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Forecasting audit opinions on financial statements: statistical algorithm or machine learning?

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Abstract: This paper examines the applicability of different algorithms in forecasting the audit opinion on the financial statements of listed companies in Vietnam. We collected data from 492 enterprises listed on the stock market from 2016 to 2020 with 2460 observations, of which 154 observations have audit reports that are unqualified opinions, accounting for 6.26%. We use logistic regression algorithms, decision trees, and random forests. We consider two research models to assess the influence of factors, including groups of financial factors, factors belonging to the Board of Directors, and other factors on the audit report with an unqualified opinion. For model machine learning algorithms, the data is divided into two sets of Training and Testing with a ratio (of 80:20). The Testing dataset is used to evaluate the effectiveness of the predictive model. The results show that the audit opinion of the previous year has the most significant influence on the audit opinion, followed by profit after tax on equity, the ratio of receivables to revenue, and the business size. In particular, the ability to accurately predict the total non-acceptance audit opinion reaches 97% for the random forest algorithm. This study contributes to the current literature by examining which algorithm is appropriate for predicting the auditor's opinion. Furthermore, this research adds empirical findings to the literature on audit reports to make the financial statement audit process more efficient.

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Keywords: Audit opinion; Decision tree; Financial statements; Machine learning; Logistic Regression; Random forests

1 Introduction

This study examines the applicability of different algorithms in forecasting the audit opinion on the financial statements of listed companies. Financial statements (financial statements) provide essential information for managers, investors, and authorities. The auditor's opinion on the audited report verifies the truthfulness and reasonableness of the financial statements. Quite a few empirical studies use the information on financial statements to build models to predict audit opinions. Dopuch et al. (1987) relies on financial and non-financial variables to show the factors that contribute to predicting the auditor's opinion, such as loss in the current year, the change in corporate profits relative to industry average returns, and related ratios of financial leverage.

Subsequent studies also show a relationship between the predictability of an audit opinion that is not an unqualified opinion and financial ratios related to solvency and performance evaluation of enterprises (Spathis et al., 2003, Caramanis and Spathis, 2006). Besides, the authors put the non-financial factors in the research model, such as the time interval between the end of the financial year and the date of signing the audit opinion (Keasey et al., 1988). Informational factors on corporate litigation Spathis (2003), size of audit firm Caramanis and Spathis (2006), company listing time Özcan (2016), the board size, several owners participating in management Keasey et al. (1988).

Choosing which algorithm is appropriate for predicting the auditor's opinion is always a concern. Many studies have examined audit opinion factors using logistic statistics and machine learning algorithms (Özcan, 2016; Pourheydari et al., 2012; Saif et al., 2013; Yaşar et al., 2015; Fernández-Gámez et al., 2016; Stanisic et al., 2019; Sánchez-Serrano et al., 2020). These studies show that the prediction ability of machine learning algorithms has higher accuracy than logistics.

No studies use machine learning algorithms to predict audit opinions in Vietnam. This study found that the percentage of audit reports with total disapproval in the sample was 6.26%. Meanwhile, a study by Lin et al. (2011) on audit opinions on the Chinese stock market from 1992 to 1999 shows that the audit opinions are not unqualified opinions accounting for 11%, the lowest in 1995 (7%) and the highest in 1999 (19.9%). The proportion of audit opinions that are not unqualified is much lower in European countries. From 1988 to 1994, 2.96% of the audit opinions were not unqualified in the UK (Lennox, 2000). The above difference leads to selecting an appropriate algorithm for forecasting different audit opinions. Therefore, we realized the research gaps for the following reasons: (i) there have not been any empirical studies in Vietnam on forecasting audit opinion; (ii) the opinion of the auditor plays an essential role in the quality of the financial statements, the rating, and consideration of the listing status of the enterprises in Vietnam.

We use logit regression and machine learning algorithms such as decision trees and random forests with the research objectives and questions above. The reason for using this method is that we want to evaluate the predictive performance of machine learning algorithms, which have been proven to predict accurately. To fully and comprehensively evaluate, we used a research sample of 492 enterprises in the five years from 2016 to 2020. We consider two research models to assess the influence of factors, including groups of financial factors, factors belonging to the Board of Directors, and other factors on the audit report with the unqualified opinion. For model machine learning algorithms, the data is divided into two sets of Training and Testing with a ratio (of 80:20). The Testing dataset is used to evaluate the effectiveness of the predictive model.

The study has found that the audit opinion of the previous year is an essential factor in predicting the total non-acceptance of the audit report. However, if this factor is not used, the built research model still has results with up to 93% predictive accuracy.

The article, in addition to the introduction, includes the following sections: (2) The theoretical basis of the audit report and the basis for the audit opinion; (3) Overview of related studies with statistical approach (studies using logit) and related studies using machine learning algorithms; (4) Research Methodology; (5) Research results and discussion and the final section (6) are some recommendations for the subjects based on the research results.

2 The basis for forming audit opinion

Auditing gathers and evaluates evidence about information to determine and report on its compliance with established standards. Qualified and independent auditors must carry out the audit process (Arens, 2012). Therefore, all audits must end with a report to confirm whether the audited information follows established standards.

According to ISA 200, auditing financial statement purpose is to increase users' reliability of financial statements. The auditor expresses whether the financial statements are under the applicable financial reporting framework. After completing the audit, the auditor should clearly express the audit opinion in writing, stating the basis for that opinion. According to the previous VSA 700, an audit report on financial statements is a written report prepared by an auditor and an audit firm. This report is published to express an official opinion on the financial statements of an audited entity. The audit report is a means of communication between the auditor and the user of the financial statements. It shows the essential part of the audit activity and presents the results of the financial statement evaluation to the users. For auditors, the audit report is the document that explains the conclusions about the audited financial statements, so it must summarize the entire work they have done. To the public, the audit report is the observable end product of a non-observable process, so it contains information crucial to those who use financial statements to make economic decisions (Butler et al., 2004).

According to the International Auditing Standard - ISA 700 and Vietnamese Auditing Standard - VSA 700, the auditor can express the following types of audit opinions:

- "*Unqualified opinion*": This is an opinion expressed when the auditor concludes that the financial statements have been prepared, based on materiality, following the applicable financial reporting framework. When an entity has an audited financial statement with an unqualified opinion, it does not mean that the auditor guarantees that the financial statements do not contain any errors but only ensures that there are no material errors.

- *"Qualified opinion"*: The auditor and the audit firm issue an audit report in the form of a qualified opinion when the auditor concludes that the overall financial statements are still materially misstated or the auditor is unable to obtain sufficient appropriate audit evidence to conclude that the financial statements as a whole are free of material misstatement.

3 Literature review

The world has many studies based on financial statements to predict qualified opinions. Quite a few studies have modeled the factors that affect the prediction of audit opinion. Dopuch et al. (1987) built a model to analyze financial and market variables to predict audit opinions. Five financial variables are included in the model by the authors: (1) The change in the ratio of total debt to total assets; (2) The book value of assets; (3) the Change in inventory/total assets ratio; (4) Change in total receivables/total assets ratio and (5) Current year profit and loss. The market variables used in the study of Dopuch et al. (1987) include (1) Listing time; (2) The difference between the company's profit and the average industry profit; (3) The change in beta risk coefficient. The research results show that all the above variables play an essential role in predicting the auditor's opinion, especially the current year loss variables, the change in the ratio of total debt to total assets, and the difference between company profits relative to the industry average.

In addition, Keasey et al. (1988) used a logistic regression model based on 12 independent financial and non-financial variables to explain the possibility of receiving a qualified audit opinion for a small-scale company.

Laitinen and Laitinen (1998) based on 17 financial and non-financial variables to explain the likelihood of large firms receiving an audit opinion that is not unqualified. The research results show that the company is more likely to receive an unqualified opinion when the company's growth rate is low, the equity/total assets ratio is low, and the number of employees is small.

In another study, Spathis (2003) used the UTADIS classification method, then the authors used the results to compare with other analytical methods. The research results show that the financial variables with the highest ability to distinguish audit opinions are the ratio of receivables to sales, profit/total assets ratio, working capital/total assets, and sales/total assets.

In addition, the non-financial variables that distinguish the audit opinion are information about the enterprise's litigation. The results show that the UTADIS analysis method is the most predictive, with the correct prediction rate of 80%. Caramanis and Spathis (2006) studied a qualified opinion prediction model by combining four financial ratios and non-financial variables such as audit firm characteristics and fees. The authors used a logistic regression model to test the sample size of 185 companies to predict the probability that the company received an unqualified opinion and added some new variables.

Research results show that the model has a high predictive ability of approximately 90%. Variables that can predict an unqualified opinion are net profit/total assets; short-term assets/short-term liabilities. Accordingly, the lower the company's net profit/total assets ratio, the lower the short-term asset/short-term debt ratio, and the higher the possibility that the company receives an unqualified opinion. Özcan (2016) has provided a model including financial and non-financial variables that impact audit opinion, tested by logistic regression. Empirical research results show that in companies with high liquidity, efficient operation, high profit, and low financial leverage ratio, auditors often give an unqualified opinion and vice versa. In addition, the longer the listing period of the company or the high percentage of independent members of the Board of Directors, the higher the likelihood that the financial statements received an unqualified opinion.

Several studies have used machine learning algorithms to consider influencing factors and predict audit opinions in audit reports and research (Saif et al., 2012; Pourheydari et al., 2012; Saif et al., 2013; Yaşar et al., 2015; Fernández-Gámez et al., 2016; Stanisic et al., 2019; Sánchez-Serrano et al., 2020).

Saif et al. (2012) studied a new approach to extracting rules from support vector machines and decision trees. Research results with support vector model, test data Qualified 22%, Unqualified 94%, overall 64.25%; training data Qualified 89%, Unqualified 99%, overall 96.53%.

Whereas Yaşar et al. (2015) predict the audit opinion on partial math acceptance using discriminant decision trees, logit, and C5.0 based on twelve financial ratios. The sample consists of 110 data by year of companies, including 55 audit opinions that accept the company's observations for the year and 55 audit opinions that carry partial audits at the Istanbul Stock Exchange (ISE) for 2010-2013. The classification results of the models show that the decision tree's C5.0 algorithm has the highest correct classification rate (Unqualified 96.4%, Qualified 100%, Total 98.2%) compared to the discrimination and logit model.

Stanisic et al. (2019) used statistical techniques and machine learning to evaluate the two scenarios separately. The first scenario shows that several methods from both fields achieve a comparable predictive performance of about 0.86, as measured by the area Under the Curve (AUC). However, in the second scenario, machine learning algorithms, especially those based on decision trees, such as random forests, perform significantly better, achieving AUC up to 0.89. Sánchez-Serrano et al. (2020) uses an audit opinion prediction model by analyzing variables that affect the probability of receiving an audit opinion. The study uses an artificial neural network technique, the multi-layer perceptron. The results show that the developed method predicts the audit opinion with an accuracy of over 86%.

4 Research methods

4.1 Research models

Dependent variable:

The dependent variable (Y) is the variable "Audit opinion" this is a dependent variable with only two expressions, coded as follows: 1 with a qualified opinion and 0 with an unqualified opinion.

Independent variables:

Previous studies have found that financial and non-financial information predicting an audit opinion is not unqualified. In general, the research results indicate the possibility that the financial statements receive a non-unqualified opinion, including two main groups of factors: the group of financial ratio factors including the company with a loss in the current year, the difference between the profit of the company and industry average, the increase in total debt/total assets ratio (Dopuch et al., 1987); low growth rate, low equity to total assets ratio (Laitinen and Laitinen, 1998); low short-term asset/total liabilities ratio and low net profit/total assets ratio (Caramanis and Spathis, 2006).

The group of non-financial factors was also discovered from previous studies, such as the company being audited by a significant auditing company, mortgage, or the time between the end of the financial year and the date of the lengthy audit opinion (Keasey et al., 1988); companies with a small number of employees (Laitinen and Laitinen, 1998), companies with information about lawsuits (Spathis, 2003), companies with a low percentage of independent members on the board, time shortlisting period (Özcan, 2016). Based on a research review, we consider three groups of main factors that affect the qualified opinion of these indicators, namely:

(1) Financial variables include seven variables: Profit from production and business activities over net revenue; Profit after tax on equity; Profit after tax on net sales; Total accrual variable on total assets; Short-term debt to total debt; Financial leverage; Debt-to-sales ratio. These indicators are based on the studies of Keasey et al. (1988), Laitinen and Laitinen (1998), Spathis (2003), Kirkos et al. (2007), Omid (2015), Özcan (2016), citecitron1992audit, Caramanis and Spathis (2006).

(2) The variables on the Board of Directors include five variables: The duality between the title of chairman of the board of directors and the chief executive officer; the Number of members of the Board of Directors who are significant shareholders; the Size of the Board of Directors; Percentage of members of the Board of Directors participating in management; Number of meetings of the Board of Directors during the year. Board variables based on studies Keasey et al. (1988), Özcan (2016).

(3) Other relevant variables include five variables: Auditors belonging to the Big 4 group; Consolidated financial report; Enterprise size; Listing time; Audit opinion of the previous year. Other relevant indicators have been considered in the studies Laitinen and Laitinen (1998), Mutchler (1986), Dopuch et al. (1987), Omid (2015), Mutchler et al. (1997).

In the study, we built two models, considering the influence of factors on the unacceptable audit opinion:

- Model 1: includes 16 indicators presented in Appendix 1 and does not include the previous year's audit opinion variable

- Model 2: includes all 17 indicators mentioned above.

4.2 Research Methods

To compare the predictive ability of algorithms, we use Logistic Regression; Machine Learning Algorithms (Decision Trees and Random Forests).

To evaluate and compare the performance of the two research models, the authors used the following parameters:

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN} \tag{1}$$

Where: TP (true positive) is genuinely positive, TN (True Negative) is a true negative, FP (false positive) is false positive, FN (False Negative) is a false negative. TP is the number of audit reports classified (true) as qualified opinions. FP is the number of audit reports with an unmodified audit opinion but is (falsely) classified as the audit report with a disapproval opinion. TN is the number of audit reports with unqualified (non-fraudulent) and classified (correctly) as audit reports with unqualified audit opinions. FN is the number of audit reports with qualified opinions and classified (false) as the audit report with an unqualified opinion. Thus, the accuracy here is the ratio of correct classifiers to the total number of classifiers.

Sensitivity is the ratio of the cases in which the audit report is classified with the qualified opinion to the total number of cases in the audit report with the qualified opinion of the research sample. Sensitivity = TP/(TP+FN) means that all audit reports with a qualified opinion are detected. However, sensitivity alone does not tell us all about the model because 100% of the sensitivity can obtain if we assign all audit reports with qualified opinions. Therefore, we need to know the model specificity information. Specificity is the ratio between the cases where the auditor's report with an unqualified opinion is correctly classified and the total number of cases where the auditor's report with the unaccepted audit opinion is correct.

A ROC (receiver operating characteristic) plot describes the relationship between sensitivity and specificity, often used to evaluate a prediction method or model. The area under the ROC curve (also called area under the curve, AUC). The sensitivity, specificity, or AUC index reflects the model's accuracy. At the same time, the study also used the following metrics:

+ Precision: The level of prediction accuracy in the predicted cases is Positive.

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

+ Recall: The degree of predictive accuracy of cases is Positive in actual cases is Positive.

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

+ F1-Score: Average harmonic between Precision and Recall is an ideal surrogate metric for accuracy when the model has a high sample imbalance rate.

$$F1\text{-Score} = \frac{2}{\frac{1}{\text{Precision}} + \frac{1}{\text{Recall}}} \tag{4}$$

Based on the research data, next to the train, select and test the model's results; we will randomly divide the data set into train/test sets. These datasets have the following meanings and roles:

+ Train set: We train the audit opinion classification model based on the input and target variables of the train set. The obtained model is evaluated on independent data sets, such as test sets.

+ Test set: This is also a data set with fields similar to the train set considered entirely new observations. The test set should have the most similar distribution to the actual data that the user generates to evaluate the model's applicability in practice.

4.3 Research data

Table 1 summarizes the research sample. The number of surveyed enterprises is 492 in 5 years from 2016 to 2020 on Vietnam's stock market.

Table 1: Summary of audit reports on audit opinions during the research period

Audit Report, Audit Opinion	Number	Percentage (%)
Unqualified opinion, no opinion	2,030	82.52
Unqualified opinion, emphasized opinion	276	11.22
Qualified opinion, except for opinion	150	6.1
Qualified opinion, disclaimer of opinion	2	0.08
Qualified opinion, adverse opinion	2	0.08
Total	2,460	100

Source: Own research

Table 2: Summary of the auditor's report on qualified opinions and unqualified opinions

Audit opinion	Year					Total	
	2016	2017	2018	2019	2020	Number	(%)
Qualified opinion	27	26	28	37	36	154	6.26%
Unqualified opinion	465	466	464	455	456	2,306	93.74%
Total	492	492	492	492	492	2,460	100.00%
Qualified opinion rate (%)	5.49%	5.28%	5.69%	7.52%	7.32%	6.26%	

Source: Own research

In table 2, the data has 154/2460 qualified opinions, accounting for 6.26%. The qualified opinions had increased from 5.49% in 2016 to 7.32% in 2020.

Figure 1 presents the qualified opinion by industry, in which the industry with the highest percentage is the materials industry (9.3%), followed by the real estate and construction industry (8.5). %), in contrast, especially the health sector (0%) has no qualified opinion; the following industry with a low rate is the energy industry (2.8%).

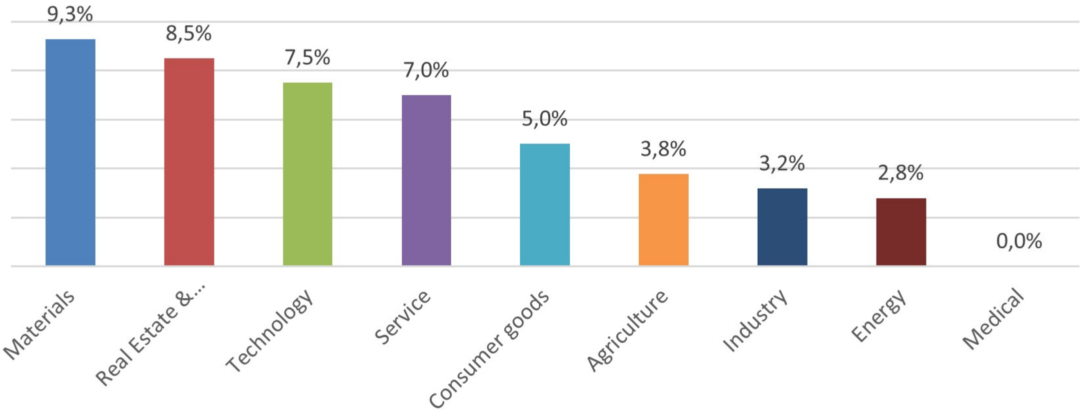

Figure 1: Audit report with the unqualified opinion of the industry

Source: Own research

The three most common reasons for auditors to give a qualified opinion are not having obtained enough confirmation about receivables and payables (18.6%) and not enough evidence to confirm investments in subsidiaries, associates, and investment provisions (17.2%). The third reason is the recording of expense items not following accounting standards, which is the cause of increasing the enterprise's profit management problem. Table 3 shows that the reason for giving a qualified opinion is 66.9% as the lack of appropriate evidence and the financial statements with a material error of 33.1%.

Table 4 shows that the audit report made by Big4 audit firms has a qualified opinion of 3.7%, while that of non-big4 audit firms has a qualified opinion for financial statements of 7.2%.

5 Results

Table 5 presents the results of the mean, the standard deviation of the indexes, and the test value for the difference between the two groups of unqualified and qualified opinions. The results show that there are 13/16 indicators with differences and statistical significance. The indicators having no difference are financial leverage (A6), the duality between the title of chairman of the board of directors and chief executive officer (A8), and the consolidated financial statements (A14).

5.1 Logistic regression

Based on Table 6, the research results for these variables consider each group of factors, financial ratios, Board of Directors, and other factors.

Table 3: Summary of the qualified opinion

The basis of qualified opinion		Percentage	
Insufficient relevant evidence has been obtained	Receivables and payables	18.6%	66.9%
	Record revenue and expenses	9.7%	
	The net value of inventories accounts receivable	13.1%	
	Investment in subsidiaries, associates, provision for investments	17.2%	
	Do not participate in witnessing the inventory	2.1%	
	Others	6.2%	
The financial statements have material errors	Revenue recognition is not up to standard	2.8%	33.1%
	Expense recognition is not by the standard	16.6%	
	No provision for inventory, receivables, and investments	7.6%	
	Incorrect record of investment in subsidiaries and associates	3.4%	
	Others	2.8%	

Source: Own research

Table 4: Summary of audit opinions by the auditing company

Year	Big4		Non-Big4		Total
	Unqualified opinion	Qualified opinion	Unqualified opinion	Qualified opinion	
2016	127	8	338	19	492
2017	139	5	327	21	492
2018	133	4	331	24	492
2019	134	8	321	29	492
2020	135	1	321	35	492
Total	668	26	1638	128	2460
Percentage	96.3%	3.7%	92.8%	7.2%	

Source: Own research

Table 5: Mean values of variables between 2 groups of audit opinions

Variable	Mean		Std. Dev.		t	sig
	Unqualified opinion	Qualified opinion	Unqualified opinion	Qualified opinion		
A1	0.073	-0.689	0.886	3.647	7.3181	0.000
A2	0.114	-0.009	0.141	0.200	10.1145	0.000
A3	0.064	-0.143	0.847	2.387	2.4524	0.0143
A4	8.334	-71.404	260.991	952.109	2.7622	0.0058
A5	0.812	0.863	0.235	0.199	-2.6586	0.0079
A6	0.485	0.483	0.225	0.214	0.1101	0.9124
A7	0.389	9.140	0.048	8.086	-4.1831	0.000
A8	0.202	0.188	0.402	0.392	0.4125	0.3406
A9	0.610	0.539	0.902	0.724	0.9532	0.0321
A10	5.559	5.312	1.394	1.296	2.1444	0.0286
A11	0.300	0.269	0.171	0.183	2.1907	0.0004
A12	10.762	7.994	9.638	5.947	3.5196	0.0012
A13	0.290	0.169	0.454	0.376	3.232	0.0012
A14	0.530	0.519	0.499	0.501	0.2617	0.7936
A15	27.599	26.919	1.610	1.600	5.0752	0.000
A16	2.038	49.852	12.668	356.668	-6.3954	0.000

Source: Own research

Firstly, for the group of financial ratio factors, 3 out of 7 financial indicators affect the qualified opinion, including the profit index from production and business activities on net revenue (A1), which affects opposite to the 5% statistical significance level. However, it is only significant in model 1 but not statistically significant in model 2. The second indicator has a substantial adverse effect and is statistically significant at 1% in both models. After-tax return on equity (A2), the metric affecting the qualified opinion in the financial group is the debt-to-sales ratio (A7). This index has a positive relationship and is statistically significant in both model 1 and model 2.

Second, the group of variables about the board of directors has almost no influence on the unqualified audit opinion. However, in model 1, the number of meetings of the Board Directors (A12) is negatively related at the 5% significance level.

Third, the group of other factors affecting the qualified opinion is the consolidated financial statement (A14), which has a positive influence and is statistically significant. Meanwhile, the Index of Enterprise Size (A15) measured by Logarithm (Total Assets) has a negative relationship and is statistically significant. Finally, the factor added to

Table 6: Logistic regression results

	Model 1	Model 2
A1	-0.209**	-0.284
A2	-2.704***	-2.016***
A3	-0.0234	0.272
A4	-0.000328	-0.00119
A5	0.604	-0.0306
A6	0.465	0.417
A7	0.164***	0.109**
A8	-0.214	-0.27
A9	-0.118	-0.0485
A10	-0.048	-0.0281
A11	-0.869	-0.321
A12	-0.0396**	-0.0244
A13	-0.419	-0.0186
A14	0.575***	0.409*
A15	-0.256***	-0.255**
A16	0.00386	0.00416
lagop1		4.024***
_cons	4.361**	3.753
N	2460	2460
Pseudo R2	0.1387	0.3726

Source: Own research

model 2 is that the previous year's audit opinion (lagop1) has a positive influence with a statistical significance of 1%, with a considerable impact on the research model. Thus, the audit opinion of the previous year (lagop1) is a critical criterion when considering the factors affecting the qualified opinion. The results also reflect the Pseudo R2 index (13.87% in model 1 and 37.26% in model 2). of Özcan (2016), Caramanis and Spathis (2006), Spathis (2003), Keasey et al. (1988).

In Table 7, the overall correct prediction rate is 93.82% for model 1 and 95.69% for model 2. When looking at more details, for model 1, the qualified opinion prediction rate is only 55.00 %, and the predicted rate of unqualified opinion reached 94.14%. Similarly, in model 2, the qualified opinion prediction rate improved and got 71.43%. The study's objective was to examine the influence of factors on qualified opinion, but the prediction result was relatively low, although the overall prediction level was high,

Table 7: Level of model prediction according to Logistic regression

		Model 1		Model 2	
Sensitivity		Pr(+ D)	7.14%	Pr(+ D)	51.95%
Specificity		Pr(- D)	99.61%	Pr(- D)	98.61%
Positive predictive value		Pr(D +)	55.00%	Pr(D +)	71.43%
Negative predictive value		Pr(D -)	94.14%	Pr(D -)	96.85%
False + rate for true D		Pr(+ D)	0.39%	Pr(+ D)	1.39%
False - rate for true D		Pr(- D)	92.86%	Pr(- D)	48.05%
False + rate for classified	+	Pr(D +)	45.00%	Pr(D +)	28.57%
False - rate for classified	-	Pr(D -)	5.86%	Pr(D -)	3.15%
Correctly classified			93.82%		95.69%

Source: Own research

above 93%. The reason is that the data has a severe imbalance between the proportion of audit reports with qualified opinion, only 6.26%. The audit report with the unqualified opinion accounts for a large proportion (93.74%). To overcome this existing problem, we deal with using machine learning algorithms in the following section.

Figure 2, the ROC (receiver operating characteristic) plot, depicts the relationship between the sensitivity and specificity of the two models. The chart also shows that the forecast level of the two models is quite good. Model 1 got 77.00%, and Model 2 got 87.09%. Thus, like previous studies Keasey et al. (1988) and Spathis (2003), the models yield less than 90% predictive results when using the traditional test method. The model has a higher predictive ability and more complex and optimal algorithms if the variables are selected appropriately.

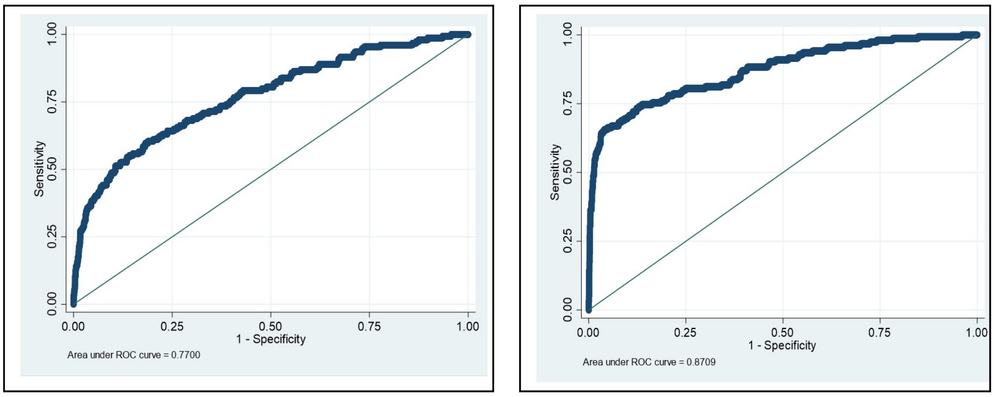

Figure 2: ROC line chart

Source: Own research

5.2 Machine learning

Figure 3 presents the importance level of 16 indicators in research model 1. Index A4 – Total accrual variable on total assets is the most important indicator, followed by index A2 – Profit after tax on equity and A1 – Profit from business activities on net sales. The least essential indicators are A10 - Size of the Board of Directors.

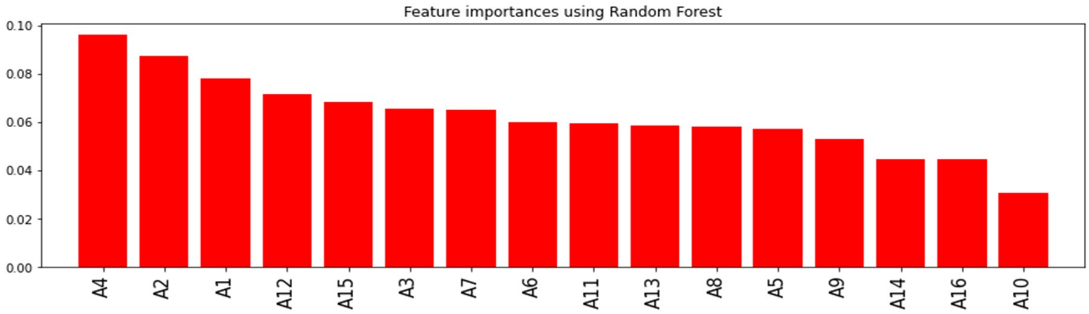

Figure 3: Importance of indicators in model 1
Source: Own research

In figure 4, for model 2, we add the previous year's audit opinion index (lagop1) with a high rate of 0.37856776. The following important, influential indicators A1 – Profit from business activities on net sales (0.06485021), then index A4 – Total accrual variable over total assets is the most critical indicator (0.05799864). The index of the lowest importance is A10 - Board size (0.0182731).

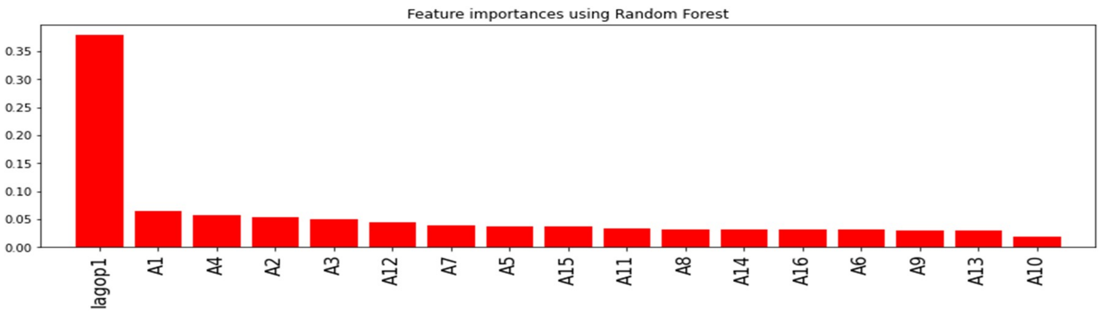

Figure 4: Importance of indicators in model 2
Source: Own research

According to the statistical results in table 2, the percentage of audit reports with total disapproval is only 6.26%. We use SMOTE (Synthetic Minority Over-sampling) techniques to deal with imbalanced data. In table 8, there is no significant difference in the measurement of the forecast level between the two groups of unqualified and qualified opinions. Specifically for model 1, according to the Random Forest algorithm, the overall forecast result is 91%. Precision, Recall, and F1-score for the non-acceptance audit report are 93%, 90%, and 91%, respectively. Next, we optimize the model by Random

Table 8: Model prediction level according to Random Forests

Model	Audit opinion	RandomForest				Random_grid.best			
		Accuracy	Precision	Recall	F1-score	Accuracy	Precision	Recall	F1-score
Model 1	Qualified opinion		0.9	0.93	0.92		0.95	0.97	0.96
	Unqualified opinion		0.93	0.9	0.91		0.97	0.95	0.96
	Weighted avg	0.91	0.92	0.91	0.91	0.96	0.96	0.96	0.96
Model 2	Qualified opinion		0.9	0.97	0.93		0.96	0.97	0.97
	Unqualified opinion		0.97	0.89	0.92		0.97	0.96	0.97
	Weighted avg	0.93	0.93	0.93	0.93	0.97	0.97	0.97	0.97

Source: Own research

grid best with optimal parameters (min_samples_split, n_estimators, max_depth), the results have increased significantly, and the prediction accuracy is up to 96%. For model 2, we consider the influence of factors on the level of prediction to qualified opinion. We add the previous year's audit opinion index (lagop1). The model's prediction level has improved, 93% for Random Forest and 97% for the Random grid best algorithm.

Figure 5 presents the forecast results according to the AUC index (area under the curve). This index measures the area under the ROC curve. It shows whether the classification ability of the group of audited ideas accepting the unqualified/qualified opinion of the decision tree and random forest algorithms is strong or weak. The larger its value, AUC $\in$ [0, 1], the better the model. For model 1, the results reached 91% of both Decision Tree and Grid Search.

Forest algorithms (using Grid Search to help finding suitable parameters for the model). For model 2, the Decision Tree algorithm achieves a high prediction accuracy rate, AUC = 0.95 and AUC = 0.93, according to the Grid Search Random Forest algorithm. Therefore, the model's predictive ability is good, and the model can apply in practice.

Decision Tree and Random Forest achieved 97% accuracy. The results of this study are similar and higher to some previous studies done Saif et al. (2012), Pourheydari et al. (2012), Saif et al. (2013), Yaşar et al. (2015), Fernández-Gámez et al. (2016), Stanisic et al. (2019), Sánchez-Serrano et al. (2020).

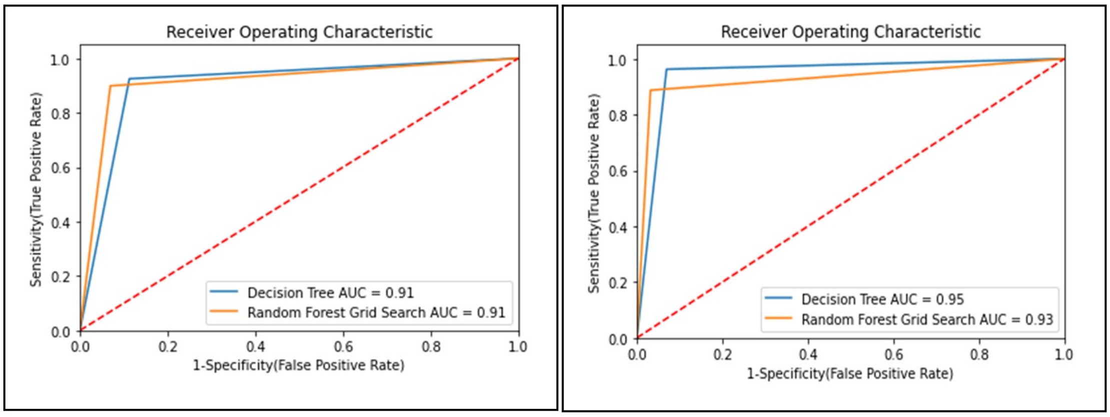

Figure 5: Forecast level according to the AUC index

Source: Own research

6 Conclusion

The study's objective is to investigate the factors affecting an audit opinion on financial statements; the selected sample is non-financial companies listed on the Vietnamese stock exchange from 2016 to 2020. A total of 492 companies met the conditions, from which the author collected 2460 audit opinions, of which 2306 audit reports have an unqualified opinion, and 154 audit reports have a qualified opinion. The collaborative study considers financial and board variables and other factors that influence the formation of audit opinion. The variables include 17 ratios divided into three main groups.

As shown in table 6, among the variables that affect the type of audit opinion, the one with the most substantial influence is the previous year's audit opinion variable (lagop1). The remaining variables have a significant effect on the audit opinion. Nevertheless, according to the model's results, the possibility of impact is not too significant compared to the previous year's audit opinion variable. The study used additional machine learning algorithms to consider the influence on predicting qualified opinion, including decision trees and random forests. The forecast results reached 97%.

Specifically, before an audit of a company's financial statements, the auditor collects data on variables that affect the formation of the audit opinion as shown in the model, and then replaces these data. Enter the model's regression equation to predict the company's probability of receiving an unqualified opinion. If a company is highly likely to receive an unqualified opinion, the auditor needs to focus more on these companies. This model can be used as a support tool in addition to the auditor's judgment, helping to make audit planning faster and saving costs and efforts. Auditors can use these models to test multiple companies in less time with faster results.

Furthermore, the results obtained from this model can assist the audit firm in evaluating potential clients, predicting the auditor's opinion under similar conditions, and helping to reduce the risk of lawsuits. In addition to the primary audience that the research aims at, auditors and audit firms, stakeholders interested in the business can also use this model as a reference information channel, providing a better overview of the company's operations.

In the prediction model, the audit opinion of the previous year plays a significant role. However, the level of impact of this variable accounts for a large proportion compared to other independent variables in the model. The audit auditors often based on the previous year's audit records and audit results to comment on the current year. However, in many cases, the auditor's over-dependence and confidence during the last year's audit results can negatively affect the audit's results. The research results show that the profitability variables can discriminate the audit opinion in the predictive model. When performing an audit, the auditors need to consider these factors when expressing opinions.

Nevertheless, the study only considers using two machine learning algorithms, Decision Tree and Random Forest, so the effectiveness of other algorithms has not been comprehensively considered. In the future, we will consider and research and use other algorithms such as neural networks (NN) and support vector machines (SVM). At the same time, we will expand our consideration of other attributes of the financial statements and governance aspects to predict an unqualified audit opinion.

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Appendix 1 - Variables in the research model

Symbol	Variable name	Measure
	Financial indicators	
A1	Profit from production and business activities on net sales	Profit from business activities t/Net revenue t
A2	Profit after tax on equity	Profit after tax t/Equity t
A3	Profit after tax on net sales	Profit after tax t/Net revenue
A4	Total accrual variable to total assets	(Profit after tax t- Net cash flow from business t)/Total assets t
A5	Short-term debt to total debt	Short-term debt t/Total debt t
A6	Financial leverage	Total liabilities t/ Total assets t
A7	Debt-to-sales ratio	(Short-term receivables from customers t – Provision for bad debts t + Long-term receivables from customers t – Provision for long-term receivables t)/Net revenue t
	Administrative Council	
A8	The duality between the title of chairman of the board of directors and chief executive officer	Identifier variable. CEO has a value of 1 if the chairman of the board is concurrently a chief executive officer; otherwise, the variable has a value of 0
A9	Number of members of the Board of Directors who are major shareholders	Number of members of the Board of Directors holding shares of more than 5%
A10	Size of the Board of Directors	Number of members in the Board of Directors
A11	Percentage of members of the Board of Directors participating in management	Salary of Executive Board members/Total number of BOD members
A12	Number of meetings of the Board of Directors during the year	Number of meetings of the Board of Directors in the year
	Other problems	
A13	Auditor of the Big 4 group	Identifier variable. BIG4 has a value of 1 if audited by a non-Big 4 company.
A14	Consolidated financial report	Identifier variable. Consolidated financial statements are 1, the rest is 0.
A15	Enterprise size	Logarithmic (Total Assets)
A16	Listing time	Number of years of listing
Lagop1	Audit opinion of the previous year	The audit opinion of the previous year is not fully accepted = 1; vice versa =0

Source: Own research