Predicting and Comparing Bankruptcy Models in Indonesian Real Estate Companies

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Abstract: - This presents the assessment of a real estate bankruptcy risk, and the purpose of its consideration is to demonstrate the effectiveness in predicting companies in Indonesia that are vulnerable to bankruptcy during the pandemic. This is important to provide predictions of company bankruptcy during the pandemic period, and so far, no research has accommodated a similar selection. Empirical research analyzed financial data from 28 observations of real estate companies in Indonesia from 2019 to 2022. The time frame allows for identifying and assessing the effectiveness of early warning models, especially during pandemic turmoil. The analysis methods used are the Z-Score, S-Score, X-Score, G-Score, and O-Score. The best bankruptcy model in the real estate sector is the X-Score. The contribution of this research is that the type of bankruptcy model specification cannot be generally applied to various companies, specifically the real estate industry. We suggest using the X-Score to predict bankruptcy alarms as one of its instruments.

Key-Words: - Bankruptcy, Predicting Bankruptcy, Bankruptcy Models, Real Estate Companies, Pandemic Period, X-Score, forecasting Bankruptcy, bankruptcy prediction.

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1 Introduction

Investors, creditors, staff members, clients, and other stakeholders of the impacted business all suffer greatly when a company files for bankruptcy. Prior studies have demonstrated that businesses under economic strain also suffer losses, and the stock prices of their strategic partners react negatively. "Like when a pebble is thrown into a lake, and the shock wave reaches far beyond the initial point of impact when a company is under financial stress, there are adverse consequences for diverse stakeholder groups...". The process of filing for bankruptcy is typically gradual rather than abrupt, with warning signals appearing years in advance of the actual occurrence. [1], the potential for business failures can be attributed to deviant policies and fraudulent activities within the fraud framework. [2], failures often stem from stakeholders deviating from established policies to pursue specific objectives that may counter legal regulations. As such, organizations should be able to take the appropriate steps to enhance their financial health and reduce the adverse socio-economic impact on stakeholders if financial troubles are a sign of potential future bankruptcy and can be identified early on. [3], highlighted is that companies in Indonesia are currently contending with many complex issues that directly influence their company value, a critical metric in assessing their performance and long-term business sustainability. Risk Management is the most important financial stability and economic growth factor in developed economies, [4]. Bankruptcy prediction models are a reliable and practically successful tool for distinguishing between financially sound and financially stressed companies on the verge of bankruptcy. The bankruptcy prediction model results in a measure of bankruptcy risk and a derivative classification of potentially insolvent companies. To improve the interpretation of the enterprise's financial status, one of the fundamental problems facing managers of modern enterprises is identifying effective methods for assessing the financial condition of an enterprise and warning against threats to the continuation of its operations. In a company, decision-making and flexible reactions to change become increasingly complicated. Tools that allow early identification of bankruptcy risks have become necessary in managing an enterprise. Discriminant analysis is helpful and has become an increasingly popular tool. However, due to several financial risk forecasting models, we need to check the reliability of several bankruptcy prediction analysis tools to select the best of these models. This paper aims to verify the effectiveness of models based on discrimination analysis, predict bankruptcies, and assess the financial condition of listed companies. In the years 2019 to 2022, the COVID-19 pandemic severely affected people's lives around the world. It caused the greatest economic downturn since the Great Depression, primarily because major cities implemented curfews and activity restrictions that restricted people's ability to move around and travel. [5], [6] ,[7], [8], [9], the spread of COVID-19 has caused severe losses and commercial interruption, among other disasters. Interestingly, based on this occurrence, ongoing long-term shocks, delays in loan payments, and uncertain real estate investment prospects have contributed to an increase in systemic vulnerability in the real estate sector, [10].

Social distancing, mass layoffs, and the failing national economy all contribute to the decline in people's purchasing power, which makes them decide not to invest in real estate or spend money. Companies would fail and go bankrupt much faster, especially in the face of deteriorating economic conditions that result in the accumulation of numerous real estate assets that cannot be sold and pose a threat to financial ratio turnover. Considerable progress has been made in modeling methodologies for the company's bankruptcy prediction over the last few decades. Financial risk indicators were used in discriminant analysis for field data at first. Next, we discuss logistic regression. Then, using hazard models, the theory behind logit predictions was enhanced.

[11], created the first model, the Altman z-score model, using multiple discriminant analysis (MDA) in 1968. Because it has more sorts of ratios than other models that might describe the entire financial situation of the organization, this model is frequently utilized in financial distress prediction research. According to research, Z-Score model is the most accurate in predicting a company's likelihood of going bankrupt, [12], [13], [14].

By utilizing multidisciplinary analysis, [15] established the second model, known as the S-Score or Springrate Model, in 1978. Additionally, S-Score model compiles a range of financial statistics that are useful in bankruptcy prediction. According to research, the S-Score Model outperforms other prediction models in terms of accuracy. The S-Score method's disadvantage is that it might lead to financial engineering or engineering of the ratio value through the use of false accounting rules. However, the lack of use of the current ratio in bankruptcy prediction is a flaw shared by the S-Score Model and the Z-Score technique. Including the current ratio will improve the accuracy of the procedure as it gauges the company's capacity to pay short-term creditors.

Using ratio analysis, [16] created the third model, the X-Score, in 1984. This model gauges a company's performance, leverage, and liquidity in relation to its predictive model. Establishing the first sample and population proportion is necessary to ascertain the frequency of financial difficulty. The X-Score method, which analyzes financial distress using the current ratio, overcomes the shortcomings of both approaches, [17], [18], [19]. According to research, the X-Score is the most accurate way to predict a company's likelihood of going bankrupt, [17], [18], [19].

The Z-Score model was designed and re-examined to produce the G-Score, the fourth model. In 1968, [20] added 13 new financial ratios to the sample based on the Z-Score. According to studies, when compared to other models, G-Score model calculates bankruptcy potential with the best degree of accuracy. The same is seen in studies carried out by Z-Score and S-Score approaches outperform G-Score method in that they employ the sales-to-total-assets ratio to analyze financial distress, effectively addressing G-Score method's shortcomings, [21], [22].

The fifth model, the O-Score Model, makes use of real estate analysis to get around issues with assumptions that crop up in Multiple Discriminant Analysis (MDA), specifically data that has been subjected to standards for data normality. O-Score model incorporates firm-size properties as research properties, which is not the case with most prediction models. The utilization of these variables is predicated on the idea that a company's size directly correlates with its chance of encountering financial issues, [23], [24].

Changes in company profit management during times of crisis, quick changes in laws and regulations, dynamic economic conditions, and changes in financial reporting can all negatively impact the performance of current bankruptcy prediction models. Since few research have provided a clear explanation for this relationship, the effect of crisis periods on bankruptcy prediction models has not been investigated. Research has shown that models used to predict bankruptcy performed better than ever following the crisis. Crises having a detrimental effect on the model only a drop in model performance during the crisis can validate a bankruptcy prediction, [25].

In order to provide two contributions to the field of bankruptcy prediction, we evaluate the bankruptcy rate that real estate businesses faced during the COVID-19 pandemic period and investigate if the outcomes of our predictions differ from those of the companies listed on the IDX between 2019 and 2022. Initially, we present a summary of bankruptcy forecasts made by five sets of bankruptcy prediction methods for Indonesia's real estate industry during the epidemic. The second is a comparison of the accuracy of the bankruptcy prediction model's performance during the epidemic.

The format of this document is as follows: An overview of pertinent research on the subject of real estate company bankruptcy prediction and the effect of crises on the effectiveness of bankruptcy prediction models is presented in Part 1. The research technique used in this study is described in Part 2, together with information on the data sample, financial ratios, and qualitative indicators. The findings of the analysis are shown in Part 3. The research findings are covered in Part 4, and the conclusion is presented in the last section.

2 Literature Review

2.1 Financial Distress

The effect of crisis periods on the effectiveness of bankruptcy models is not well-analyzed in research. The study of [26] was one of the earliest studies that were done. The research, which looked at 46 Korean businesses between 1991 and 1998, revealed that those that filed for bankruptcy during the Asian crisis did not perform as well financially prior to filing (high debt ratio). Nonetheless, the study's logit bankruptcy prediction models continued to perform at around the same levels for both the pre-crisis and crisis periods, ranging from 76% to 87%. Furthermore, they conclude that the accuracy of the model is unaffected by macroeconomic conditions in light of their findings. Through discriminant analysis, they employed the Z-score and changed the original form for 1,090 UK enterprises (of which 1000 were successful and 90 were not) between 2000 and 2013. Among the conclusions is that the pre-crisis era had the lowest accuracy. Higher detection models make bankruptcy detection easier by requiring noticeably weaker financial performance from insolvent enterprises. However, research found that compared to pre-crisis eras, predictive model performance was lower during and after crisis periods, [27].

Since financial troubles are viewed as harmful to the company and its stakeholders, they have been a prominent topic in corporate finance for many years. With the current global economic unrest and severe economic downturn, businesses are exposed to a more complex economic landscape than in the past, increasing their risk of suffering severe financial setbacks. Thus, for contemporary financial researchers and practitioners, foreseeing financial problems is crucial. When a business misses payments or anticipates that its cash flow will not allow it to make them, financial issues usually follow. Management must regularly review and assess the company's financial accounts utilizing financial ratios in order to preserve the viability of the business. Financial statements provide a comprehensive overview of the company's financial situation during a given time period and also forecast its future status, [28], [29], [30].

A corporation may experience financial trouble due to a number of factors, most of which are twofold: external and internal signs. Indicators that provide access to general corporate information in financial markets are referred to as external indicators. Internal indicators, on the other hand, are defined as those that come from the cash flow statements of the business and include things like management plans and financial statements. Law No. 1 of 1998 enumerates the legal foundation that governs financial crisis situations in Indonesia. Modern insolvency laws are designed to address situations where a debtor is unable to meet their financial obligations, ensuring fair treatment of all creditors and minimizing damage, [31].

2.2 Bankruptcy Prediction Model

2.2.1 Z-Score Model

When using the Z-Score model for analysis, it's important to identify the financial ratios that impact an organization's success. A standard procedure with a specific formula is used for comparison and research:

$$Z = 1.2X1 + 1.4X2 + 3.3X3 + 0.6X4 + 1.0\,X5 \tag{1}$$

Information:
Z: Overall Index (*z-score*)
X1: Investment in Capital Assets to Total Assets
X2: Retained Earnings to Total Assets Ratio
X3: Return on Total Assets (ROTA)
X4: Market Value to Debt Ratio
X5: Asset Turnover Ratio
Value *Cut-off* or the limits of the Z-Score model are as follows, [32]:

Table 1. Z-Score Analysis

Z	Classification
Z > 2.99	Healthy
1.81 < Z < 2.99	*Grey Zone*
Z < 1.81	Bankrupt

2.2.2 S-Score Model

S-Score model uses Multiple Discriminant Analysis approach and multiple financial ratios to predict bankruptcy:

$$S = 1{,}030X1 + 3{,}070X2 + 0{,}660X3 + 0{,}40X4 \tag{2}$$

Information:
S: Overall Index (*S-Score*)
X1: Ratio of Working Capital to Total Assets
X2: Ratio of Earnings Before Interest and Tax to Total Assets
X3: Profit Before Tax Ratio to Total Current Liabilities
X4: Sales to Total Assets Ratio

In bankruptcy analysis, the Springate Model shows company performance or the likelihood of bankruptcy based on its calculations. These are the cutoff or bounds of the S-Score model, [33]

Table 2. S-Model Model Analysis

S	Classification
S > 0.862	Healthy
S < 0.862	Bankrupt

2.2.3 X-Score Model

The X-Score model uses financial ratios to forecast business insolvency. The model's formula is as follows:

$$X = -4{,}3 - 4{,}5X1 + 5{,}7X2 - 0{,}004X3 \tag{3}$$

Information:
X: Overall Index (*x-score*)
X1: Profit net to Total Assets
X2: Total Debt against Total Assets
X3: Assets Current to Current Liabilities
The X-Score Model's bankruptcy study indicates a positive correlation between a company's performance and the model's calculation results, with the following cutoff or bounds, [34]

Table 3. X-Score Model Analysis

X	Classification
X > 0	Bankrupt
X < 0	Healthy

2.2.4 G-Score Model

G-Score model equations were obtained by rebuilding the selection and adding 13 financial ratios. It was then assessed. The following formula is employed in G-Score model, [35]

$$G = 1{,}6500X1 + 3{,}4040X2 - 0{,}0160X3 + 0{,}0570 \tag{4}$$

Information:
G: Overall Index (*G-score*)
X1: Capital Work on Total Assets
X2: Profit before Interest and Tax (EBIT) on Total Assets
X3: Profit net to Total Assets (ROA)

A bankruptcy study using the G-Score Model can indicate a company's performance or its likelihood of bankruptcy. The model has specific cutoffs and limits:

Table 4. G-Score Model Analysis

G	Classification
G ≥ 0.01	Healthy
G ≤ -0.02	Bankrupt

2.2.5 O-Score Model

Allowing the evaluation of various samples without assuming MDA limitations, [36]:

$$O = -1{,}320 - 0{,}4070X1 + 6{,}030X2 - 1{,}430X3 + 0{,}07570X4 - 2{,}370X5 - 1{,}830X6 + 0{,}2850X7 + 1{,}720X8 - 0{,}5210X9 \quad (5)$$

Information:
O: Composite Score (O-score)
X1: Logarithm of Total Assets versus GNP Price Index
X2: Ratio of Total Assets to Total Liabilities
X3: Net Working Capital to Total Assets
X4: Ratio of Current Assets to Current Liabilities
X5: Indicator Variable for Solvency (1 if total liabilities exceed total assets; 0 otherwise)
X6: Net Profit to Total Assets
X7: Operating Cash Flow to Total Liabilities
X8: Binary Variable for Negative Net Income (1 if net income is negative; 0 if positive for two consecutive years)
X9: Year-over-Year Net Profit Change Ratio:

Table 5. O-Score Model Analysis

O Score	Classification
O < 0.38	Healthy
O > 0.38	Bankrupt

Based on this explanation, the hypotheses formed are:

***Hypothesis 1**: ”There are differences in results on bankruptcy prediction models between the Z-Score, S-Score, X-Score, G-Score, and O-Score Models in real estate sector companies for the period 2019-2022.”*

***Hypothesis 2**: “There are differences in the accuracy of bankruptcy prediction models in real estate sector companies”*

3 Methodology

3.1 Data

The study uses a quantitative approach, drawing data from the annual financial statements of real estate companies listed on the Indonesia Stock Exchange between 2019 and 2022 as its secondary source. Access the financial statements at [37]. Sampling follows specific criteria:

1. Real estate companies that were listed sequentially between 2019 and 2022.
2. The business released full, audited financial statement information for the years 2019 through 2022.
3. From 2019 to 2022, all of the data related to the variables utilized in this study will be accessible.

Seven companies meeting the criteria after four years were selected, totaling 28 observations.

3.2 Data Analysis Techniques

3.2.1 Normality Test

To validate the suggested model, a comprehensive model conformance test is used, involving a thorough normality assumption examination.

3.2.2 Differentially Test

To assess the model's alignment with the data, a comprehensive model conformance test is utilized. The Kruskal-Wallis test, a non-parametric statistical method, effectively determines significant differences between independent and dependent variables. The test's hypotheses assume continuous distributions of the examined variables.

3.2.3 Accuracy Test

The accuracy of each bankruptcy prediction model is calculated to identify the most accurate predictor by comparing predictions with actual conditions. This computation also helps find the most accurate model for predicting company bankruptcy within the study sample, yielding appropriate and accurate classifications contrasting with bankruptcy model predictions [38]. The accuracy and error levels are computed using the formula below, [38]:

Accuracy Level= (number of correct predictions)/(number of samples) x 100% (6)

Error type rate= (number of predictions wrong)/(number of samples) x 100% (7)

4 Discussion

4.1 Descriptive Statistics

The first step in the analysis is to calculate predictions according to each formula for each model, next step is to compare the calculation results of each model with the bankruptcy prediction classification by referring to Table 1 for Z-Score, Table 2 for Analysis S-Score Model, Table 3 for X-Score Model Analysis, Table 4 for G-Score Model Analysis and Table 5 for O-Score Model Analysis. Furthermore to ascertain the values of the five prediction models in this study's lowest (minimum), highest (maximum), average (mean), and standard deviation, using a descriptive statistical model, the data were described. Two categories comprise the evaluated companies: businesses in the real estate industry. A financial report or annual report for the years 2019 through 2022 that was obtained from the www.idx.co.id website makes up the processed data. Table 6 displays the findings of the descriptive statistical test for the real estate industry:

Table 6. Real Estate Sector Descriptive Statistical Test Results

Variable	**N**	**Min**	**Max**	**Mean**	**Std. Deviation**
Z-Score	28	0,057199	11,19182	2,630438	3,62866
S-Score	28	-0,66706973	0,621899018	-0,09594218	0,354866439
X-Score	28	-4,01567	2,316245	-1,73852	1,794596
G-Score	28	-0,34901	0,929902	0,093842	0,354048
O-Score	28	-67,3032	316,2015	45,43657	120,2404

According to the outcomes of the real estate industry's descriptive statistical test, the Z-Score variable's value falls between 0.057199 and 11.19182. This variable has an approximate average of 2.630438 and a standard deviation of 3.62866. The S-Score variable has an average of roughly -0.09594218 and a range of -0.66706973 to 0.621899018. With an average that is almost zero, this data seems to be more concentrated than the Z-Score variable. Similar to Z-Score model, the X-Score model variable exhibits significant swings as well, with an average value of roughly -1.73852 and a range of -4.01567 to 2.316245. The values of G-Score variable model range from -0.34901 to 0.929902. This variable has a mean value of approximately 0.093842 and a standard deviation of approximately 0.354048. With an average value that is almost equal to zero, this data is more concentrated than the Z-Score variable model and is comparable to the S-Score variable model. The values of the O-Score variable model fluctuate widely, from -67.3032 to 316.2015. With a fairly high standard deviation of approximately 120.24004, the average value of this variable is approximately 45.43657. The data for this variable exhibits extraordinary fluctuation, mostly because of its very high maximum value and substantial standard deviation.

4.2 Normality Test

A normality test is performed to determine whether the data usually circulates or not. the Table 7 displays the normality test results for the real estate sector data in the context of this study:

Table 7. One-Sample Kolmogorov-Smirnov Test

	Zscore: Financial Distress
N	28
Kolmogorov-Smirnov Z	6.2210
Asymp. Sig. (2-tailed)	.0001
Exact Sig. (2-tailed)	.0001
Point Probability	.0001

a. Test distribution is Normal.
b. Calculated from data.

The One-Sample Kolmogorov-Smirnov Test results are displayed in the Table 7. The test results do not match the normalcy test criteria, as evidenced by the significant p-value ($p < 0.005$) and high Z-score statistical value. In this study, a non-parametric test was employed to guarantee the validity and consistency of the analytical results.

4.3 Non Parametric Test

Five models of financial distress evaluation were utilized in this study: G-Score model, O-Score model, X-Score model, Z-Score model, and S-Score model. A more thorough understanding of a company's financial stability and possible financial issues can be obtained with this model. The measure of financial hardship in the real estate industry is a non-parametric test. Table 8 presents the results of non-parametric tests and shows the mean rank values for each approach.

Table 8. Table Ranks Real Estate Sector

	Financial Distress Measurement Method	N	Mean Rank
Financial Distress	Z-Score	28	58.13
	S-Score	28	37.50
	X-Score	28	98.79
	G-Score	28	77.18
	O-Score	28	80.91
	Total	140	

Out of the four approaches, the X-Score model variable has the highest mean rank value (98.79), as the above Table 8 illustrates. These results suggest that real estate companies usually or frequently use the X-Score model variable to measure financial distress, which is different from the other four models in this sample. However, the average value of the S-Score model is the lowest. This variable received the lowest ranking of all the approaches, indicating that the S-Score model was either not used at all or used less frequently to gauge financial distress. The mean rank values of G-Score model, Z-Score model, and O-Score model were 77.18, 58.13, and 80.91, respectively, for X-Score model, which ranked first and second, respectively.

4.4 Test the Hypothesis

Statistical tests to evaluate the H1 and H2 hypotheses, two hypotheses. Statistical tests are used to process data in order to test this premise. Results of the test statistic that show the exact value. Table 9 shows the sig to estimate the significance level:

Table 9. Test Statistics,[b] in the Real Estate Sector

	Financial Distress
Chi-Square	49.0860
Df	4,0
Asymp. Sig.	.0001
Exact Sig.	.0001
Point Probability	.0001

a. Kruskal Wallis Test
b.Grouping Variable: Financial Distress Measurement Method

It is evident from the preceding Table 9 that the Chi-Square test findings are highly significant. If the Exact Sig is less than 0.05, then the five financial distress methodologies' test results differ from one another. In summary, hypothesis H1 is agreed upon. Stated otherwise, there exist variations in the bankruptcy prediction model outcomes for real estate sector companies for the 2019–2022 timeframe between the Z-Score, S-Score, X-Score, G-Score, and O-Score models. Thus, this analysis finds that among the real estate companies examined in 2019–2022, there is a considerable variation in the outcomes of the highest accuracy prediction models.

4.5 Accuracy Test

The goal of calculating each bankruptcy prediction model's accuracy rate is to determine which one is the most accurate predictor. By comparing prediction results with real conditions, accuracy tests can identify prediction models with the highest accuracy level and the proportion of error types owned. This computation is also done to find the best model to predict the bankruptcy of the company that is being used as a study sample. Table 10 displays the findings of this study's computation of the five models' accuracy levels and the error rate for businesses in the real estate industry.

Table 10. Calculation of Accuracy Rate and Rate *Error* in the Real Estate Sector

	Z-Score	S-Score	X-Score	G-Score	O-Score
Number of Observations	28	28	28	28	28
Predictions Accordingly	8	0	24	15	17
Inappropriate predictions	**20**	28	4	13	11
Error *Rate*	72%	100%	14%	46%	39%
Accuracy Rate	28%	0%	86%	54%	61%

The accuracy rate for each of the five real estate company bankruptcy prediction models is calculated and displayed in Table 10. The models that were employed were G-Score, O-Score, X-Score, Z-Score, and S-Score. With eight comparable predictions made from 28 observations, the Z-Score model yielded an accuracy rate of 28% and an error rate of 72%. With 28 observations, the S-Score model generates 0 corresponding predictions, yielding an accuracy rate of 0% and an error rate of 100%. This demonstrates that the S-Score variable's predictive power for bankruptcies in the real estate industry is quite poor. With a high accuracy rate of 86% and a low error rate of 14%, X-Score model only produced 24 related predictions from 28 observations and four forecasts that matched reality. With 28 observations, G-Score model produced 13 inaccurate predictions, yielding an accuracy rate of 54% and an error rate of 46%. With 28 observations, O-Score made 11 inaccurate predictions, yielding a 39% error rate and a 61% accuracy rate.

The five models can be compared to determine which is the most accurate by calculating the accuracy and error rate level in the real estate industry. The comparison's outcomes are displayed in Table 11.

Table 11. Comparison Table of Accuracy and *Error* Levels in Real Estate Sectors

Type	Accuracy Rate	Error Rate	Rating The most accurate models
X-Score	86%	14%	1
O-Score	61%	39%	2
G-Score	54%	46%	3
Z-Score	28%	72%	4
S-Score	0%	100%	5

With an accuracy rate of 86%, X-Score model comes in first place as the most accurate model, according to Table 11. With a 61% accuracy rate, O-Score model is the second most accurate of the five models examined, only surpassed by X-Score model. G-Score model, which had a 54% accuracy rate, ranked third. The S-Score model is a variable that maintains the last order because it has a reasonably large mistake rate of 100% with a low accuracy rate of 0%. The Z-Score model comes in fourth place with an accuracy rate of 28%. This explanation leads to the conclusion that the X-Score model is the most effective bankruptcy model for the real estate industry.

4.6 Discussion

The comparison of the Z-Score, S-Score, X-Score, G-Score, and O-Score models for bankruptcy prediction in real estate sector enterprises for the years 2019–2022 reveals variations in these models. This could support the study's initial hypothesis. The degree to which bankruptcy prediction models are able to recognize risk indicators that are appropriate for the particular business environment can have an impact on their success. Better outcomes might come from using a more trustworthy model to describe the state of the business. Timely forecasts are crucial for businesses and investors when assessing risk or averting bankruptcy. This is due to the signaling hypothesis, which postulates that when investors make investment decisions, information conveys signals to them. This signal may be used to anticipate or indicate whether a business will be declared bankrupt or not. The findings of this study are consistent with a number of earlier investigations that seek to identify the most suitable and accurate model as a tool for predicting a company's bankruptcy, [39], [40], [41], [42].

The second hypothesis, according to which there are variations in the accuracy of bankruptcy prediction models in real estate sector enterprises, is accepted, which supports this finding. The accuracy of each model in predicting corporate bankruptcy is demonstrated by the results of data analysis conducted in the real estate company sector. The X-Score model was shown to be a suitable model for predicting financial difficulty in real estate sector companies listed on the IDX in 2019–2022, based on the accuracy calculation. With the highest accuracy rate of 86%, our model accurately predicted the bankruptcy conditions for every instance examined in the real estate industry.

The claim that the X-Score model is the most appropriate for forecasting financial issues in real estate sector enterprises is robustly supported by our research findings. Our results are in line with the empirical research of [43], [44], The importance of technological capability in improving risk management in the real estate sector further underscores the need for robust predictive models like the X-Score, which can be enhanced with additional financial and macroeconomic variables to provide more accurate forecasts. This accuracy shows that the algorithm is reliable in identifying troubled real estate enterprises even in difficult times, like the years 2019 to 2022. Notably, the Z-score, Revised Z-score, and S-Score methods identify several corporations as being vulnerable to bankruptcy. Before investing their hard-earned money, investors can prevent potential losses by avoiding financially unsound enterprises by using the X-Score model's threshold as an effective cautionary indicator, [45].

After the X-Score model, Type O-Score was the second most accurate model. The model can be examined in light of an enterprise's real circumstances. Research indicates that the X-Score method yields a higher degree of accuracy when applied to determine the financial position of the organization. These results demonstrate that X-Score model yields comparable results, and they suggest that a shortage of working capital could be the cause of future bankruptcy. In the real estate industry, Type Z-Score and S-Score are not very good at predicting insolvency. Certain business situations cannot be accurately predicted by these models. This result shows the X-Score model is the most accurate tool for predicting a company's likelihood of going bankrupt.

5 Conclusion and Recommendation

A company's financial situation can be evaluated using the financial distress analysis approach as a standard. It could be taken into account when a business is having financial issues. The analysis's findings can also be used by investors to select a business to invest in.

The accuracy rate is a crucial parameter in this analysis that evaluates how well bankruptcy prediction models perform. Higher accuracy models are thought to be more trustworthy when it comes to forecasting the financial health of real estate companies. Several judgments about Testing can be made based on the outcomes, specifically: There are variations in the forecast outcomes of the five models between the Z-Score, S-Score, X-Score, G-Score, and O-Score Models in Real estate Sector Companies for the 2019–2022 timeframe, according to the five financial distress prediction models that have undergone distinct testing. The results also demonstrate variations in the real estate industry companies' bankruptcy prediction models' accuracy. When it comes to predicting bankruptcy in real estate sector enterprises, X-Score performs the best in the model real estate sector, while the S-Score technique performs the worst.

An effective contribution from this research is made to creditors, investors, and management. This research confirms that the overall financial distress model serves as a signal for the state of the company's finances, helping to both identify and favorably evaluate a financial manager's strategy for forecasting operational difficulty or liquidation. Furthermore, no model that is ever made is flawless. As such, the outcomes of these forecasts cannot be regarded as definitive. Only indicators are included in the prediction results, advising creditors or investors to investigate further and be extra cautious when dealing with businesses that are expected to face financial difficulties. By combining artificial intelligence with the features of each industry, future research can create a bankruptcy prediction model that is more precise. It is also possible to take into account external elements including macroeconomic conditions, government initiatives, and regulatory changes. In order to evaluate the model and ascertain whether or not the two market conditions offer nearly the same level of accuracy, the next development analyzes market conditions under favorable and unfavorable circumstances.

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During the preparation of this work the author used Grammarly in order to improve grammar in English and improve word choice and better sentences. After using this tool/service, the author reviewed and edited the content as needed and take full responsibility for the content of the publication.

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- Lilik Purwanti was involved in Substantial contributions to the conception, methodology, analysis, and interpretation of data for the work and Final approval of the version to be published;
- Iwan Triyuwono Work in Investigation, reviewing critically for important intellectual content; Soelchan Arief Effendi design of the work and methodology;
- Melinda Ibrahim and Rino Tam Cahyadi are collecting, curation and data processing and Aryo Prakoso Writing draft preparation, visualization and project administration.

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