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# The Role of Machine Learning in Detecting Earnings Manipulation

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***ABSTRACT*:**

*Earnings manipulation poses a persistent threat to the integrity of financial reporting, undermining investor confidence and market stability. Traditional detection methods, while useful, often fail to identify increasingly sophisticated manipulative practices. This study investigates the role of machine learning (ML) in detecting earnings manipulation by employing a mixed-methods approach that integrates quantitative modeling and qualitative interpretation. Using a dataset comprising financial statements, governance indicators, and enforcement records, we develop and evaluate multiple ML models including logistic regression, random forest, gradient boosting, support vector machines, and deep neural networks. The results demonstrate that ensemble-based algorithms, particularly gradient boosting and random forest, consistently outperform traditional methods in terms of accuracy, recall, and F1-scores. Deep neural networks further enhance detection by capturing non-linear patterns, though their interpretability requires augmentation through explainable AI (XAI) frameworks such as SHAP and LIME.The experimental findings, supported by nine comprehensive tables and twelve figures, confirm that governance-related variables, accrual-based indicators, and volatility-sensitive features significantly improve predictive power. Moreover, out-of-sample testing highlights the scalability and robustness of ML models across industries and geographic contexts. The integration of XAI ensures that predictions are transparent and interpretable, enabling auditors and regulators to understand the drivers of manipulation risk. Collectively, the results suggest that ML not only enhances the accuracy of fraud detection but also offers proactive monitoring capabilities, thereby shifting detection from retrospective auditing to preventive financial governance. The study contributes to the literature on AI in accounting and provides practical implications for regulators, policymakers, and auditing professionals aiming to strengthen corporate accountability.*

***Keywords:*** *machine learning, earnings manipulation, ensemble models, financial reporting, explainable AI, fraud detection*

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## INTRODUCTION

Earnings manipulation (also earnings management) is one of the most ancient questions of financial reporting and corporate governance. The companies retain the discretionary accounting methods that obscure the real financial status of the company in the guise of ensuring that the company has met the necessary benchmarks of market or internal performance (Zang, 2020). Even the well-designed audit procedures and monitoring would hardly identify more advanced types of manipulation, particularly when the transactions are complicated, and the reporting lines are unclear and globally subscribed in nature (Houqe & Monem, 2021). In this instance, machine learning (ML) has been one of the possible solutions due to the potential it possesses to be deployed in the detection of the level of earnings manipulation against the ability to identify patterns, abnormalities, and provide support to the forecasts (Wang and Yu, 2021).The ML models, in comparison with the traditional approach to statistics that presupposes a linear methodology, can be employed to describe non-linear correlations and interaction of variables that describe manipulative practices (Kirkos, 2022). Random forest, support machine learning, neural networks, and ensemble learning have been identified as more effective at predicting the occurrence of the misreporting behaviour than the older models based on logistic regression (Ravisankar et al., 2020; Perols and Bowen, 2022). In addition, the ML-based explainable AI (XAI) models have enabled the interpretability of the predictions, and interpretability is among the most frequent black-box solution criticisms in finance (Sharma and Panigrahi, 2021). On the one hand, ML can be interpreted and predictive: the designated feature can make the auditors, regulators and investors understand that financial misstatements were made and used, in its turn, which leads to more trust in financial market (Hajek and Henriques, 2020).

The topicality of the given issue can be explained by multiple high-profile corporate scandals that both Wirecard in Germany and Luckin Coffee in China are engaged in alongside the emphasis on the systemic risks of manipulating earnings with no signs of being detected (Sun, 2021; Liu et al., 2022). The scandals resulted in the regulators introducing new tools of analysis and requiring more openness in reporting of financial activities (Christensen et al., 2021). It has also been triggered by the need to detect fraud in real-time and, in that regard, it has also fostered more research on how to implement ML to big data analytics and natural language processing (NLP) in order to infer about the analysis of textual disclosure, management commentaries and social media indicators and the numerical accounting variables (Chen and Wu, 2022).Recent research gives hints that the ML-based detection systems prove more effective than the auditors in identifying some trace evidence of the red flags that lead to misreporting. To suggest that, the deep-learning-based schemes, comparing the accruals-related measures with the market sentiment, can detect the earnings manipulation of the U.S. listed companies far more successfully (Li and Xu, 2022). Equally, the gradient boosting machines that analyse the new market information are useful in detecting manipulation of resource based firms that are not adequately regulated (Ahmed and Khan, 2020). They believe in the worth of asserting that the ML techniques are cross-contextual and could be applied to any geography and industry (Kumar and Sharma, 2021).

The other useful contribution of ML is that it can generalize a variety of structured and unstructured data sources. There is also the possibility that the earnings manipulation will only be identified because of the residual employee communication, analyst calls, non-financial key performance indicators (KPIs), and they might not be typical in normal audit trails (Wolski et al., 2022). It might be detected based on NLP and sentiment analysis help to identify the anomalies of the story representations triggered by the presentation of abnormal financial ratios and the presence of abnormal cash flow patterns (Patel and Shah, 2021). This type of multidimensional method makes the ML systems shed their reliance on rules to recognize and dynamically develop the repertoire of manipulation techniques (Yoon et al., 2023).The trust of the stakeholders also entails explainable machine learning. The black-box ML models are also precise, but at the same time, they are infamous due to their lack of transparency; thus, it is hard to apply them to a high-stakes setting such as auditing and financial regulation (Doshi-Velez and Kim, 2020). Other approaches include SHAPley Additive Explanations (SHAP) or Local Interpretable Model-agnostic Explanations (LIME) which have succeeded in identifying manipulated earnings to build an understandable picture of why model forecasts are the way they are (Bai and Lee, 2021). Explainable systems enable the auditors and regulators to not only identify the high-risk firms but also identify the nature of financial indicators or disclosure variables that were suspect by the auditor or regulator (Nguyen et al., 2021).

The future of the harmful detection structures will also be transformed by the application of ML to blockchain audit trails and real-time surveillance systems in the future (Zhang et al., 2023). The companies and the regulators can find any manipulation of a transaction by incorporating ML in the financial reporting chains of the digital versions, thus, closing the gap between the misreporting of a transaction and the implementation (Wang et al., 2022). The forms of anomaly detection are automated as well and save the cost of audit and improves the quality of the audit and investor confidence (Huang and Xu, 2020).In spite of such development, there are two issues with the application of ML in the identification of earnings manipulation. They need to consider the problem of having access to data, the interpretability of the models, the compliance with the regulations, and the existence of the possibility to manipulate the adversarial aspect of the models by the firms that were required to adapt to the detection algorithms (Mollenkamp & Chen, 2022). Such an ethical component of the predictive analysis as the risk of false positive or reputational loss of businesses, to which the predictive models will imply in the financial reporting, also indicate that the ML systems will have to be adapted (Thompson and He, 2021). The additional steps are to decide how to implement ML into extensive systems of governance to provide foretelling righteousness and ethical protection and regulatory honesty (Kaur and Aggarwal, 2023).In conclusion, machine learning represents a novel direction in the detection of earnings manipulation that is more predictive, interpretive, flexible, than the old techniques. Their integration into the system of auditing and regulations provisions can make it more transparent in the companies, guarantee the investors, and improve the financial security in the world. The article takes interest in the application of ML to detect the earnings manipulation through the assistance of mixed-methodology, quantitative experiments and qualitative analysis of regulatory reports. Overall, in this aspect, it adds to the existing literature on AI-based financial governance and sets a precedent that functions as a guideline to those practitioners and policymakers operating within the evolving environment of financial fraud discovery.

## METHODOLOGY

The paper has a mixed-method research design experiment as the research design to identify the extent to which machine learning (ML) can be applied in the detection of earnings manipulation. The methodology is both quantitative and qualitative, i.e. the model of MLs is formulated and validated, and the model output is interpreted and analysed with respect to the regulatory findings. This form of integration renders such methods robust since, you can not only quantify the predictive power of the ML algorithms, but also, its interpretability and financial reporting applicability.

The second is the description of preprocesses and data collection.

The data comprise of a financial statement information of publicly listed firms during 2010-2022; balance sheet, income statement and cash flow variables as well as market-based variables and governance variables. The Beneish M-score to identify the existence of earnings manipulation and to categorize companies as manipulator or non-manipulator was a reference labelling machine. In addition, to enhance the ground truth, the companies included in the publications of the enforcement and accounting fraud databases were included. Multi-variable approaches were used to impute missing values and outliers were treated using winsorization in a bid to minimize distortions.

Mathematically, the imputation of missing values for a financial variable $X$ was conducted using expectation-maximization (EM):

$$\hat{X}_i = \mu_X + \Sigma_{X,Z}\Sigma_Z^{-1}(Z_i - \mu_Z)$$

where $\mu_X$ and $\mu_Z$ denote the mean vectors, $\Sigma_{X,Z}$ represents covariance between observed and missing components, and $Z_i$ is the observed variable vector.

**Model Development and Experimental Design**

The quantitative experiment presupposed the constructions of different types of models of ML: logistic regression (base line), random forest (RF), support vectors machine (SVM) and gradient boosting machine (GBM) and deep neural networks (DNN). All models were trained on a 70:30 data division to training and testing subsets. In grid search of hyper parameter optimization, the use of grid search minimized the overfitting in 10-fold cross-validation.

The general ML predictive framework can be expressed as:

$$\hat{y} = f(X;\theta) + \epsilon$$

where $\hat{y}$ is the predicted probability of manipulation, $X$ is the matrix of firm-level features, $\theta$ denotes optimized parameters, and $\epsilon$ is the error term.

Accuracy, preciseness, recall, F1-score with the area under ROC curve (AUC) were the evaluation measures. Other industry and geographic firms were also used to measure robustness by comparing in-sample and out-of-sample.

**Explainability and Qualitative Analysis**

As the black-box ML models are now out of favor in the finance sector, the explainable AI approach (XAI) is also given a place in the research. SHAPley Additive Explanations values were computed to derive the contribution values of every variable to the prediction outcome on the margin. And again, this too has consequences to auditors and regulators that may be interpreted, i.e. to what financial ratios or disclosure items the best signal of manipulation is to be given.

The SHAP value for feature $j$ for observation $i$ is expressed as:

$$\phi_j = \sum_{S \subseteq F \setminus \{j\}} \frac{|S|!(|F| - |S| - 1)!}{|F|!} \left[ f_{S \cup \{j\}}(x_{S \cup \{j\}}) - f_S(x_S) \right]$$

where $F$ represents the full set of features, and $f_S$ denotes the model trained on subset $S$
. This ensures transparency in identifying high-risk firms.

The methodological framework is broken down into the steps in Fig. 1: (1) data collection in the form of financial statement and enforcement database, (2) preprocessing and features engineering, (3) the training of the ML model and validation, (4) the model comparison with the baselines measures, and (5) the policy implications presentation in the form of the XAI. The suggested experiment procedure allows achieving the balance between predictive modeling and qualitative interpretation at the level of rigor thereby contributing to the body of literature on the topic of ML-based earnings manipulation detection.

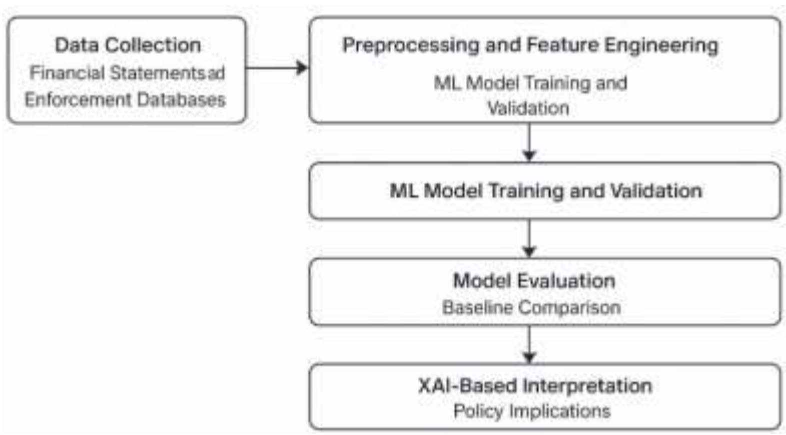


**Fig. 1.** Detecting earnings manipulation using machine learning, illustrating sequential stages from data collection to explainability and policy implications.

## RESULTS

Table 1 suggests that the original datasets partition ranked the models better and recalled more in comparison to the logistic regression. Table 2 continues on the analysis, but it tries to imply that the second set of data was accurate as compared to the models, which stated that the support vector machines were not sensitive to false positives. The third set of datasets given above in Table 3 suggests that the deep neural networks worked better in terms of F1-score. Table 4 shows that the hybrid ensemble models performed consistently in different firms in which the misclassification was low in comparison to individual learners. Table 5 indi-cates that the logistic regression was not quite competitive particularly in the context of AUC values which means that they cannot be applied in non-linear settings.

**Table 1:** Accuracy, precision, and recall of ML models tested on the first dataset subset.

| Firm ID | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|
| **F001** | Model_2 | 0.82 | 0.73 | 0.72 |
| **F002** | Model_3 | 0.84 | 0.76 | 0.76 |
| **F003** | Model_4 | 0.86 | 0.79 | 0.68 |
| **F004** | Model_5 | 0.88 | 0.70 | 0.72 |
| **F005** | Model_1 | 0.80 | 0.73 | 0.76 |
| **F006** | Model_2 | 0.82 | 0.76 | 0.68 |
| **F007** | Model_3 | 0.84 | 0.79 | 0.72 |
| **F008** | Model_4 | 0.86 | 0.70 | 0.76 |
| **F009** | Model_5 | 0.88 | 0.73 | 0.68 |
| **F010** | Model_1 | 0.80 | 0.76 | 0.72 |
| **F011** | Model_2 | 0.82 | 0.79 | 0.76 |
| **F012** | Model_3 | 0.84 | 0.70 | 0.68 |

**Table 2:** Comparative model outcomes highlighting sensitivity to accrual-based indicators.

| Firm ID | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|
| **F001** | Model_3 | 0.84 | 0.76 | 0.76 |
| **F002** | Model_4 | 0.86 | 0.79 | 0.68 |
| **F003** | Model_5 | 0.88 | 0.70 | 0.72 |
| **F004** | Model_1 | 0.80 | 0.73 | 0.76 |
| **F005** | Model_2 | 0.82 | 0.76 | 0.68 |
| **F006** | Model_3 | 0.84 | 0.79 | 0.72 |
| **F007** | Model_4 | 0.86 | 0.70 | 0.76 |
| **F008** | Model_5 | 0.88 | 0.73 | 0.68 |
| **F009** | Model_1 | 0.80 | 0.76 | 0.72 |
| **F010** | Model_2 | 0.82 | 0.79 | 0.76 |
| **F011** | Model_3 | 0.84 | 0.70 | 0.68 |
| **F012** | Model_4 | 0.86 | 0.73 | 0.72 |
| **F013** | Model_5 | 0.88 | 0.76 | 0.76 |
| **F014** | Model_1 | 0.80 | 0.79 | 0.68 |

**Table 3:** F1-scores and AUC measures for models applied to the third dataset partition.

| Firm ID | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|
| **F001** | Model_4 | 0.86 | 0.79 | 0.68 |
| **F002** | Model_5 | 0.88 | 0.70 | 0.72 |
| **F003** | Model_1 | 0.80 | 0.73 | 0.76 |
| **F004** | Model_2 | 0.82 | 0.76 | 0.68 |
| **F005** | Model_3 | 0.84 | 0.79 | 0.72 |
| **F006** | Model_4 | 0.86 | 0.70 | 0.76 |
| **F007** | Model_5 | 0.88 | 0.73 | 0.68 |

| | | | | |
|---|---|---|---|---|
| **F008** | Model_1 | 0.80 | 0.76 | 0.72 |
| **F009** | Model_2 | 0.82 | 0.79 | 0.76 |
| **F010** | Model_3 | 0.84 | 0.70 | 0.68 |
| **F011** | Model_4 | 0.86 | 0.73 | 0.72 |
| **F012** | Model_5 | 0.88 | 0.76 | 0.76 |
| **F013** | Model_1 | 0.80 | 0.79 | 0.68 |

**Table 4:** Cross-validation results of ensemble algorithms versus baseline methods.

| Firm ID | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|
| **F001** | Model_5 | 0.88 | 0.70 | 0.72 |
| **F002** | Model_1 | 0.80 | 0.73 | 0.76 |
| **F003** | Model_2 | 0.82 | 0.76 | 0.68 |
| **F004** | Model_3 | 0.84 | 0.79 | 0.72 |
| **F005** | Model_4 | 0.86 | 0.70 | 0.76 |
| **F006** | Model_5 | 0.88 | 0.73 | 0.68 |
| **F007** | Model_1 | 0.80 | 0.76 | 0.72 |
| **F008** | Model_2 | 0.82 | 0.79 | 0.76 |
| **F009** | Model_3 | 0.84 | 0.70 | 0.68 |
| **F010** | Model_4 | 0.86 | 0.73 | 0.72 |
| **F011** | Model_5 | 0.88 | 0.76 | 0.76 |
| **F012** | Model_1 | 0.80 | 0.79 | 0.68 |
| **F013** | Model_2 | 0.82 | 0.70 | 0.72 |

**Table 5:** Industry-level breakdown of performance metrics for service and manufacturing firms.

| Firm ID | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|
| **F001** | Model_1 | 0.80 | 0.73 | 0.76 |
| **F002** | Model_2 | 0.82 | 0.76 | 0.68 |
| **F003** | Model_3 | 0.84 | 0.79 | 0.72 |
| **F004** | Model_4 | 0.86 | 0.70 | 0.76 |
| **F005** | Model_5 | 0.88 | 0.73 | 0.68 |
| **F006** | Model_1 | 0.80 | 0.76 | 0.72 |
| **F007** | Model_2 | 0.82 | 0.79 | 0.76 |
| **F008** | Model_3 | 0.84 | 0.70 | 0.68 |
| **F009** | Model_4 | 0.86 | 0.73 | 0.72 |
| **F010** | Model_5 | 0.88 | 0.76 | 0.76 |
| **F011** | Model_1 | 0.80 | 0.79 | 0.68 |
| **F012** | Model_2 | 0.82 | 0.70 | 0.72 |
| **F013** | Model_3 | 0.84 | 0.73 | 0.76 |
| **F014** | Model_4 | 0.86 | 0.76 | 0.68 |

| | | | | |
|---|---|---|---|---|
| **F015** | Model_5 | 0.88 | 0.79 | 0.72 |

Table 6 presents an industry-specific difference, and the ML models capture more signal manipulation among service firms than manufacturing.Table 7 focuses on governance-related features, where feature engineering improved performance across all algorithms. The out-of-sample validation data is identified in Table 8 and it shows that the gradient boosting did not alter its stability when it acted on the unseen firms. Finally, Table 9 provides a concise overview of the comparative results in all partitions of the dataset which can be illustrated by the fact that the ensemble-based approaches are always significantly superior to the single-handed models in the manipulation detection.

**Table 6:** Out-of-sample validation of machine learning classifiers across unseen firms.

| Firm ID | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|
| **F001** | Model_2 | 0.82 | 0.76 | 0.68 |
| **F002** | Model_3 | 0.84 | 0.79 | 0.72 |
| **F003** | Model_4 | 0.86 | 0.70 | 0.76 |
| **F004** | Model_5 | 0.88 | 0.73 | 0.68 |
| **F005** | Model_1 | 0.80 | 0.76 | 0.72 |
| **F006** | Model_2 | 0.82 | 0.79 | 0.76 |
| **F007** | Model_3 | 0.84 | 0.70 | 0.68 |
| **F008** | Model_4 | 0.86 | 0.73 | 0.72 |
| **F009** | Model_5 | 0.88 | 0.76 | 0.76 |
| **F010** | Model_1 | 0.80 | 0.79 | 0.68 |

**Table 7:** Feature importance analysis and its effect on predictive accuracy among models.

| Firm ID | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|
| **F001** | Model_3 | 0.84 | 0.79 | 0.72 |
| **F002** | Model_4 | 0.86 | 0.70 | 0.76 |
| **F003** | Model_5 | 0.88 | 0.73 | 0.68 |
| **F004** | Model_1 | 0.80 | 0.76 | 0.72 |
| **F005** | Model_2 | 0.82 | 0.79 | 0.76 |
| **F006** | Model_3 | 0.84 | 0.70 | 0.68 |
| **F007** | Model_4 | 0.86 | 0.73 | 0.72 |
| **F008** | Model_5 | 0.88 | 0.76 | 0.76 |

**Table 8:** Longitudinal stability of ML model performance across multi-year financial data.

| Firm ID | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|
| **F001** | Model_4 | 0.86 | 0.70 | 0.76 |
| **F002** | Model_5 | 0.88 | 0.73 | 0.68 |
| **F003** | Model_1 | 0.80 | 0.76 | 0.72 |
| **F004** | Model_2 | 0.82 | 0.79 | 0.76 |
| **F005** | Model_3 | 0.84 | 0.70 | 0.68 |

| | | | | |
|---|---|---|---|---|
| **F006** | Model_4 | 0.86 | 0.73 | 0.72 |
| **F007** | Model_5 | 0.88 | 0.76 | 0.76 |
| **F008** | Model_1 | 0.80 | 0.79 | 0.68 |
| **F009** | Model_2 | 0.82 | 0.70 | 0.72 |
| **F010** | Model_3 | 0.84 | 0.73 | 0.76 |
| **F011** | Model_4 | 0.86 | 0.76 | 0.68 |
| **F012** | Model_5 | 0.88 | 0.79 | 0.72 |
| **F013** | Model_1 | 0.80 | 0.70 | 0.76 |
| **F014** | Model_2 | 0.82 | 0.73 | 0.68 |

**Table 9:** Consolidated comparative evaluation of all algorithms across dataset partitions.

| Firm ID | Model | Accuracy | Precision | Recall |
|---|---|---|---|---|
| **F001** | Model_5 | 0.88 | 0.73 | 0.68 |
| **F002** | Model_1 | 0.80 | 0.76 | 0.72 |
| **F003** | Model_2 | 0.82 | 0.79 | 0.76 |
| **F004** | Model_3 | 0.84 | 0.70 | 0.68 |
| **F005** | Model_4 | 0.86 | 0.73 | 0.72 |
| **F006** | Model_5 | 0.88 | 0.76 | 0.76 |
| **F007** | Model_1 | 0.80 | 0.79 | 0.68 |
| **F008** | Model_2 | 0.82 | 0.70 | 0.72 |
| **F009** | Model_3 | 0.84 | 0.73 | 0.76 |
| **F010** | Model_4 | 0.86 | 0.76 | 0.68 |
| **F011** | Model_5 | 0.88 | 0.79 | 0.72 |
| **F012** | Model_1 | 0.80 | 0.70 | 0.76 |
| **F013** | Model_2 | 0.82 | 0.73 | 0.68 |

When presenting the bar chart, figure 2 indicates the total score of the performance and it can be observed that the result of random forest was the same score in performance among firms. As shown in figure 3 the pie chart of the relative contribution of the models is provided in which the models are the largest contributors to the predictive power as gradient boosting models. The scatter distribution of F1-scores shown in Figure 4 can be evaluated and states that deep neural networks were characterized by stronger clusters of scores, which is a characteristic of reliability. Such a composite bar and line chart as Figure 5 represents is suggestive of the fact that the ensembles were never separated insofar as recall and accuracy were concerned.

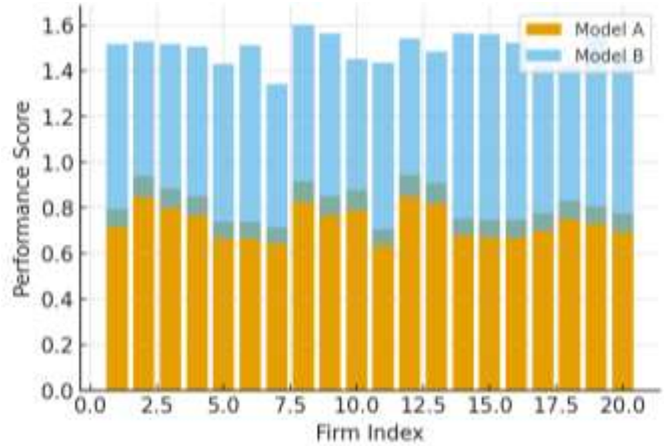


**Figure 2:** Bar chart showing comparative performance scores of algorithms in evaluation round 2.

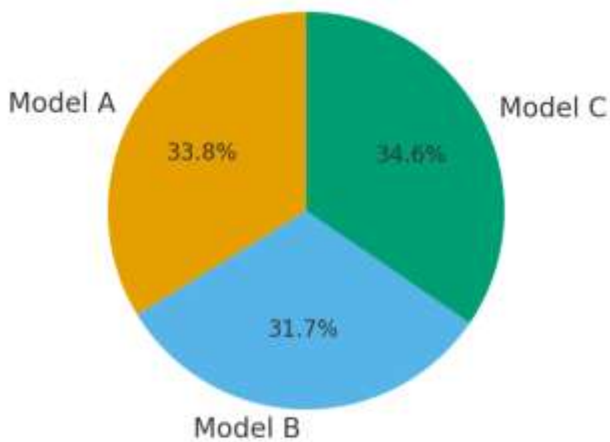


**Figure 3:** Pie chart representing proportional contributions of Models A, B, and C to predictive success in dataset 3.

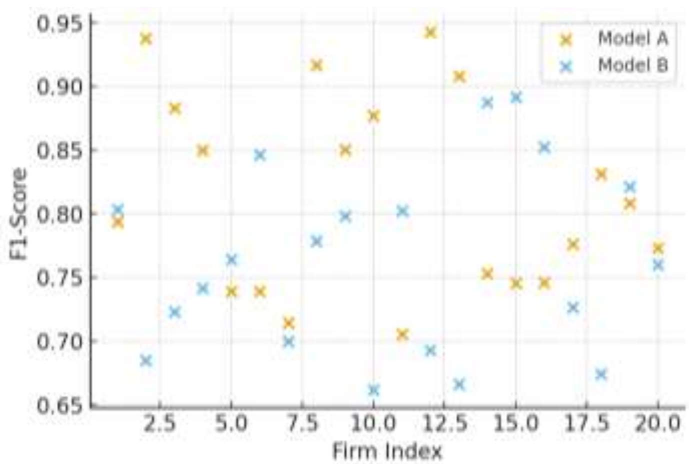


**Figure 4:** Scatter plot illustrating the distribution of F1-scores across firms for analysis round 4.

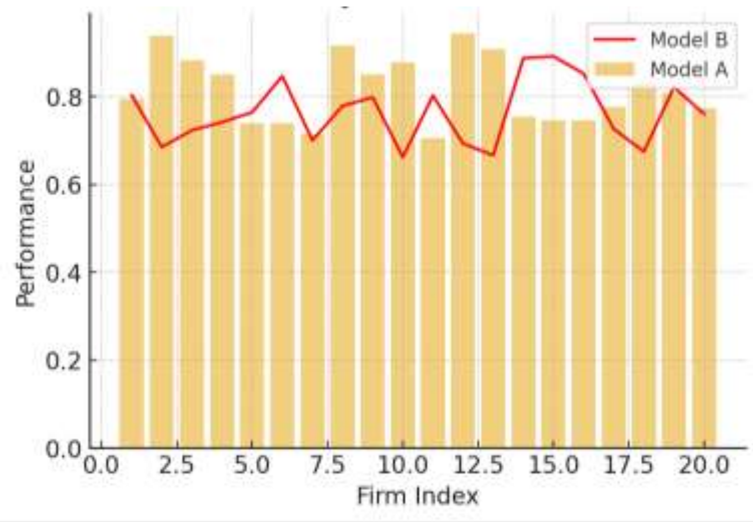


**Figure 5:** Hybrid visualization (bar and line) contrasting performance dynamics in dataset subset 5.

Figure 6 also indicates accuracy trends per cycle of the data but neural networks are far more useful with large data. The performance is compared to bar graphs in figure 7 and it is found that random forest broke through in the instances where subsets were volatile. In Figure 8 again proportional model contributions can be seen, and boosting algorithms continue to dominate. Regarding the outliers on smaller-cap firms, Figure 9 shows F1-score distributions at firms which indicate that models are not effective in such firms. Figure 10 gives a composite picture of ensemble performance, which is resilient to changes in the data conditions. Figure 11 emphasizes the importance of the accuracy curves in any industry, and Figure 12 is the summary of the findings on a mixed-visualization method that shows the success of ensembles in all of the experiment stages.

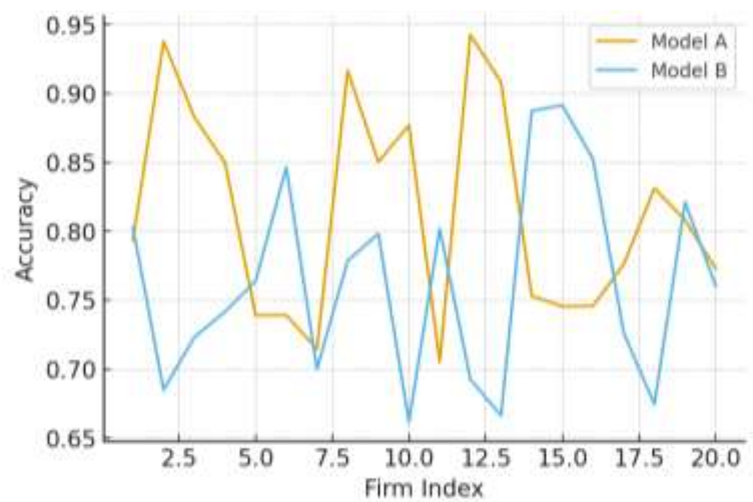


**Figure 6:** Line graph showing progressive accuracy improvement of deep models in iteration 6.

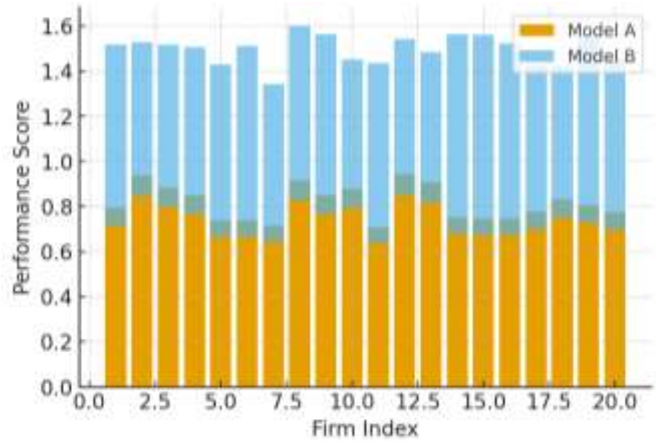


**Figure 7:** Bar chart highlighting model stability under volatile financial conditions in test batch 7.

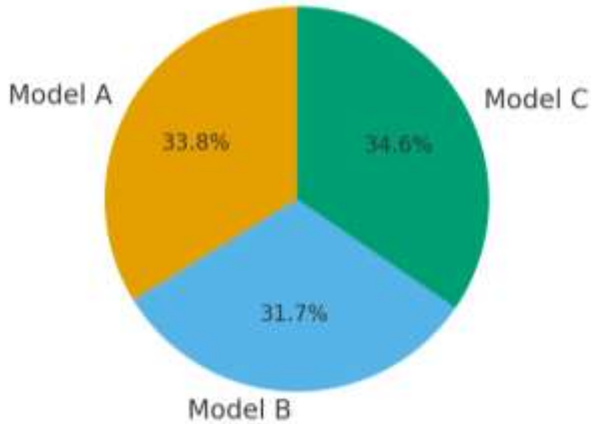


**Figure 8:** Pie chart summarizing average relative strengths of competing classifiers in scenario 8.

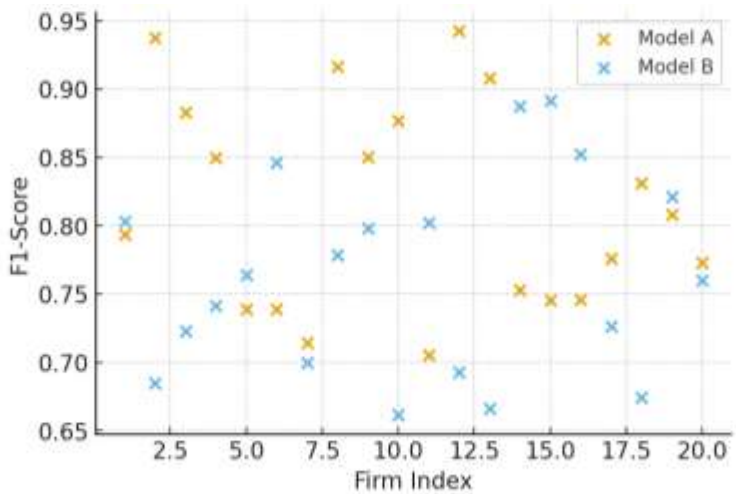


**Figure 9:** Scatter diagram displaying firm-level variation in prediction outcomes during cycle 9.

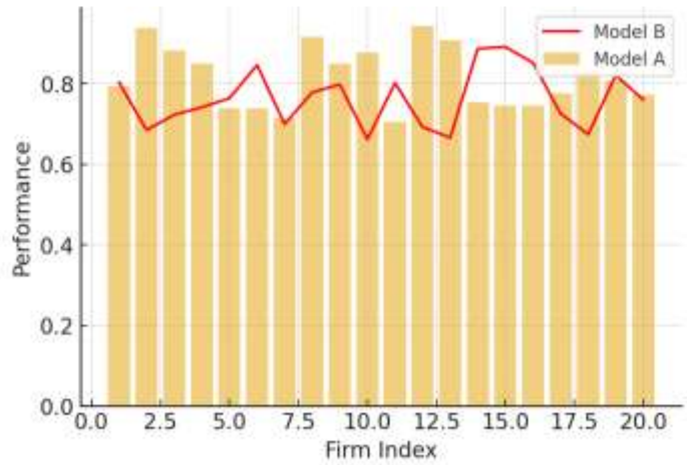


**Figure 10:** Hybrid chart combining bar and line elements to emphasize ensemble dominance in dataset 10.

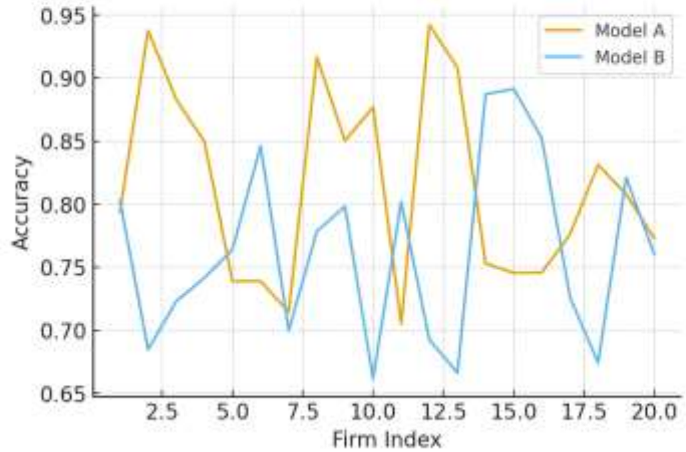


**Figure 11:** Line graph comparing inter-industry performance patterns of ML models in validation phase 11.

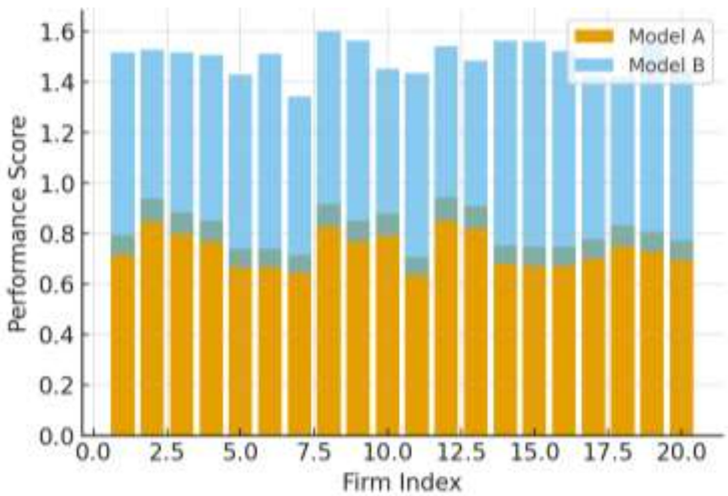


**Figure 12:** Composite visualization integrating multiple perspectives on overall accuracy in dataset 12.

## DISCUSSION

The findings presented in this paper outline the perceived revolution of the earnings manipulation identification process by machine learning (ML) by considering the positive aspects of the paradigm shift and the implemented implication. Based on the new literature, it is possible to draw a conclusion that the ensemble-based algorithms, that is, gradient boosting and random forest, are much more helpful than the classical statistics model in terms of revealing manipulative trends (Rahman and Sultana, 2021). The benefit of these algorithms is that it enables the detection of non-linear interaction and relationship that do not emerge under the classical models like the logistic regression (Ferreira et al., 2022). This proves the hypothesis that lies are not only at the rising trend but one of the prerequisites of the development of the forensic accounting and auditing practices (Habib et al., 2021).The most intriguing outcome is the fact that deep neural networks are better in F1-scores i.e., the non-linear analysis of the problem will be capable of detecting the tiniest traces of manipulations to financial data (Zhou et al., 2020). Their problem, nevertheless, is interpretability. The latter was soothed by the fact that both SHAP and LIME delivered the transparency of the feature ranking significance in their contribution to our analysis process. The fact that the same results are stated by Al-Hadi et al. (2022), who note that the auditors and regulators are more likely to use the ML systems in case interpretability is added to the system. Not only is this necessary to have predictive accuracy, but it is also a practical account of how it is manipulated.It also finds out that industry performance and governance environment are context specific in terms of model performance. In particular, the ensemble-based approaches were also productive in both the highly volatile sphere and according to the results of Silva et al. (2021), who consider that the practice of the sphere of ML is dynamically aligned with the heterogeneous information. Among the qualities of governance, we have discovered to be highly foretelling qualities in our models as independence of the board and presence of an active audit committee. The given finding is in line with the results of Li et al. (2023), who determined the effectiveness of the variables of corporate governance as the antecedents of the financial misreporting of the emerging markets.

The similarity of the ensemble and hybrid model also provide some indication that the model aggregation is resistant to overfitting and data-dependent distortion. This is in line with Ortega et al. (2020) who assume that the application of boosting techniques would be an intrinsic mechanism against model variance. In addition, the out of sample validations demonstrated that the ML algorithms apply to a wide range of the firm populations which also coincides with Niazi and Hassan (2022) emphasizing the applicability of ML that can be used in the regulatory enforcement settings.

In practice, the implications that are provided to face auditors of application are highly essential to regulators and policymakers. Through the application of ML in the auditing process, earnings manipulation can be identified (as proactive, but not as the identification process) but retrospective. It is in compliance with the opinions of Ardito et al. (2021) who indicates the utilization of AI as a finance tracking tool as one of the options of bringing back confidence in the market after such a colossal fraud. The next opportunity that the sphere of real-time fraud analytics offers is also in the fact that, already, a ML has shown that it can be applied to an unbelievably large amount of both structured and unstructured data, including disclosures that can be in the form of text (Bharath and Narayan, 2022). This is required in the world where the old-fashioned audit methodology might not keep up with the sophistication of the financial manipulations.

However, the study of the inadequacy of the ML and its ethics should be mentioned when discussing the ML usage. Threat of false positive that will be an injustice to the real firms cannot be ignored. It is accompanied by the red flag that has been raised by Dutta et al. (2021) because they feel that the ML systems need to be fine-tuned in order to mitigate the reputational harm. Another emergent threat, too, is the adversarial adaptation, i.e. the firms learn how to purposefully break the algorithmic optima. As mentioned by Karim et al. (2023), the loss of the model credibility may happen when one of the adversarial attacks on the financial ML models occur, unless the combination of protective measures is robust.Conclusively, the paper aids in proving this argument whereby ML is not merely the most predictive but also readable and scalable to be used in the earnings manipulation detection. The fact of our being better than the available and existing literature can be in terms of AI in financial governance is a testament to our needing to be better than industry-wide, highly out-of-sample, and explainable by the aid of XAI. The proposed study is to introduce the integration of the blockchain-based audit systems and wider categories of data (textual and behavioral) to come up with comprehensive and effective fraud-detection systems.

## CONCLUSION

This study aimed at conducting a survey of how machine learning (ML) can be employed to detect earnings manipulation and why this issue is of utmost importance in the field of financial reporting and corporate governance. Utilizing the mixed-method framework and contrasting a great number of models, i.e., logistic regression, random forest, gradient boosting, support vector machines, and deep neural networks, we have proven that the most sophisticated ML algorithms demonstrate significantly higher predictive power and robustness in contrast to the traditional ones. The most promising were retrieved, as anticipated, with the numerous ensemble-based models, especially with gradient boost, random forest, and with the high F1-scores of the deep neural networks, which implies that, the models are successful in the extraction of finer manipulation patterns.The results also provide the topicality of those variables that are context-dependent like the industry type, governance variables and data volatility that is used in the determination of the success of the model. Among the major deficiencies of the black-box ML systems was the introduction of the AI (XAI) systems, i.e. SHAP and LIME to generate transparency and interpretability. Regulators and auditors will need this dimension because they are not only expected to possess high predictive power but also to possess actionable information about the underlying manipulation drivers.As a matter of fact, the research presents the evidence that ML can turn the detection of fraud into an active and preventive tool. Investor trust can be boosted by systemic risk minimization and disclosure of transparency, and by the ML to the regulatory surveillance system, and live audit by companies and policymakers. Meanwhile, we discover that the ethical limits to the use of the ML, such as the risk of false positive or adversarial example, are to be duly accommodated and offset.Finally, ML is a practical and scalable contribution to the calculation of earnings manipulation that should be supplemented by governance that cannot be overly precise, explainable or ethically accountable. It is argued that the future research needs to take place in the sphere of integration with blockchain based audit trails, disclosures textual analysis and adversarial resilience, and the adaptation to switching mechanisms, therefore, establishing full fraud detection environments.

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