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Accuracy Analysis of the Financial Distress Prediction Model Using Altman Z-Score, Springate, Zmijewski And Grover in the Oil, Gas and Geothermal Mining Subsectors Listed on the Indonesian Stock Exchange (BEI)

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Article Info	ABSTRACT
Keywords: Financial Distress, Altman Z-Score, Springate, Zmijewski, Grover	This study is to ascertain the accuracy of the financial distress prediction model in oil, gas, along with geothermal mining subsector firms for the 2018–2022 period by applying the Altman Z–Score, Springate, Zmijewski, also Grover models. The research methodology employed in this study is descriptive quantitative, utilizing secondary data taken from the financial accounts of the organization. Using a purposive sample approach, the study's sample consisted of 10 firms, whereas the population consisted of 16 companies. The analysis technique utilized is the degree of accuracy as well as type of error using Microsoft Excel 2019 software. The outcomes of this study show that the Grover model has the highest accuracy percentage of 76%, preceding the Altman Z-Score model 24%, Springate 22% as well as Zmijewski 60%.
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INTRODUCTION

A company is an organization that has certain goals, one of the company's goals is to generate profit. Many parties with an interest in the firm will suffer from the financial health of a company that is having difficulties with finances, because financial difficulties are able to cause a company to go bankrupt. Curry & Banjarnahor [1] stated that financial distress is a state where a firm's finances are in decreasing or unhealthy state before bankruptcy or a liquidation process occurs.

According to an investigation done by the Central Statistics Agency (BPS), Indonesia's economy is still growing well. Indonesia's economic growth was reported to have remained strong in the fourth quarter of 2022, at 5.01% in the midst of global economic growth which is currently trending. Slowing down, with these developments, Indonesia's overall growth in economy in 2022 was recorded at 5.31% (YoY), a substantial increase from the previous year's accomplishment of 3.70%. (YoY) [2].

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Furthermore, in 2022 all business sectors will experience positive growth in Quarter IV. The Indonesian economy in 2022 will grow by 5.31%. The business field that experienced the highest growth was Transportation and Warehousing at 19.87%, followed by Accommodation and Food and Drink Provision at 11.97%. Meanwhile, the Processing Industry which has a dominant role grew 4.89%. Meanwhile Mining and Quarrying grew by 4.38%. [3].

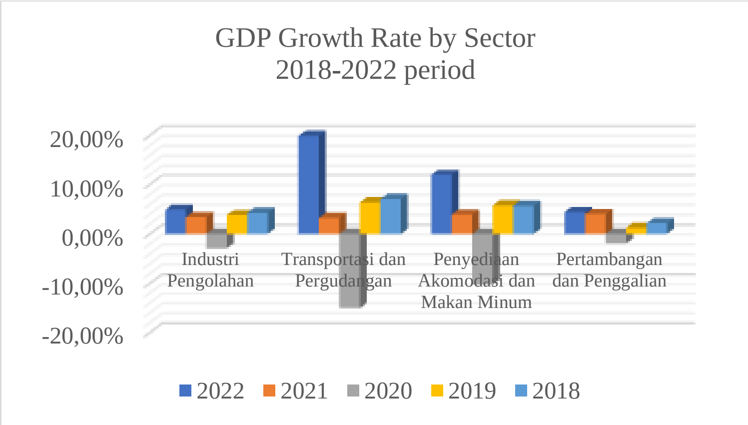

Figure 1 GDP Growth Rate by Sector for the 2018-2022 Period
Source: BPS (Data processed, 2023)

According to data on the GDP growth rate by sector for the 2018-2022 period, GDP growth is according to the four sectors contributing to the largest GDP. In the processing industry sector, it can be seen that in 2018-2019 it tended to be stable, then experienced a decline in 2020 of -2.93% and returned to stability in the following year. For the transportation and warehousing sector, it can be seen that in 2018-2020 it tended to be stable, but in 2020 there was a sharp decline of -15.05%, then there was an increase in 2022 of 19.87%. Furthermore, the accommodation and food and drink provider sector had fluctuating growth in 2018-2022 with the highest growth in 2022 amounting to 11.97% and the lowest decline in 2020 amounting to -10.26%. Then, for the mining and quarrying sector in 2019-2020 there was a constant decline, so that in 2020 there was a decline of -1.95%, but in the following year the mining and quarrying sector experienced an increase.

From the explanation above, it can be seen that all sectors experienced a decline in 2020 due to the impact of Covid-19 and an increase in 2022 despite the geopolitical conflict between Russia and Ukraine. Regarding the growth rate of the four sectors above, the mining and quarrying sector had the smallest GDP growth, namely 4.38%, but this sector also had a negative decline in 2020 and the negative decline in this sector was the smallest decline compared to the other three sectors. .

According to Kusdiana et al., [4] Oil and Gas (Migas) is still a source of foreign exchange earnings and a supplier of domestic energy needs, so that oil and gas is the mainstay of the economy, especially Indonesia. Despite the yearly reduction in oil and gas output, Indonesian oil as well as gas corporations are forced to search for new reserves due

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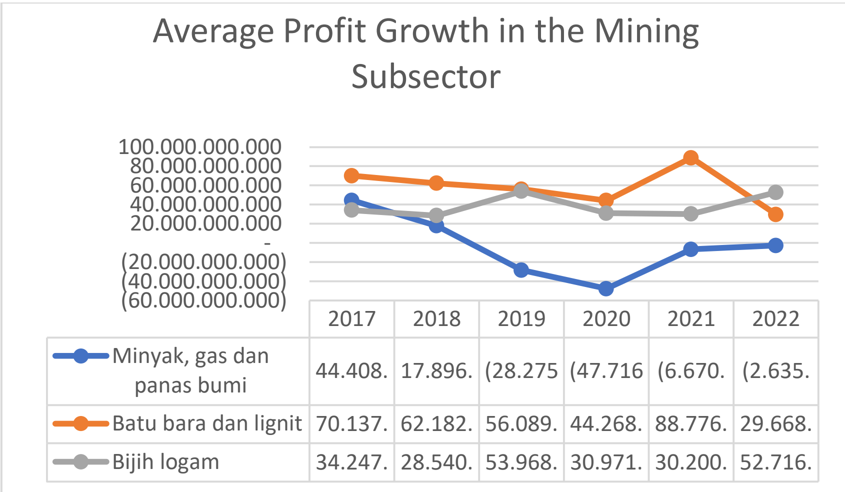
to the country's growing demand for these resources from both the industrial sector and the general public.

The GDP growth rate in the mining and quarrying sector is inversely proportional to the average profit earned by the oil, gas and geothermal mining subsectors. The oil, gas and geothermal mining subsector actually experienced a slowdown in profits during 2018-2022, even profit growth in 2019-2022 was at a negative number. This condition contradicts research conducted by Fadillah [5], which states that an increase in GDP reflects an increase in consumer purchasing power in a country. As company sales increase, the company's opportunity to gain profits will also increase. However, this research states that GDP in the mining and quarrying sector increased, but profit growth in the oil, gas and geothermal mining subsectors decreased, even in negative numbers.

The following is a picture of the average profits of companies in the oil, gas as well as geothermal mining subsector for the 2018-2022 period:



	2017	2018	2019	2020	2021	2022
Minyak, gas dan panas bumi	44.408.	17.896.	(28.275	(47.716	(6.670.	(2.635.
Batu bara dan lignit	70.137.	62.182.	56.089.	44.268.	88.776.	29.668.
Bijih logam	34.247.	28.540.	53.968.	30.971.	30.200.	52.716.

Figure 1 Average Profit Growth in the Mining Subsector
Source: www.idx.co.id (Data reprocessed, 2023)

In accordance to the picture above, it is known that only the oil, gas and geothermal mining subsectors show profit instability compared to the other two sectors which have positive profits in each period.

According to Whitaker, a company is able to be deemed to be in financial distress or problematic if the company experiences negative earnings for several years. [6]. Company management can find out indications that a company will experience financial distress using several prediction models. As management becomes more aware of the indications of bankruptcy, they can carry out improvements and evaluations of the company. There are several prediction models of financial distress that have been found and developed by linking various ratios in financial statement data that have been developed and found, but each of these predictive models has a varying level of accuracy.

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In conducting financial distress prediction research, long-term company financial data is needed, because financial distress cannot be predicted in the short term. Usually two to five years are used as the endurance limit for performance decline [7]. Therefore, researchers chose a five-year research period starting from 2018-2022.

In accordance to the background as well as previous research, the authors were interested in the research object to analyze the financial condition, namely the oil, gas and geothermal mining subsector, then testing the degree of accuracy of every bankruptcy prediction model that is suitable to be implemented in the oil, gas and geothermal mining subsector. The models for predicting financial distress utilized in this research are Altman Z-Score, Zmijewski, Springate, as well as Grover. The reason for selecting these four models is because they use the Multiple Discriminant Analysis (MDA) method in formulating the formula and the financial ratios used are in accordance with the characteristics of the oil, gas and geothermal mining subsectors. Apart from that, these four financial distress prediction models are quite popular for use in research, are easy to process data and have a high level of accuracy [8]. Thus, the title of this research is "Analysis of the Accuracy of Financial Distress Prediction Models utilizing Altman Z-Score, Springate, Zmijewski as well as Grover in the Oil, Gas and Geothermal Mining Subsectors registered on the Indonesia Stock Exchange (BEI) for the 2018-2022 Period".

The purpose of this study was:

1. To learn how to forecast oil gas as well as geothermal mining subsectors financial distress registered on BEI for the 2018-2022 period utilizing the Altman Z-Score model.
2. To learn how to forecast oil gas as well as geothermal mining subsectors financial distress registered on the BEI for the 2018-2022 period utilizing the Springate model.
3. To learn how to forecast oil gas as well as geothermal mining subsectors financial distress registered on the BEI for the 2018-2022 period utilizing the Zmijewski model.
4. To learn how to forecast oil gas as well as geothermal mining subsectors financial distress registered on the BEI for the 2018-2022 period utilizing the Grover model.
5. To find out which prediction model is the most accurate in estimating financial distress in the oil, gas as well as geothermal mining subsectors registered on the BEI for the 2018-2022 period.

Literature Review

Signalling Theory

In accordance with Brigham & Houston [9], signaling Corporate management uses theory as a tool to educate investors about the company's future prospects. The signal referred to in this study utilizing the company's financial statements which later be analyzed to produce information that is useful for its management in managing the company as well as conveying the information obtained to investors

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Financial Distress

In accordance with Curry & Banjarnahor [1], a financial distress is a situation where the business's finances are in a declining or unhealthy state before bankruptcy or liquidation happens. Meanwhile, according to Kristanti [10], a period of financial hardship known as "financial distress" is defined by declining or even negative profitability.

Altman Z-Score Model

Edward I. Altman (1968) implementing Multiple Discriminant Analysis. A diagnostic statistical method called discriminant analysis confirms some of the financial elements deemed to be crucial in determining an event's worth, then expand them into a method with the aim of facilitating it to be simpler to draw inference from certain event. [11].

Springate Model

This model is a model that is almost similar to the Altman method which uses Multiple Discriminant Analysis (MDA). However, the Springate model is only used with four ratios which are the same as the Altman modification, but the difference lies in the fourth variable which uses sales to total assets [12]

Zmijewski Model

This research model was developed by Zmijewski in 1984 where to determine one main thing that was done, namely initially determining the proportion of the sample and population, this was done in order to obtain a projected level of financial distress prediction in a company [12]

Grover Model

The Altman Z-Score model was redesigned and evaluated to create the Grover model. In 1968, Jeffrey S. Grover introduced thirteen additional financial ratios to the Altman Z-Score model and employed a sample based on that model [13].

Bankruptcy

Bankruptcy is a state where a company is ceased to be capable to honor its respponsibilities due to the companies are experiencing a lack and insufficiency of funds to run or continue its business, which results in the company's original objectives not being realized. Bankruptcy can cause the loss of all company operating activities and relationships between parties related to the company [14].

METHOD

Research Methods

In this research, the method implemented is a quantitative approach. According to Sugiyono (2019), the quantitative approach method is a positivist-based research technique that satisfies scientific principles in a tangible or empirical form that is objective, measurable, logical, and methodical. This makes it a scientific or scientific method.

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Descriptive research is the quantitative approach method that the author employed to perform this study. The data in this research is quantitative. It is called quantitative because this research consists of data in the form of numbers.

Determination of Population and Sample

The 16 firms that are registered on the BEI for the 2018–2022 term in the oil, gas, along with geothermal mining subsector comprise the population of this study. Purposive sampling was the method employed to conduct sampling in this study. Below are the criteria that have been determined in selecting samples using purposive sampling:

1. Oil, gas and geothermal mining subsector companies registered on the BEI consecutively for the period 2018-2022
2. Companies that publish consistent as well ascomplete financial reports for the 2018-2022 period
3. Companies that have experienced negative net profit for at least one year during the 2018-2022 period
4. Companies that have complete data required for research.

In accordance to the purposive sampling criteria that have been determined, 10 companies were chosen that will be used in the research. The companies sampled in this research are as follows:

Table 1 Company Sample

NO	Company Code	Company Name
1	MEDC	PT Medco Energi Internasional Tbk
2	PGAS	PT Perusahaan Gas Negara Tbk
3	ENRG	PT Energi Mega Persada Tbk
4	APEX	PT Apexindo Pratama Duta Tbk
5	ESSA	PT Surya Esa Perkasa
6	SURE	PT Super Energy Tbk
7	MITI	PT Mitra Investindo Tbk
8	PKPK	PT Perdana Karya Perkasa Tbk
9	ARTI	PT Ratu Prabu Energi Tbk
10	MTFN	PT Capitalinc Investment Tbk

Source: www.idx.co.id

Data Types and Sources

This research uses panel data (pooled data), namely integrated data between time series as well as cross section data or data consisting of several objects and several time periods, where the sample in this study is 10 companies with a period of 5 years, namely 2018-2022.

A secondary data source was employed to collect this research's data, namely financial reports of oil, gas and geothermal mining companies registered on the BEI. This secondary data was obtained from the IDX website and websites belonging to oil, gas and geothermal mining companies which were samples in this research in the 2018-2022 period.

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Data Collection Technique

In this research, researchers utilizing documentation data collection techniques or search for data based on past events, namely documents as statistics from the yearly financial report of companies listed in the oil, gas, also geothermal mining subsector on the BEI for the 2018-2022 period. This document is published by the BEI via www.idx.co.id or published on company sampled's website in this research.

Data Collection Technique

The data that has been obtained through documentation techniques is then processed for data analysis. The data processing technique in this research is only editing and tabulating using Microsoft Excel Office 2019 software tools.

Data Analysis Technique

By taking into account the type of inaccuracy, the data analysis approach employed in this study aims to evaluate the financial distress prediction model's accuracy. The following variables were utilized in this study:

Altman Z-Score Model

The formula used is:

$$\boxed{Z = 6{,}56X_1 + 3{,}26X_2 + 6{,}72X_3 + 1{,}05X_4}$$

Information:
Z = Index
X_1 = *Working Capital/Total Asset*
X_2 = *Retained Earnings/Total Asset*
X_3 = *Earnings Before Interest and Taxes/Total Assets*
X_4 = *Book Value of Equity/Book Value of Total Liabilities*
Or according to Rezeki et al., [16]:
Z = Index
X_1 = Working Capital/Total Assets
X_2 = Retained Earnings/Total Assets
X_3 = EBIT/Total Assets
X_4 = Total Capital/Total Debt
With score criteria based on the Z-Score value as follows:
$Z < 1{,}1$: *Financial distress*
$1{,}1 < Z < 2{,}6$: *Grey Area*
$Z > 2{,}6$: *Non-financial distress*/health

Springate Model

The formula used is:

$$\boxed{S = 1{,}03X_1 + 3{,}07X_2 + 0{,}66X_3 + 0{,}4X_4}$$

Information:
S = Indeks

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X1 = *Working Capital/Total Assets*
X2 = *Earnings Before Interest and Taxes/Total Asset*
X3 = *Earnings Before Taxes/Current Liabilities*
X4 = *Sales/Total Assets*

The Springate model has a cut-off value that applies if the S-Score value is <0.862, then the company is vulnerable to financial distress. However, if the S-Score value is > 0.862 then the company is in the non-financial distress/healthy category.

Zmijewski Model

The formula used is:

$$\boxed{X = -4{,}3 - 4{,}5X_1 + 5{,}7X_2 - 0{,}004X_3}$$

Information:
X1 = *Return On Asset* (ROA)
X2 = *Debt Ratio* (DR)
X3 = *Current Ratio* (CR)

With score criteria based on the X-Score value as follows:

- If the X score > 0 is categorized as being in financial distress
- If the score X < 0 is categorized as not being in a state of financial distress.

Grover Model

The formula implemented is:

$$\boxed{G = 1{,}650\ X_1 + 3{,}404\ X_2 + 0{,}016\ ROA + 0{,}057}$$

Information:
X1 = *Total Asset*
X2 = *EBIT/Total Asset*
ROA = *Net Income/Total Asset*

With the stipulation that if the G value is < -0.02, it is experiencing financial distress, while the company is categorized as currently in a state of non-financial distress/healthy if the G value is > 0.01.

Accuracy Test of the Financial Distress Prediction Model

The level of accuracy is used to test how accurate a model is in predicting a state of financial distress in the sample company. The model accuracy level is able to be calculated using the formula below [17]:

$$\boxed{\text{Level of accuracy} = \frac{Large\ number\ of\ predictions}{Number\ of\ Samples}\ x}$$

After carrying out the accuracy test, the model error will be calculated. The model error rate is divided into two types, type I also type II. In calculating the type I error rate, where the error is measured from the fact that the company is in a considition of distress but the prediction outcomes show that the company is non-distressed. In calculating the type II error rate, where the error is measured based on the fact that the company is in a non-distress condition but in the prediction that the company is in a condition of distress. The error rate calculation is calculated using the following formula [17]:

$$\textit{Error Type I} = \frac{\textit{Number of Type I errors}}{\textit{Number of Samples}} \text{ x } 100\%$$

$$\textit{Error Type II} = \frac{\textit{Number of type Type II}}{\textit{Number of Samples}} \text{ x } 100\%$$

High accuracy indicates that the number of correct estmations is the number of sample companies declared financially distressed/non-financial distress when calculated using each model. Apart from a high degree of accuracy, a low error rate also indicates that a model is good for use in predicting financial distress conditions.

RESULT AND DISCUSSION

After carrying out financial distress prediction calculations using the four models, the calculation results are grouped based on the cut off value of each model in this study to be able to see whether the sample companies in the oil, gas and geothermal mining subsector are in a healthy condition, have the potential to go bankrupt or experience bankrupt.

ALTMAN Z-SCORE MODEL

Below are the outcomes of financial distress prediction utilizing the Altman Z-Score model.

Table 2 Financial Distress Prediction Model Altman Z-Score

NO	CODE	YEAR				
		2018	2019	2020	2021	2022
1	MEDC	2.5262	2.3577	1.6221	2.0323	2.3724
2	PGAS	2.5607	2.9210	1.8345	2.5119	2.8381
3	ENRG	-2.1692	-0.7811	-0.3748	0.6717	0.7635
4	APEX	-5.9469	-0.0388	0.5404	0.9168	0.0541
5	ESSA	1.5968	1.6238	0.7663	2.0332	5.9960
6	SURE	-3.6269	-1.9059	5.8324	4.9984	4.0215
7	MITI	22.3267	10.7066	3.9751	6.3683	16.4007
8	PKPK	1.3051	-7.8043	-5.1545	-2.7468	-6.2247
9	ARTI	3.5341	-1.3132	-5.6896	-7.6152	-7.9248
10	MTFN	0.4518	0.4518	0.6275	0.3546	0.0619

Source: Processed data, 2023

Information: Red = Bankrupt, Yellow = Gray Area and Green = Healthy

Table 1 shows that financial distress estimation utilizing the Altman Z-Score model in 2018 for companies in the oil, gas and geothermal mining subsector, there were 4 companies in bankruptcy, 5 companies in gray area conditions, also 2 companies in healthy

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state. In 2019, 6 companies were in bankruptcy, 2 companies were in gray area also 2 companies were in healthy state. In 2020, 6 companies were in bankruptcy, 2 companies were in gray area also 2 companies were in healthy state. In 2021, 5 companies are in bankruptcy, 3 companies are in gray area as well as 2 companies are in healthy condition. Finally, in 2022, 5 companies will be in bankruptcy, 1 company will be in a gray area also 4 companies will be in a healthy condition.

SPRINGATE MODEL

The following are the outcomes of financial distress prediction utilizing the Springate model.

Table 3 Financial Distress Prediction Model Springate

NO	CODE	YEAR				
		2018	2019	2020	2021	2022
1	MEDC	0.7236	0.6882	0.3075	0.6882	1.2409
2	PGAS	1.0547	1.0353	0.3594	0.9387	1.0669
3	ENRG	-0.0053	0.6592	0.5415	0.7456	0.7617
4	APEX	-0.9287	1.1742	4.7287	0.5776	-3.1265
5	ESSA	0.5063	0.3428	0.0686	0.7131	3.2804
6	SURE	-0.3573	-0.0253	0.3868	-0.4456	-0.5502
7	MITI	6.5976	-1.2893	0.3007	0.9875	2.8044
8	PKPK	0.0051	-0.4654	-0.0823	-1.8479	-0.1187
9	ARTI	0.5091	-1.0119	-1.5096	-1.3954	-1.2538
10	MTFN	0.3752	0.6783	0.6379	0.3162	0.2054

Source: Processed data, 2023

Information: Red = Bankrupt and Green = Healthy

Table 2 shows the outcomes of financial distress prediction utilizing the Springate model. In 2018, there were 8 companies in the oil, gas and geothermal mining subsector that were bankrupt and 2 other companies were in a healthy condition. In 2019, 8 companies were in bankruptcy and 2 other companies were in healthy condition. In 2020, 9 companies were in bankruptcy and 1 other company was in healthy condition. In 2021, 8 companies are in bankruptcy and 2 other companies are in bankruptcy. Then in 2022, 6 companies will go bankrupt and 4 other companies will be in good health.

ZMIJEWSKI MODEL

Below are the outcomes of financial distress prediction utilizing the Springate model.

Table 4 Financial Distress Prediction Model Zmijewski

NO	CODE	YEAR				
		2018	2019	2020	2021	2022
1	MEDC	-0.1428	0.0423	0.1068	0.1221	-0.3970
2	PGAS	-1.0749	-1.1451	-1.8056	-2.2501	-2.8065
3	ENRG	0.7751	0.3284	-0.3484	-1.1873	-1.3296

4	APEX	3.9606	0.5897	-1.3621	-0.7542	-1.1322
5	ESSA	-4.4651	-4.5867	-4.0788	-4.3502	-5.4827
6	SURE	0.5209	0.5806	-1.6562	-1.3383	-0.9041
7	MITI	-1.7403	9.4783	-3.4873	-3.0727	-3.4847
8	PKPK	-1.0044	2.8500	-2.3135	-2.1262	2.3968
9	ARTI	-2.6620	-2.4213	4.5023	3.2159	3.2685
10	MTFN	1.3613	1.2289	1.3399	1.5656	1.6458

Source: Processed data, 2023

Information: Red = Bankrupt and Green = Healthy

Table 3 indicates the outcomes of financial distress prediction utilizng the Zmijewski model. In 2018, 4 companies in the oil, gas as well as geothermal mining subsector were in bankruptcy and 6 other companies were in good health. In 2019, 7 companies were in bankruptcy and 3 other companies were in good health. In 2020, 3 companies were in bankruptcy and 7 other companies were in good health. In 2021, 3 companies are in bankruptcy and 7 other companies are in good health. Then in 2022, 3 companies will go bankrupt and 7 other companies will be in good health.

GROVER MODEL

Below are the outcomes of financial distress prediction utilizing the Grover model.

Table 5 Grover's Financial Distress Prediction Model

NO	CODE	YEAR				
		2018	2019	2020	2021	2022
1	MEDC	0.6947	0.6398	0.4246	0.5888	0.7587
2	PGAS	0.7997	0.8657	0.4490	0.6114	0.7067
3	ENRG	-0.3556	0.2140	0.1301	0.3288	0.3635
4	APEX	-1.2088	0.2467	0.2219	0.3854	0.5019
5	ESSA	0.4356	0.4065	0.1144	0.6440	1.7347
6	SURE	-0.8143	-0.3302	0.8860	0.5495	0.3255
7	MITI	6.8236	-0.2253	0.1744	1.0344	3.0998
8	PKPK	0.5593	-0.7441	-0.3307	0.2214	-0.0390
9	ARTI	0.4720	-0.3145	-1.4813	-1.9162	-1.9219
10	MTFN	0.2469	0.3528	0.3494	0.2270	0.1258

Source: Processed data, 2023

Information: Red = Bankrupt and Green = Healthy

Table 4 shows the results of financial distress prediction utilizing the Grover model. In 2018, 3 companies in the oil, gas also geothermal mining subsector were in bankruptcy and 7 other companies were in good health. In 2019, 4 companies were in bankruptcy and 6 other companies were in good health. Then in 2020, 2 companies were in bankruptcy and 8 other companies were in good health. Then in 2021, 1 company is in bankruptcy and 9 others are in good health. Finally, in 2022, 2 companies will go bankrupt and 8 other companies will be in good health.

TEST THE ACCURACY OF THE FINANCIAL DISTRESS PREDICTION MODEL

After going through the inspection, it can be seen that none of the companies sampled in this study have actually experienced delisting. Thus, the following are the results of the accuracy test of the financial distress prediction model.

Table 6 Accuracy Test of the Financial Distress Prediction Model

Calculation	Model Financial Distress Prediction			
	Altman Z-Score	Springate	Zmijewski	Grover
Accuracy Level	24%	22%	60%	76%
Type Error II	52%	78%	40%	24%
Grey Area	24%	-	-	-
Amount	100%	100%	100%	100%

Source: Processed data, 2023

Table 5 is a recapitulation table of the accuracy of the financial distress prediction model used in this research. Based on the calculations that have been executed, the accuracy test results of the four models show that the Grover model has the highest level of accuracy compared to the Altman Z-Score, Springate as well as Zmijewski models. The accuracy degree of the Zmijewski model reached 76% with the lowest Type II Error, namely 24%. The outcomes of this test are in agreement with research Kusdimanto & Nurmatias (2023) conducted, which shows that the Grover financial distress prediction model has a higher degree of accuracy in contrast with other prediction models.

CONCLUSION

In accordance to the results of research as well as discussion about financial distress prediction in oil, gas, also geothermal mining subsector companies registered on the Indonesia Stock Exchange (BEI) for the 2018-2022 period using 4 financial distress prediction models, namely Altman Z-Score, Zmijewski, Springate, also Grover, the conclusions are able to be drawn below: The outcomes of calculations utilizing the Altman Z-Score financial distress prediction model indicate that in the oil, gas and geothermal mining subsectors listed on the BEI for the 2018-2022 period, the MITI company is in a non-financial distress or healthy state, more continued MEDC, PGAS, ESSA also SURE are in a Gray Area condition or have the potential to be faced with financial distress, also ENRG, APEX, PKPK, ARTI and MTFN are in a condition of financial distress or bankruptcy. The outcomes of calculations utilizing the Springate financial distress prediction model show that in the oil, gas and geothermal mining subsectors listed on the BEI for the 2018-2022 period, PGAS, ESSA and MITI companies are in a healthy state or non-financial distress, meanwhile the MEDC, ENRG, APEX, SURE, PKPK, ARTI and MTFN companies are in an unhealthy condition or have the potential to be faced with financial distress or go

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bankrupt. The outcomes of calculations utilizing the Zmijewski financial distress prediction model show that in the oil, gas and geothermal mining subsector listed on the BEI for the 2018-2022 period, the companies MEDC, PGAS, ENRG, ESSA, SURE, MITI and PKPK is in a healthy state or non-financial distress, meanwhile the APEX, ARTI and MTFN companies are in an unhealthy state or have the potential to be faced with financial distress or go bankrupt. The outcomes of calculations utilizing the Grover financial distress prediction model show that in the oil, gas, also geothermal mining subsector listed on the BEI for the 2018-2022 period, the companies MEDC, PGAS, ENRG, APEX ESSA, SURE, MITI and MTFN are in a healthy state or non-financial distress, meanwhile the PKPK as well as ARTI companies are in an unhealthy state or have the potential to be faced with financial distress or go bankrupt. Calculation outcomes of financial distress prediction models for oil, gas, as well as geothermal mining subsector companies listed on the BEI for the 2018-2022 period using 4 financial distress prediction models, namely Altman Z-Score, Zmijewski, Springate, also Grover. Shows that the Grover model has the highest degree of accuracy in contrast to the other three models, where the accuracy level of the Grover model is 76% with the lowest Type II Error amongst the other models, namely 24%.

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