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An Interpretable Machine Learning Framework for Imbalanced Audit Opinion Prediction

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Abstract

Audit opinion prediction is important for capital-market monitoring because non-unqualified audit opinions may signal financial distress, reporting uncertainty, and elevated information risk. This study develops an interpretable machine learning framework for predicting non-unqualified audit opinions under severe class imbalance using firm-year observations of Vietnamese listed companies from 2015 to 2024. The proposed framework is based on a Modified Random Forest approach that integrates imbalance-aware sub-sampling, performance-based tree selection, ensemble probability aggregation, and decision-rule extraction. The framework is designed to improve minority-class detection while preserving transparent and economically interpretable risk signals. The empirical analysis compares the proposed framework with several benchmark models, including logistic regression, Support Vector Machine, k-nearest neighbours, Random Forest, XGBoost, Random Forest with synthetic minority oversampling, cost-sensitive Random Forest, and Balanced Random Forest. Predictive performance is evaluated using three validation strategies: a random 70/30 train-test split, an out-of-time split in which observations from 2015-2021 are used for training and observations from 2022-2024 are reserved for testing, and k-fold cross-validation. The proposed framework achieves the strongest overall performance across these settings, with area under the receiver operating characteristic curve values of 0.829, 0.811, and 0.793, respectively, while also improving minority-class recall and F1-score relative to benchmark models. The extracted decision rules indicate that audit opinion modifications are associated with persistent and interacting financial vulnerabilities, particularly prior modified opinions, weak profitability, leverage pressure, limited debt-servicing capacity, liquidity constraints, and asset-structure risk. Methodologically, the study contributes by integrating imbalance-aware ensemble learning with interpretable rule-based analysis. Practically, the framework may serve as a complementary early-warning tool for auditors, regulators, and investors in financial reporting risk assessment within emerging markets.

Keywords: Audit opinion prediction, Interpretable machine learning, Modified Random Forest, Financial distress, Vietnam

1. Introduction

Independent auditing plays a central role in capital markets by enhancing the credibility of financial reporting and mitigating information asymmetry between firms and external stakeholders. Investors, creditors and regulators rely on audited financial statements to assess firm performance, financial risk and corporate transparency. Within this monitoring framework, audit opinions provide a concise and externally validated signal regarding the reliability of financial statements. In particular, non-unqualified audit opinions such as qualified, adverse and disclaimer opinions often indicate material reporting issues, financial distress or uncertainty regarding firm viability (Dopuch et al. [1], Habib [2]). Because such opinions may influence investor perception, borrowing costs and regulatory scrutiny, understanding and predicting audit opinion modifications has become an important issue in both accounting and financial research.

A substantial body of literature has examined the determinants of audit opinion outcomes. Prior studies consistently document that financial distress indicators such as declining profitability, high leverage and liquidity constraints are strongly associated with the likelihood of receiving modified audit opinions (Keasey et al. [3]; Habib [2]; Zarei et al. [4]). These findings suggest that audit modifications reflect underlying balance-sheet vulnerability rather than isolated reporting irregularities. However, most existing studies rely on traditional econometric approaches, particularly logistic and probit models, which primarily focus on statistical inference and impose restrictive assumptions on functional form

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and linearity (Yaşar et al. [5]; Pham [6]). As a result, these models may not fully capture complex nonlinear relationships and interactions among financial variables that characterize firm risk in modern capital markets.

Recent advances in machine learning offer new opportunities to improve predictive modelling in this context. Compared with conventional methods, machine learning algorithms can capture nonlinear patterns, high-dimensional interactions and heterogeneous effects across firms (Sánchez-Serrano et al. [7]; Todorović et al. [8]; Rahimzadeh et al. [9]). Consequently, tree-based ensemble models and other learning algorithms have been increasingly applied in corporate risk prediction and audit analytics. Nevertheless, two important limitations remain.

First, audit opinion prediction is inherently an imbalanced classification problem, as non-unqualified opinions typically represent a small proportion of observations. Models that fail to account for class imbalance may achieve high overall accuracy while performing poorly in detecting economically important minority outcomes. Prior studies in imbalanced learning therefore propose approaches such as synthetic minority oversampling (SMOTE), cost-sensitive learning and balanced ensemble methods (Chawla et al. [10]; He and Garcia [11], Zhao and Bai [12]). However, the effectiveness of these approaches in audit prediction settings may be limited for several reasons. Synthetic oversampling approaches such as SMOTE generate artificial minority observations by interpolating existing samples. In financial reporting environments, distressed firms often exhibit highly heterogeneous and nonlinear combinations of financial characteristics. Consequently, synthetically generated observations may not fully preserve the underlying economic structure of financially distressed firms and may introduce noisy or less economically representative minority patterns.

Second, many machine learning applications emphasize predictive performance without providing sufficient interpretability. In auditing and financial reporting contexts, however, decision-makers require transparent and explainable signals rather than opaque model outputs. In this study, interpretability is considered from three complementary perspectives: comprehensibility, fidelity and relative consistency. Comprehensibility refers to the ability of extracted rules to provide transparent and understandable if-then decision structures. Fidelity refers to the extent to which extracted rules remain broadly consistent with the predictive logic of the underlying ensemble model. Relative consistency refers to the recurrence of similar rule patterns across retained trees and validation settings.

The theoretical foundations of the study further inform both feature construction and rule interpretation. Financial distress theory suggests that declining profitability, leverage pressure, liquidity constraints and debt-servicing difficulties increase financial reporting uncertainty and going-concern risk. Accordingly, variables such as return on assets, leverage, current ratio, cash ratio and interest coverage are incorporated to capture different dimensions of financial vulnerability. Agency theory and information asymmetry perspectives further suggest that governance characteristics and prior audit outcomes may serve as observable signals of monitoring quality and unresolved reporting risk. This theoretical reasoning motivates the inclusion of governance-related variables and the prior modified audit opinion indicator within the prediction framework. Consequently, the extracted decision rules are interpreted not merely as statistical associations, but as economically grounded representations of persistent and interacting financial risk mechanisms.

This study addresses these challenges by developing an interpretable machine learning framework for imbalanced audit opinion prediction. The proposed approach builds on a Modified Random Forest (MRF) integrates imbalance-aware ensemble learning with rule-based interpretation to improve the detection of non-unqualified audit opinions while preserving transparency in financial risk assessment. Rather than functioning solely as a predictive model, the framework is designed to generate economically interpretable risk signals that support audit-related decision-making.

The empirical analysis focuses on Vietnamese listed firms over the period 2015-2024. Vietnam provides a particularly relevant setting as an emerging market characterized by rapid capital-market expansion, evolving regulatory frame works and heterogeneous corporate governance practices. In such a transitional institutional environment, financial distress signals may play a more pronounced role in audit reporting outcomes, and the informational value of audit opinions becomes especially important for market discipline and investor protection. The dataset captures a broad cross-section of industries, allowing for the identification of common financial patterns associated with audit opinion modifications.

This study contributes to the literature in three ways. First, it develops an interpretable machine learning framework that explicitly addresses class imbalance in audit opinion prediction, improving the detection of economically significant minority outcomes. Second, it bridges the gap between predictive modelling and economic interpretation by translating model outputs into stable and transparent decision rules that reflect financial distress mechanisms. Third, it provides new empirical evidence from an emerging market context, illustrating how structural financial vulnerabilities and institutional conditions jointly shape audit reporting outcomes.

The remainder of this paper is organised as follows. Section 2 reviews the theoretical background and related literature. Section 3 describes the data and research methodology. Section 4 presents the empirical results and discusses the economic implications. Section 5 concludes and suggests directions for future research.

2. Theoretical Background and Literature Review

2.1. Audit opinions as signals of financial distress

From an economic perspective, audit opinions function as externally certified signals that mitigate agency conflicts and reduce information asymmetry between managers and external stakeholders. According to Agency Theory (Jensen and Meckling [13] managers may have incentives to engage in opportunistic financial reporting when monitoring mechanisms are weak. Similarly, information asymmetry in capital markets can lead to adverse selection and moral hazard problems, resulting in inefficient resource allocation (Akerlof [14]; Bergh et al. [15]). Independent auditing therefore serves as an important governance mechanism that enhances the credibility of financial statements and reduces informational frictions.

Within this framework, non-unqualified audit opinions including qualified, adverse and disclaimer opinions are typically interpreted as signals of elevated financial reporting risk. Prior empirical studies consistently show that firms receiving modified audit opinions exhibit weaker financial performance, higher leverage and greater uncertainty regarding going-concern status (Dopuch et al. [1]; Keasey et al. [3]; Habib [2], in a comprehensive meta-analysis, finds that profitability deterioration, liquidity constraints and leverage are among the most robust predictors of audit opinion modifications. These findings suggest that audit outcomes are closely linked to underlying financial distress and balance-sheet vulnerability rather than isolated accounting anomalies.

An important stylised fact in this literature is the persistence of audit opinions. Firms that receive modified opinions in one period are more likely to receive similar opinions in subsequent periods, indicating that financial weaknesses and reporting deficiencies are not easily resolved (Yaşar et al. [5]; Zarei et al. [4]). From an economic standpoint, this persistence reflects structural vulnerabilities that carry forward over time and increase the probability of repeated audit concerns.

2.2. Empirical approaches to audit opinion prediction

Empirical research on audit opinion prediction can be broadly classified into three main methodological approaches.

The first stream relies on traditional statistical models, primarily logistic and probit regressions. Seminal studies such as Dopuch et al. [1], Keasey et al. [3], Yaşar et al. [5], and Zarei [4] employ these models to estimate the probability of audit qualification based on financial ratios and firm characteristics. While these approaches provide interpretable coefficient estimates and statistical inference, they are constrained by linearity assumptions and may not fully capture complex interactions among financial variables.

The second stream focuses on conventional machine learning models, including decision trees (DT), artificial neural networks (ANN), and support vector machines (SVM). Prior studies suggest that these models generally outperform traditional econometric approaches in predictive accuracy. For example, Sánchez-Serrano et al. [7] show that ANN and SVM effectively capture nonlinear relationships in audit data, while decision trees offer the advantage of extracting if-then rules for interpretation. Nawaiseh et al. [16] apply SVM, ANN and k-nearest neighbours (k-NN) to predict audit opinions for firms in the United Kingdom and Ireland, finding that SVM and ANN achieve strong classification performance. However, these models present important limitations: neural networks and SVM often lack interpretability, making it difficult to derive clear decision criteria, whereas standalone decision trees are prone to overfitting and may suffer from instability when applied to complex datasets.

The third stream involves ensemble learning and advanced machine learning techniques, such as Random Forest (RF) and gradient boosting methods (e.g., XGBoost). Stanišić et al. [17] compare a wide range of statistical and machine learning models and conclude that tree-based and ensemble methods generally outperform linear models, particularly when incorporating information such as prior audit opinion. Similarly, Todorović et al. [8] employ XGBoost combined with SHAP values to enhance both predictive performance and variable interpretability. Despite these advances, most existing studies focus primarily on improving classification accuracy and variable importance, with limited attention to addressing class imbalance and extracting stable, interpretable decision rules that can be directly applied in practice.

In terms of research context, recent studies have increasingly extended from developed markets to emerging economies. For instance, Kardeş and Kandemir [18] analyse 2,093 observations from Borsa Istanbul, while Rahimzadeh et al. [9] examine 1,606 firm-year observations from the Tehran Stock Exchange using multiple machine learning algorithms. These studies consistently find that nonlinear models provide strong predictive performance in emerging market settings, where financial conditions and institutional environments may be more volatile.

In Vietnam, existing research has primarily focused on the determinants and economic consequences of audit opinions rather than predictive modelling. For example, Pham [6] examines the determinants of going-concern audit opinions for listed firms using logistic regression, providing evidence on the role of financial and firm-specific characteristics. In addition, Nguyen Vinh Khuong et al. [19] investigate the impact of audit opinions on the cost of debt, showing that audit outcomes have important economic implications for corporate financing decisions. These studies highlight the significance of audit opinions in the Vietnamese context but do not explicitly address prediction. More recent studies have begun to apply machine learning techniques, including logistic regression, Random Forest (RF), support vector machines (SVM) and XGBoost, to predict audit opinions for Vietnamese listed firms. Tan [20], for example, finds that RF achieves relatively strong predictive performance compared with other models.

Despite these advances, the existing literature remains fragmented in addressing the joint challenges of predictive accuracy, class imbalance, and interpretability in audit opinion prediction. Most prior studies either focus on improving predictive performance without explicitly addressing the severe imbalance inherent in audit opinion data, or employ advanced machine learning models that offer limited transparency for practical decision-making. Consequently, there remains a need for an integrated prediction framework that simultaneously improves minority-class detection and provides interpretable rule-based outputs suitable for audit-related applications. These unresolved limitations motivate the present study to develop a Modified Random Forest (MRF) framework for audit opinion prediction in the Vietnamese context.

2.3. Class imbalance and interpretability in audit prediction

A critical challenge in audit opinion prediction is the presence of class imbalance. In most empirical settings, non-unqualified audit opinions represent a relatively small proportion of observations, despite their substantial economic significance. This imbalance creates a bias in conventional predictive models, which tend to favour the majority class and may fail to adequately detect minority outcomes. As a result, models with high overall accuracy may still perform poorly in identifying firms at elevated risk of audit modification.

Various approaches have been proposed to address class imbalance, including resampling techniques, cost-sensitive learning and ensemble-based strategies. Among these, ensemble methods that construct balanced sub-samples have shown promise in improving minority-class detection while maintaining predictive stability. However, the application of such imbalance-aware frameworks remains limited in the audit literature, particularly in emerging market contexts.

Another important issue concerns model interpretability. While advanced machine learning algorithms such as neural networks and boosting methods often achieve strong predictive performance, they are frequently criticised as “black-box” models. In auditing and financial reporting environments, interpretability is essential because decision-makers require transparent and explainable criteria for risk assessment. Models that do not provide interpretable outputs may therefore have limited practical applicability.

Tree-based models offer a potential solution by combining predictive performance with interpretability. In particular, ensemble methods such as Random Forest can capture complex nonlinear relationships while allowing for the extraction of decision rules. However, standard implementations often prioritise predictive accuracy over interpretability and do not explicitly address class imbalance. This creates a need for modelling frameworks that jointly improve minority-class detection and generate stable, interpretable decision rules.

3. Research Methodology

3.1. Data

The empirical analysis is based on firm-level panel data for Vietnamese listed firms over the period 2015-2024. The 2015-2024 period was selected to provide a sufficiently long and recent panel spanning multiple macroeconomic conditions, including the COVID-19 period, thereby enhancing the practical relevance of the empirical setting. The dataset is constructed from financial statements and audit reports obtained from the Vietstock database. Observations for the initial year are excluded where lagged variables are required for model construction.

After data cleaning and preprocessing, the final sample consists of 12,625 firm-year observations across a broad range of sectors, providing sufficient cross-sectional heterogeneity to examine financial risk patterns in an emerging market context. Non-unqualified audit opinions account for approximately 8.9% of the sample, indicating a highly imbalanced classification setting consistent with the rarity of modified audit opinions in prior audit prediction studies. Although relatively rare, such outcomes are economically significant, as they may influence investor perception, borrowing conditions and regulatory oversight.

3.2. Variable measurement

The dependent variable is a binary indicator of audit opinion type. Let Yi = {0,1}, where Yi = 0 if the financial statements receive an unqualified audit opinion, and Yi = 1 if they receive a non-unqualified audit opinion (including qualified, adverse, disclaimer or other modified opinions). The explanatory variables consist of 18 firm-level predictors derived from financial statements and governance characteristics. Collectively, these variables capture three main dimensions of firm risk, including profitability and operating performance, financial risk, liquidity and asset structure and firm characteristics and governance which are included as proxies for monitoring quality and may influence auditor risk assessment through their effect on internal oversight and reporting discipline.

In addition, the model includes a prior-year audit opinion indicator, which is widely documented as a strong predictor of audit outcomes due to the persistence of financial distress and reporting issues over time. All variables are constructed following established definitions in the audit and financial distress literature. A detailed description of variable definitions is provided in table 1.

Table 1. Variable Measurement

Symbol	Measurement	References
ROA	Net income / Average total assets	Laitinen and Laitinen [21]; Spathis [22]; Pham [6]; Altawalbeh [23]
OP_MARGIN	Operating profit / Net revenue	Laitinen and Laitinen [21]; Yaşar et al. [5]
LEV	Total liabilities / Total assets	Laitinen and Laitinen [21]; Hartanto [24]; Altawalbeh [23]
CURRENT_RATIO	Current assets / Current liabilities	Laitinen and Laitinen [21]; Altawalbeh [23]
CASH_RATIO	(Cash + Cash equivalents) / Total assets	Laitinen and Laitinen [21]; Spathis [22]
INT_COVER	Earnings before interest and taxes (EBIT) / Interest expense	Foster et al. [25]; Hartanto et al. [24]; Altawalbeh [23]
DEPR_RATIO	Depreciation expense / Tangible fixed assets	Laitinen and Laitinen [21]; Spathis [22]; Yaşar et al. [5]
GROSS_MARGIN	Gross profit / Net revenue	Spathis [22]; Yaşar et al. [5]
INV_RATIO	Inventory / Total assets	Laitinen and Laitinen [21]; Spathis [22]; Yaşar et al. [5]
REC_RATIO	Accounts receivable / Total assets	Laitinen and Laitinen [21]; Spathis [22]; Yaşar et al. [5]
PPE_RATIO	Net tangible fixed assets / Total assets	Laitinen and Laitinen [21]; Spathis [22]

SIZE	Natural logarithm of total assets	Laitinen and Laitinen [21]; Pham [6]; Hartanto et al. [24]; Altawalbeh [23]
FIRM_AGE	Number of years since establishment to year t	Zdolšek et al. [26]
LOSS	Dummy variable: 1 if net income < 0, 0 otherwise	Devitamala and Apollo [27]; Pham [6]
GROWTH_SALES	(Revenue_t − Revenue_{t−1}) / Revenue_{t−1}	Laitinen and Laitinen [21]
PRIOR_MOD	Dummy variable: 1 if the firm received a modified audit opinion in year t−1, 0 otherwise	Altawalbeh [23]
BOARD_SIZE	Number of board members	Oruke et al. [28]; Moradi et al. [29]
BOARD_FEMALE	Proportion of female board members	Hossain et al. [30]; Moradi et al. [29]

Observations containing missing or non-finite values in the selected variables were removed during data cleaning. To mitigate the influence of extreme observations, all continuous financial variables were winsorized at the 1st and 99th percentiles.

3.3. Research design and evaluation strategy

Figure 1 illustrates the overall research process and methodological framework adopted in this study.

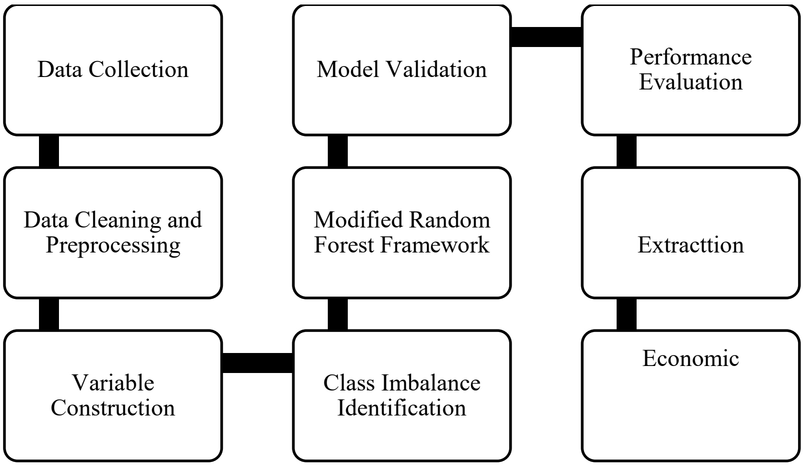

Figure 1. Research framework and methodological workflow

The study adopts a supervised learning framework to predict audit opinion outcomes. A central challenge in this setting is the severe class imbalance, which may lead to biased model performance if not properly addressed. To ensure robust evaluation, multiple validation strategies are employed. First, the dataset is randomly split into training and testing sets using a 70/30 ratio. Second, a k-fold cross-validation procedure is implemented to assess model stability under different sample partitions. Third, an out-of-time validation approach is applied. The out-of-time validation is implemented by splitting the dataset based on time. Specifically, observations from 2015 to 2021 are used as the training set, while observations from 2022 to 2024 are reserved as the testing set, thereby mimicking a realistic forecasting setting and mitigating look-ahead bias by evaluating performance on chronologically unseen observations.

All benchmark models were hyperparameter-tuned using grid search with five-fold cross-validation on the training data. Hyperparameter selection was based on average precision due to the imbalanced nature of audit opinion prediction. The tuning process focused on parameters controlling model complexity and ensemble structure. Specifically, logistic regression tuning considered C = {0.01, 0.1, 1, 10}; SVM tuning considered C = {0.1, 1, 10} and γ = {scale, 0.01, 0.1}; k-NN tuning considered n_neighbors = {3, 5, 7, 9} and weight specifications {uniform, distance}; Random Forest tuning considered n_estimators = {300, 500}, max_depth = {None, 5, 10}, and min_samples_leaf = {1, 3, 5}; while XGBoost tuning considered n_estimators = {300, 500}, max_depth = {3, 4, 5}, learning_rate = {0.03, 0.05, 0.1}, subsample = {0.8, 1.0}, and colsample_bytree = {0.8, 1.0}. All models were implemented in Python using scikit-learn, imbalanced-learn, and XGBoost with random_state = 42.

Model performance is evaluated using multiple metrics, including the area under the receiver operating characteristic curve (AUC), accuracy and the F1-score for the minority class. The study compares several baseline models commonly used in the literature, including logistic regression, support vector machines (SVM), k-nearest neighbours (k-NN), Random Forest (RF) and XGBoost. These models serve as benchmarks to evaluate the incremental value of the proposed framework.

3.4. Modified Random Forest framework

MRF constructs multiple relatively balanced sub-datasets by combining all minority-class observations with different randomly sampled subsets of the majority class. Formally, each balanced sub-dataset can be represented as:

$$D_k = D_{min\,ority} \cup D^{(k)}_{majority}, k = 1,2,\ldots,K \tag{1}$$

$D_{\min oriry}$ contains all minority-class observations and $D^{(k)}_{majority}$ denotes a randomly selected subset of majority-class observations for sub-dataset k.

For each balanced sub-dataset, a Random Forest classifier is trained and its individual decision trees are evaluated on the corresponding internal validation subset. The retention criterion is based on tree-level validation accuracy. Specifically, the predicted class of each tree is obtained using a probability threshold of 0.5, and its accuracy is calculated on the validation subset. Trees with validation accuracy greater than or equal to the average validation accuracy of all trees in the same Random Forest are retained in the final MRF ensemble. Let A_k denote the validation accuracy of classifier k. Only classifiers satisfying the following condition are retained in the final ensemble:

$$A_k \geq A_{avg} \tag{2}$$

A_{avg} represents the average validation accuracy across all sub-models. The retained trees are then aggregated to generate final predictions based on average predicted probabilities. The final predicted probability for observation i is calculated as:

$$P(y_i = 1) = \frac{1}{M}\sum_{m=1}^{M} p_m(y_i = 1) \tag{3}$$

M denotes the number of retained classifiers and $p_m(y_i = 1)$ represents the predicted minority-class probability generated by classifier m.
The full algorithmic procedure is summarised as follows.

Algorithm 1. Performance-Guided Balanced Random Forest (PG-BRF)

Input: Training dataset D, minority class observations $D_{\min}$, majority class observations, $D_{\max}$ number of balanced subsets K, trees per subset T.
Output: Final MRF ensemble and extracted decision rules
1. Partition the training data into minority and majority classes002E
2. For each subset k =1, …, K:
    a. Randomly sample observations from the majority class.

b. Combine sampled majority observations with all minority observations to form balanced subset D_k.

c. Train a Random Forest with T trees on D_k.
3. Evaluate individual tree performance and retain trees with above-average predictive accuracy.
4. Aggregate retained trees into the final ensemble.
5. Compute predicted probabilities by averaging outputs across retained trees.

Extract frequently recurring if-then rules from retained trees based on support frequency.

4. Results and Discussion

4.1. Predictive performance and model comparison

Table 2 presents the predictive performance of the proposed MRF framework in comparison with benchmark models under three validation settings: a random 70/30 split, time-based split and k-fold cross-validation.

Table 2. Predictive performance of models under different validation settings.

Model	70/30 Split				Time-based Split				k-fold Cross-validation			
	AUC	PR-AUC	Recall (Class 1)	F1-score (Class 1)	AUC	PR-AUC	Recall (Class 1)	F1-score (Class 1)	AUC	PR-AUC	Recall (Class 1)	F1-score (Class 1)
Logistic Regression	0.787	0.285	0.690	0.340	0.790	0.330	0.554	0.391	0.775	0.391	0.687	0.373
SVM	0.736	0.333	0.718	0.304	0.740	0.227	0.696	0.334	0.784	0.281	0.711	0.372
k-NN	0.799	0.293	0.673	0.315	0.719	0.208	0.598	0.351	0.739	0.262	0.643	0.319
RF	0.808	0.380	0.718	0.371	0.798	0.386	0.728	0.368	0.788	0.398	0.713	0.373
XGBoost	0.773	0.286	0.732	0.314	0.796	0.385	0.781	0.354	0.782	0.400	0.701	0.379
MRF	0.829	0.381	0.747	0.411	0.811	0.392	0.826	0.483	0.793	0.411	0.716	0.392
RF_SMOTE	0.767	0.256	0.239	0.260	0.716	0.212	0.293	0.280	0.762	0.305	0.283	0.299
Cost_sensitive_RF	0.766	0.292	0.056	0.104	0.738	0.276	0.076	0.135	0.770	0.322	0.051	0.094
Balanced_RF	0.740	0.257	0.662	0.298	0.743	0.258	0.739	0.302	0.760	0.319	0.679	0.304

The results show a clear and consistent advantage of the MRF model across all evaluation metrics. In the 70/30 split, the MRF framework achieves the highest AUC (0.829), PR-AUC (0.381), recall (0.747) and F1-score (0.411). Similar patterns are observed in the time-based split, where MRF attains an AUC of 0.811, PR-AUC of 0.392, recall of 0.826 and F1-score of 0.483, outperforming all benchmark models. Under k-fold cross-validation, MRF continues to deliver the best overall performance, particularly in PR-AUC (0.411) and F1-score (0.392). This indicates that the proposed model not only provides strong overall discrimination ability but also significantly improves the identification of non-unqualified audit opinions. In contrast, traditional models such as logistic regression, SVM and k-NN exhibit relatively weaker performance, particularly in capturing minority-class observations.

The superiority of the MRF model is especially pronounced in minority-class metrics. Given the imbalanced nature of audit opinion data, the F1-score and recall provide a more meaningful assessment of model performance than overall accuracy. The results suggest that the MRF framework is more effective in detecting firms at risk of receiving modified audit opinions, thereby reducing the likelihood of overlooking economically significant cases.

To further assess whether the superior performance of MRF is merely attributable to imbalance correction, additional benchmark models incorporating established imbalance-handling techniques were estimated, including Random Forest with SMOTE, cost-sensitive Random Forest, and Balanced Random Forest. The results show that MRF consistently outperforms these alternative approaches across all validation settings. For example, in the 70/30 split, RF with SMOTE and Balanced Random Forest achieve F1-scores of only 0.260 and 0.298, respectively, compared with 0.411 for MRF. Similarly, in the time-based split, MRF attains an F1-score of 0.483, substantially exceeding RF with SMOTE (0.280), cost-sensitive RF (0.135), and Balanced RF (0.302). These findings suggest that the predictive superiority of the proposed framework cannot be explained solely by imbalance correction, but also reflects the effectiveness of the overall framework design in capturing complex financial risk patterns.

In addition, the performance of the MRF model remains stable across different validation strategies, including cross-validation and out-of-time testing. This consistency indicates that the model captures robust underlying patterns in the data rather than overfitting to specific samples. Overall, the empirical evidence confirms that the proposed framework provides a reliable and well-balanced solution for audit opinion prediction.

Nevertheless, the improvement in minority-class recall should be interpreted alongside the potential increase in false-positive classifications. In audit opinion prediction, higher recall reduces the likelihood of overlooking firms with elevated reporting risk, which is particularly important in early-warning and regulatory screening contexts. However, increasing sensitivity may also result in a larger number of firms being incorrectly classified as high risk, thereby potentially increasing monitoring costs and unnecessary audit attention.

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In this study, the relatively balanced improvement in F1-score and PR-AUC suggests that the proposed framework improves minority-class detection without excessively sacrificing predictive precision. Accordingly, the MRF framework should be interpreted as a risk-screening and decision-support mechanism intended to prioritise potentially vulnerable firms for further professional assessment rather than as a fully automated replacement for auditor judgment.

4.2. Decision rules and interaction effects

Table 3 presents the selected decision rules extracted from the MRF model. These rules provide detailed insights into how combinations of financial conditions lead to audit opinion modifications.

Table 3. Selected decision rules extracted from the MRF model

Rule	Support	A	B	C	D	E	F
R1	74	PRIOR_MOD > 0.500	LEV > 0.211	FIRM_AGE ≤ 35.500	REC_RATIO > 0.070		
R2	68	PRIOR_MOD > 0.500	FIRM_AGE ≤ 35.500	LEV > 0.211			
R3	63	PRIOR_MOD > 0.500	INV_RATIO ≤ 0.522	PPE_RATIO ≤ 0.526			
R4	62	PRIOR_MOD > 0.500	CASH_RATIO ≤ 0.114	OP_MARGIN > -1.633	INV_RATIO ≤ 0.532	LEV > 0.211	FIRM_AGE ≤ 40.500
R5	60	PRIOR_MOD > 0.500	CASH_RATIO ≤ 0.114	INV_RATIO ≤ 0.625	SIZE > 27.115		
R6	56	PRIOR_MOD > 0.500	DEPR_RATIO ≤ 0.060	INV_RATIO ≤ 0.532	DEPR_RATIO ≤ 0.034		
R7	54	PRIOR_MOD > 0.500	ROA > -0.502	INV_RATIO ≤ 0.625	BOARD_SIZE ≤ 5.500		
R8	53	INT_COVER ≤ 1.144	CURRENT_RATIO ≤ 0.825	SIZE ≤ 31.470			
R9	53	PRIOR_MOD > 0.500	FIRM_AGE ≤ 33.500	GROWTH_SALES > -0.650			
R10	53	PRIOR_MOD > 0.500	INT_COVER ≤ 1129.104	INV_RATIO ≤ 0.532	SIZE > 27.115	PPE_RATIO ≤ 0.526	

A striking feature of the extracted rules is the dominant and pervasive role of prior audit opinion (PRIOR_MOD). This variable appears in almost all high-support rules, indicating a strong persistence effect in audit outcomes. From an economic perspective, this persistence reflects the path-dependent nature of financial distress. Firms receiving modified audit opinions often face structural weaknesses such as governance deficiencies, poor internal controls, or unresolved financial risks that cannot be fully corrected within a single reporting period. As a result, prior audit opinion acts not merely as a predictor, but as a cumulative signal of unresolved risk carried over time. However, PRIOR_MOD should not be interpreted as the sole driver of model performance, but rather as one informative signal within a broader multi-factor framework that jointly incorporates contemporaneous financial indicators related to profitability, leverage, liquidity, and debt-servicing capacity.

The rules reveal that audit risk is not driven by isolated financial indicators, but by the interaction of multiple risk dimensions. Rules such as R1 and R4 combine prior audit opinion with high leverage, weak liquidity and specific asset structure conditions. This suggests that auditors assess financial risk in a multidimensional manner, where the coexistence of several adverse conditions significantly increases the likelihood of issuing a modified opinion. The decision rules capture nonlinear and interaction effects that are difficult to identify using traditional regression models.

The role of asset structure variables such as inventory ratio (INV_RATIO), receivables ratio (REC_RATIO), depreciation ratio (DEPR_RATIO) and fixed asset ratio (PPE_RATIO) is particularly noteworthy. These variables frequently appear in conjunction with liquidity and leverage conditions, indicating that not only the level of assets but also their composition matters in audit assessments. A high proportion of inventories or receivables may signal lower asset quality or potential valuation uncertainty, which increases audit risk when combined with weak financial performance. This highlights the importance of balance-sheet composition as a determinant of audit outcomes.

The presence of rules such as R8 demonstrates the ability of the MRF framework to identify high-risk firms even in the absence of prior modified opinions. Specifically, firms characterized by low interest coverage, weak short-term liquidity and relatively small size are consistently classified as high risk. This finding is particularly important, as it shows that the model is not solely relying on persistence effects but is also capable of detecting emerging financial distress signals. In practical terms, this enhances the usefulness of the model as an early-warning system rather than merely a tool for confirming existing risk patterns.

The relatively high support values of the extracted rules (ranging from 48 to 74) indicate that similar financial risk patterns repeatedly emerge across multiple retained trees within the ensemble structure. Rules that frequently recur across multiple trees are more likely to reflect persistent relationships in the data rather than sample-specific patterns. However, support frequency should be interpreted as an indicator of recurrent rule presence rather than formal statistical evidence of rule stability. Compared with standalone decision trees, the ensemble-based structure of the MRF framework nevertheless provides greater robustness against small variations in the training data.

4.3. Variable importance and stability across validation settings

Table 4 presents the frequency ranking of variables appearing in decision rules under different validation settings, providing additional insights into the structure and stability of audit risk factors. The results highlight the consistently important role of profitability and financial performance. Return on assets (ROA) appears among the top-ranked variables in both validation settings, indicating that firm performance is a fundamental determinant of audit outcomes. From an economic perspective, declining profitability reduces internal financing capacity and increases uncertainty regarding future operations, thereby raising the likelihood of audit opinion modifications. The repeated appearance of ROA across different sample splits suggests that this relationship is robust rather than sample-specific.

Table 4. Variable frequency ranking across different validation settings

Rank	70/30 Split	Time-based Split
1	ROA	INV_RATIO
2	PRIOR_MOD	ROA
3	INT_COVER	INT_COVER
4	CASH_RATIO	LEV
5	SIZE	CURRENT_RATIO
6	OP_MARGIN	GROWTH_SALES
7	REC_RATIO	PRIOR_MOD
8	GROWTH_SALES	SIZE
9	CURRENT_RATIO	CASH_RATIO
10	INV_RATIO	REC_RATIO

Prior audit opinion (PRIOR_MOD) remains a key predictor, although its ranking varies across validation strategies. This reinforces the persistence effect identified in the decision-rule analysis. Importantly, its slightly lower ranking in the time-based split suggests that while historical audit outcomes are important, current financial conditions may play a more dominant role in out-of-sample prediction. This provides evidence that the model does not rely excessively on lagged information but also captures contemporaneous risk signals.

Variables related to debt burden and financial sustainability particularly interest coverage (INT_COVER) and leverage (LEV) consistently appear among the top-ranked predictors. The stable presence of INT_COVER across both validation settings indicates that the ability to service debt is a central factor in auditor assessments. This finding is consistent with the notion that auditors place significant weight on going-concern risk, especially in environments where financial distress may escalate quickly.

Liquidity and asset structure variables also play an important role, although their rankings vary across validation settings. This variation suggests that while these factors are important, their relative influence may depend on specific sample conditions or economic periods. In particular, the prominence of INV_RATIO in the time-based split indicates that asset composition becomes more informative in out-of-sample forecasting, possibly reflecting changing market conditions or industry-specific dynamics.

The presence of firm size (SIZE) and growth indicators (GROWTH_SALES) among the top-ranked variables highlights the role of firm characteristics in shaping audit risk. Smaller firms and firms with unstable growth patterns may face greater financial uncertainty and weaker governance structures, increasing the likelihood of modified audit opinions. These variables complement financial ratios by capturing broader structural aspects of firm risk.

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Although governance-related variables were theoretically motivated by agency theory and monitoring-quality perspectives, their empirical importance in the predictive framework appears relatively limited compared with financial distress indicators and prior audit outcomes. Although governance variables appear less frequently than financial indicators in the extracted rules, their inclusion remains theoretically relevant as complementary controls for board-level monitoring quality. One possible explanation is that variables such as profitability deterioration, leverage pressure, liquidity constraints, and prior modified opinions provide more direct and immediate signals of audit-related reporting risk.

From a methodological perspective, an important insight from this table is the relative stability of key predictors across different validation strategies. Although the exact ranking of variables changes, the core set of risk factors including profitability, prior audit opinion, debt-servicing capacity and liquidity remains consistent. This suggests that the MRF framework captures fundamental and economically meaningful relationships rather than overfitting to a particular sample.

Although support frequency provides useful insight into recurrent rule patterns within the retained ensemble structure, the study does not formally evaluate statistical rule stability using bootstrap confidence intervals or rule-consistency metrics. Future research may extend the framework by incorporating more rigorous stability-validation procedures for interpretable ensemble learning.

Finally, the table demonstrates that audit risk is inherently multidimensional. No single variable dominates the ranking across all settings; instead, different dimensions of firm risk performance, leverage, liquidity, asset structure and firm characteristics jointly contribute to audit outcomes. This finding supports the use of ensemble-based and rule-based models, which are better suited to capturing complex interactions among variables compared to traditional linear approaches.

4.4. Economic interpretation and practical implications

These findings are broadly consistent with established theories of financial distress and information asymmetry. In particular, the prominence of profitability, leverage, and debt-servicing indicators aligns with financial distress theory, which predicts that deteriorating operating performance and debt sustainability increase going-concern risk and the likelihood of adverse audit assessments. Likewise, the importance of prior audit opinion and liquidity-related variables is consistent with information asymmetry and agency-based perspectives, under which persistent financial weakness and unresolved reporting concerns serve as observable signals of elevated monitoring risk to external auditors.

The combined evidence from predictive performance, decision rules and variable rankings suggests that audit opinion modifications are primarily driven by persistent and interacting financial vulnerabilities. First, the strong presence of prior audit opinion confirms the path-dependent nature of audit outcomes. Firms experiencing financial distress or reporting issues are likely to face continued audit concerns over time.

Second, profitability, leverage and debt-servicing capacity emerge as central determinants of audit risk. Firms with declining performance, high debt levels and weak interest coverage face greater financial pressure, increasing the likelihood of receiving modified audit opinions. Third, liquidity constraints and asset structure further amplify financial vulnerability. Firms with weak short-term solvency and lower-quality asset composition are more exposed to audit risk, particularly in an emerging market context where external financing conditions may be less stable.

From a methodological standpoint, the results demonstrate the importance of addressing class imbalance in audit prediction. The superior performance of the MRF framework indicates that imbalance-aware ensemble methods can significantly improve the detection of economically important minority outcomes. From a practical perspective, the interpretability of the model enhances its potential applicability as a decision-support tool. The extracted decision rules provide transparent and actionable criteria for identifying high-risk firms, supporting auditors, regulators and investors in early risk assessment. Nevertheless, practical implementation would require consideration of data availability, institutional constraints and model governance requirements, and the framework should be viewed as a complement to rather than a substitute for professional judgment.

From an operational perspective, the proposed framework may be integrated into existing audit and regulatory risk-screening procedures as a supplementary early-warning tool rather than as a substitute for professional judgment. For audit firms, the model may assist engagement teams during client risk assessment and audit planning by identifying firms exhibiting elevated probabilities of modified audit opinions based on combinations of financial distress indicators

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and prior reporting risk signals. This may help auditors allocate additional attention to high-risk engagements, particularly under resource and time constraints.

For regulators and stock-market supervisory authorities, the framework may support periodic monitoring of listed firms by generating risk-based screening indicators for financial reporting quality and going-concern vulnerability. The extracted decision rules may also improve transparency by allowing users to identify the underlying financial conditions associated with elevated audit risk rather than relying solely on black-box probability outputs. Nevertheless, practical implementation would require appropriate data governance, periodic model recalibration, and professional oversight to ensure that predictive outputs remain consistent with evolving reporting environments and regulatory standards.

5. Conclusion

This study develops an interpretable machine learning framework for imbalanced audit opinion prediction, with empirical evidence from Vietnamese listed firms. By integrating imbalance-aware sampling, tree selection and rule extraction, the proposed MRF approach addresses two key challenges in the literature: reliable minority-class detection and model interpretability. The empirical results show that the MRF framework outperforms conventional models across multiple evaluation metrics and provides superior detection of modified audit opinions. More importantly, the extracted decision rules reveal that audit opinion modifications are associated with persistent and interacting financial vulnerabilities, including prior audit opinions, weak profitability, high leverage and liquidity constraints.

These findings highlight the value of combining predictive modelling with economic interpretation in audit research. The proposed framework offers a practical tool for auditors, regulators and investors to identify firms with elevated reporting risk. The study limitations and future research: First, the analysis focuses on listed firms and may not fully capture audit dynamics in non-listed or smaller enterprises. Second, the model relies primarily on quantitative financial indicators and does not incorporate qualitative information such as governance quality or auditor characteristics. Third, the performance-based tree selection mechanism in the MRF framework may reduce ensemble diversity and cause extracted decision rules to remain partially sample-dependent. Future research may extend the framework by integrating alternative data sources and exploring more advanced interpretable machine learning techniques.

6. Declarations

6.1. Author Contributions

Conceptualization: N.T.H; Methodology: N.T.H.; Software: N.T.H.; Validation: N.T.H.; Formal Analysis: N.T.H.; Investigation: N.T.H.; Resources: N.T.H.; Data Curation: N.T.H.; Writing Original Draft Preparation: N.T.H.; Writing Review and Editing: N.T.H.; Visualization: N.T.H.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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