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DETECTION OF EARNINGS MANAGEMENT USING MACHINE LEARNING: INSIGHTS FROM VIETNAM

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Abstract: *This study investigates the application of machine learning algorithms to detect earnings management among non-financial firms listed on the Vietnamese stock market (HOSE and HNX) from 2000 to 2024, results to dataset of 8,371 observation from 630 listed firms. Using discretionary accruals estimated through the Modified Jones Model with performance adjustment as the proxy for earnings management, firm-year observations are classified into managing and non-managing groups. A set of financial ratios, firm characteristics, and governance indicators are employed as predictors. Five machine learning algorithms—logistic regression, support vector machine, random forest, multilayer perceptron, and extreme gradient boosting (XGBoost) are trained and evaluated using 10-fold cross-validation. Among these, XGBoost consistently outperforms others across key metrics, confirming its superior predictive performance and reliability. SHAP analysis further reveals the relative importance of key variables such as firm size, accrual quality, and liquidity indicators. The study contributes methodologically by demonstrating the power of advanced classification models in detecting earnings manipulation, and contextually by offering empirical insights specific to an emerging market. These findings underscore the potential of machine learning as a decision-support tool for regulators, auditors, and investors concerned with financial reporting quality.*

Keywords: *Earnings management, Machine learning, Ensemble Algorithms, Vietnam.*

JEL codes: *C55, M41, G38*

1. Introduction

Earnings management is a widely documented phenomenon in financial reporting, referring to the deliberate manipulation of accounting figures by managers to achieve specific objectives, such as meeting earnings benchmarks, influencing stock prices, or securing favorable financing conditions (Healy & Wahlen, 1999). This practice distorts the true economic performance of firms and undermines the reliability of financial statements, posing significant risks to investors, regulators, and other stakeholders. The prevalence of earnings management is particularly concerning in emerging markets such as Vietnam, where enforcement mechanisms, audit quality, and corporate governance structures remain underdeveloped relative to those in advanced economies (Dang & Khanh Dung, 2024; Tran et al., 2022). In such contexts, the risk of earnings manipulation is exacerbated by limited market discipline and weak institutional monitoring, making it imperative to develop reliable detection tools tailored to these environments.

Traditionally, the detection of earnings management has relied on accrual-based models, most notably the Modified Jones Model and its performance-adjusted variant proposed by Kothari et al. (2005). These models estimate discretionary accruals as proxies for manipulation by isolating the portion of total accruals not explained by normal business activities. Empirical applications of these models have been widely adopted, including in Vietnam (Lokanan et al., 2019; Phong et al., 2024), but they face limitations due to their underlying linearity assumptions and sensitivity to model specification. While these approaches offer a structured method for estimating abnormal accrual behavior, they may oversimplify the complex, often non-linear patterns associated with managerial discretion, especially in diverse operating environments.

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To address these methodological constraints, recent research has increasingly explored the use of machine learning techniques to enhance earnings management detection. Machine learning models such as decision trees, support vector machines, and neural networks are capable of identifying subtle interactions and non-linear dependencies within financial data that traditional models may overlook (Bao et al., 2020; Hammami & Hendijani Zadeh, 2022; Huy et al., 2025). For example, Schultz Jr et al. (2011) and Baranes and Palas (2019) demonstrated that support vector machines and ensemble models outperform classical logistic regression in detecting financial manipulation. Furthermore, studies by Kang and Park (2021) and Rahman et al. (2021) confirm the practical utility of machine learning in accounting applications, especially in the context of earnings prediction and fraud detection. However, a critical limitation of this emerging literature is its geographic concentration in developed markets. There remains a significant gap in applying machine learning-based predictive analytics to earnings management within the Vietnamese capital market, despite its rapid growth, increased foreign participation, and evolving corporate governance landscape.

This study aims to fill that gap by developing and evaluating machine learning models that predict earnings management in Vietnam using firm-year financial data from 2000 to 2024. The study focuses on non-financial firms listed on the Ho Chi Minh Stock Exchange (HOSE) and the Hanoi Stock Exchange (HNX), excluding financial institutions due to their unique reporting structures. Earnings management is proxied through discretionary accruals derived from the Modified Jones Model with performance adjustment (Kothari et al., 2005), and firm-year observations in the top quartile of absolute accruals are classified as manipulated. Predictor variables include a comprehensive set of financial ratios, firm characteristics (such as size, age, and growth), and a governance indicator (auditor type). Five machine learning algorithms are deployed: logistic regression, random forest, extreme gradient boosting (XGBoost), support vector machine (SVM), and multilayer perceptron (MLP). These models are selected to capture a range of linear and non-linear relationships, from interpretable benchmarks to deep learning architectures. Hyperparameters are tuned using 10-fold cross-validation, and performance is evaluated through standard classification metrics, including accuracy, precision, recall, F1 score, and AUC-ROC.

This research is significant in several ways. First, it contributes to the literature by applying a modern analytical framework to a high-risk reporting environment, expanding the geographic scope of earnings management studies. Second, it provides empirical evidence on the effectiveness of various machine learning techniques in detecting manipulation, offering practical insights for auditors, investors, and regulators in Vietnam. Third, the integration of SHAP values and feature importance rankings helps interpret model outputs, enhancing transparency and facilitating the application of these models in real-world oversight mechanisms.

The remainder of this paper is organized as follows. Section 2 reviews relevant theoretical and empirical studies on earnings management and machine learning applications in financial reporting. Section 3 outlines the dataset, variable definitions, discretionary accrual estimation, and model development procedures. Section 4 presents the empirical findings, including model performance and interpretability analyses. Section 5 concludes with a summary of key contributions, practical recommendations, and directions for future research.

2. Literature review

2.1 Background theories

Earnings management refers to the intentional manipulation of financial statements by managers to influence reported outcomes, often to meet performance benchmarks, avoid regulatory scrutiny, or influence investor perception (Healy & Wahlen, 1999). This behavior is primarily explained through the lens of Agency Theory, which posits that managers (agents), entrusted with controlling corporate resources on behalf of shareholders (principals), may not always act in the best interests of those principals due to

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conflicting incentives and information asymmetry (Jensen & Meckling, 2019). Managers, possessing superior knowledge of the firm's internal operations, can exploit flexibility in accounting standards to misrepresent financial performance. Agency Theory thus provides a foundational rationale for why earnings management arises and highlights the importance of detecting such practices to reduce agency costs and enhance transparency.

Complementing this view is Positive Accounting Theory, which focuses on explaining and predicting accounting choices as rational responses to economic incentives (Watts & Zimmerman, 1986). According to this theory, managers select accounting policies to maximize personal or organizational benefit in contexts shaped by compensation contracts, political costs, and debt covenants. This theoretical lens assumes that earnings management is a predictable behavior under certain firm conditions. For instance, larger firms with greater public scrutiny or those under performance pressure may be more inclined to manage earnings to reduce perceived volatility or meet stakeholder expectations. Together, Agency Theory and Positive Accounting Theory suggest that financial and organizational variables, such as profitability, leverage, auditor type, and firm size are useful indicators for detecting manipulation.

Empirically, researchers have operationalized earnings management through the concept of discretionary accruals, which represent the portion of total accruals influenced by managerial discretion rather than routine business activity. The Modified Jones Model, particularly in its performance-adjusted form proposed by Kothari et al. (2005), is widely used to estimate discretionary accruals by controlling for expected accruals based on firm performance and asset structure. The residual component from this model serves as a proxy for earnings management and enables researchers to label firm-years based on the magnitude of manipulation. This method has been extensively validated in accounting literature (Dechow et al., 1995) and is particularly relevant for settings, such as the Vietnamese stock market, where access to granular audit data may be limited.

Finally, although traditional statistical models rely on linear assumptions, recent studies have demonstrated that machine learning techniques can uncover complex, non-linear patterns in financial data, offering more accurate and robust detection of earnings management (Bao et al., 2020; Schultz Jr et al., 2011). These models align well with the theoretical expectations of Agency and Positive Accounting Theory by using observable firm characteristics to infer latent managerial behavior. Therefore, the integration of machine learning into earnings management research not only enhances prediction accuracy but also contributes to a deeper understanding of how financial indicators reflect underlying reporting incentives.

2.2 Empirical studies

Prior research on earnings management has evolved from early econometric models to more advanced data-driven techniques. Foundational empirical studies have relied heavily on accrual-based models to detect earnings manipulation, particularly those derived from the Modified Jones framework. For example, Dechow et al. (1995) tested several accrual models and concluded that the Modified Jones Model was the most powerful for detecting income-increasing earnings management around seasoned equity offerings. This method estimates expected (non-discretionary) accruals based on changes in revenues and property, plant, and equipment, with the residual component serving as a proxy for discretionary behavior. Subsequent refinements, such as the performance-matched approach proposed by Kothari et al. (2005), improved this model by controlling for firm profitability, thereby enhancing accuracy in distinguishing discretionary accruals from normal operations (Jackson, 2018; Mosebach & Simko, 2010).

Empirical studies have consistently demonstrated that firm-specific variables are associated with earnings management incentives. For instance, studies show that leverage, profitability, firm size, and auditor type are systematically related to accrual manipulation (Klein, 2002; Xie et al., 2003). These studies support the notion that, in echo with some other studies (Alzayed et al., 2023; Chen et al., 2020; Cohen et al., 2012).

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However, such studies predominantly use linear regression or logistic models, which may oversimplify the relationships between variables and fail to capture interaction effects or nonlinear dependencies that are common in complex financial settings.

In response to these limitations, a growing body of literature has incorporated machine learning techniques into earnings management detection. Schultz Jr et al. (2011) were among the first to apply classification algorithms to distinguish between firms engaging in earnings management and those involved in outright fraud. They found that decision trees, neural networks, and support vector machines outperformed traditional logistic regression in terms of predictive accuracy, similar to the work of Hammami and Hendijani Zadeh (2022) and Huy et al. (2025) . Similarly, Baranes and Palas (2019) employed support vector machines and other learning models to detect fraudulent reporting, emphasizing the potential of machine learning to identify subtle, nonlinear patterns not captured by classical approaches. These studies validate the relevance of machine learning for financial statement analysis and demonstrate the feasibility of applying such tools in the accounting domain, which are supported by Kang and Park (2021) and Rahman et al. (2021).

Despite these advancements, most empirical research has focused on developed economies, particularly the United States and Europe, where data availability, enforcement mechanisms, and governance structures are well-established. Relatively few studies have examined emerging markets such as Vietnam, where the institutional environment, enforcement quality, and firm transparency may differ significantly. Research by Tran et al. (2022) and Dang and Khanh Dung (2024) provided some early evidence of earnings management among Vietnamese listed firms using traditional accrual models, but there remains a gap in applying predictive analytics and machine learning in this context. Thus, this study contributes to the literature by combining a well-established accrual-based labeling framework with machine learning techniques to analyze firm-level data from the Vietnamese capital market (Lokanan et al., 2019; Phong et al., 2024). It responds to calls for more localized, data-driven research on financial reporting quality in transitional economies.

3. Methodology

3.1 Data

This study utilizes secondary data collected from the Refinitiv Eikon database, which provides standardized financial information and firm-level data for publicly listed companies. The sample consists of non-financial firms listed on the Ho Chi Minh Stock Exchange (HOSE) and the Hanoi Stock Exchange (HNX) over the period 2000 to 2024. The initial dataset includes all firm-year observations for which full annual financial statements are available during this 25-year period. The dataset includes 630 firms with 8,371 observations. To ensure consistency in financial reporting and comparability across firms, financial institutions, including banks, insurance companies, and other firms classified under financial services are excluded. These firms follow industry-specific accounting standards and are subject to different regulatory regimes, which would introduce heterogeneity in accrual measurement and earnings manipulation behavior. The study defines two primary categories of variables: the target variable (earnings management label), and predictor variables used in model development.

Table 1. Variable measurement

Variable Name	Symbol	Measurement
Earnings Management Indicator	EM	Binary variable: 1 if absolute discretionary accruals in top 25%, 0 otherwise

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Return on Assets	ROA	Net Income / Total Assets
Current Ratio	CR	Current Assets / Current Liabilities
Quick Ratio	QR	(Current Assets – Inventory) / Current Liabilities
Leverage Ratio	LEV	Total Liabilities / Total Assets
Debt to Equity Ratio	D/E	Total Liabilities / Shareholders' Equity
Asset Turnover	AT	Net Sales / Total Assets
Operating Margin	OM	Operating Income / Net Sales
Net Profit Margin	NPM	Net Income / Net Sales
Cash Flow to Assets	CFOA	Operating Cash Flow / Total Assets
Accrual Quality	AQ	(Net Income – Operating Cash Flow) / Total Assets
Firm Size	FSIZE	Natural logarithm of Total Assets
Firm Age	FAGE	Number of years since incorporation or listing
Sales Growth	SGROWTH	($Sales_t$ – $Sales_{t-1}$) / $Sales_{t-1}$
Market-to-Book Ratio	MTB	Market Capitalization / Book Value of Equity
Auditor Type	AUDTYPE	Dummy: 1 = Big Four auditor; 0 = otherwise

Source: by author

Notably, big4 means the firm is audited by the neither one in four biggest audit firms in Vietnam, include: PwC, Deloitte, EY and KPMG. The dependent variable is a binary indicator of earnings management, derived from the Modified Jones Model with performance adjustment (Kothari et al., 2005), which estimates discretionary accruals. Firms are classified as engaging in earnings management if their absolute discretionary accruals fall within the top 25% (top quartile) of the distribution in a given year. Firm-years in the bottom 75% are classified as non-earnings-managed. This classification is used to train and evaluate supervised learning models. The earning management binary variable is evaluated by the equation below:

$$\frac{TA_{it}}{A_{i,t-1}} = \alpha_1\left(\frac{1}{A_{i,t-1}}\right) + \alpha_2\left(\frac{\Delta REV_{it} - \Delta REC_{it}}{A_{i,t-1}}\right) + \alpha_3\left(\frac{PPE_{it}}{A_{i,t-1}}\right) + \alpha_4\left(\frac{ROA_{it}}{A_{i,t-1}}\right) + \varepsilon_{it}$$

- TA_{it} = Total accruals in year t, equal to Net income minus Cashflow from Operations
- $A_{i,t-1}$ = Total assets at beginning of year
- ΔREV_{it} = Change in revenues
- ΔREC_{it} = Change in accounts receivable
- PPE_{it} = Gross property, plant, and equipment
- ROA_{it} = Return on assets
- ε_{it} = Residuals, interpreted as discretionary accruals (DA)

Prior to modeling, the dataset undergoes several preprocessing steps to ensure data quality and comparability. First, extreme values are addressed by excluding outliers based on a Z-score threshold of ±3, thereby reducing the influence of anomalous observations. Second, accrual estimations are normalized within each industry-year group to account for structural differences across sectors and time, enhancing the

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comparability of discretionary accrual measures. Third, firm-year observations with missing values in key financial statement components or accrual calculations are removed through listwise deletion to maintain data integrity. Lastly, all continuous predictor variables are standardized using z-score scaling to facilitate model convergence and comparability, particularly for algorithms sensitive to variable magnitude such as support vector machines and k-nearest neighbors.

3.2 Models

To predict the likelihood of earnings management, this study adopts a supervised learning framework using binary classification. Firm-year observations are labeled based on whether their absolute discretionary accruals fall within the top quartile of the annual distribution, reflecting elevated manipulation. The dataset is randomly split into a training set (70%) and a testing set (30%). Within the training set, 10-fold cross-validation is conducted to ensure stable estimation and robust out-of-sample performance. This approach allows each observation to serve as both training and validation data across different folds, reducing overfitting and providing a reliable assessment of model generalizability (James et al., 2013).

Five machine learning algorithms are selected for their theoretical advantages and empirical success in financial classification problems. The first is logistic regression, which serves as a baseline model due to its simplicity, interpretability, and well-established use in earnings management literature (Chen & Guestrin, 2016). It assumes a linear relationship between predictors and the log-odds of the dependent variable, making it a useful benchmark for evaluating improvements offered by more complex methods.

To model non-linear relationships and interactions among financial variables, this study incorporates random forest, an ensemble method that combines multiple decision trees to improve predictive accuracy and reduce variance. Random forest is chosen because it performs well on structured financial data and is less prone to overfitting than single-tree models (Breiman, 2001). It is configured with 200 trees, a maximum depth of 10, and a minimum of 5 samples per leaf. These hyperparameter values are chosen to provide sufficient tree complexity while limiting overfitting and computational cost (Fernández-Delgado et al., 2014).

The extreme gradient boosting (XGBoost) algorithm is included for its ability to optimize model performance through sequential tree learning. XGBoost is known for superior predictive power and fine-grained regularization capabilities, making it well-suited to high-dimensional financial datasets (Xu et al., 2023). It is trained using 300 estimators, a learning rate of 0.05, maximum depth of 6, and L2 regularization (lambda = 1.0). These settings are selected based on grid search and prior empirical studies, balancing depth to capture interaction effects with regularization to control overfitting.

The support vector machine (SVM) classifier is selected for its ability to create optimal separating hyperplanes in high-dimensional space, especially where relationships between predictors and outcomes are not linearly separable. SVM has been successfully applied in detecting financial anomalies, including fraud and manipulation (Kirkos et al., 2007). The SVM uses a radial basis function (RBF) kernel with a penalty parameter (C) of 1.0 and a kernel coefficient (γ) of 0.01. These values are chosen to allow moderate flexibility in decision boundaries without creating excessive model complexity.

Finally, the multilayer perceptron (MLP) neural network is used to capture deep, non-linear interactions among features. MLPs have shown promise in modeling complex financial patterns, including bankruptcy prediction and fraud detection (Elhoseny et al., 2025). The model consists of three hidden layers with 64, 32, and 16 neurons, using ReLU activation and trained with the Adam optimizer. A batch size of 64, learning rate of 0.001, and early stopping are applied to balance convergence speed and generalization. This architecture is selected to provide sufficient model capacity without overfitting, given the size and structure of the dataset.

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These models are chosen not only for their complementary strengths, ranging from interpretability to flexibility, but also to allow a comparative analysis of how different algorithmic frameworks perform in detecting earnings management. Performance is evaluated using accuracy, precision, recall, F1 score, and AUC-ROC, all of which are standard metrics for binary classification (Fawcett, 2006). The best-performing models are further interpreted using feature importance rankings and SHAP values to identify which financial and governance variables most influence the model's predictions (Lundberg & Lee, 2017).

4. Results & Discussion

4.1 Descriptive Analysis

The descriptive statistics presented in Table 2 provide an overview of the distributional properties of the financial, firm-specific, and governance variables used in the analysis. Across 8,371 firm-year observations, return on assets (ROA) exhibits a mean of 6%, with a moderate skewness of 0.64 and a kurtosis of 11.52, suggesting a distribution with mild right tail and some outliers. Liquidity indicators such as the current ratio (CR) and quick ratio (QR) show highly right-skewed distributions (skewness > 11), reflecting the presence of firms with unusually large short-term asset buffers. Similarly, leverage measures (LEV and debt-to-equity ratio) demonstrate considerable dispersion and extreme values, particularly for D/E, which has a maximum of 140.32 and kurtosis exceeding 870, indicating substantial variation in capital structure across firms.

Table 2. Descriptive analysis

	count	mean	std_dev	min	median	max	iqr	skewness	kurtosis
ROA	8371	0.06	0.08	-0.9	0.05	0.78	0.07	0.64	11.52
CR	8371	2.56	3.9	0.03	1.58	146.92	1.37	11.88	288.49
QR	8371	1.92	3.71	-0.02	1.07	146.92	1.17	13.37	354.77
LEV	8371	0.47	0.22	-0.29	0.48	1.29	0.34	-0.07	-0.79
D/E	8371	1.51	3.63	-7.23	0.92	140.32	1.36	25.57	871.78
AT	8371	1.23	1.34	-2.71	0.92	13.92	1.09	3.62	19.92
OM	8371	0.11	4.07	-39.87	0.07	366.2	0.11	86.83	7823.15
NPM	8371	0.04	1.82	-114.11	0.05	34.17	0.1	-39.67	2160.41
CFOA	8371	0.07	0.15	-0.96	0.06	2.17	0.15	1.73	17.67
AQ	8371	-0.01	0.15	-2.33	-0.01	1.01	0.13	-2.54	33.02
FSIZE	8371	27.38	1.65	23.22	27.28	34.36	2.19	0.39	0.24
FAGE	8371	15.74	8.14	1	15	64	10	1.05	1.95
SGROWTH	8371	0.28	3.27	-80.94	0.08	127.46	0.33	24.51	945.3
MTB	8371	0.14	0.51	-12.61	0.12	17.7	0.29	4.85	271.32
AUDTYPE	8371	0.25	0.43	0	0	1	1	1.15	-0.68

Source: by author

Efficiency and profitability ratios further reveal notable heterogeneity. Asset turnover (AT) and operating margin (OM) have high variance, with OM and net profit margin (NPM) demonstrating extreme skewness and leptokurtic behavior—indicating the presence of both large outliers and firms with volatile performance. Accrual quality (AQ) clusters around zero, with a slight negative skew and relatively low dispersion. Firm size (FSIZE) is more normally distributed, while firm age (FAGE) and sales growth (SGROWTH) again show wide variation, with SGROWTH especially affected by extreme outliers (max = 127.46, skewness = 24.51). The market-to-book ratio (MTB) is also highly skewed and kurtotic, consistent

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with patterns observed in emerging markets. Lastly, the auditor type variable (AUDTYPE), coded as a binary indicator for Big Four auditors, shows moderate skewness (1.15), reflecting a lower proportion of firms audited by Big Four firms. Overall, the data reflect characteristics typical of financial disclosures in emerging markets, with frequent presence of extreme values and non-normal distributions.

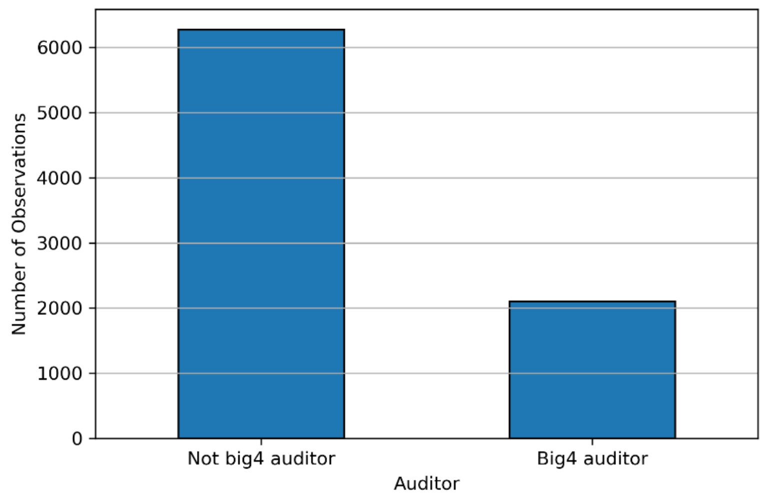

Figure 1. Distribution of Big4 auditor in dataset

Source: by author

Figure 1 illustrates the distribution of Big4 auditor affiliations among the firm-year observations in the dataset. The majority of firms, exceeding 6,000 observations, are audited by non-Big4 auditors, while only around 2,000 firm-years are associated with Big Four auditors. This imbalance highlights the limited penetration of global auditing firms in the Vietnamese market over the study period. The prevalence of non-Big4 auditors may have implications for financial reporting quality, investor confidence, and the likelihood of earnings management, aligning with prior studies that suggest Big4 auditors are generally associated with higher audit quality and greater scrutiny.

4.2 Results

Figure 2 presents a boxplot comparison of the five selected machine learning algorithms in terms of classification accuracy. Among the models, XGBoost demonstrates the highest and most consistent accuracy, with values clustering tightly around 0.89–0.90, indicating both strong predictive performance and low variability across validation folds. Random Forest and the Multilayer Perceptron (MLP) neural network also perform well, achieving average accuracies above 0.87, suggesting that ensemble learning and deep learning techniques are well-suited for capturing complex patterns in financial data. In contrast, Logistic Regression shows the lowest accuracy, with a median below 0.81 and greater dispersion, reflecting the limitations of linear models in handling non-linear interactions. Support Vector Machine (SVM) with a radial basis kernel achieves moderate accuracy but lags behind tree-based models, possibly due to sensitivity to hyperparameters or the high dimensionality of encoded financial variables. Overall, the results suggest that non-linear and ensemble methods offer substantial improvements over traditional classifiers in predicting earnings management.

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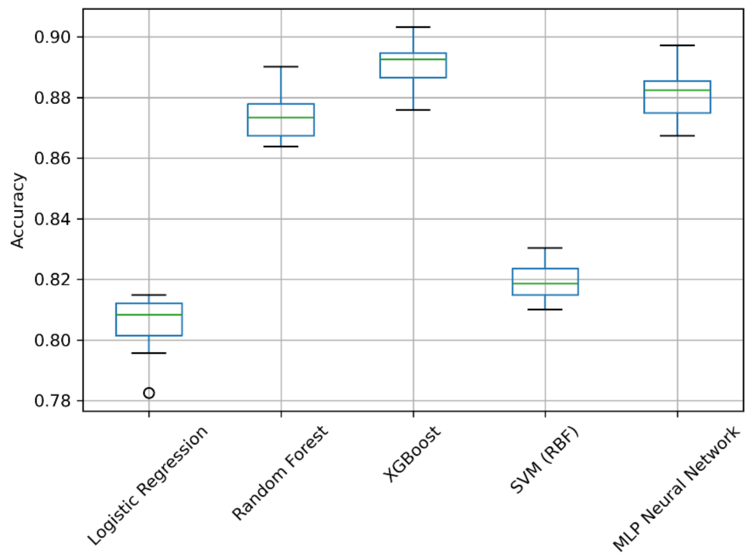

Figure 2. Algorithms compare by accuracy

Source: by author

Figure 3 shows the precision scores of the five classification algorithms, providing insight into their ability to correctly identify earnings-managed firm-years without generating false positives. Notably, Support Vector Machine (SVM) achieves the highest precision, with scores consistently above 0.95, indicating a strong ability to make accurate positive predictions. Random Forest also performs well, followed by XGBoost, which, despite leading in accuracy (as shown in Figure 2), shows slightly lower precision than SVM and Random Forest. This suggests that XGBoost may classify more true positives overall but at the cost of more false positives. Logistic Regression again trails behind, with both the lowest median and the widest spread in precision scores, highlighting its weaker discriminatory power in this context. The Multilayer Perceptron maintains balanced precision, though not as strong as its accuracy ranking, emphasizing that model evaluation should consider multiple performance metrics beyond overall accuracy.

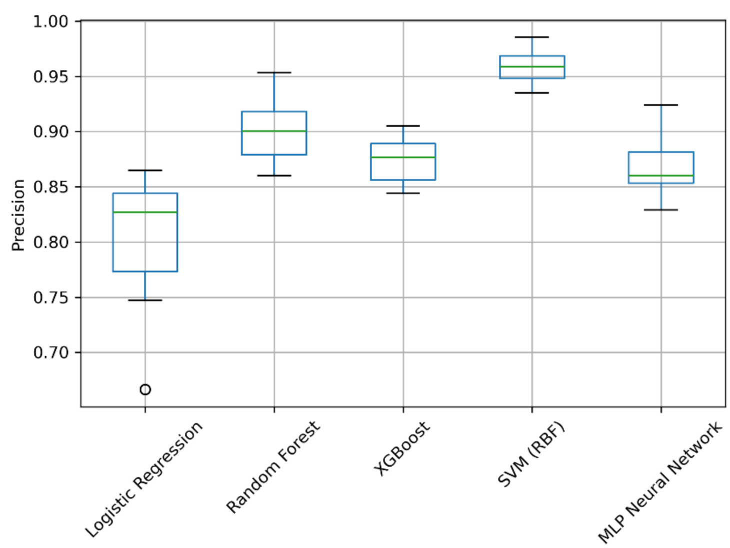

Figure 3. Algorithms compare by precision

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Source: by author

Figure 4 compares the recall performance of the five models, highlighting their effectiveness in identifying all actual cases of earnings management. XGBoost achieves the highest median recall, around 0.67, reinforcing its strong overall classification capability as seen in Figure 2 (accuracy) and partially in Figure 3 (precision). The Multilayer Perceptron also performs well, with consistent recall scores slightly below XGBoost, indicating its ability to detect a substantial proportion of true positives. In contrast, Support Vector Machine, despite having the highest precision in Figure 3, records one of the lowest recall scores, reflecting a conservative classification tendency that minimizes false positives at the expense of missing true positives. Logistic Regression again underperforms, with recall scores clustering around 0.30, while Random Forest provides a balanced trade-off, moderately high across all metrics. These results emphasize the importance of evaluating precision and recall together, as high precision does not guarantee strong recall, and optimal model selection should be based on the specific costs of false negatives versus false positives in the context of earnings management detection.

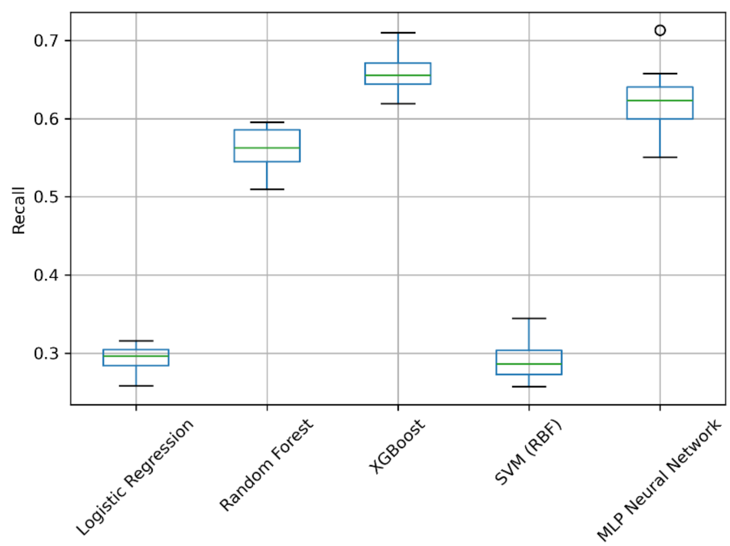

Figure 4. Algorithms compare by recall

Source: by author

Figure 5 presents the comparison of F1 scores across the five machine learning algorithms, offering a holistic measure that balances precision and recall. XGBoost achieves the highest F1 scores, consistently outperforming others, which aligns with its strong results in both recall (Figure 4) and accuracy (Figure 2), making it the most robust model for detecting earnings management. The Multilayer Perceptron and Random Forest also perform well, with F1 scores above 0.70, suggesting they strike an effective trade-off between detecting true positives and limiting false positives. In contrast, Support Vector Machine and Logistic Regression lag behind, with F1 scores below 0.50, confirming the earlier observation that these models either suffer from low recall (SVM in Figure 4) or low precision and recall overall (Logistic Regression). The F1 results underscore that tree-based and neural models provide more reliable performance when both detection power and classification accuracy are critical, which is often the case in identifying complex patterns like earnings management.

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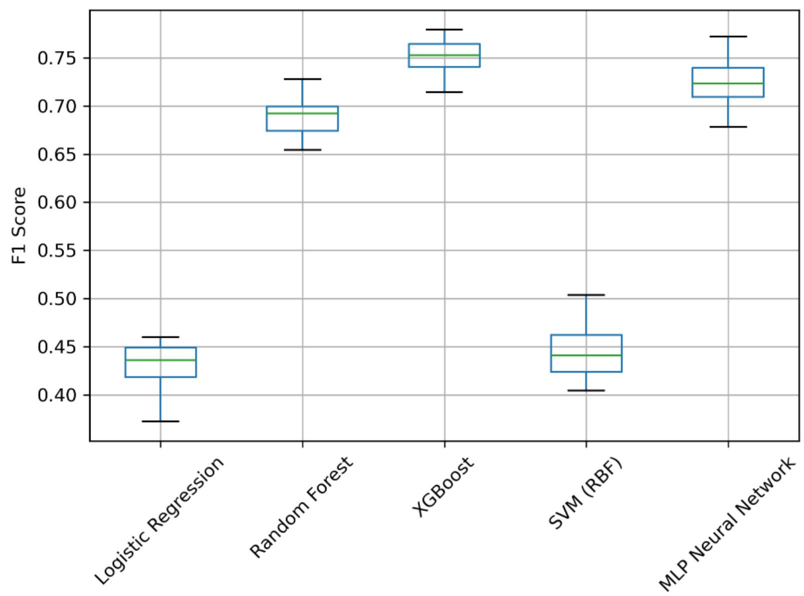

Figure 5. Algorithms compare by F1

Source: by author

Figure 6 compares the average time consumed by each algorithm during 10-fold cross-validation, reflecting the computational efficiency of the models. Support Vector Machine (SVM) with the radial basis function kernel is by far the most time-consuming, requiring nearly 10 seconds on average per run, which may limit its practicality for large-scale or real-time applications. Random Forest and the Multilayer Perceptron (MLP) neural network show moderate training times, reflecting the iterative nature of deep learning and the ensemble process of tree-based models. XGBoost, despite being an ensemble method, demonstrates excellent computational efficiency, likely due to its optimized implementation and early stopping features. Logistic Regression is the fastest by a wide margin, consuming a negligible amount of time, though at the cost of significantly lower predictive performance (as seen in Figures 2–5). These findings emphasize the importance of balancing accuracy and efficiency, especially when scalability and responsiveness are critical considerations in financial analytics.

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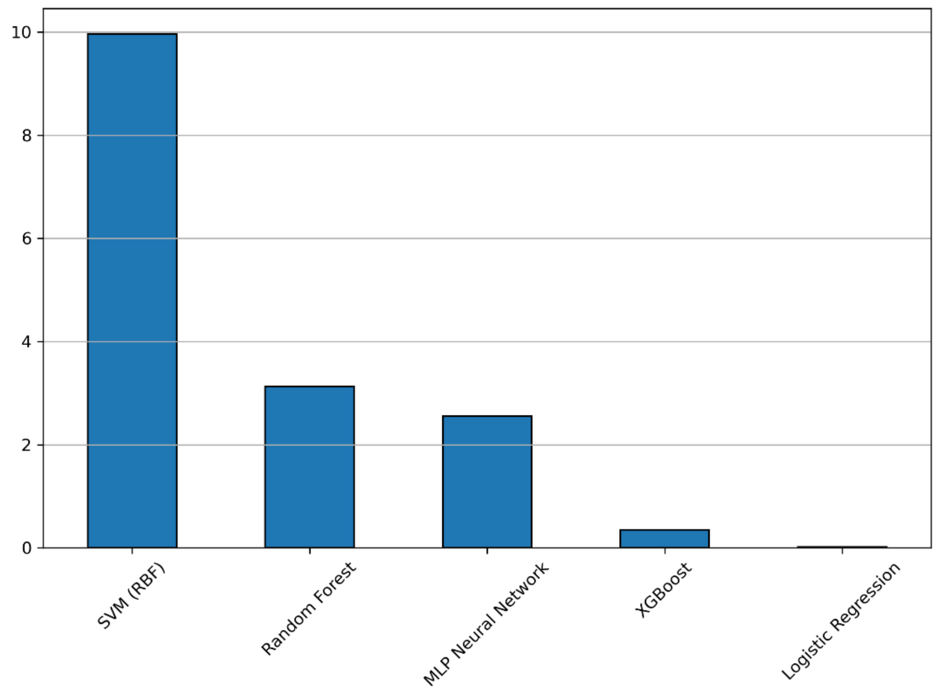

Figure 6. Algorithms compare by time consumed

Source: by author

Figure 7 presents the Receiver Operating Characteristic (ROC) curves for all five classification algorithms, providing a graphical assessment of their ability to distinguish between earnings-managed and non-managed observations across all decision thresholds. XGBoost achieves the highest Area Under the Curve (AUC) score of 0.93, confirming its strong discriminative power and consistency with earlier findings on accuracy and F1 score. The Multilayer Perceptron closely follows with an AUC of 0.91, indicating comparable robustness in classification performance. Random Forest also performs well, achieving an AUC of 0.90, reinforcing the effectiveness of ensemble methods in handling complex financial data. In contrast, Support Vector Machine and Logistic Regression yield lower AUC values of 0.80 and 0.74, respectively, reflecting their relatively weaker ability to rank predictions across threshold values. Overall, the ROC-AUC results support the superiority of tree-based and deep learning models in the context of earnings management prediction, while highlighting the limitations of traditional linear and kernel-based classifiers.

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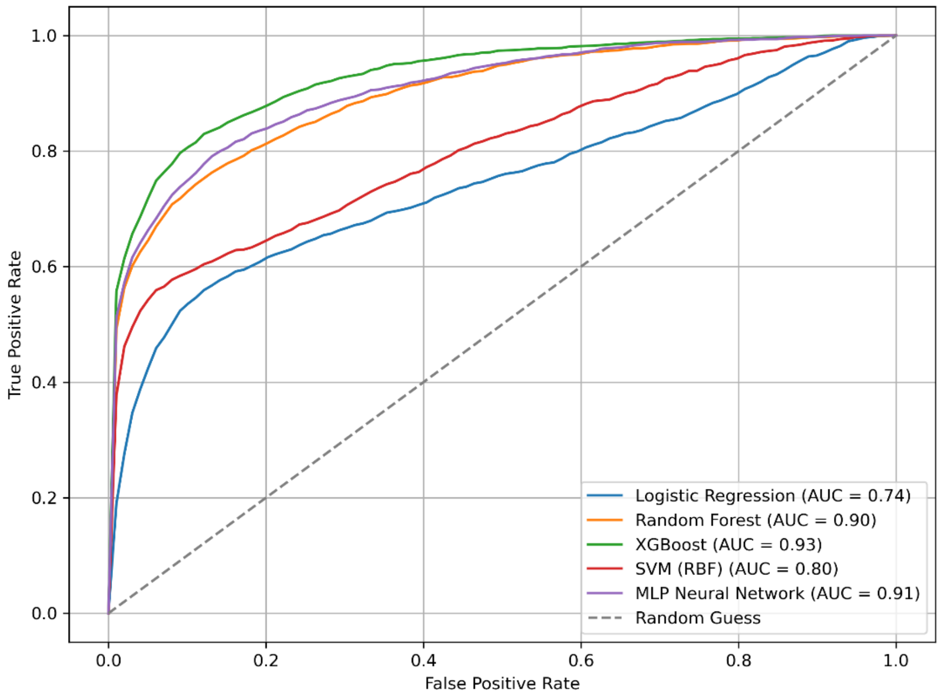

Figure 7. Algorithms compare by time ROC-AUC

Source: by author

Based on the comparative evaluation across multiple performance metrics including accuracy, precision, recall, F1 score, and ROC-AUC, XGBoost consistently emerges as the best-performing algorithm for predicting earnings management. Its superior discriminative power, coupled with efficient computational performance, justifies its selection for further analysis of feature importance. Figure 8 presents the top 20 most influential features identified by the XGBoost model. Firm size (FSIZE) and accrual quality (AQ) are the two most important predictors, suggesting that larger firms and those with irregular accrual patterns are more likely to engage in earnings management. Liquidity (CR), profitability (OM), and leverage-related metrics (D/E, LEV) also rank highly, underscoring their relevance in distinguishing manipulated financial reporting. Additionally, firm age, auditor type, and market valuation measures (MTB) contribute meaningfully, reflecting the multifaceted nature of the determinants of earnings management. These insights support the economic and theoretical rationale for incorporating a diverse set of financial and governance variables and motivate the use of SHAP analysis to further explore their marginal and interaction effects.

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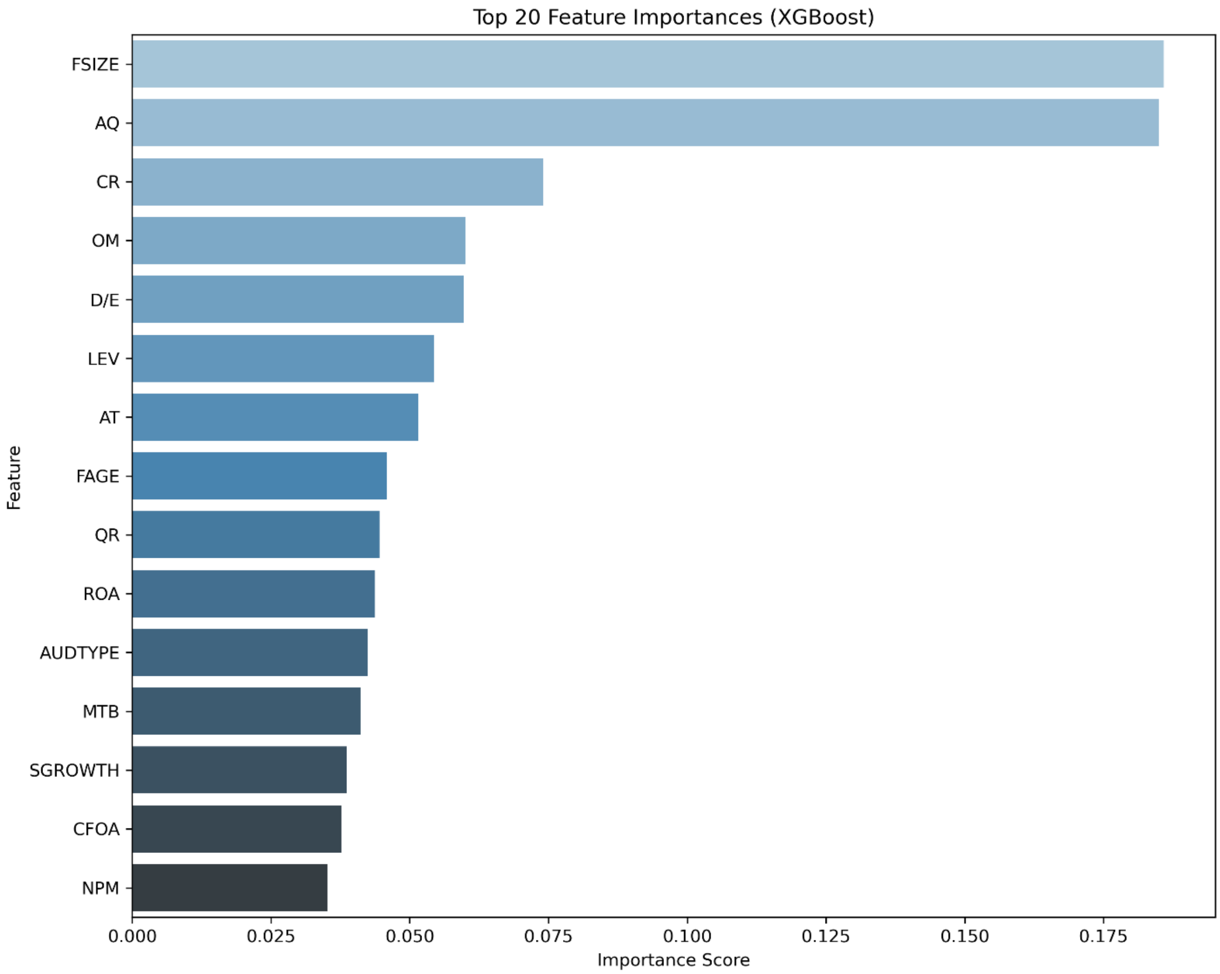

Figure 8. Feature importances for XGBoost

Source: by author

Figure 9 presents the SHAP (SHapley Additive exPlanations) summary plot for the XGBoost model, illustrating the marginal contribution of each feature to the model's prediction of earnings management. The horizontal axis represents the SHAP value, which quantifies the direction and magnitude of a feature's impact on the model output. Features are ranked by their average absolute SHAP values, indicating their overall importance. Among all variables, accrual quality (AQ) and firm size (FSIZE) exhibit the most significant impact, with high AQ and large FSIZE values generally associated with an increased probability of earnings management. This aligns with theoretical expectations that larger firms may have greater flexibility in reporting practices and that poorer accrual quality is a direct signal of potential manipulation.

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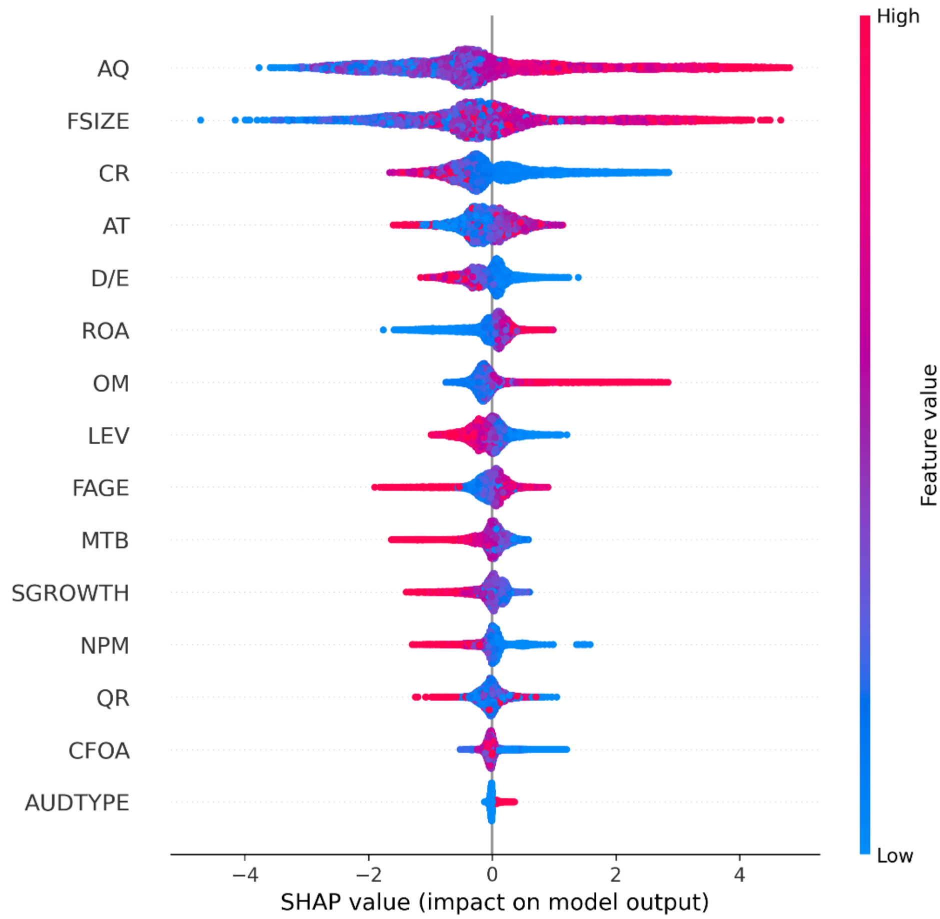

Figure 9. SHAP analysis for XGBoost

Source: by author

The color gradient in the plot from blue (low feature values) to red (high feature values) provides additional interpretive insight. For example, high values of current ratio (CR) and asset turnover (AT) tend to positively influence the likelihood of earnings management, as shown by the concentration of red points on the right side of the SHAP axis. In contrast, low values of return on assets (ROA), operating margin (OM), and leverage (LEV) are associated with increased SHAP values, suggesting that underperformance and weak financial health can drive incentives for manipulation. Interestingly, auditor type (AUDTYPE), though ranked lower, still shows a distinguishable pattern, with non-Big Four audit firms contributing slightly to higher SHAP values, implying weaker audit quality may facilitate earnings management. These SHAP results provide a nuanced, interpretable understanding of the model's decision logic and further validate the theoretical and empirical choices of variables used in the study.

5. Conclusion & Recommendation

5.1 Conclusion

The findings of this study offer clear support for the use of advanced machine learning models, particularly XGBoost, in predicting earnings management, positioning it as a superior approach relative to traditional econometric methods. This represents a significant evolution from prior research that primarily relied on logistic regression, linear discriminant analysis, or simple decision trees. For example, studies such as

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Dechow et al. (1995) employed static financial models based on accounting ratios to flag manipulation, but lacked the ability to capture complex non-linear interactions or adapt to high-dimensional feature spaces. Similarly, recent applications in emerging markets like Vietnam have tended to use linear regression or binary classification frameworks (e.g., Phong et al. (2024)), often reporting modest accuracy and limited generalizability due to methodological constraints. In contrast, our findings demonstrate that XGBoost, by leveraging sequential learning and regularization, significantly improves prediction quality and maintains consistency across multiple performance metrics including accuracy, recall, and F1 score.

Notably, the strong performance of tree-based models like Random Forest and XGBoost is in line with Fernández-Delgado et al. (2014), who evaluated 179 classifiers across diverse datasets and found that ensemble methods consistently outperformed simpler classifiers, including support vector machines and logistic regression. In the financial domain, Chen et al. (2020) and Xu et al. (2023)reported that gradient boosting methods effectively identify financial distress and fraudulent reporting in Chinese firms, which aligns with the present study's findings in the Vietnamese context. Furthermore, the interpretability of SHAP values used in this study builds on the model transparency advocated by Lundberg and Lee (2017), making it possible to validate the algorithm's predictions against established economic theories, something prior studies relying on black-box models could not offer. Thus, this research not only confirms the findings of existing literature but also expands the methodological toolkit available for financial accounting researchers.

In terms of feature selection and interpretation, this study offers empirical confirmation of previously reported determinants of earnings management, while adding new evidence on their relative importance in a machine learning framework. For instance, the dominance of firm size (FSIZE) and accrual quality (AQ) in the XGBoost importance ranking echoes the findings of Kothari et al. (2005) and Dechow et al. (1995), who showed that larger firms and those with poor accrual reliability are more likely to manipulate earnings. Likewise, the significance of leverage and liquidity ratios aligns with studies such as Hammami and Hendijani Zadeh (2022), who identified financial pressure and short-term obligations as key drivers of earnings management. However, unlike most earlier studies that treat these variables independently, the machine learning models used here account for their interactions and non-linear effects, offering a more realistic and nuanced understanding of manipulation behavior.

By embedding this methodological advancement in a Vietnamese market context, this research contributes to a relatively underexplored area in global accounting literature. Compared to studies in developed economies, few papers have applied machine learning to earnings management in transitional markets, where corporate governance mechanisms are still evolving and audit quality varies widely. Recent Vietnamese studies such as Dang and Khanh Dung (2024) and Huy et al. (2025) have highlighted the role of board characteristics and auditor type, but their methodological scope was limited to regression models. This study bridges that gap by showing how algorithmic methods can capture both financial and governance influences in a holistic, predictive framework. Consequently, it not only affirms established theoretical expectations but also extends empirical insights into new geographic and methodological territory, setting a precedent for future research in emerging capital markets.

5.2 Recommendation

Based on the empirical findings and theoretical discussions presented in this study, several targeted recommendations are proposed for regulatory bodies, auditors, investors, and corporate managers to enhance the detection and prevention of earnings management in the Vietnamese capital market. First, for regulatory authorities such as the State Securities Commission of Vietnam and stock exchange operators (HOSE and HNX), the results support the adoption of advanced analytical technologies, particularly machine learning models like XGBoost as part of their financial surveillance and enforcement systems. The study demonstrates that traditional approaches are less effective in identifying subtle and complex

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manipulation patterns. Therefore, integrating data-driven, algorithmic screening tools into routine financial monitoring can significantly improve the timeliness and accuracy of fraud detection. Regulatory frameworks should also promote greater standardization and transparency in financial reporting to improve the quality and comparability of input data used in such predictive models.

Second, auditing firms, especially those outside the Big4 should consider enhancing their audit procedures by incorporating data analytics and model-based red-flag systems. The finding that firms audited by non-Big Four auditors are more likely to engage in earnings management suggests the need for improved audit quality and technological adoption among these firms. Auditors should be trained not only in accounting standards but also in interpreting algorithmic insights such as SHAP values, which offer concrete, variable-level evidence of manipulation risk. This can assist audit teams in prioritizing client reviews and strengthening audit assurance.

Third, investors and financial analysts can benefit from incorporating predictive analytics into their due diligence processes. As shown in this study, firm-level financial ratios and governance indicators contain predictive signals that, when processed through machine learning algorithms, yield valuable foresight into earnings quality. Institutional investors, in particular, can build internal monitoring models that flag high-risk firms based on similar frameworks. The interpretability of SHAP analysis makes such tools practical for decision-making and portfolio risk assessment.

Lastly, corporate managers and boards of directors should recognize the increasing capability of stakeholders to detect earnings manipulation through technology. Transparency, internal control, and ethical financial reporting should be emphasized as strategic advantages, not merely compliance obligations. Companies should invest in internal data systems and financial reporting quality to ensure that their true performance is reflected accurately. Additionally, boards should ensure that audit committees are informed and equipped to engage with data-informed oversight mechanisms, especially in firms with high financial complexity or growth volatility. Collectively, these recommendations aim to promote a more transparent, accountable, and data-literate financial ecosystem in Vietnam, aligning with the study's evidence that machine learning tools are not only theoretically appropriate but also practically implementable in detecting earnings management.

5.3 Limitations & Further research

While this study provides robust empirical evidence on the effectiveness of machine learning in predicting earnings management, several limitations should be acknowledged. First, the analysis is restricted to accrual-based earnings management using the Modified Jones Model with performance adjustment, which may not capture real activity manipulation or classification shifting. Second, the binary classification approach simplifies earnings management into a high-versus-low framework, potentially overlooking subtler gradations in manipulation intensity. Third, although the dataset covers a long period (2000–2024), structural changes in accounting standards, auditing practices, or economic conditions over time may introduce unobserved heterogeneity that the models do not explicitly control for. Lastly, the generalizability of the findings may be limited to the Vietnamese context, given differences in institutional environments across countries.

Future studies can extend this research by incorporating alternative proxies for earnings management, such as real activities manipulation or abnormal production costs, to provide a more comprehensive detection framework. Additionally, time-series models or dynamic learning algorithms could be employed to account for temporal dependencies and evolving manipulation strategies. Cross-country comparisons using similar machine learning frameworks would also be valuable for understanding how institutional quality, investor protection, and enforcement mechanisms shape the effectiveness of earnings management detection.

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Finally, integrating unstructured data sources such as textual analysis of financial disclosures or earnings call transcripts may enrich predictive models and enhance their explanatory power.

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