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Machine Learning-Based Detection of Financial Statement Fraud: Integrating Beneish Ratios, Linguistics, and Stock Volatility on the Indonesia Stock Exchange

Abdurrochman Halomoan Hasibuan*, Vidyarto Nugroho
Universitas Tarumanagara, Indonesia
Email: abdurrochman.125249201@stu.untar.ac.id*, vidyarton@fe.untar.ac.id

Keywords
Fraudulent Financial Statement; Machine Learning; Beneish M-Score; Sentimen Analysis, MD&A; Gradient Boosting.

Abstract
This research aimed to develop and evaluate a financial statement fraud (FSF) detection model for companies listed on the Indonesia Stock Exchange (IDX) during the 2024–2025 period using a machine learning approach. An ablation study design was employed to test 27 model combinations across three feature scenarios: Beneish M-Score financial ratios, linguistic features extracted from Management Discussion and Analysis (MD&A) texts using the InSet lexicon, and 30-day stock price volatility. Nine classification algorithms were evaluated using precision, recall, and F1-score metrics. The best-performing model combined financial ratios and linguistic features using Gradient Boosting, achieving an F1-score of 0.545. In contrast, the addition of stock price volatility as a feature did not improve model performance and instead reduced the classification ability of all tested algorithms. These findings indicate that the Indonesian capital market may have limited ability to anticipate indications of financial statement fraud before related information is publicly disclosed. This study concludes that integrating accounting and linguistic information is more effective than relying solely on financial ratios or incorporating market data. These findings contribute to the development of machine learning-based FSF detection literature in Indonesia and provide an alternative approach for auditors, investors, and regulators to enhance the effectiveness of early financial statement fraud detection.

INTRODUCTION

Financial Statement Fraud (FSF) represents a significant threat that undermines trust and stability in global capital markets. Beyond being an accounting violation, FSF involves deliberate misrepresentation or manipulation of financial information intended to deceive stakeholders, potentially resulting in corporate failure, loss of investment value, and broader economic consequences (Rezaee, 2005). This concern is supported by the global report of the Association of Certified Fraud Examiners (ACFE) in 2024, which found that although FSF is the least frequently occurring fraud scheme, accounting for only 5% of reported cases, it causes the most substantial financial damage, with a median loss of $766,000 per case (ACFE, 2024).

This issue is also highly relevant in the Indonesian capital market. Despite the established supervisory frameworks implemented by regulators such as the Financial Services Authority (Otoritas Jasa Keuangan [OJK]) and the Indonesia Stock Exchange (IDX), evidence indicates that financial statement manipulation continues to occur in the Indonesian capital market (Wibowo & Istianah, 2025). This phenomenon is not isolated and has affected several prominent companies, including state-owned enterprises. These cases demonstrate that FSF remains a significant and urgent challenge requiring more sophisticated and proactive detection mechanisms. Several notable FSF cases in Indonesia are presented in Table 1.

Table 1. Summary of Leading Financial Statement Fraud Cases in Indonesia

Company Name	Year of Occurrence	Case Summary	Impact
PT Garuda Indonesia (Persero) Tbk	2018	Prematurely acknowledging revenue from a cooperation agreement with PT Mahata Aero Teknologi, which artificially converts significant losses into pseudo-net profit (detikFinance, 2019; Dewi et al., 2023).	Administrative sanctions from the OJK and IDX, the freezing of the licenses of the auditors involved, the sharp decline in stock prices, and the destruction of public trust in national airlines (Dewi et al., 2023; Financial Services Authority, 2019).
PT Asuransi Jiwasraya (Persero)	2006-2019	Systematically carrying out accounting engineering practices (*window dressing*) for many years to present "pseudo-profits" and cover up solvency conditions that are actually severely negative (CNBC Indonesia, 2020; Hikam, 2020).	State losses reach trillions of rupiah, massive defaults on customer policies, legal proceedings against the board of directors, and a crisis of trust in the state-owned insurance industry (BPK, 2020; Yuliana, 2022).
PT Waskita Karya (Persero) Tbk	2004-2022	Allegations of manipulation of financial statements by reporting profits over the years despite consistently negative cash flows from operating activities. This practice was revealed by the Ministry of SOEs as the presentation of reports that are not in accordance with real conditions (Ministry of SOEs, 2023; Tempo.co, 2023; CNN Indonesia, 2023).	Drastic decline in stock prices, debt defaults, withdrawal of State Capital Participation (PMN), investigations by BPKP, and a plummeting investor confidence in SOEs in the work sector (Kumparan, 2023; CNN Indonesia, 2023).

Source: Compiled from various news sources and official reports

The detection of Financial Statement Fraud (FSF) has undergone continuous evolution in response to the limitations of existing methods and the increasingly sophisticated strategies employed by fraud perpetrators. Major corporate scandals have repeatedly highlighted the “repeated failures of audit methodologies” in detecting and preventing fraudulent activities (Lokanan & Sharma, 2025). Traditional audit methodologies, which rely heavily on manual procedures, have limitations due to their inability to examine entire data populations, making them vulnerable to fraudulent schemes specifically designed to avoid detection through audit sampling. Furthermore, these approaches often face challenges in identifying collusion among top-level management and distinguishing between unintentional errors and deliberate manipulation, particularly when auditors experience client pressure or are influenced by confirmation bias (Lokanan & Sharma, 2025).

In response to the limitations of traditional audit approaches, researchers developed more systematic quantitative models. One of the most widely recognized models is the Beneish M-Score, a forensic accounting model that utilizes a set of financial ratios to estimate the likelihood of earnings manipulation (Narsa et al., 2023). This model has demonstrated effectiveness as a cost-efficient tool for generating early warning signals (red flags) of potential financial statement manipulation. Several studies conducted in the Indonesian market have also confirmed the predictive ability of the Beneish model, showing that certain ratios, such as the Gross Margin Index (GMI) and Total Accruals to Total Assets (TATA), are significant indicators in detecting FSF (Tarjo & Herawati, 2015).

However, rule-based static models such as the Beneish M-Score also have limitations. Over time, fraud perpetrators may understand how these models operate and manipulate financial figures to avoid detection. These limitations have encouraged the development of a new generation of FSF detection methods supported by artificial intelligence, particularly machine learning (ML) (Lu et al., 2025). Unlike static models, ML algorithms can learn from historical data and identify complex, nonlinear, and hidden patterns that may not be detected through conventional analytical methods (Wibowo & Istianah, 2025; Lokanan & Sharma, 2025; Aftabi et al., 2023). Various studies have demonstrated the effectiveness of ML approaches, where algorithms such as Decision Trees, Neural Networks, Support Vector Machines (SVM), and ensemble learning models, including Gradient Boosting and Random Forest, have consistently achieved strong performance in distinguishing fraudulent companies from non-fraudulent companies (Kirkos et al., 2007; Achakzai & Peng, 2023; Lokanan & Sharma, 2025; Wibowo & Istianah, 2025).

The transition from manual auditing procedures to static financial ratio models and, subsequently, to dynamic ML-based models represents a significant technological advancement in FSF detection. On one hand, auditors, regulators, and researchers continue to develop increasingly sophisticated detection tools. On the other hand, fraud perpetrators continuously adapt by creating more complex schemes to avoid detection. When auditors relied primarily on manual procedures, management could conduct relatively simple forms of manipulation. When ratio-based models such as the Beneish M-Score were introduced, fraud perpetrators adapted by engineering financial indicators to avoid triggering detection thresholds. The emergence of ML represents a direct response to the increasing sophistication of fraudulent practices. This indicates that no single detection method can permanently resolve FSF challenges; instead, detection approaches must continuously innovate and evolve. This research integrates multiple data sources into an ML-based detection framework and introduces additional variables, positioning the study not only as a technical application but also as a contribution to strengthening capital market integrity (Abiodun, Jinadu, Alaka, Igba, & Ezeh, 2024; Ahmmed, 2025; Ejiofor, 2023; Juma'h, Chuang, & Harfouche, 2026; Ma, 2025).

Despite these advancements, previous studies have predominantly focused on either financial ratios or textual analysis separately, with limited integration of multiple data sources in the Indonesian context. Research combining financial ratios, linguistic features, and market-based variables simultaneously remains limited, particularly when utilizing recent data and advanced machine learning techniques (Chen & Ji, 2025; Drakulic, 2026; El-Harouni & Ouda, 2026; Liu & Jia, 2025; Venkataraman & Kerry, 2026). Furthermore, the effectiveness of stock price volatility as a leading indicator of FSF in the Indonesian capital market has not been systematically examined. The novelty of this research lies in three aspects: first, the integration of three distinct data sources—Beneish M-Score financial ratios, linguistic features extracted from Management Discussion and Analysis (MD&A) texts using the InSet lexicon, and stock price volatility—within a unified detection framework; second, the application of an ablation study design that systematically evaluates 27 model combinations across three feature scenarios and nine classification algorithms to identify the most effective configuration; and third, the use of SHAP analysis to provide interpretable insights into the decision-making mechanisms of the best-performing models, an approach that remains relatively limited in FSF research in Indonesia.

Based on this background, this study aimed to develop and evaluate a financial statement fraud detection model for companies listed on the Indonesia Stock Exchange during the 2024–2025 period by integrating financial ratios, linguistic features, and stock price volatility using a machine learning approach. It also aimed to identify the most effective feature-algorithm combination for early FSF detection. This research was expected to provide both theoretical and practical contributions. Theoretically, this study contributes to the development of FSF detection literature by providing empirical evidence regarding the effectiveness of multimodal data integration in the Indonesian capital market context and by expanding understanding of the role of linguistic features in identifying financial manipulation. Practically, the findings provide an alternative detection model that can be utilized by auditors, investors, and regulators, including the Financial Services Authority (Otoritas Jasa Keuangan [OJK]) and the Indonesia Stock Exchange (IDX), to improve the early identification of potential financial statement fraud and strengthen the integrity and reliability of the Indonesian capital market.

METHOD

This study employed a quantitative approach with explanatory and predictive research designs. The explanatory design was used to examine the relationships between the independent variables (financial ratios, linguistic features, and stock price volatility) and the dependent variable (financial statement fraud). The predictive design focused on developing and evaluating machine learning models to estimate the probability of financial statement fraud and support the development of an early detection system.

The research object was the phenomenon of financial statement fraud in publicly listed companies. The study focused on non-financial companies listed on the Indonesia Stock Exchange (IDX), excluding banking and pure insurance sectors due to their distinct reporting standards and financial structures. However, IDX-listed companies classified under the Financial Services sector, such as multifinance companies, securities firms, and financial holding companies, were included because their financial reporting formats and disclosure requirements were comparable to other non-financial issuers and were compatible with the application of Beneish M-Score ratios. The research sample was selected using purposive sampling based on predetermined criteria relevant to the research objectives.

This study used secondary data obtained from three sources: (1) financial statement data used to calculate Beneish M-Score ratios, collected from annual reports and the IDX website; (2) Management Discussion and Analysis (MD&A) text data extracted from annual reports for linguistic analysis using the InSet lexicon; and (3) stock price data used to measure volatility, obtained from Yahoo Finance and IDX, covering 30 trading days prior to financial statement publication.

Data analysis was conducted through several stages. The first stage involved data preprocessing, including MD&A text cleaning, missing value handling, and numerical feature normalization. The second stage involved feature extraction, including the calculation of financial ratios based on the Beneish M-Score model, extraction of linguistic features using the InSet lexicon, and calculation of stock price volatility based on stock returns. The third stage involved model development using an ablation study design, which evaluated 27 model combinations consisting of three feature scenarios: X1 (M-Score only), X2 (M-Score and linguistic features), and X3 (M-Score, linguistic features, and volatility), combined with nine classification algorithms: Naïve Bayes, Logistic Regression, Decision Tree, Random Forest, Gradient Boosting, XGBoost, Support Vector Machine (SVM), K-Nearest Neighbors (KNN), and Neural Network.

The fourth stage involved model evaluation using precision, recall, and F1-score metrics, with the dataset divided into 70% training data and 30% testing data. The fifth stage involved model interpretation using SHAP (SHapley Additive exPlanations) analysis to identify influential features and explain model predictions. All analyses were performed using Python with Scikit-learn, XGBoost, and SHAP libraries.

RESULTS AND DISCUSSION

Results

After evaluating through Feature Importance to determine the global ranking of features, this study uses SHAP (SHapley Additive exPlanations) analysis to dissect the model's decision-making mechanisms in more depth. If conventional feature importance only shows which variables are considered important by the algorithm, SHAP analysis provides an idea of the direction and magnitude of each variable's contribution to the probability of a company being classified as potential fraud.

Model 1: M-Score (Naïve Bayes)

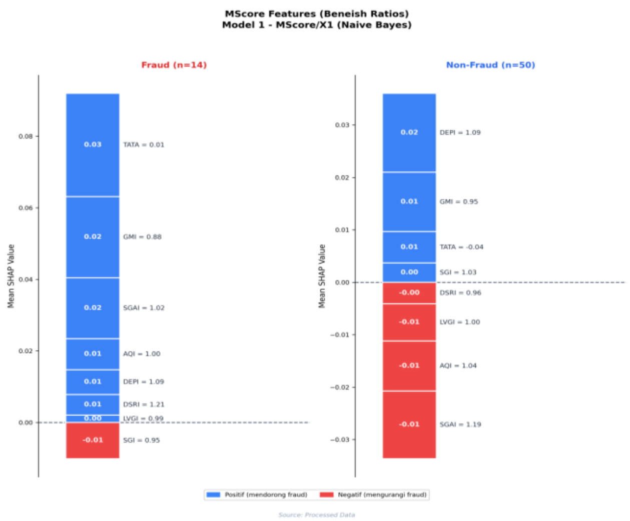

Figure 1. Number of Indonesian Stock Investors
Source: Indonesia Stock Exchange (IDX), 2025

In the group of companies identified as *potential fraud*, there are financial signals that consistently drive model predictions:

1. TATA (Total Accruals to Total Assets): Being the strongest driving factor (0.03 SHAP value). The high non-cash accrual component is the main technical indicator of potential fraud through profit manipulation.
2. GMI (Gross Margin Index): The decrease in gross profit margin at 0.88 made a significant contribution (0.02 SHAP value). This confirms the existence of economic pressure that triggers potential fraud.
3. SGAI (Sales, General & Admin Index): An inefficient increase in operational costs acts as a complementary signal that increases the probability score of potential fraud.

In contrast, in companies classified as non-fraud, variables such as SGAI and AQI contribute negatively (red bars). This means that stability in operational costs and asset quality are the restraints that keep companies away from the classification of potential fraud.

Model 2: Integration of M-Score and Linguistics (Gradient Boosting)

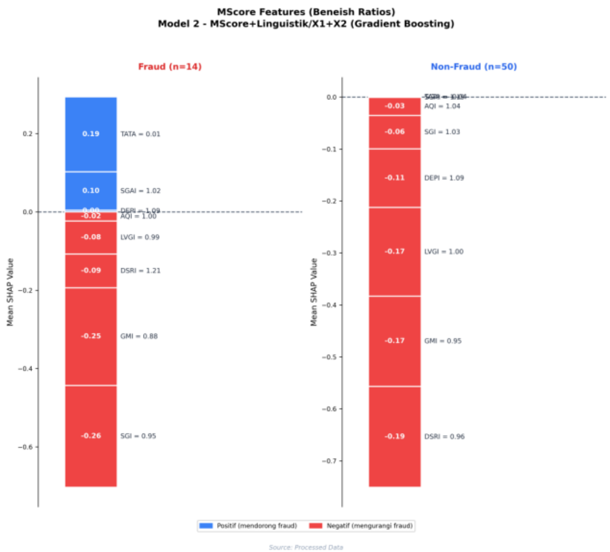

Figure 2. SHAP Analysis Model 2 – Mscore
Source: Data processed using Python with SHAP library (2025)

On financial variables, the Gradient Boosting model shows a very sharp pattern:

1. TATA (Total Accruals to Total Assets) = 0.01: Remains the most dominant financial variable with a contribution of 0.19 SHAP value in the potential fraud group. This reaffirms that the manipulation of profits through the accrual component is the "digital footprint" that cannot be hidden at all.
2. SGAI (Sales, General & Admin Index) = 1.02: Provides a positive boost (0.10 SHAP value), indicating that operational cost inefficiencies often accompany potential fraud schemes.
3. Non-Fraud Factors: In the healthy group of companies, the DSRI (-0.19), GMI (-0.17), and LVGI (-0.17) variables showed very long red bars. This means that stability on receivables, profit margins, and *leverage* levels are the strongest holding combinations that convince the model that the company is not cheating.

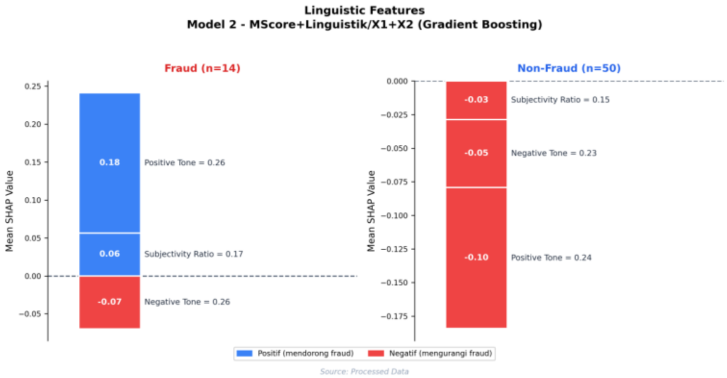

Figure 3. SHAP Analysis Model 2 - Linguistic Features
Source: Data processed using Python with SHAP library (2025)

The first part of the visualization shows the contribution of the tone and subjectivity of the MD&A report:

1. Positive Tone (0.26): Being the strongest driver (0.18 SHAP value) for the classification of potential fraud. This finding is particularly interesting because it indicates a pattern of *over-optimism*. Management in potential fraud companies tends to use very positive language excessively to cover up financial anomalies or build a positive image in the midst of the company's actual problematic conditions.
2. Subjectivity Ratio (0.17): Makes a positive contribution (0.06 SHAP value). This suggests that narratives that are opinional or subjective, rather than objective facts, increase the risk of companies being detected as potential fraud.
3. Non-Fraud Characteristics: In contrast, in the non-fraud group, a moderate *Positive Tone* value (0.24) actually makes a large negative contribution (-0.10 SHAP value), which means that in healthy companies, a positive tone is considered a reflection of real conditions and keeps the company away from the label of potential fraud.

Model 3: Multidimensional Integration (Random Forest - All Features)

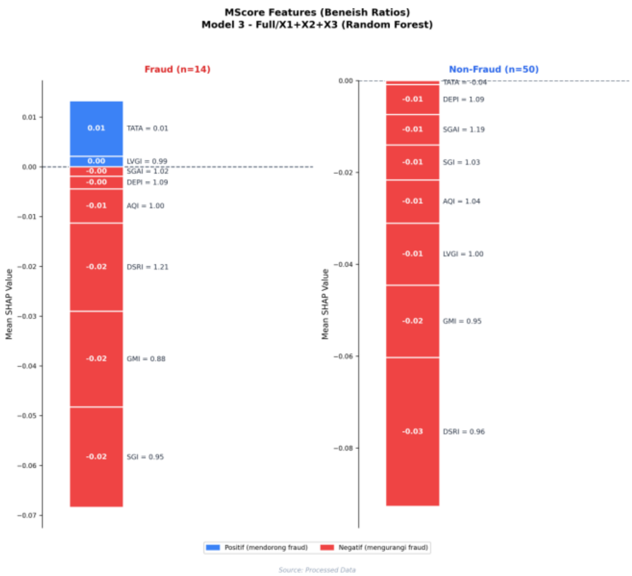

Figure 4. SHAP Analysis Model 3 – Mscore
Source: Data processed using Python with SHAP library (2025)

Based on data on MScore Features - Model 3:

1. TATA (Total Accruals to Total Assets) = 0.01: This is the only financial variable that provides a significant positive boost (+0.01 SHAP value) in the potential fraud group.
2. Anomalies in Other Ratios: In contrast to the previous model, variables such as SGI, GMI, and DSRI actually contribute negatively (red bars) to fraud predictions, even in the potential fraud group. Critically, this shows that in a Random Forest algorithm with too many features, these ratios lose their detectability and actually make it difficult for the model to confirm potential fraud status.

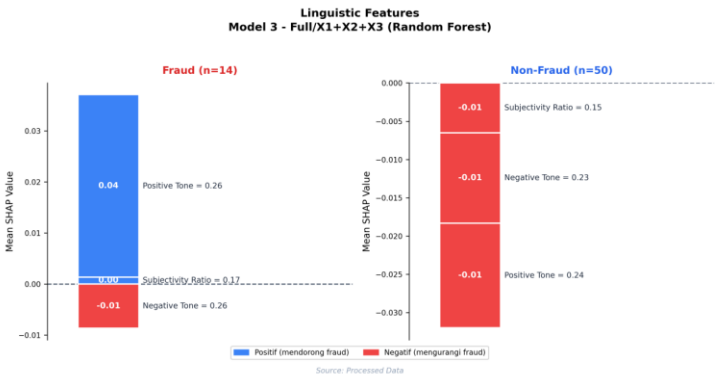

Figure 5. SHAP Analysis Model 3 - Linguistic Features
Source: Data processed using Python with SHAP library (2025)

Based on the data in Linguistic Features - Model 3:

1. Positive Tone (0.26): Remains the main driving factor towards the classification of potential fraud with a contribution of +0.04 SHAP value. This shows the consistency of the behavior of problematic company managers who tend to use highly optimistic narratives as an impression strategy.
2. Subjectivity Ratio (0.17): Provides minimal positive contribution, while Negative Tone (0.26) actually acts as a holding factor (-0.01).

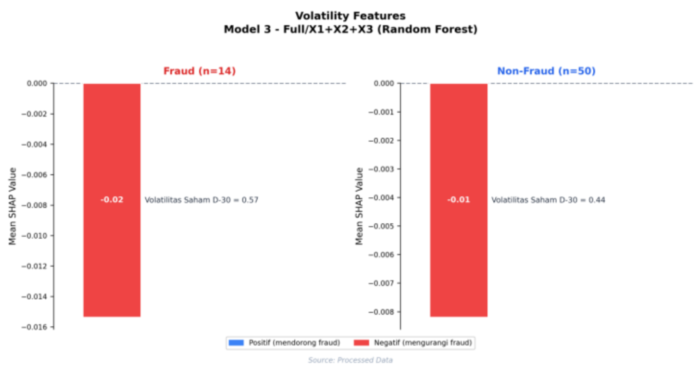

Figure 6. SHAP Analysis Model 3 - Volatility Features
Source: Data processed using Python with SHAP library (2025)

Based on data on Volatility Features - Model 3, D-30 Stock Volatility (0.57): In the potential fraud group, this market variable surprisingly contributes negatively (-0.02 SHAP value).

Theoretically, high volatility is usually associated with risk. However, SHAP points out that for this model, higher volatility values actually keep companies away from the classification of potential fraud. This proves the previous argument that the external variable (X3) acts as noise that is out of sync with the internal cheating signal, thus confusing the algorithm's decision-making process.

The results of the experiment provide crucial findings regarding the effectiveness of integrating internal and external variables in the detection of financial statement fraud. The main point in this discussion is the fact that the addition of the stock price volatility variable (X3) does not automatically increase the sophistication of the model, but rather decreases the performance of the equilibrium metric (F1-Score).

Research Hypothesis Analysis

Based on the results of the model test in Chapter 4, the following are the threshold mean importance and features that meet the significance criteria for each model:

Table 2. Significant Features of each Model

Models	**Number of Features**	**Mean Threshold**	**Significant Features (above the threshold)**
Model 1 (NB)	8	0,0047	GMI, SGAI, AQI, TATA, LVGI, DSRI
Model 2 (GB)	11	0,0909	GMI, SGI, DEPI, TATA, DSRI, LVGI, Positive Tone
Model 3 (RF)	12	0,0833	GMI, Volatilitas D-30, DSRI, Positive Tone

Source: Data processed using Python with Scikit-learn and SHAP libraries (2025)

1. Hypothesis 1 (H1): M-Score Financial Ratio Affects Fraud Detection (Accepted). GMI (Gross Margin Index) consistently emerged as the most dominant predictor, occupying the first position in Feature Importance Model 1 (0.034) and Model 2 (0.197). This suggests that pressure on gross profit margins is the most powerful and consistent signal of financial anomalies in identifying potentially fraudulent companies. The TATA, DSRI, and SGAI variables make complementary contributions that strengthen the overall detection power of the model. The Naive Bayes ability to achieve a Recall of 0.857 in the X1 scenario confirms that internal financial indicators remain at the forefront of early screening for potential fraud.
2. Hypothesis 2 (H2): inSET's Linguistic Features Affect Fraud Detection (Accepted). The integration of linguistic features (X1+X2) proved to result in the most stable model with the highest F1-Score (0.545) and AUC (0.661). This advantage shows that the narrative tone of management provides significant added value beyond financial figures.
3. Hypothesis 3 (H3): Stock Price Volatility Affects Fraud Detection (Rejected). Independently, volatility does have an important contribution to the formation of the model (as seen in the feature *importance* of Random Forest). However, the effect is isolated and disharmonious when combined with other internal features, in Model 3, the D-30 Volatility has a Feature Importance value of 0.1077 which exceeds the mean threshold of 0.0833. However, the acceptance of the hypothesis is not solely based on *Feature Importance*, but rather on the real impact of the variable on the overall performance of the model. Evidence

that D-30 volatility does not have a positive effect on FSF detection is shown by three facts: (1) Model 3's F1-Score (0.444) is lower than Model 2's (0.545); (2) all 9 algorithms experience F1 decline when volatility is added; and (3) SHAP Analysis showed a negative value (-0.02) for D-30 volatility in the potential fraud group, meaning that this variable actually pushed the model away from the fraud classification. Thus, H3 is rejected based on the impact on model performance, even though its Feature Importance exceeds the threshold.

4. Hypothesis 4 (H4): Full integration (x1+x2+x3) is the most effective scenario (rejected). This hypothesis is not empirically proven. The results showed that the addition of X3 to the full integration scenario actually lowered the F1-Score from 0.545 to 0.444. This confirms that the integration of all features does not result in the most advanced model.

The phenomenon of F1-Score decreasing when the volatility variable (X3) is added can be explained through the following logical arguments:

1. Statistical Disturbance (*Noise*): Stock price volatility is a highly sensitive variable to macro market sentiment, rumors, and global economic conditions that are often not directly related to the manipulation of financial statements at the company's internal level. Incorporating X3 into the integration model introduces "noise" that obscures the already sharp *fraud* signals in internal data (Financial and Text Ratio).
2. Data Source Misalignment: Financial ratios and MD&A text are static and definite (based on annual reports), while stock volatility is dynamic and external. This misalignment of data characters causes *machine learning* algorithms to have difficulty finding consistent relationship patterns, so their classification power decreases.

Redundancy Effect: The pressure signals that volatility wants to capture are actually represented more accurately through negative tones in linguistic features. As a result, the addition of volatility does not provide unique new information, but rather complicates the algorithm's decision-making process.

CONCLUSION

This study developed a financial statement fraud (FSF) detection model for companies listed on the Indonesia Stock Exchange (IDX) during the 2024–2025 period using a machine learning approach by evaluating 27 model combinations consisting of three feature scenarios and nine classification algorithms. The results showed that Beneish M-Score financial ratios remained the most important source of information for detecting FSF, with the Gross Margin Index (GMI) emerging as the most consistent and dominant predictor. These findings indicate that financial pressure reflected in declining gross profit margins represents a key indicator of potential financial statement manipulation. This study also demonstrated that integrating linguistic features extracted from Management Discussion and Analysis (MD&A) texts using the InSet lexicon improved model performance. The Positive Tone variable emerged as the strongest linguistic predictor, suggesting that companies potentially involved in fraudulent reporting tended to use more optimistic narratives in their corporate disclosures. The combination of financial ratios and linguistic features produced the best performance, with the Gradient Boosting algorithm applied to Model 2 (X1 + X2) achieving an F1-score of 0.545.

In contrast, the addition of stock price volatility measured over the 30 days prior to financial statement publication did not improve model performance. These findings suggest that the Indonesian capital market may have limited ability to anticipate indications of financial statement fraud before related information is officially disclosed. The inclusion of market-based features reduced the classification performance of all tested algorithms, indicating that the quality of information signals may be more important than the quantity of features incorporated into the model. Overall, this study demonstrated that a multimodal approach integrating accounting and linguistic information was more effective than relying solely on financial ratios or incorporating market data. These findings contribute to the development of machine learning-based FSF detection literature in Indonesia and provide an alternative model that can be utilized by auditors, investors, regulators, and other stakeholders to improve the early identification of potential financial statement fraud.

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