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PREDICTING FINANCIAL FAILURE: EMPIRICAL EVIDENCE FROM PUBLICLY – QUOTED FIRMS IN DEVELOPED AND DEVELOPING COUNTRIES[*]

Finansal Başarısızlığın Tahmini: Gelişmiş ve Gelişmekte Olan Ülkelerdeki Halka Açık Şirketlerden Ampirik Kanıtlar

Yavuz GÜL[**] & Serpil ALTINIRMAK[***]

Keywords:
Financial Failure, Logistic Regression, Artificial Neural Networks, Decision Trees

JEL Codes:
C13, C15, C38, G33

Abstract

This paper analyzes the data of 570 firms from developed and developing countries between 2010 and 2019 in an attempt to create high–accuracy financial failure prediction models. In this sense, we utilize three different methods, namely logistic regression (LR), artificial neural networks (ANN), and decision trees (DT), and compare the classification accuracy performances of these techniques. Using 16 financial ratios as independent variables, ANN is able to generate the most accurate prediction and outperforms the other methods in predicting failure. Otherwise said, ANN yields a correct classification accuracy of 98.1% one year prior to failure while LR and DT achieve accuracy rates of 94.7% and 96.1%, respectively. Furthermore, the empirical results demonstrate that the classification accuracy rate reaches 92.5% by ANN, 91.1% by DT, and 84.4% by logistic regression two years in advance. The findings of current research provide valuable insights into financial failure prediction and may entice practical implications for stakeholders, especially investors and regulatory bodies, by indicating that the use of the ANN approach may be more effective.

Anahtar Kelimeler:
Finansal Başarısızlık, Lojistik Regresyon, Yapay Sinir Ağları, Karar Ağaçları

JEL Kodları:
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Öz

Çalışmada yüksek doğruluğa sahip finansal başarısızlık tahmin modelleri oluşturmak üzere gelişmiş ve gelişen ülkelerden 570 şirket 2010 – 2019 dönemi için analiz edilmektedir. Bu çerçevede, lojistik regresyon (LR), yapay sinir ağları (YSA) ve karar ağaçları (KA) uygulanmış ve bahsedilen yöntemlerin sınıflandırma doğrulukları karşılaştırılmıştır. 16 finansal oran bağımsız değişken olarak kullanılmış ve YSA en doğru tahmin sonuçlarını üreterek başarısızlık tahmininde diğer yöntemlere üstünlük sağlamıştır. Diğer bir ifadeyle, YSA başarısızlıktan bir yıl öncesi için %98,1 sınıflama doğruluğu üretirken, LR ve KA sırasıyla %94,7 ve %96,1 doğruluk oranlarına ulaşmışlardır. Buna ek olarak, ampirik sonuçlara göre başarısızlıktan iki yıl öncesi için ANN %92,5, KA %91,1 ve LR %84,4 sınıflama doğruluğu sağlamışlardır. Mevcut çalışmanın bulguları finansal başarısızlık tahminine yönelik ışık tutmaktadır ve YSA yönteminin kullanılmasının daha efektif olabileceğini işaret ederek, özellikle yatırımcılar ve düzenleyici otoriteler gibi paydaşlar açısından pratik sonuçlar ortaya koymaktadır.

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[**] Res. Asst., Istanbul Beykent University, Faculty of Economics and Administrative Sciences, Department of Business Administration, Türkiye, yavuzgul@beykent.edu.tr
[***] Prof. Dr., Anadolu University, Eskişehir Vocational School, Department of Wholesale and Retail Sales, Türkiye, saltinirmak@anadolu.edu.tr

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1. Introduction

Predicting the financial failure of a firm is one of the subjects that has been intensively studied for many years. In these researches, we can see the different definitions of financial failure (Beaver, 1966; Altman, 1968; Deakin, 1972; Blum, 1974). Today, firms operating in intense competition conditions must efficiently utilize their resources in order to gain an advantage against their competitors. If firms fail to allocate scarce resources efficiently or cannot keep up with the latest technological advancements, they may enter the bankruptcy process. Financial failures have the potential to affect not only firms but also could cause massive economic damage. Firms that experience financial difficulties due to internal and/or external factors may take several precautions to overcome this condition with the least damage as long as they use financial failure prediction models and forecast the failure before it takes root. Creditors and investors, on the other side, will be able to make better decisions in matters such as loan options and investment choices according to the current and future state of the firm. Also, the government will have a chance to revise the policies in a timely manner.

Each model developed to predict failure has its own set of advantages and disadvantages. For instance, some models can be easy and simple to use while some of them are more complicated but they may produce more accurate results. Despite the developments in forecasting methods over the years, the fact that a “perfect” model still does not exist is the most important reason why research on financial failure continues today. This paper aims to guide stakeholders by creating models that can predict financial failure one year and two years in advance with high accuracy and hence help avoid possible business failure. We include firms that have different characteristics and operate in different countries and/or under various economic conditions to add depth and richness to the study. We, in this vein, focus on the firms listed in the benchmark stock market indices in G – 20 countries over the period from 2010 to 2019. Results show that ANN is the most efficient in predicting financial failure and profit margins are crucial for financial success. The main contributions of the paper are the following: (1) It builds models to predict the probability of a financial failure by including firms listed on different stock exchanges (2) It provides evidence on which model yields a higher prediction rate and which financial ratios play a role in the prediction of financial failure (3) It draws attention to the importance of early detection of financial failure, thus increases the interest in this field and enriches the literature.

With the first section being an introduction, the rest of the paper is structured as follows: Section 2 provides the theoretical background of the dimensions and concept of financial failure. Section 3 reviews the relevant literature. Section 4 presents the methodology and dataset while Section 5 outlines the empirical findings. Finally, section 6 concludes the paper.

2. Theoretical Background

Firms may face significant financial challenges due to various factors such as inadequate cash flow management, market conditions, and risks. The term financial failure can be defined in several ways based on the different perspectives and refers, in its broadest sense, to the inability of a firm to meet its financial obligations or to have difficulty fulfilling them (İçerli and Akkaya, 2006: 413). Altman (1968) uses the word “bankruptcy” and considers the legal filing for bankruptcy and the appointment of a trustee or the granting of the right to reorganize under the “National Bankruptcy Act” as a financial failure while Beaver (1966) defines financial failure as the inability to pay its financial obligations as they came due. According to Deakin (1972), financial failure means being insolvent, bankrupt, or liquidated. Blum (1974) argues that financial failure is when a firm is unable to pay its debts when due, applying for bankruptcy, or signing an agreement with creditors to waive their receivables.

Financial failure comes in four forms: business failure, technical failure, having a negative net worth, and bankruptcy. These are essentially the types of financial failure and bring to mind the final stages of the failure path. It is generally claimed that firms encounter problems in the initial stage, followed by technical failure, namely liquidity issues and then having a negative net worth and bankruptcy. Although financial failure and bankruptcy are terms often used interchangeably, bankruptcy is a situation where the liabilities exceed the assets by virtue of financial failure and emerges as a special case of failure. In some cases, asserting that firms experiencing financial failure will go bankrupt may not be correct, however. Firms can get out of bankruptcy and continue their operations healthily again by making arrangements.

In the common literature, financial and non–financial indicators are adopted to measure financial stress and these criteria can be bifurcated into two subsections: numerical and non–numerical. Numerical indicators are expressed through financial statements and fall into two main groups: indicators based on market value and indicators based on book value (Özdemir, 2011: 52-53). Contrarily, no specific reference point is mentioned for financial failure in non–numerical indicators, e.g., delisting of shares, transferring the shares in the watchlist market, filing for bankruptcy, stopping or slowing down production, and layoffs.

There are many reasons why a firm falter financially. Financial failures can occur due to internal issues caused by poor management, excessive borrowing, insufficient cash flow, inadequate working capital management, lack of effective budgetary control system, and absence of a cost management system (Mills and Robertson, 1991; Cemalcılar et al., 1985 as cited in Karacan and Savcı, 2011), as well as external factors such as economic climate, politics, market structure – related conditions, technological changes, legal conditions and environmental issues.

The major objectives of the analyses conducted and the steps taken are to ensure the survival of the failed firm. At this point, precautionary actions that turned out successful may not yield the same results when applied to other firms in similar circumstances, since firms may experience failure due to different reasons and the degree of the failure may vary significantly. The high number of business failures may have a negative impact on the country's economy. Financial failures also constitute an obstacle to the efficient use of resources and lead to an increase in unemployment rates. Investors and creditors can avoid or reduce investment losses, thanks to failure prediction models. Prediction of financial failures is of vital importance due to the spillover effects of such events. Researchers have devoted a great deal of time since the 1960s, e.g., Altman (1968), to predict financial failures and to develop early warning systems. Considering the growing attention towards the financial services industry, distress prediction models are gaining momentum in parallel. The current study contributes to the existing literature by developing prediction models.

3. Literature Review

In the early days of studies on financial failure prediction, we see that the methods such as linear regression and linear discriminant analysis were widely used but the idea of determining a financial failure using a single variable began to be deemed risky in subsequent years. Thus, methods such as multiple regression, multiple discriminant analysis, logistic regression, and probit regression, which allow to include of more than one explanatory variable, have come to the fore. The study conducted by Altman (1968), using multiple discriminant analysis, is one of the pioneering studies in the financial failure literature. He examined 33 bankrupt and 33 non–bankrupt firms over the period 1946 – 1965 and accurately classified 95% of the firms one year in advance and 72% of them two years in advance. Meyer and Pifer (1970) compared 39 pairs of failed and sound banks from 1948 to 1965 through a multiple regression analysis and achieved classification accuracy of 80% for one or two years before the failure occurred. In another research, Edmister (1972) applied a multiple discriminant analysis on the data of 32 failed and 562 successful firms in the USA during the period 1954 – 1969 to classify failed and non–failed firms with an accuracy of 90%. In the following years, Ohlson's (1980) pioneering work introduced logistic regression into financial failure prediction. The author created three different models and reported that these models yield an overall correct classification accuracy of 96.12%, 95.55%, and 92.84%, respectively. He also stated that the firm size, liquidity, capital structure, and profitability statistically significantly affect the likelihood of failure. Among the studies aiming to predict financial failure using the probit model, the research conducted by Zmijewski (1984) stands out. Zmijewski (1984) examined 81 unsuccessful and 1600 successful firms in the USA and correctly predicted the failure for 62.5% of failed firms and 99.5% of successful firms. Canbaz (1998), using a sample of 60 firms operating in Türkiye, applied a multiple discriminant analysis to predict financial failure and obtained an accuracy of 95.7%. In a similar research, Ünsal (2001) employed data from 16 failed and 55 successful firms from Türkiye and achieved a classification accuracy of 95.77%. While Aktaş et al. (2003), utilized discriminant analysis, multiple regression, and ANN along with logistic regression and emphasized that ANN is the most successful in predicting financial failure, Altaş and Giray (2005) included 33 textile firms and built a model by logistic regression and factor analysis. They were able to achieve an overall classification accuracy of 74.2%. Doğanay et al. (2006) analyzed a unique set of 19 failed and 23 non–failed banks for the period 1997–2002 and reached, one year prior to failure, the accuracy rate of 78.9% by probit regression, 89.5% by multiple regression and 84.2% by discriminant analysis for failed banks. A study conducted by Chung et al. (2008) focused on 10 unsuccessful and 35 successful firms in New Zealand and correctly predicted the failure for 62% of firms using multiple discriminant analysis. Authors also claimed that failed firms are less profitable and have lower liquidity. Gepp and Kumar (2008) used Cox SA, discriminant analysis, and logistic regression to predict the likelihood of financial failure of 117 successful and 72 unsuccessful firms over 1974 – 1991 and found that all three methods attained 96% accuracy one year in advance. Lin (2009) used 20 financial ratios to analyze 96 unsuccessful and 158 successful firms in Taiwan employing probit regression, logistic regression, multiple discriminant analysis, and ANN. They provided evidence that the probit regression method was the most successful and stable model. Using multiple discriminant analysis, Yap et al. (2010) examined the dataset of 32 successful and 32 unsuccessful firms in Malaysia over the period 1996 – 2005 and stated that classification accuracy ranged from 88% to 94% five years prior to failure. Lastly, Büyükarıkan and Büyükarıkan (2018) attempted to forecast the probability of failure and suggested that the classification accuracy reached 87.27% with probit regression, 89.1% with logistic regression, 88.2% with multiple discriminant analysis 86.36% with multiple regression.

Technological advancements have altered life around the world and resulted in increasing use of techniques such as DT, random forest (RF), ANN, support vector machines (SVM), and deep learning, which can effectively handle massive datasets, in financial studies. For instance, Odom and Sharda (1990) developed a model using ANN and compared the predictive power of this model with the prediction ability of discriminant analysis. The authors examined a total of 129 firms, 65 of which filed for bankruptcy and 64 of which did not go bankrupt, for the period 1975 – 1982 and stated that ANN was more successful in the prediction. In a related research, Atiya (2001) built a model to predict financial failure three years in advance using ANN and reported a classification accuracy ranging from 81.46% to 89.41%. Similarly, Yıldız (2001) analyzed 53 successful and 53 unsuccessful firms listed on the stock exchange and/or subject to Capital Markets Board of Türkiye (CMB) regulations by ANN and produced a classification accuracy of 94.4% while Ravi and Pramodh (2008) examined 66 Spanish and 40 Turkish banks using combined ANN and principal component analysis to reveal that the models achieved an accuracy rate of 97.5% for Spain and 100% for Türkiye. Likewise, Wu et al. (2008) utilized ANN in a dataset of 48 firms operating in the Chinese manufacturing sector and obtained an 87.5% accuracy one year in advance and 81.3% accuracy three years in advance. Çelik (2010) examined 36 private banks with 36 financial ratios and delivered, using ANN, 100% classification accuracy one year prior to failure and 89.4% classification accuracy two years prior to failure. Gregova et al. (2020) compared the performances of RF, logistic regression, and ANN in failure prediction and discovered that ANN had the highest accuracy. Hui and Sun (2006) employed support vector machines, ANN, and logistic regression in their research conducted in China. According to the authors, support vector machines were more stable compared to the other methods. In a similar vein, Vieira et al. (2009) analyzed the data of 600 successful and 600 unsuccessful French firms for the period 2002 – 2007 applying logistic regression, ANN, and support vector machines, and stated that support vector machines were the most accurate in predicting the financial failure. Bae (2012) achieved the same results. The author used the data from 1888 firms in South Korea and concluded that support vector machines performed better than the other methods. Supporting these results, Altınırmak and Karamaşa (2016), analyzing 17 unsuccessful and 13 successful banks over the period 1996 – 2000, found that support vector machines outperform ANN by providing better prediction accuracy. These results are in line with Mselmi et al. (2017), who emphasized that support vector machines achieved a classification accuracy of 88.57% and emerged as the most efficient technique. In another study, Aksoy and Boztosun (2021) included 86 firms traded in Borsa Istanbul (BIST) and documented that SVM was the most effective in predicting failure with an accuracy of 92.31%. Based on a sample of 1443 banks from 2007 to 2013, Gogas et al. (2018) suggested that support vector machines reached a classification accuracy of 99.22%. Le and Viviani (2018) applied support vector machines, ANN, k – nearest neighbor algorithm (KNN), logistic regression, and discriminant analysis on the data of 1438 failed and 1562 non-failed banks and noted that support vector machines had an accuracy score of 71.6%. The study of Aktan (2011) focused on 180 firms publicly traded in BIST and applied classification–regression trees, ANN, and support vector machines to affirm that classification and regression trees yielded more accurate results. Yakut and Elmas (2013) analyzed 140 publicly listed firms from 2005 to 2008 and claimed that DT lead to rather accurate classification results. Çöllü et al. (2020), using the data of 20 firms traded in BIST from 2016 to 2018, determined that the CART method provided the most efficient classification with 95 percent accuracy. A study conducted in Taiwan for the period 2010 – 2016 reported that the XGBoost algorithm showed the highest accuracy among the four models (Huang and Yen, 2019). More recently, Malakauskas and Lakstutiene (2021) analyzed a dataset of 12000 firms from Estonia, Latvia, and Lithuania to predict financial failure using RF, ANN, and logistic regression. They stated that RF demonstrated the best performance. Similar results were obtained by Petropoulos et al. (2020). Researchers tried to predict bank failures in the USA by RF, discriminant analysis, logistic regression, support vector machines, and ANN and uncovered that RF yielded more successful results than all other methods. Noviantoro and Huang (2021) and Yousaf et al. (2022) also confirmed that RF was the top performer in terms of prediction accuracy.

Based upon the findings of our literature review, we infer that machine-learning techniques have been used extensively in recent years. In addition, most empirical studies have concentrated on firms in a single country (Jo et al., 1997; Aktaş et al., 2003; Benli, 2005; Doğanay et al., 2006; İçerli and Akkaya, 2006; İşseveroğlu and Gücenmez, 2007; Chung et al., 2008; Wu et al., 2008; Lin, 2009; Çelik, 2010; Bae, 2012; Altunöz, 2013; Cengiz et al., 2015; Kulalı, 2016; Gogas et al., 2018; Le and Viviani, 2018; Huang and Yen, 2019; Gregova et al., 2020; Tang et al., 2020; Aksoy and Boztosun, 2021; Halim et al., 2021; Jan, 2021; Noviantoro and Huang, 2021; Oribel and Hanggraeni, 2021; Qian et al., 2022; Yousaf et al., 2022). In the current study, to mitigate the limitations of this, we create failure prediction models by including firms both from developed and developing countries, thus adding dimension to the present body of literature.

4. Data and Methodology

We include the firms traded on the stock markets of G – 20 members and use the financials of the firms (that is, balance sheet and income statement) as a starting point. The fact that publicly traded firms are required to present and disclose financial reports, special circumstances, and material events in a timely and transparent manner in accordance with the disclosure principles is the reason why we prefer firms listed in capital markets. We remove firms operating in the financial sector or carrying little or no inventory due to the nature of their activities (such as waste management, information technology, and asset management firms) from the sample. Additionally, we exclude firms from the analyses if they have missing data and then divide the sample into two types of countries based on IMF (International Monetary Fund) classification: developed and developing. Table 1 presents the stock market indexes adopted in the study.

Table 1. Stock Market Indices

Country	Index	Country	Index
Germany	DAX40	India	BSE30
USA	DOW30	UK	FTSE100
Argentina	S&P MERVAL	Italy	FTSE MIB
Australia	ASX50	Japan	TOPIX100
Brazil	BOVESPA	Canada	TSX60
China	SSE50	Mexico	S&P BMV IPC
Indonesia	LQ45	Russia	RTS
France	CAC40	Saudi Arabia	MSCI TADAWUL30
South Africa	JSE TOP40	Türkiye	BIST50
South Korea	KOSPI50		

Our entire period spans from January 1, 2010 to December 31, 2019. The 2008 Global Financial Crisis and the COVID–19 outbreak, which started in early 2020, have had severe consequences and implications on economies and firms, we therefore start the study period on January 1, 2010 and end on December 31, 2019. We collect data from Thomson Reuters, various databases and corporate websites of firms.

We classify firms with two or more successive losses as having been unsuccessful and the others as successful. We then create a dependent variable to represent their successful (1) or unsuccessful (0) status and consider financial ratios as independent variables. We identify the financial ratios by conducting an in-depth systematic review of literature (Jo et al., 1997; Atiya, 2001; Aktaş et al., 2003; Altaş and Giray, 2005; Torun, 2007; Chung et al., 2008; Vuran, 2009; Aktan, 2011; Terzi, 2011; Yakut and Elmas, 2013; Cengiz et al., 2015; Selimoğlu and Orhan, 2015; Ural et al., 2015; Huang and Yen, 2019; Gogas et al., 2018; Gregova et al., 2020; Aksoy and Boztosun, 2021; Jan, 2021) and hence include 16 financial ratios in the study (Table 2).

Table 2. Financial Ratios

Liquidity Ratios	**Efficiency Ratios**	**Profitability Ratios**	**Leverage Financial Ratios**	**Growth Ratios**
X1 Current ratio	X3 Receivables turnover ratio	X5 Gross profit margin	X11 Debt to equity	X13 Sales growth rate
X2 Quick ratio	X4 Inventory turnover ratio	X6 Net profit margin	X12 Interest coverage ratio	X14 Gross profit growth rate
		X7 Return on equity (ROE)		X15 EBITDA growth rate
		X8 Return on assets (ROA)		X16 Net profit growth rate
		X9 Operating profit margin		
		X10 Earnings per share (EPS)		

5. Experimental Results

The data set consists of a total of 91200 points (570 firms, 10 years, 16 ratios). We perform logistic regression (LR), ANN, and DT analysis to predict financial failure.

5.1. Logistic Regression

The outputs of our first model are summarized in Table 3. The Nagelkerke R^2 value shows that 82.4% of the change in the dependent variable is explained by the model. According to the results, net profit margin, ROE, ROA, operating profit margin, and interest coverage ratio have statistically significant effect on financial failure. Thus, equation (1) can be written as follows:

$$Z1 = 0.553 + 42.698X6 + 7.198X7 - 32.842X8 + 12.000X9 + 0.196X12 \quad (1)$$

Table 3. LR Classification Results 1-Year Prior to Failure (Overall)

Variable	Ratios	B	S.E.	Wald	df	Sig.
X6	Net profit margin	42.698	11.863	12.954	1	0.000
X7	ROE	7.198	1.887	14.547	1	0.000
X8	ROA	-32.842	16.340	4.039	1	0.044
X9	Operating profit margin	12.000	4.678	6.580	1	0.010
X12	Interest coverage ratio	0.196	0.070	7.792	1	0.005

	Observed		Predicted		
			0.00	1.00	Percentage Correct
Step 1	Success (1) – Failure (0)	0.00	78	6	92.9
		1.00	24	462	95.1
	Overall Percentage				94.7

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	118.309	0.467	0.824

Our model correctly classifies the failed firms by 92.9% and non–failed firms by 95.1% for one year before failure. The overall correct classification rate of the firms is 94.7%.

The findings of the model estimated for developed–country firms are reported in Table 4. As shown in the table below, the net profit margin reaches statistical significance at a 1 percent level (p<0.01). Along with this, ROA and interest coverage ratio are statistically significant at the level of 0.05. These variables contribute significantly to the predictive power of the model and equation (2) is written as follows:

$$Z2 = -0.387 + 70.225X6 - 68.026X8 + 0.234X12 \quad (2)$$

Table 4. LR Classification Results 1-Year Prior to Failure (Developed-Country Firms)

Variable	Ratios	B	S.E.	Wald	df	Sig.
X6	Net profit margin	70.225	26.215	7.176	1	0.007
X8	ROA	-68.026	34.224	3.951	1	0.047
X12	Interest coverage ratio	0.234	0.114	4.208	1	0.040

	Observed		Predicted		
			0.00	1.00	Percentage Correct
Step 1	Success (1) – Failure (0)	0.00	33	3	91.7
		1.00	15	267	94.7
	Overall Percentage				94.3

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	57.444	0.409	0.807

In Table 4, the model is able to accurately classify 33 of the 36 failed firms, leading to correct classification in the case of 91.7% of failed firms. The model, on the other hand, has a classification percentage of 94.7% of non–filed firms and percent 5.3 indicates the type II error. For this model, the overall percentage of correctly classified firms is 94.3%.

The summary of the model developed using data from 252 firms listed on developing country stock markets is given in Table 5. Net profit margin has a statistically significant influence on financial failure at the 1% level (p<0.01). In the meantime, the interest coverage ratio acquires a significance level of 0.014 smaller than the 0.05 significance level. Equation (3) is specified as follows:

$$Z3 = -4.277 + 83.485X6 + 0.783X12 \quad (3)$$

Table 5. LR Classification Results 1-Year Prior to Failure (Developing-Country Firms)

Variable	Ratios		B	S.E.	Wald	df	Sig.
X6	Net profit margin		83.485	30.821	7.337	1	0.007
X12	Interest coverage ratio		0.783	0.320	5.977	1	0.014
	Observed			**Predicted**			
				0.00	**1.00**	**Percentage Correct**	
Step 1	Success (1) – Failure (0)	0.00		47	1	97.9	
		1.00		6	198	97.1	
	Overall Percentage					97.2	
Step	**-2 Log likelihood**		**Cox & Snell R Square**		**Nagelkerke R Square**		
1	29.698		0.575		0.924		

The model correctly classified 97.9 percent of failed firms and 97.1 percent of non–filed firms. For Type I errors, the probability of classifying a failed firm as non–filed is 2.1 percent while for Type II errors, the probability of classifying a non–filed as failed is 2.9 percent. The model yields an overall correct classification accuracy of 97.2% one year prior to failure.

The outputs of the model built to predict the probability of financial failure two years in advance are illustrated in Table 6. Cox Snell and Nagelkerke R^2 suggest that the variation in the probability of financial failure explained by the financial ratios ranges between 25.7% and 45.3%. ROA is statistically significant at the 1% level ($p<0.01$) and gross profit margin exhibits a statistical significance at the 5% level ($p<0.05$). Equation (4) can be expressed as follows:

$$Z4 = -0.045 + 2.248X5 + 28.845X8 \tag{4}$$

Table 6. LR and Classification Results 2-Years Prior to Failure (Overall)

Variable	Ratios		B	S.E.	Wald	df	Sig.
X5	Gross profit margin		2.248	1.113	4.076	1	0.043
X8	ROA		28.845	7.271	15.737	1	0.000
	Observed			**Predicted**			
				0.00	**1.00**	**Percentage Correct**	
Step 1	Success (1) – Failure (0)	0.00		62	22	73.8	
		1.00		67	419	86.2	
	Overall Percentage					84.4	
Step	**-2 Log likelihood**		**Cox & Snell R Square**		**Nagelkerke R Square**		
1	307.707		0.257		0.453		

According to Table 6, our model attains 73.8% accuracy in the classification of failed firms while the classification accuracy rate for non–failed firms is 86.2%. The model yields an overall correct classification accordance of 84.4% two years prior to failure.

We then create a model to predict the failure of publicly listed firms in developed–country markets two years prior to distress and find that only ROA is statistically significant at the level of significance of 1% (Table 7). All other variables in the model seem to be statistically insignificant. Equation (5) is shown below:

$$Z5 = -1.051 + 35.472X8 \tag{5}$$

Table 7. LR Classification Results 2-Years Prior to Failure (Developed-Country Firms)

Variable	Ratios	B	S.E.	Wald	df	Sig.
X8	ROA	35.472	12.791	7.690	1	0.006

	Observed		Predicted		
			0.00	1.00	Percentage Correct
Step 1	Success (1) – Failure (0)	0.00	25	11	69.4
		1.00	23	259	91.8
	Overall Percentage				89.3

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	147.505	0.215	0.425

Table 7 shows that two years before failure, the correct classification rate of failed firms was 69.4%. According to the percentage of the correctly classified non–failed firms’ cases, the model achieves 91.8% accuracy and results in a total correct classification rate of 89.3%.

The model designed to predict the financial failure of developing-country firms two years ahead of failure is presented in Table 8. The table indicates that ROA is statistically significant at the 0.05 significance level ($p<0.05$). Accordingly, Equation (6) is written as follows:

$$Z6 = -0.501 + 22.639X8 \tag{6}$$

Table 8. LR Classification Results 2-Years Prior to Failure (Developing-Country Firms)

Variable	Ratios	B	S.E.	Wald	Df	Sig.
X8	ROA	22.639	10.601	4.561	1	0.033

	Observed		Predicted		
			0.00	1.00	Percentage Correct
Step 1	Success (1) – Failure (0)	0.00	38	10	79.2
		1.00	39	165	80.9
	Overall Percentage				80.6

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	133.996	0.357	0.574

According to Table 8, the model correctly predicts 79.2 percent of the failed firms and is 80.9% accurate in predicting the likelihood of financial failure of non-failed firms. Our model produces an overall correct classification rate of 80.6%.

5.2. Artificial Neural Network (ANN)

The results obtained with the ANN approach to forecast financial failure one year and two years before it occurs are given in Table 9. Results suggest that the classification accuracy of non-failed firms is 100% and the correct classification rate of failed firms is 91.3%. The model yields an overall classification accuracy of 98.1%. This implies that the model achieves good prediction performance. The classification accuracy of successfully developed-country firms is 87.5% while ANN correctly classifies 100 percent of 486 non–failed firms. The overall classification performance percentage is 98.6%. Further, in the case of developing-country firms, ANN correctly predicts the failure for 85.7% of failed firms and 100% of successful firms, making an overall wrong estimate is occurred only for 2.1%.

Table 9. Classification Results of ANN

	N	One Year Prior to Failure	Two Years Prior to Failure
Entire sample	570	98.1%	92.5%
Failed	84	91.3%	57.9%
Non – failed	486	100.0%	99.0%
Developed – country firms	318	98.6%	96.6%
Failed	36	87.5%	75.0%
Non – failed	282	100.0%	98.2%
Developing – country firms	252	97.9%	94.4%
Failed	48	85.7%	75.0%
Non – failed	204	100.0%	97.8%

Table 9 indicates that the percentage of correct classification of failed firms two years before the failure is 57.9%. The model correctly classifies 99.0% of successful firms and yields an overall correct classification accuracy of 92.5% two years prior to failure. The accuracy of our model for correctly predicted failed developed-country firms is 75.0%, and 98.2% for appropriately assigned non-failed developed-country firms. The overall prediction accuracy is 96.6%. Our model, additionally, is able to classify correctly the failed firms 75.0% and successful firms 97.8% accurately. Overall, the model properly classifies 94.4% of the developing-country firms.

The ranked importance of each dependent variable, that is, financial ratios, is shown in Table 10. Net profit margin is the most important in determining the success or failure of the firm one year in advance. ROA seems to be another significant variable for predicting financial failure. Contrarily, the inventory turnover ratio is the least important one among financial ratios.

Table 10. Ranked Variable Importance

Financial ratios	One year prior to failure			Two years prior to failure		
	Entire Sample	**Developed-Country Firms**	**Developing-Country Firms**	**Entire Sample**	**Developed-Country Firms**	**Developing-Country Firms**
Current ratio	11	16	16	10	**3**	8
Quick ratio	13	14	15	13	10	10
Receivables turnover ratio	6	11	10	16	15	9
Inventory turnover ratio	15	15	14	14	16	16
Net profit margin	**1**	**1**	**1**	4	8	**2**
Gross profit margin	10	6	12	7	13	12
Operating profit margin	9	13	9	5	9	6
ROE	**2**	9	**2**	8	14	5
ROA	5	**2**	6	**1**	**2**	**1**
Earnings per share	7	7	8	**2**	6	11
Debt to equity	8	10	11	15	7	**3**
Interest coverage ratio	14	12	13	9	4	13
Sales growth rate	12	**3**	**3**	11	11	14
Gross profit growth rate	16	5	7	6	**1**	4
EBITDA growth rate	4	4	4	12	12	7
Net profit growth rate	**3**	8	5	**3**	5	15

According to the failure prediction models developed using ANN to predict financial failure two years in advance, the most critical factor affecting financial success is ROA. This factor is followed by the gross profit growth rate. The top three financial ratios to predict the financial failure of developed-country firms one year in advance are net profit margin, ROA, and sales growth rate, while only ROA is replaced by ROE for developing-country firms. Besides, gross profit growth rate, ROA, and current ratio seem to be the most important ratios for predicting the failure of developed-country firms two years in advance, while ROA, net profit margin, and debt to equity emerge as the significant variables with regard to developing-country firms.

5.3. Decision Trees (DT)

The classification accuracies of the models derived using the CHAID algorithm are presented in Table 11. The model correctly predicts 94 percent of failed firms and 96.5 percent of non-failed firms. The overall predictive accuracy (one year before the failure) is 96.1%. Furthermore, the second model is able to accurately classify 97.2% of failed developed-country firms and 95.7% of non-failed developed-country firms. For this model, the overall percentage of correctly classified firms is 95.9%. Our third model attains 87.5% accuracy in the classification of failed firms, while the classification accuracy rate for non-failed firms is 96.1%. The model produces an overall correct classification accordance of 94.4% one year prior to failure.

Table 11. Classification Results of CART

	N	One Year Prior to Failure	Two Years Prior to Failure
Entire sample	570	96.1%	91.1%
Failed	84	94.0%	53.6%
Non – failed	486	96.5%	97.5%
Developed – country firms	318	95.9%	92.1%
Failed	36	97.2%	58.3%
Non – failed	282	95.7%	96.5%
Developing – country firms	252	94.4%	91.3%
Failed	48	87.5%	68.8%
Non – failed	204	96.1%	96.6%

In Table 11, our model accurately discriminates 97.5 percent of the non-failed firms but is only 53.6 percent accurate at predicting the financial failure of unsuccessful firms two years in advance. The overall predictive accuracy of the model is 91.1%. In addition, the fifth model manages to correctly classify non-failed developed-country firms by 96.5% and failed ones by 58.3%. The model achieves an overall correct classification accuracy of 92.1%. The last model, in the case of developing-country firms, accurately predicts 96.6 percent of the non-failed firms and 68.8 percent of the failed firms and thus results in a total correct classification rate of 91.3%.

The model created to predict financial failure one year in advance using DT is given in Table 12. Accordingly, the decision tree starts with a root node which is the net profit margin. This means that the most important variable influencing the financial success of the firms is the net profit margin (p=0.000). Firms with a net profit margin of less than -4.95% are split into subgroups based on their interest coverage ratio with a 1% level of significance (p=0.000). Another ratio affecting the likelihood of financial failure is the earnings per share, which is also a key metric of a firm's profitability ($p<0.01$). EBITDA growth rate seems to be another critical parameter that demonstrates the overall financial performance of firms ($p=0.000$).

Table 12. DT Based Failure Prediction Model 1-Year Prior to Failure (Overall)

Profile	Node	Net Profit Margin	Interest Coverage Ratio	Earnings Per Share	EBITDA Growth Rate
1	1	≤ -0.049			
2	2	-0.049 – 0.011			
3	3	> 0.011			
4	4	≤ -0.049	≤ 3.730		
5	5	≤ -0.049	> 3.730		
6	6	-0.049 – 0.011		≤ 0.000	
7	7	-0.049 – 0.011		> 0.000	
8	8	> 0.011			≤ -0.278
9	9	> 0.011			> -0.278

The tree generated, using the data of 318 developed-country firms, by the CHAID algorithm is presented in Table 13. According to the table, the net profit margin is at the root of the model and is statistically significant ($p = 0.000$). Firms with a net profit margin between -1% and 2.34% and with a net profit margin higher than 2.34% are divided into two subgroups based on their earnings per share ($p<0.01$) and operating profit margin ($p<0.01$), respectively.

Table 13. DT Based Failure Prediction Model 1-Year Prior to Failure (Developed-Country Firms)

Profile	Node	Net Profit Margin	Earnings Per Share	Operating Profit Margin
1	1	≤ -0.010		
2	2	-0.010 – 0.023		
3	3	> 0.023		
4	4	-0.010 – 0.023	≤ 0.280	
5	5	-0.010 – 0.023	> 0.280	
6	6	> 0.023		≤ 0.052
7	7	> 0.023		> 0.052

From Table 14, we can infer that the model obtained using data from 252 developing–country firms emphasizes the importance of three financial ratios, namely net profit margin, gross profit margin, and earnings per share. The net profit margin forms the root as in the previous models ($p = 0.000$). Firms with a net profit margin of less than -1.76% and with a net profit margin between -1.76% and 2.2% are further classified into two sub-categories according to their gross profit margin ($p<0.01$) and earnings per share ($p<0.05$), respectively.

Table 14. DT Based Failure Prediction Model 1-Year Prior to Failure (Developing-Country Firms)

Profile	Node	Net Profit Margin	Gross Profit Margin	Earnings Per Share
1	1	≤ -0.017		
2	2	-0.017 – 0.022		
3	3	> 0.022		
4	4	≤ -0.017	≤ 0.2954	
5	5	≤ -0.017	> 0.2954	
6	6	-0.017 – 0.022		≤ 0.000
7	7	-0.017 – 0.022		> 0.000

Results of the failure prediction model which tries to forecast the financial failure two years in advance are shown in Table 15. The most important variable and also the root node is ROA (p=0.000), followed by interest coverage ratio (p<0.05). Firms with ROA between 2.0% and 6.7% are split into two subgroups according to their interest coverage ratio. One can, therefore, claim that the interest coverage ratio appears as the second most important variable. Further, firms with ROA between 2.0% and 6.7% and having an interest coverage ratio higher than 2.96 are classified based on the gross profit growth rate (p<0.01). Lastly, firms with ROA higher than 6.7% are divided into two subgroups according to, once again, their gross profit growth rate (p<0.01).

Table 15. DT Based Failure Prediction Model 2-Years Prior to Failure (Overall)

Profile	Node	ROA	Interest Coverage Ratio	Gross Profit Growth Rate
1	1	≤ 0.006		
2	2	0.006 – 0.020		
3	3	0.020 – 0.067		
4	4	> 0.067		
5	5	0.020 – 0.067	≤ 2.960	
6	6	0.020 – 0.067	> 2.960	
7	9	0.020 – 0.067	> 2.960	≤ 0.090
8	10	0.020 – 0.067	> 2.960	> 0.090
9	7	> 0.067		≤ 0.158
10	8	> 0.067		> 0.158

Table 16 provides an illustration of the model built for predicting the failure of developed-country firms two years in advance. ROA shows up as the most important variable (p=0.000). We see that, in general, the probability of failure decreases as the return on assets increases. Firms that generate ROA both between 0.7% - 4.07% and higher than 4.07% are divided into subgroups according to their EBITDA growth rate, meaning that the second most important variable is the EBITDA growth rate. Besides, firms that have ROA between 0.7% and 4.07% and also have EBITDA growth rates larger than -22.2% are reclassified according to the gross profit growth rate (p<0,01). While ROA is between 0.7% and 4.07%, firms having an EBITDA growth rate higher than -22.2% and a gross profit growth rate higher than 6.7% are divided into two sub-categories based on the debt-to-equity ratio (p<0.05). So, another crucial variable seems to be debt to equity in predicting financial failure.

Table 16. DT Based Failure Prediction Model 2-Years Prior to Failure (Developed-Country Firms)

Profile	Node	ROA	EBITDA Growth Rate	Gross Profit Growth Rate	Debt to Equity
1	1	≤ 0.007			
2	2	0.007 – 0.040			
3	3	> 0.040			
4	4	0.007 – 0.040	≤ -0.2220		
5	5	0.007 – 0.040	> -0.2220		
6	8	0.007 – 0.040	> -0.2220	≤ -0.1863	
7	9	0.007 – 0.040	> -0.2220	-0.1863 – 0.067	
8	10	0.007 – 0.040	> -0.2220	> 0.067	
9	11	0.007 – 0.040	> -0.2220	> 0.067	≤ 0.6994
10	12	0.007 – 0.040	> -0.2220	> 0.067	> 0.6994
11	6	> 0.040	≤ 0.3108		
12	7	> 0.040	> 0.3108		

Table 17 demonstrates the decision tree model which is created to predict the likelihood of financial failure of developing-country firms two years before the failure occurs. The root node of the constructed tree is ROE (p=0.000). Firms having a ROE between -1.4% - 8.15% and greater than 8.15% are both divided into sub-categories according to their net profit growth rate. Firms with ROE higher than 8.15% and net profit growth rate between 10.29% - 131.34% are split into two subgroups based on operating profit margin (p<0.05).

Table 17. DT Based Failure Prediction Model 2-Years Prior to Failure (Developing-Country Firms)

Profile	Node	ROE	Net Profit Growth Rate	Operating Profit Margin
1	1	≤ -0.014		
2	2	-0.014 – 0.081		
3	3	> 0.081		
4	4	-0.014 – 0.081	≤ 0.2313	
5	5	-0.014 – 0.081	> 0.2313	
6	6	> 0.081	≤ -0.3541	
7	7	> 0.081	-0.3541 – 0.1029	
8	8	> 0.081	0.1029 – 1.3134	
9	9	> 0.081	> 1.3134	
10	10	> 0.081	0.1029 – 1.3134	≤ 0.0991
11	11	> 0.081	0.1029 – 1.3134	> 0.0991

When we consider all the models, we observe that the profitability ratios, growth ratios, and leverage financial ratios come to the fore. Although both profit margins and growth are important and necessary for a firm to be successful and remain in business, they may not be sufficient for business continuity. Firms must provide a balance between financial structure (financial statements are all linked and dependent on each other) and continuing operations. On the flip side of the coin, suggesting that every firm that makes a loss will eventually go bankrupt or shut down might not be true or, for example, firms with negative net working capital and/or high debt can continue their operations with no interruption if they can maintain a healthy cash flow. So in short, as much as firms are interested in preserving and improving their profit-making ability, they should also strive to determine the right balance between debt and equity, establish effective cash management and stock control policies, and adopt a good corporate governance structure. In addition, investor relations play a crucial role in providing reliable and transparent information to investors and building loyal relationships with their existing and potential investors, so firms must attach more importance to investor relations practices.

6. Concluding Remarks

Although much research has been carried out in the field of financial failure prediction to date, the fact that a model that can be defined as perfect and can be applied to every firm still has not yet been designed is one of the reasons why studies related to financial failure continue at high speed and our main motivation stems from this point. We analyze the data available from January 1, 2010 to December 31, 2019, and use the financial ratios of 570 firms traded on the stock markets of G – 20 members to create models and predict the probability of financial failure by logistic regression, ANN, and DT. Results show that ANN exhibits better classification performance than the other methods. This is parallel to previous findings by Jo et al. (1997), Aktaş et al. (2003) and Gregova et al. (2020). In these researches, similar to the current one, the authors concluded that ANN outperforms the other methods. ANN is followed by the DT and logistic regression, respectively. One can argue that machine learning techniques attain superior results compared to traditional methods and ANN is useful for predicting financial failure. It is worth bearing in mind that advancements in technology and computer science affect financial studies and application of machine learning techniques and algorithms in financial analysis may yield superior results.

The models created show that profitability ratios are some of the most critical financial ratios in achieving and maintaining financial success. It would also be appropriate to claim that growth and leverage financial ratios provide valuable insights into financial stability and a firm’s overall health. Achieving more favorable profit margins according to the nature of business, the country in which it operates and sector averages and ensuring profitable growth are the key factors to success. However, it is also crucial that firms should pay special attention not only to their profit margins but also to their operating cash cycle. Thus, they will be able to increase profit margins in the coming years.

As is the case with all studies, we acknowledge some limitations and those should be taken into consideration when generalizing the findings of our study. We exclude financial institutions (banks, insurance firms, brokerage firms, etc.) -because their financial statements differ in structure-, service sector firms, software firms, and waste management firms from the study. Second, the essence of our analyses is based on a set of financial ratios, which are derived from financial statements. Considering the possibility of window dressing of financial statements, the ratios may not reflect the firm’s real situation and may show a better position than the actual. Since information asymmetry arises among managers and market participants, it is of vital importance to carefully evaluate the results of the current research. The value of the study, on the other hand, lies in two aspects: (1) Our study period coincides with the globally stable period (2) The models we develop are universal since we include firms from different countries and do not focus on the effect of firm size.

The methods do not seem to be equally accurate for predicting failed and non – failed firms because successful firms are classified more accurately. Investors, therefore, cannot completely avoid investing in firms likely to fail. As a consequence of the classification of a failing firm as successful, corrective actions may not be taken by the firm or it may already be too late. Future studies should focus on techniques that will reduce the risk of making a Type II error. In addition, researchers may succeed in improving classification accuracy by utilizing different financial ratios and including various macroeconomic indicators and non–financial variables such as firm size, age, ownership structure, and number of employees. It is also possible to collect data over a longer period of time and to use support vector machines, RF, or deep learning.

Declaration of Research and Publication Ethics
This study does not require ethics committee approval and/or legal/specific permission complies with the research and publication ethics.

Researcher’s Contribution Rate Statement
The authors declare that the first author contributes 60% while the second author contributes 40%.

Declaration of Researcher’s Conflict of Interest
There is no potential conflicts of interest in this study.

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