Applied Mathematics and Computational Intelligence
Volume 14, No. 1, 2025 [148-156]

Predicting Bankruptcy Risk using Grover's Model: A Case study in Malaysia Companies

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Received: 19 May 2024
Revised: 9 October 2024
Accepted: 12 November 2024

ABSTRACT

A bankruptcy prediction is one of the main critical problems for financial decision-makers. In this study, we aim to investigate the accuracy of Grover's model in predicting bankruptcy risk and further measure the risk of 5 Malaysian companies' financial failures using the model. Purposive sampling was used in this study, with five firms being chosen to be sampled in predicting bankruptcy risk. Meanwhile, the data from 292 US companies is used to test the accuracy of Grover's model in predicting bankruptcy risk. The predicted results are classified into three different zones to indicate different consequences. The predicted results were then compared to the actual data. The result shows that 4 out of 5 companies are predicted correctly with approximately 80% accuracy. The results are corroborated by 292 companies maintaining a 75% accuracy. Conclusively, the computed outcome from the case study suggests that Grover's model effectively predicts bankruptcy risk with an accuracy ranging between 75% and 80%.

Keywords: Grover's model, financial distress, financial literacy, bankruptcy risk, prediction bankruptcy model

1 INTRODUCTION

The study delves into the intricacies of bankruptcy, a legal process corporation undertake to discharge financial obligations. [1] notes that declaring bankruptcy adversely affects credit records in India, posing challenges in obtaining new loans for those seeking a fresh start. Research done in [2] highlights the impact of the COVID-19 pandemic, with 1,246 companies closing in Malaysia, leading to approximately 10,317 bankruptcy registrations. In the United States, bankruptcy cases have surged compared to the past decade, with 22,482 filings in 2019 rising to 23,114 in 2020.

Recent years have witnessed an increased focus on bankruptcy prediction as a critical concern for financial decision-makers [3]. Findings from [4] emphasize their role in forecasting financial stress that may culminate in bankruptcy. Essentially, bankruptcy prediction aims to ascertain the likelihood of a financial corporation going bankrupt. Factors such as financial economics, calamity, and fraud, identified by [3], contribute to this phenomenon. Accurate forecasting becomes crucial as it empowers stakeholders to make informed decisions, preventing bankruptcy and minimizing economic losses [4].

The evolution of bankruptcy prediction, explored since 1930, has witnessed various models, from early univariate statistical approaches to contemporary multivariate ones like Altman, Grover, Springate, and Zmijewski. Machine learning techniques, including logistic regression, neural networks, and decision trees, have gained prominence in this realm. This research evaluates the accuracy of Grover's model in predicting bankruptcy risk for five selected Malaysian companies.

2 LITERATURE REVIEW

The landscape of bankruptcy prediction models has witnessed diverse methodologies aiming to assess companies' susceptibility to financial distress. [5] and [6] illuminated the intricate relationship between market risk and firm performance, highlighting the detrimental impact of heightened market risk and the protective effect of a higher Interest Coverage Ratio (ICR) in mitigating financial distress.

In the realm of predictive modeling, machine learning techniques, as exemplified by [7]. have gained prominence. Their use of boosting algorithms to refine predictive precision underscores the evolving sophistication in bankruptcy prediction methodologies. Conversely, [8] employed a discriminant analysis model, emphasizing shareholder value measures in forecasting bankruptcy risks. These diverse approaches showcase the versatility of modeling techniques, each offering unique insights into the complex landscape of financial risk assessment.

Established frameworks, like the Z-score model employed by [9] provide foundational insights into a company's financial health, categorizing them into risk and good zones. The probabilistic perspective introduced by the Gulka model, as demonstrated by [10], contributes to the toolkit available for financial risk assessment.

Among these models, the Grover method has emerged with notable accuracy. [11] and [12] applied Grover's method in predicting bankruptcy, showcasing its effectiveness in sectors like coal and telecommunications. [13] comparative analysis highlighted significant differences between Altman, Springate, and Grover models in the pulp and paper industry. [14] explored the Zmijewski score, offering a unique perspective on financial distress prediction.

Building on these insights, [15] identified Grover's model as highly suitable for predicting bankruptcy in Indonesian manufacturing companies, attaining an impressive 92.03% accuracy. [16] and [17] affirmed Grover's method's reliability in Indonesian contexts, reporting 100% accuracy in financial distress measurement. In light of this extensive literature, this study strategically employs the Grover method to assess the risk of bankruptcy in selected Malaysian companies, considering its proven accuracy and adaptability across sectors and geographical contexts.

3 METHODOLOGY

3.1 Data

To investigate the accuracy of Grover's model, data from a global model for bankruptcy prediction is used (refer [18]). The dataset chosen consisted of 12 attributes, including the dependent variable (bankruptcy risk) with 340 samples in the American region. There are three countries in the dataset: Bermuda, Canada, and the United States. However, only one country, the United States, is focused on this study. This is because the United States has the most developed financial sector in the world. Hence, the data from the other two countries were deleted. Next, data cleaning is conducted by deleting the missing data (NA). After excluding the missing data in the dataset, 292 samples of companies in the United States of America (refer [18]) were selected for our case study. These 292 USA samples are used to test Grover's Model's accuracy in predicting bankruptcy risk.

Once the accuracy has been investigated, five samples of Malaysian companies are selected: Company A, Company B, Company C, Company D, and Company E. The selection of these companies for this study is justified by their representation of diverse sectors in the Malaysian economy, ensuring a thorough evaluation of Grover's model across various industries. These well-established companies with significant market influence contribute to the study's robustness, while the availability of publicly published annual financial statements for the year ending December 31, 2021, ensures the reliability of the data. The robustness of these companies is evident through their significant market influence and the availability of publicly published annual financial statements, ensuring the reliability and transparency of their financial data. By focusing on local entities, the study addresses the specificity of the Malaysian business environment, offering insights into the applicability of Grover's model to predict bankruptcy risk in this context. The strategic selection aims to provide a comprehensive and contextually relevant assessment of the model's effectiveness in the Malaysian landscape.

3.2 Grover’s Model

In this study, the utilization of Grover's model to predict the risk of bankruptcy stems from its unique approach, developed by Jeffrey S. Grover through a meticulous modification and reassessment of the Altman Z-Score model [12]. Grover's model relies on three key financial ratios—working capital to total assets, earnings before interest and tax to total assets, and net income to total assets—for predicting the risk of bankruptcy [12]. Notably, the scarcity of studies employing Grover's model in predicting bankruptcy underscores its distinctive nature. Therefore, the deliberate choice of Grover's model for this study is motivated by the opportunity to contribute novel insights into its effectiveness, especially in predicting bankruptcy for the selected five companies. To assess its accuracy, the study leverages a dataset comprising 292 companies from the USA, offering a robust validation of Grover's model across a diverse range of enterprises and further justifying its selection as a predictive tool in this research.

The G-score formula is written as:

$$G\text{-}Score = 1.650X1 + 3.404X2 - 0.016\,ROA + 0.057 \qquad (1)$$

where *X1 = Working Capital/Total Assets*

X2 = Earnings Before Interest and Tax/Total Assets

ROA = Net Income/Total Asset

**Working Capital=Current Assets - Current Liabilities*

In Grover's model, the lower the G-score value, the higher the probability of a company going bankrupt. Three zones are divided to predict bankruptcy using a G-score model, which are the Distress Zone, Grey Zone, and Safe Zone. When the G-score of a company is less than or equal to -0.02 (Distress Zone), this means that the company may have a big chance of going bankrupt. Besides, the company has a moderate chance of going bankrupt if the G-score is between -0.02 and 0.01(Grey Zone). A G-score that is equal to or above 0.01 (Safe Zone) shows that there is almost no risk of going bankrupt.

To determine the accuracy of Grover's model, a 3x3 confusion matrix table is to be used. The confusion matrix is a method to visualize the prediction model's performance. In the confusion matrix table in Table 1, each actual result and the predicted result consist of three classes, which are 0, Grey, and 1.

Table 1: Confusion Matrix Table

		Predicted Result		
		0	**Grey**	**1**
Actual Result	**0**	**T0**	F0G	F01
	Grey	FG0	**TG**	FG1
	1	F10	F1G	**T1**

There are some labels in the 3 by 3 confusion table.

T: True, when actual and predicted results are the same.
F: False, when actual and predicted results are different.
0: Safe zone
G: Grey zone
1: Distress zone

Hence, the label can be understood as below,

T0: Actual and predicted results are the same (true), which is in the 0 zones (safe zone).
F0G: Actual and predicted results are different (false). The actual result is in the 0 zones (safe zone), while the predicted result is in the G zone (Grey zone).

F01: Actual and predicted results are different (false). The actual result is in the 0 zones (safe zone), while the predicted result is in 1 zone (distress zone).
FG0: Actual and predicted results are different (false). The actual result is in the G zone (Grey zone), while the predicted result is in the 0 zones (safe zone).
TG: Actual and predicted results are the same (true), which is in the G zone (Grey zone).
FG1: Actual and predicted results are different (false). The actual result is in the G zone (Grey zone), while the predicted result is in 1 zone (distress zone).
F10: Actual and predicted results are different (false). The actual result is in 1 zone (distress zone), while the predicted result is in the 0 zones (safe zone).
F1G: Actual and predicted results are different (false). The actual result is in 1 zone (distress zone), while the predicted result is in the G zone (Grey zone).
T1: Actual and predicted results are the same (true), which is in 1 zone (distress zone).

The accuracy is calculated by using the formula

$$Accuracy = \frac{T0 + TG + T1}{T0 + TG + T1 + F0G + F01 + FG0 + FG1 + F10 + F1G} x100\% \tag{2}$$

According to [19], accuracy between 60-70% is recognized as a "poor" model; accuracy between 70-80% is a good model; accuracy between 80-90% is an excellent model, and accuracy between 90-100% is probably an overfitting case.

4 RESULTS AND DISCUSSION

4.1 Accuracy of Grover's Model

To verify that Grover's model is a good model with high accuracy for predicting bankruptcy, 292 USA sample companies are used. This is because, according to [20], a larger sample size will cause the prediction to become more accurate, and the study based on these estimates is seen as more trustworthy. Based on the dataset, the three financial ratios and the actual result are given. Hence, only the G-score value is calculated, and the Vlookup function is used to classify the zone.

Table 2: Predicted Result of 292 USA Companies

Result	No. of Companies (Predicted)
0	223
Grey	1
1	68

Table 2 shows the predicted result of 292 USA companies using the G-score model. From the result, Grover's model predicts that 223 out of 292 companies are in the safe zone, one company is in the grey zone, and 68 companies are in the distress zone. The confusion matrix table for USA companies is shown in the table below:

Table 3: Confusion Matrix Table of USA Companies

		Predicted		
		0	**Grey**	**1**
Actual	**0**	**150**	0	0
	Grey	0	**0**	0
	1	73	1	**68**

From Table 3, we can observe that 218 out of 292 companies are predicted correctly. At the same time, 74 companies were misclassified. Grover's model predicted 73 companies are 0 (Not Bankrupt), but the actual result is 1 (Bankrupt). Besides, Grover indicates one company in the Grey zone, but the actual result is 1 (Bankrupt). By using the previous formulation, the accuracy of Grover's model among the 292 USA companies is at 75%.

4.2 Accessing Risk of Bankruptcy among Malaysian Companies

Table 4 shows the result of 3 financial ratios, G-Score, zone, predicted, and actual zone in each selected company.

Table 4: Actual and Predicted Results of Five Malaysian Companies

Company	ROA	X1	X2	G-Score	Zone	Predicted Result	Actual Result
Company A	0.0199	0.0277	0.0189	0.1666	Safe	0	0
Company B	0.0061	0.1392	0.0057	0.3059	Safe	0	0
Company C	0.0149	0.0966	0.0105	0.2519	Safe	0	0
Company D	-0.1615	-0.1397	-0.1580	-0.7088	Distress	1	0
Company E	0.0078	0.0187	0.0093	0.1194	Safe	0	0

As mentioned in the previous section, five companies' data are applied to the G-Score model by substituting the value of the variable, X1, X2, and ROA into the G-Score formulation. For example, the ROA, X1, and X2 values for Company A are 0.0199, 0.0277, and 0.0189, respectively. The G-Score result for the company is 0.1666. We illustrate the sample calculation below.

The same procedure was applied to compute the G-Score value for four other companies. Next, the zone is classified using the Vlookup function in Google Spreadsheet based on the G-score value. Again, using the Vlookup function, the companies are classified as 0 (Not Bankrupt) and 1 (Bankrupt), which is shown in the "Predicted Result" column according to the zone predicted. The table shows that only Company D shows negative financial ratios among the five companies. Hence, when calculating the

G-Score of this company, it shows a negative value (-0.7088), which is less than -0.02 and is classified as a distress zone. On the contrary, the other four companies have positive value financial ratios. Thus, since the G-Score value of these four companies is positive and is greater than 0.01, which is classified as a safe zone.

In short, we can see that Grover's model predicted that 4 out of 5 companies are in a safe zone, where the companies are at no risk of going bankrupt. And, only one company, Company D, is in a distress zone, which is a zone that indicates the company is facing a risk of bankruptcy. From the result, we can observe that the actual and the predicted results of Company A, Company B, Company C, and Company E are the same, located in the safe zone. However, the company, Company D, which is in the distress zone, shows that it differs from the actual one as it is located in the safe zone. The misclassification indicates the model is not accurate. Therefore, the accuracy of Grover's model is calculated.

Table 5: Confusion Matrix Table of Five Malaysian Companies

		Predicted		
		0	**Grey**	**1**
Actual	**0**	**4**	0	1
	Grey	0	**0**	0
	1	0	0	**0**

Table 5 shows the confusion matrix table of the five companies. The table shows that there is one misclassified company, where the actual result is 0 (Not Bankrupt), and the predicted result is 1 (Bankrupt). Using the formula of accuracy mentioned in Section 3.2, the accuracy of Grover's model among the five Malaysian companies is 80%. Hence, we can conclude that the bankruptcy result predicted from Grover's model is only 80% accurate and has a 20% probability of predicting wrongly.

In conclusion, the accuracy of Grover's model among the five Malaysian companies is about 80%, while the accuracy among the 292 USA companies is about 75%. Thus, we can conclude that the accuracy of Grover's model, which is used to predict the risk of bankruptcy, is around 75%-80%, which shows that Grover's model is a "good" model for predicting bankruptcy.

5 CONCLUSION

The study addresses the issue of bankruptcy prediction, employing Grover's model with varying sample sizes to enhance reliability. The accuracy, crucial for model dependability, reaches approximately 75% with 292 companies. The model categorizes outcomes into safe (non-bankrupt), grey, and distress (bankrupt) zones, focusing specifically on predicting bankruptcy for five Malaysian companies. Notably, only Company D is inaccurately predicted, resulting in an overall accuracy of about 80%. This indicates Grover's model is a robust tool for predicting bankruptcy, applicable to diverse Malaysian companies involved in this study, whether listed or unlisted. Practical implications include using the model to guide financial adjustments, such as improving net working capital or enhancing earnings before interest and taxes to mitigate bankruptcy risks. Overall, Grover's model emerges as a valuable instrument for monitoring, maintaining, and improving the financial performance of companies, offering early indicators for effective management interventions.

ACKNOWLEDGEMENT

Gratitude goes to Universiti Utara Malaysia, the School of Quantitative Sciences, and the respondents for their support in this study.

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