D
20	KICI	0,117*	-0,252	-0,530*	-0,431*	0,359*	-0,147	S
21	LION	-2,041*	-2,036*	-2,179*	-2,221*	-2,206*	-2,137	D
22	LMPI	0,127*	-0,106	0,052*	0,305*	0,762*	0,228	D
23	LMSH	-1,493*	-1,966*	-2,462*	-2,101*	-1,792*	-1,963	D
24	MBTO	-1,849*	-2,703*	-2,249*	-3,070*	-2,444*	-2,463	D
25	MRAT	-1,927*	-1,970*	-1,988*	-2,017*	-2,262*	-2,033	D
26	MYTX	-1,065*	-1,678*	-1,954*	-0,945*	-1,034*	-1,335	D
27	PICO	-1,118*	-1,385*	-1,601*	-2,128*	-2,159*	-1,678	D
28	PRAS	-2,428*	-2,439*	-2,624*	-2,427*	-2,4868	-2,481	D
29	PSDN	-0,061	-0,668*	-0,278	-0,690*	-1,025*	-0,545	D

No	Company Code	2017	2018	2019	2020	2021	Average	Information
30	RICY	-1,163*	-1,216*	-1,261*	-1,521*	-1,549*	-1,342	D
31	RMBA	-1,753*	-1,617*	-1,625*	-2,393*	-1,588*	-1,795	D
32	SMCB	-1,820*	-1,834*	-1,533*	-1,419*	-1,454*	-1,612	D
33	TIRT	-1,597*	-1,878*	-2,026*	-3,683*	-2,441*	-2,325	D
34	WSBP	-1,261*	-1,406*	-1,498*	-3,227*	-2,263*	-1,931	D
35	YPAS	-1,516*	-1,499*	-1,403*	-1,005*	-1,260*	-1,336	D

Information:

*	The company is predictable in condition distress (>0,3)
	The firms is predicted being in good health (<0.3)
D	Distress
S	Healthy

According to the results of the calculation the financial ratios of the CA-Score model, there are as many as 35 sample firms to which it is anticipated suffer financial distress future, and the remaining 1 sample company predictions state that healthy or not to experience financial distress.

4.7. Results and Model Accuracy Levels Early Warning System

Calculation of the level of accuracy is also depending on the findings of comparisons between the six models early warning system. In addition to the level of accuracy, type percentage calculations are also performed error of the six detection model's financial distress. Type error II, namely errors that occur whenever the model anticipates that the sample will financial distress in reality did not possess financial distress or healthy (Altman, 2013).

Table 7. Calculation of Early Warning System

Prediction	Altman Models	Zavgren Models	Fulmer Models	Ohlson Models	Taffler Models	CA-Score Models
Distress	21	20	1	33	16	34
Grey Area	13	-	-	-	-	-
Healthy	1	15	34	2	19	1
Total Sample	**35**	**35**	**35**	**35**	**35**	**35**
Level of accuracy	60,00%	57,14%	2,86%	94,29%	45,71%	97,14%
Type Error II	2,86%	42,86%	97,14%	5,71%	54,29%	2,86%
Grey Area	37,14%	-	-	-	-	-

Calculation:

$$\text{Accuracy Level} = \frac{\text{Total Correct Predictions}}{\text{Total Sample}} \text{ X } 100\%$$

$$\text{Type Error II} = \frac{\text{Total Type Error II}}{\text{Total Sample}} \text{ X } 100\%$$

4.8. Discussion

Based on Table 7 it can be seen that the CA-Score model has the highest rate of accuracy of 97.14% and type error II of 2.86% in identifying financial hardship in manufacturing firms. The CA-Score model uses three calculation ratios as indicators to predict the financial distress of a company. This means that the use of signal theory is relevant to the results of this research, which explains that theory of signals is an indication of important information about the financial condition of a company, which can be seen through some of the financial ratios contained in the financial statements, then served as a clue or signal to investors (Spence, 1973).

Similarly, the stakeholder theory that explains that management is obliged to present its financial statements in a transparently because the information from financial accounts can be used to determine whether a company is in good or bad condition (financial distress) that can be seen through some financial rasio (Komarudin et al., 2019). This study is consistent with research Nenengsih (2018) whose results show that among the five predictor models tested, the CA-Score prediction model is the best delisting prediction compared to the Altman-modified models, the Zmijewski model, the Springate model, and the Grover model. However, Kartikasari & Hariyani (2019) research shows that the CA -Score model obtains the lowest accuracy rate of 30% of the other predictive models tested.

The findings of this study contradict Wulandari et al., (2014) which shows that the CA-Score model cannot be used in predicting a firm's financial difficulties. As a result, in the regression test, the CA-Score model has a significant value t greater than the probability value and the F-significance value is larger than the probability value. Fulmer model analysis has the lowest accuracy level of 2.86% and type II error of 97.14% in predicting a company's financial distress, compared to Altman, Zavgren, Ohlson, Taffler, and CA-Score models. Fulmer's model uses nine ratios as indicators in forecasting a firm's financial distress. The results of this study are consistent with Kartikasari & Hariyani (2019), Shalih & Kusumawati (2019), Wirawan & Pangestuti (2022) whose results show that the Fulmer model has the lowest results compared to other predictive models.

However, the results of the study are not consistent with Peter et al., (2021) and Masdiantini & Warasniasih (2020) whose research results show that the Fulmer model is the most accurate prediction which is where the accuracy level is 100%. However, in this study the model with the lowest level of accuracy is the Fulmer model. Therefore, the result of the prediction of this model is an early warning system in predicting financial distress and each model developed is not always perfect. Thus, the results of this prediction cannot be considered as a definite or fixed result. Prediction results are only indicators and warnings to investors and creditors to be more careful and learn more about the company in question to avoid risks.

5. Conclusion, Implications, and Limitations

This study used a sample of thirty-five manufacturing firms listed on the IDX in 2017-2021. Based on the findings of the analysis data obtained, It may be concluded that: Based on the model accuracy calculation level, it can be concluded that the six analysis models can be applied, namely; the Altman, Zavgren, Fulmer, Ohlson, Taffler, and CA-Score models as early warning systems in predicting financial crisis in manufacturing firms for the 2017-2021 period. From the results of the equation for the level of accuracy using the Altman, Zavgren, Fulmer, Ohlson, Taffler, and CA-Score models, there are differences in the degree of accuracy. The accuracy in the Altman scale Model is 60.00% and type error II is 2.86%, the Zavgren Model's degree of accuracy is 57.14% and type error II is 42.86%, the Fulmer Model accuracy rate is 2.86% and type error II is 97.14%, the accuracy of the Ohlson Model is 94.29% and type error II is 5.71%, the Taffler Model's precision is 45.71% and the type error II of 54.29%, and the accuracy of the CA-Score Model is 97.14% and the type error II of 2.86%. Of the six prediction models that have the highest level of accuracy and are accurate for predicting financial distress in Manufacturing companies for the 2017-2021 period is the CA-Score Model with an accuracy level of 97.14% and type error II of 2.86%. The Ohlson model then follows, with a precision rate of 94.29% and type error II of 5.71%.

It is hoped that this research will be beneficial to provide contributions and benefits in the process of developing research on predictive models financial distress. In addition, in this study it is suspected that the corporation is expected to encounter financial hardship or not by using the Altman, Zavgren, Fulmer, Ohlson, Taffler, and CA-Score models. This research is also information anticipated to be provided and advice to interested parties such as investors/creditors in making decisions by using an analytical model as a predictive tool to evaluate the firm's condition.

The limitations of this study are that this research sample only focuses on manufacturing companies. In addition, this study only analyzes the level of accuracy of each model without creating a new predictive model. For creditors and investors before investing their funds in a company, it is necessary to predict the company's financial situation, including whether or not a financial crisis is expected. For further research, it is recommended that we no longer do model comparisons. However, more to develop or create new predictive models. It is also expected to be able to use the company's delisting as a research object to see the level of accuracy of the model.

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