Financial reporting quality and its determinants: A machine learning approach

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Abstract

The high-quality of financial reporting provides suitable information for economic decision-making of the country whilst, the low quality of financial reporting causes a serious impact on the economy. This research aims to classify financial reporting quality (FRQ) as well as determines the drivers of FRQ. This study uses a panel dataset from 2014 to 2020 that is collected from the Vietnamese listed companies. The study applies machine learning algorithms to classify and assess FRQ of non-financial companies on the Vietnamese stock exchange. New contribution considers the FRQ, on the auditor's opinion and the variance between pre-audit and post-audit profit. This research classifies FRQ into normal and poor categories, and a rate of 9.35% in the sample is considered poor FRQ. This research shows that the return on assets' ratio and the ownership concentration have the most important influence on FRQ. Furthermore, the results which are predicting FRQ by using the random forest algorithm have an accuracy rate of 94%. This study is valuable for the forecast of FRQ and for the support of stakeholders in decision-making. With the high accuracy of machine learning techniques and its usage, it can help analysts and investors in generating reliable accounting information for decision-making purposes. Corporate sector needs to pay attention towards financial ratios and reinforcement of corporate governance.

1. Introduction

Financial reporting provides information related to the financial position, operations performances, cash flows, and other relevant data that assists users in making decisions (Epstein & Jermakowicz, 2008; Mackenzie et al., 2013). Profits are becoming increasingly important for stakeholders in measuring a firm's performance and predicting cash flows in the future (Dechow, Kothari, & Watts, 1998). The financial information is heavily dependent on the accuracy of data earnings(Ball & Shivakumar, 2005). In the stock markets, listed companies have owner-manager separation and ownership dispersion, so the demand for public information is greater among these companies (Hope, Langli, & Thomas, 2012). The financial reporting of listed companies is higher accrual quality and more conservative than private companies (Hope, Thomas, & Vyas, 2013). However, there is a large gap between disclosed information in financial reporting and user expectations in listed companies because of their managed earnings, profit manipulation, restatement, or demand reduction for their financial information (Qiu, He, & Luo, 2019; Siddiqui & Ahmed, 2020; Zhang, Huang, & Habib, 2018). Financial

information gap can lead to less capital investment. Thus, financial reporting quality is crucial for investors and other stakeholders in making decisions.

The International Accounting Standards Board (IASB, 2008) emphasizes on the importance of high-quality financial statements while the other problems are also operationalised in previous studies. Many studies measure FRQ indirectly through behaviors such as financial restatement, earnings management, or fraudulent financial statements (i.e., Schipper and Vincent (2003); Cohen, Krishnamoorthy, and Wright (2004)). On the other hand, the limitation of FRQ measurement in the prior studies is considered the aspect of financial information. The information does not stop with financial statements which provide aid in decision-making because some financial information is provided through financial reporting while others are provided through formal financial statements (Kieso, Weygandt, & Warfield, 2014). In addition to the need of financial information in desicion making and finanacial requirements in formal statement, it is needed outside the business (e.g., investors and analysts). It is required in non-financial information such as supplementary schedules on the corporate annual report, audit reports, management's forecasts, and environmental impact statements (Beest, Braam, & Boelens, 2009; Kieso et al., 2014).

In a developing market like Vietnam, the fluctuation in the stock market has a considerable impact on investors as wrong statements or restatement of finances occur due to poor financial reporting quality, and there is a significant difference in accounting information before and after the audit work. For example, in 2022, the Vietnamese State Securities Committee (VSSC) decided to penalize some listed companies, (e.g., A Cuong Mineral Group JSC with stock code ACM) their errors/fraud disclosures in the 2020 financial year (Bui, 2022). There are lack of resources available for investors and other stakeholders in making decisions due to the limited evidence of FRQ from research with a dataset of Vietnam. In addition, few studies employ hybrid approaches combining accounting and auditing, such as Tang, Chen, and Lin (2016) measure the quality of financial reporting, while several recent studies, i.e., Barać and Bilić (2021) and Saleh, Marei, Ayoush, and Afifa (2022) have applied machine learning techniques to determine critical factors of FRQ and which enhance the accuracy of forecasting models as well.

To enhance the quality of financial reporting, some studies which are based on different theories and approaches, have investigated its factors of influence. There are a lot of factors that are combined together into six categories (Dechow, Ge, & Schrand, 2010). However, the effect of determinants of FRQ in previous studies is inconsistent, such as an opposite effect of the age of the chief executive officer (CEO) on FRQ in the study of Huang, Rose-Green, and Lee (2012) and Nguyen and Nguyen (2017). Jensen (1993) argued that a large board results in ineffective supervision, while Fathi (2013) stated that a large board improves supervisory functions which ultimately improves the quality of financial reporting. As a result, additional research is required to examine the effect of all factors on FRQ in different contexts.

This study aims to categorize the quality of financial reporting of listed companies in Vietnam which finds out the critical factors of FRQ's high accuracy of forecasting model. The study operationalizes FRQ's measurement which follows a combination of accounting and auditing and applies machine learning techniques in forecasts. The findings have many meanings in theory and in practical application. The organization of this study in the following section includes a conceptual framework section, a methodology section, a result and discussion section, and a conclusion and recommendations section.

2. Conceptual Framework
2.1. Financial Reporting Quality
Financial reporting provides high-quality financial information about the reporting entity that can be used by current and potential equity investors, lenders, and other creditors when they decide whether they have to provide resources to the firm (IASB, 2008). According to Kieso et al. (2014) financial statements are the principal means that communicate and provide financial statement, changes in equity, income statement, and cash flows to stakeholders. In Vietnam, the financial statement of corporate sector, including the balance sheet, income statement, cash flow statement, and notes of statement reflect the financial status of the corporate. In addition, some financial and non-financial information can be informal financial statements such as environmental impact statements or management forecasts. There are several views on measuring FRQ, such as measuring from an accounting viewpoint, from an auditing viewpoint, and a combined viewpoint of accounting and auditing perspective.

From accounting viewpoint, FRQ can be measured by the qualitative attributes/characteristics of information quality or earning's quality. The IASB described the qualitative accounting information attributes that determine helpful information for decision-making. FRQ is measured by the accounting information quality, and its fundamental qualities are: relevance, faithful representation and enhancing qualities which are consistency and comparability (Beest et al., 2009; Jara, Ebrero, & Zapata, 2011; Kieso et al., 2014). Some researchers measure FRQ by focusing on earnings quality with some proxies: accrual quality, earnings management, sustainability of earnings, predictability of earnings, fair value, prudence, and timeliness (i.e., Dechow et al. (2010); Van Linh, Hung, and Binh (2022); Van and Hung (2022)). From an auditing viewpoint, some studies measure FRQ by the audit opinions, i.e., Caramanis and Spathis (2006); Gaynor, Kelton, Mercer, and Yohn (2016) or by fraudulent financial reporting, i.e., Cressey (1953); Beasley (1996); Perols (2011). These

studies depend on the auditor's opinions in the audit report and fraud in financial statements for the evaluation of FRQ.

Financial reporting is management representation, and auditors provide their guarantees on the legitimacy of those representations (Krishnan, 2005). As a result, FRQ can be determined by the characteristics of both accounting and auditing. Tang et al. (2016) uses six indicators to measure FRQ: three indicators focus on accounting and the remainder stressing audit characteristics. In addition, the utilization of machine learning has been on the rise for the purpose of verifying FRQ. Several recent research studies have employed machine learning algorithms to identify fraudulent financial statements, such as Green and Choi (1997), Feroz, Kwon, Pastena, and Park (2000), Perols (2011), and Sharma and Kumar Panigrahi (2012). These techniques have also been applied to forecast audit reports with an unqualified opinion, as demonstrated by Saif, Sarikhani, and Ebrahimi (2013), Fernández-Gámez, García-Lagos, and Sánchez-Serrano (2016), Stanišić, Radojević, and Stanić (2019) and Sánchez-Serrano, Alaminos, García-Lagos, and Callejón-Gil (2020). Furthermore, Barać and Bilić (2021) have employed machine learning to evaluate the quality of financial statements.

2.2. Determinants of Financial Reporting Quality

Dechow et al. (2010) discuss the factors that influence financial reporting quality and classify these factors into six categories such as, business characteristics, financial reporting practices, controls and governance, auditors, capital market motivations, and extrinsic factors. Some studies have investigated the effect of these factors on FRQ in the worldwide context and researchers focus on corporate characteristics and corporate governance and control factors as determinants of the FRQ of corporate.

Corporate governance is defined as those supervision efforts conducted by the board of directors (BOD) and audit committee that assure the integrity and accuracy of corporate financial statements (Public Oversight Board, 1993). Several studies show traits of corporate operations that are connected with several proxies for the quality of financial reporting. Dechow et al. (2010) discuss insight about four specific business traits: business performance, debt, investment and growth, and the size of firms. Alves (2014) studied the influence of business traits such as cash flows, financial leverage, the size of firms, and investment opportunities on the FRQ in Portugal. In addition to firm size, growth of assets, profitability, and leverage, Harymawan and Nurillah (2017) reveal that firm reputation positively influences the FRQ of Indonesian enterprises.

Corporate governance relating to internal control and bonding mechanism are determinants of the financial statement quality (Dechow et al., 2010). The proxies of governance and controls are characteristics of the BOD, management change, managerial remuneration, managerial share ownership, and internal control processes (Dechow et al., 2010). The BOD is formed to supervise executives on behalf of their investors (Eisenhardt, 1989). The researchers use diverse BOD traits in their studies, such as board meeting, audit and nomination, and compensation committee (Abbadi, Hijazi, & Al-Rahahleh, 2016; Cohen et al., 2004; Qinghua, Pingxin, & Junming, 2007). Some researchers employ other proxies to represent the BOD characteristics such as board independence (Aifuwa & Embele, 2019; Alves, 2014), board expertise (Abbadi et al., 2016; Aifuwa & Embele, 2019; Zhang, 2019), and board diversity (Aifuwa & Embele, 2019; Nguyen & Nguyen, 2017). Moreover, some studies use characteristics of CEO and chief finance officer (CFO) who are responsible for the day-to-day management of companies as corporate governance indexes. Because the fraudulent triangle theory and other theories of corporate governance demonstrate that managers have a lot of reasons to manipulate FRQ. Some proxies representing CEO or CFO characteristics are overconfidence, gender, or turnover (Habib & Hossain, 2013; Kyaw, Olugbode, & Petracci, 2015) and CEOs age or their working experience (Hung & Binh, 2021; Nguyen & Nguyen, 2017; Zhang, 2019).

3. Methodology
3.1. Research Model and Variable Measurement

This study used the model with the dependent variable as the binary variable and independent variables as factors which are discussed in the literature review section as follows:

$$FRQ_{i,t} = \beta_0 + \beta_1 * ROA_{i,t} + \beta_2 * SIZE_{i,t} + \beta_3 * LV_{i,t} + \beta_4 * LIQ_{i,t} + \beta_5 * DIV_i, + \beta_6 * FOWN_{i,t} + \beta_7 * SOWN_{i,t} + \beta_8 * SIZEB_{i,t} + \beta_9 * DUAR_{i,t} + \beta_{10} * BLOCK_{i,t} + \beta_{11} * TIME_{i,t} + \varepsilon_{i,t}$$

The quality of financial reporting is evaluated on the basis of results of audited financial statements and the auditor's opinion on the audit report. FRQ is classified into two levels, poor and normal. This research examined the effect of two categories of determinants on FRQ, following the classification of Dechow et al. (2010) and Barać and Bilić (2021). Independent variables in the research include firm characteristics such as return on assets (ROA), debt to total assets (LV), current ratio (LIQ), dividend policy (DIV), firm size (SIZE), and listed time (TIME) and governance and controls such as foreign ownership (FOWN), State ownership (SOWN), ownership concentration (BLOCK), board size (SIZEB), and concurrent BOD (DUAR). Table 1 depicts the measurement of the variables in the research model.

Table 1. Variable measurement.

Dependent variables		
FRQ	Profit variance between pre-audit and post-audit	Audit opinions
Poor	≥ 20%	Qualified opinion, adverse opinion, disclaimer opinion
Normal	< 20%	Unqualified opinion, emphasis of matter
Independent variables		
Abbreviations variable	Variable name	Formula
ROA	Return on assets	Net profit /Total assets
LV	Debt to total assets	Total debt/Total assets
LIQ	Current ratio	Current assets/Total assets
DIV	Dividend policy	The ratio of dividends paid to net profit
SIZE	Firm size	Log_{10}(Total assets)
TIME	Listed time	Number of years listed on the stock market
FOWN	Foreign ownership	The proportion of shares held by foreign shareholders
SOWN	State ownership	The proportion of the state ownership in an enterprise
BLOCK	Ownership concentration	The number of BOD members holding equal to or greater than 5% share capital
SIZEB	Board size	Number of members on the BOD
DUAR	Concurrent BOD	DUAR = 1 if the chairman and CEO are the same people; otherwise, 0.

3.2. Applying Techniques and Model Performance Measurement

Machine learning is vital in many fields, and its applications are part of real life. The study of computing methods for automating the process of acquiring knowledge from examples is known as machine learning (Langley & Simon, 1995). Machine learning techniques have been used to find a pattern and order in a training data set and then to categorize or forecast the actions of new and strange objects (Bose & Mahapatra, 2001). Machine learning techniques are used to filter email spam, predict the weather or medical diagnostics, detect fraud or bankruptcy, and so on. This study employs six popular machine learning methods, including random forest, support vector machine (SVM), Bayesian network, logistic regression, K-nearest neighbour (KNN), and decision tree, to classify the level of FRQ and determine the determinants of FRQ.

This study used a combined measure, accuracy, and area under the curve (AUC), to evaluate the predictive performance of the research model. AUC is a measure that represents the relationship between sensitivity and specificity (Fangyu & Hua, 2018). The research model classifies FRQ into two categories, normal or poor FRQ. The quality of the *predictive model* is classified based on the *AUC value* as satisfactory (from *0.6* to 0.7), *good* (from 0.7 to *0.8*), very *good* (from *0.8* to *0.9*), and *excellent* (from *0.9* to 1.0). A model has higher accuracy and AUC, which means better predictive performance.

3.3. Sample Dataset

This article uses a dataset gathered from the Vietnamese stock exchange from 2014 to 2020. The data is gathered from audited financial statements of listed companies after excluding: banking, securities, and insurance. Due to the specific accounting regulations, their financial reporting is different from non-financial companies. After preprocessing the data, the sample used to carry out the analysis and forecast is 2225 observations, depicted in Table 2 by industry and by year.

Table 2. Demographic of data.

Panel 1: By years			Panel 2: By industry		
Year	**No.**	**%**	**Industry**	**No.**	**%**
2014	314	14.11	Construction and real estate	749	33.66
2015	323	14.52	Technology	69	3.1
2016	328	14.74	Industry	289	12.99
2017	328	14.74	Service	215	9.66
2018	319	14.34	Consumer goods	183	8.22
2019	327	14.7	Energy	204	9.17
2020	286	12.85	Agriculture	242	10.88
			Materials	198	8.9
			Medical-pharmacy	76	3.42
Total	2,225	100	Total	2,225	100

The sample data is randomly divides the dataset into a test set and training set to train, select and test the performance of the research model. The training set is a subset to train a model based on the input variables and

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target the training set, and we train the FRQ classification model. The test set and the training set have the exact attributes, considered completely new observations.

4. Results and Discussion

The descriptive statistical results are shown in Table 3 and Table 4. Based on the sample data, FRQ is classified and presented in Table 3. FRQ, at a poor quality level, has 208 observations, accounting for 9.35%. And FRQ, at a normal level, has 2017 observations, accounting for 90.65%.

Table 3. Summary of FRQ of sample data.

The quality of financial reporting	No. of observations	%
Normal	2017	90.65
Poor	208	9.35

Independent variables are presented in Table 4, regarding firm characteristics and the return on assets of listed companies in the dataset is 6.3%, the average debt to total assets ratio is 48.1%, the average current ratio is 2.981, and the dividend policy is 38.8%. Moreover, the size of firms by assets after the logarithm is 28,103%, whereas the average listing time of enterprises is 9.5 years. Regarding governance and controls, the mean foreign ownership ratio is 13.5%, while the average state ownership ratio is 67.2%. The mean of ownership concentration, calculated by the number of BOD members holding equal or greater than 5% share capital accounts for 9.8%. The mean of BOD is 5.72 members, with the highest BOD being 18 people and the lowest BOD being three people. In the sample data, the firms with the CEO and chairman positions are held concurrently by a person, taking up 21.9%.

Table 4. Descriptive statistics.

	Variable	Obs.	Mean	Std. dev.	Min.	Max.
ROA	Return on assets	2225	0.063	0.082	-0.853	0.784
LV	Debt to total assets	2225	0.481	0.214	0.001	1.294
LIQ	Current ratio	2225	2.981	21.231	0.050	982.486
DIV	Dividend policy	2225	0.388	1.671	-1.217	75
SIZE	Firm size	2225	28.103	1.366	23.779	33.677
TIME	Listed time	2225	9.53	4.695	2	21
FOWN	Foreign ownership	2225	0.135	0.157	0	0.95
SOWN	State ownership	2225	0.672	0.272	0.01	1
BLOCK	Ownership concentration	2225	0.098	0.152	0	0.8
DUAR	Concurrent BOD	2225	0.219	0.413	0	1
SIZEB	Board size	2225	5.72	1.539	3	18

The study applies the random forest algorithm, which belongs to the class of ensemble model, to classify good attributes for prediction. The results in Figure 1 show the importance of attributes in the research model. The ROA factor has the most significant importance to the predictability of FRQ, followed by the ownership concentration factor. In contrast, the concurrent BOD factor for predictability is the least important.
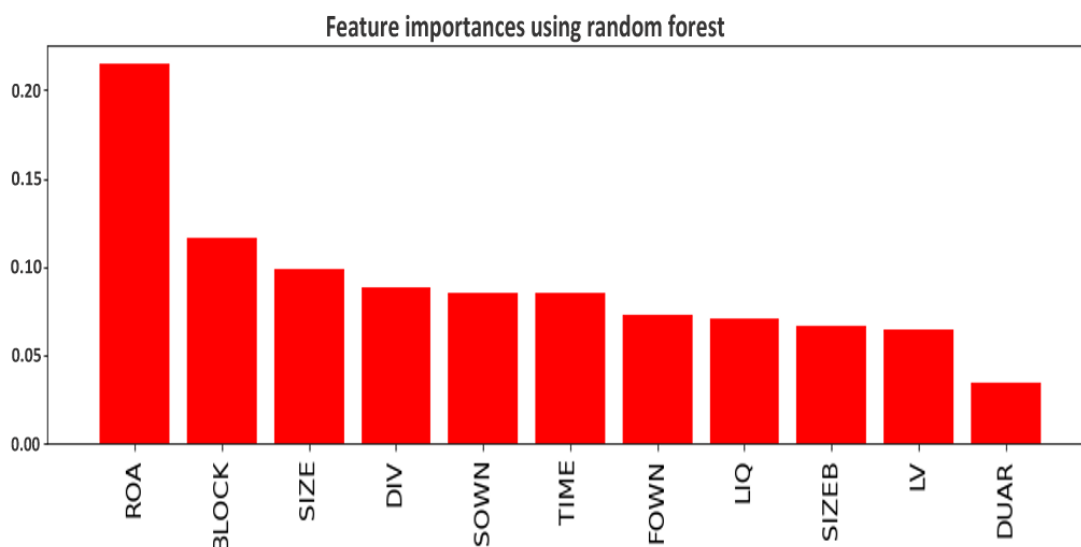

Figure 1. The coefficient of influence factors on FRQ.

Table 5 shows the quality of predictive models using accuracy. Decision tree, logistic regression, SVM, and Bayesian network show a low accuracy, and values are 0.88, 0.75, 0.75, and 0.71, respectively. Random forest and KNN algorithms have excellent accuracy, and values are 0.94 and 0.93, respectively. Six algorithms are used in the FRQ predictive model, the random forest algorithm reached the highest accuracy rate of 94%.

Table 5. The accuracy of predictive algorithms and methods

No	Method	Accuracy
1	Logistic regression	0.75
2	SVM	0.75
3	Decision tree	0.88
4	Random forest	0.94
5	KNN	0.93
6	Bayesian network	0.71

In addition to the accuracy, we use AUC to examine the predictive model comprehensively. The AUC measures the area under the ROC curve, indicating whether the models' algorithms are strong or weak in categorizing the level of FRQ into normal or poor groups. The AUC has a value from 0 to 1, and the larger its value, the better the model. Figure 2 presents the Grid Search random forest (using Grid Search as a technique to find suitable parameters for the model) and KNN algorithms achieve an excellent prediction rate, AUC = 0.93. This result shows that the predictive model can be applied when employing the model of Grid Search random forest or KNN algorithms.
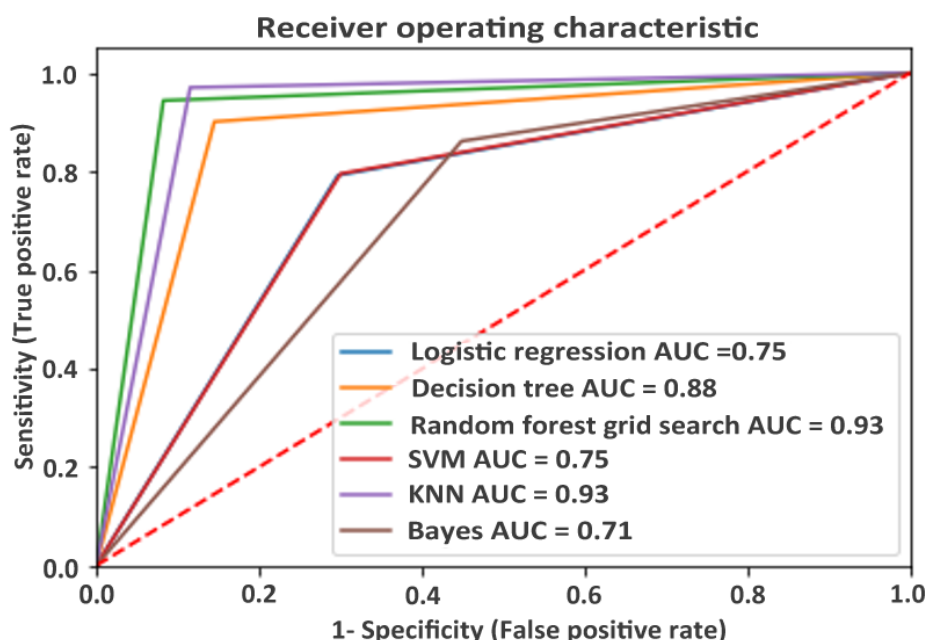

Figure 2. The AUC values of the FRQ predictive model with six algorithms.

Table 3 reveals that with a threshold of 20% of the variance between profit before and after-audit showing the findings indicate that between 2014 and 2020, 208 observations (accounting for 9.35%) of sample data have poor FRQ. The demand for high-quality accounting information among listed companies is high not only in developed countries like the US (Hope et al., 2013) or Canada (Saleh et al., 2022) but also in developing countries like Vietnam. A high rate of Vietnamese listed companies with a poor FRQ is dangerous for stakeholders such as investors, regulators, and other agencies. Some efforts or actions of the VSSC or other Stated agencies penalize fraudulent companies can motivate the trust of investors, but these actions are often delayed than the investor's decision, for example, in 2022, the VSSC sanctioned the company's fraudulent 2020 financial statements (as reflected by Bui (2022)). Therefore, the poor FRQ still causes loss to investors. Detecting fraudulent companies with poor FRQ is essential. Our study also reinforces the effect of factors on FRQ. The result of the determinants in the forecasting model indicates that return on assets (ROA) and ownership concentration (BLOCK) are the most significant drivers of the FRQ. There are a lot of studies stating the effect of profitability proxies, such as ROA, on FRQ (i.e., Nguyen and Nguyen (2017); Barać and Bilić (2021)) and the finding in this research are consistent with the initial results. The business characteristics proxies are effective measure to forecast FRQ of corporate. The effect of corporate governance factors, including ownership concentration, has also been investigated by many previous studies. Our finding in this research is consistent

with the result of Huang et al. (2012) about the negative effect of owner concentration on FRQ. The finding reinforces that corporates with block holders and concentrated ownership are likelier to possess a poor FRQ. This lack of FRQ can lead to low levels of transparency and accountability, making it difficult for investors and stakeholders to accurately assess the firm's financial position. Block holders may be focused on short-term gains rather than long-term sustainability, which can further contribute to a poor FRQ. Thus, it is crucial for corporates with concentrated ownership to maintain a high-quality financial statements.

Researchers and practitioners have worked to enhance the statistical validity of FRQ which analyses over time by employing more sophisticated statistical models (Barać & Bilić, 2021). In our research, we apply six algorithms to test the accuracy of the forecasting model and the findings demonstrate that machine learning techniques are effective in predicting the quality of financial reporting, especially random forest (accuracy = 0.94, AUC = 0.93) and KNN (accuracy and AUC = 0.93). The predictive performance in our forecasting model is higher than the prior studies, i.e., the AUC values of random forest and KNN are 0.93 in comparison with the AUC value of around 0.89 in the research of Stanišić et al. (2019). The previous studies stated that using machine learning is trend in fraud detection. Statistical and machine learning algorithms are the potential in discovering and detecting bankruptcy (Hung & Binh, 2021) or fraudulent financial statements (Perols, 2011). For instance, Barać and Bilić (2021) used the M5 algorithm, Saleh et al. (2022) adopted Big Data analytics (BDA), and the findings of these authors illustrated a high accuracy in FRQ prediction. Our results posit that random forest and KNN are also effective machine learning techniques in FRQ recognition and prediction. Our findings further extend the contribution of machine learning techniques in predicting FRQ.

5. Conclusion and Policy Implications

The study handles a sample of 2225 observations in non-financial firms listed on the Vietnamese stock market from 2014 to 2020 that test the influencing factors of FRQ and the performance of the predictability model based on machine learning algorithms. Using a threshold of 20% of the variation in profit before and after-audit in the financial statements, this research classifies FRQ into two categories, including poor FRQ and normal FRQ. The study shows that the return on assets ratio and ownership concentration are two critical factors affecting the predictability of FRQ. Meanwhile, the concurrent BOB, where a person concurrently holds the chairman and CEO functions, is the least important factor to FRQ. Furthermore, the finding shows that the random forest is the most accurate algorithm, with a forecasting ability of up to 94%. Research findings propose some policy implications for stakeholders.

Firstly, the results of our empirical research provide trustworthy evidence for corporates sector and they can establish valuable solutions for themselves. Expressly, the finding of our study confirms that ROA has an important influence on the FRQ enterprises. Firms should pay more attention in operating activities, especially those which are affecting the corporate's profitability. Besides, enterprises need to understand the role of the BOD in ensuring the FRQ. Enterprises should fulfil the model of the BOD according to the Organization for Economic Cooperation and Development (OECD) guidelines and who are the major shareholders (OECD, 2011).

Secondly, to attract the attention of investors, enterprises should supply more information about FRQ evaluation models and support analysts and investors with complete information in make decisions. The financial statements provide the essential information for the predictive models. However, investors need to spend a lot of time in synthesizing and processing data and to understand the financial statements structure as well. Hence, it is possible in the future, enterprises would be adding details about the consideration of the FRQ on the annual report to improve investors' trust.

Thirdly, investors can also consider the size of the business and the dividend policy when making investment decisions because the findings show that the FRQ increases with the company size. This evidence provides valuable information for investors and other stakeholders in making the right decisions and guarantee their investment as well. The audit reports contain a lot of valuable information about firm through the audit opinion. Therefore, Investors can evaluate the FRQ and make appropriate investment decisions based on the information contained in the audited financial statements and audit reports. And listed companies and auditing firms need to increase the application of technology in supporting audit activities, using machine learning tools to forecast enterprises' FRQ.

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