The American Journal of Engineering and Technology
ISSN 2689-0984 | Open Access

TYPE Original Research
PAGE NO. 166-175
DOI 10.37547/tajet/Volume07Issue09-11

Enhancing Financial Statement Fraud Detection through Machine Learning: A Comparative Study of Classification Models

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OPEN ACCESS

SUBMITED 05 January 2025
ACCEPTED 11 April 2025
PUBLISHED 17 September 2025
VOLUME Vol.07 Issue 09 2025

CITATION
Mohammad Musa Mia, Abdullah Al Mamun, Md Parvez Ahmed, Sanjida Akter Tisha, S M Ahsan Habib, & Fariha Noor Nitu. (2025). Enhancing Financial Statement Fraud Detection through Machine Learning: A Comparative Study of Classification Models. The American Journal of Engineering and Technology, 7(09), 166–175. https://doi.org/10.37547/tajet/Volume07Issue09-11

Abstract: Financial statement fraud is a persistent challenge that undermines investor trust, corporate governance, and financial market stability. Traditional auditing approaches often fail to capture subtle manipulations within complex financial data, highlighting the need for advanced computational methods. In this study, we investigate the effectiveness of machine learning models in detecting fraudulent financial reporting. Using a publicly available dataset, we applied rigorous preprocessing, feature selection, and feature extraction techniques before evaluating five models: Logistic Regression, Support Vector Machines, Random Forest, Gradient Boosting

Machines, and Deep Neural Networks. The results indicate that Gradient Boosting Machines achieved the best overall performance, with an accuracy of 94%, precision of 91%, recall of 88%, and an AUC-ROC score of 0.96. Random Forest also demonstrated strong performance, particularly in balancing recall and F1-score. These findings suggest that ensemble-based models are highly effective for identifying complex fraud patterns in financial statements. The study provides empirical evidence supporting the integration of machine learning into auditing and financial risk management systems, offering a scalable and reliable approach to strengthen fraud detection practices.

Keywords: Machine Learning, Fraud Detection, Financial Statements, Gradient Boosting, Random Forest, Ensemble Models, Predictive Analytics

Introduction

Financial statement fraud has become a pressing issue in both developed and emerging economies, causing significant losses for investors, corporations, and regulators. High-profile scandals such as Enron, WorldCom, and Parmalat revealed how manipulation of financial statements can mislead stakeholders, undermine trust in capital markets, and destabilize economies. According to the Association of Certified Fraud Examiners (ACFE), financial statement fraud is one of the most costly types of occupational fraud, with median losses far exceeding those from asset misappropriation or corruption (ACFE, 2022). Traditional methods of fraud detection, such as manual audits and rule-based systems, have proven insufficient due to their reliance on retrospective data and limited ability to capture evolving fraud strategies.

With the growth of digital financial records and big data, machine learning (ML) has emerged as a promising tool to enhance fraud detection. ML algorithms can analyze vast amounts of structured and unstructured financial data, detect hidden patterns, and adapt to new forms of fraudulent behavior. Unlike traditional statistical models, ML approaches are capable of handling nonlinear relationships, high-dimensional feature spaces, and imbalanced datasets, which are typical characteristics of financial fraud detection tasks.

This study seeks to design and evaluate a machine learning framework for detecting fraudulent financial statements. We investigate a range of algorithms—including logistic regression, support vector machines, random forests, gradient boosting machines, and deep neural networks—and compare their performance in identifying fraudulent reporting. By doing so, we aim to contribute both theoretically and practically to the growing body of knowledge on AI-driven fraud detection and offer practical guidance for industry adoption.

Literature Review

The detection of fraudulent financial statements has traditionally relied on audit procedures, financial ratio analysis, and statistical methods. Early research focused on developing rule-based models that flagged anomalies in key ratios such as debt-to-equity, current ratio, and profit margins (Beasley, 1996). While these approaches provided useful insights, they were often limited in scalability and adaptability, particularly as fraud schemes became increasingly sophisticated.

The integration of machine learning into fraud detection began gaining momentum in the early 2000s. Kirkos, Spathis, and Manolopoulos (2007) applied decision trees, neural networks, and Bayesian belief networks to financial statement data, finding that machine learning methods outperformed traditional rule-based approaches. Similarly, Cecchini, Aytug, Koehler, and Pathak (2010) demonstrated the potential of support vector machines for detecting misrepresented financial statements, achieving higher classification accuracy than logistic regression models.

Ensemble learning methods have since emerged as a dominant trend in fraud detection research. Perols (2011) conducted a comparative analysis of logistic regression, support vector machines, and random forests, concluding that ensemble methods significantly improve detection rates due to their ability to capture nonlinear relationships. More recently, Rashid, Asim, and others (2020) emphasized the effectiveness of boosting techniques such as XGBoost in fraud detection tasks, highlighting their robustness against imbalanced datasets.

Deep learning approaches have also attracted attention in recent years. Wang and Li (2021) explored the application of deep neural networks to financial statement fraud detection, reporting strong performance in identifying complex fraud patterns, albeit at the cost of interpretability. This raises important questions for practical adoption, as auditors and regulators often require transparent and explainable models (Doshi-Velez & Kim, 2017).

Despite these advances, challenges remain. The scarcity of publicly available fraud datasets limits reproducibility and benchmarking, while class imbalance often skews model performance toward majority (non-fraud) classes. Recent studies advocate for the integration of data resampling techniques (e.g., SMOTE) and hybrid approaches combining statistical models with ML algorithms to address these issues (Nguyen et al., 2018).

In summary, the literature demonstrates clear progress from rule-based auditing methods to advanced machine learning models, with ensemble techniques and deep learning showing particular promise. However, the trade-off between predictive accuracy and model interpretability continues to be a central issue. Our study builds on this body of research by conducting a comparative evaluation of multiple machines learning models and discussing their applicability in industry settings.

Methodology

In this study, we designed a machine learning framework to detect fraudulent activities within financial statements by systematically following six major steps: data collection, data preprocessing, feature selection, feature extraction, model development, and model evaluation. Our approach integrates both statistical methods and advanced machine learning techniques to ensure that the developed models are not only accurate but also interpretable and applicable in real-world auditing and financial forensics.

Data Collection

We began our study by sourcing data from publicly available repositories that provide benchmark datasets for fraud detection in financial statements. The primary dataset was derived from the Enron Financial Statement Fraud Dataset, which has been widely used in previous research due to its comprehensive coverage of fraudulent corporate practices. To strengthen the robustness of our models, we augmented this dataset with financial disclosures from additional corporate fraud cases curated from the UCI Machine Learning Repository and Kaggle datasets focusing on corporate financial irregularities.

The dataset encompassed a wide variety of financial indicators, including balance sheet accounts, income statement figures, and cash flow variables. It also included categorical data such as auditor opinions and company sector classifications. Importantly, each record was labeled as either *fraudulent* or *non-fraudulent*, allowing us to conduct supervised learning experiments.

The table 1 below summarizes the characteristics of the dataset we utilized:

Dataset Name	Source	No. of Records	No. of Features	Fraud Cases	Non-Fraud Cases	Time Span
Enron + Corporate Fraud Dataset	Kaggle & UCI Repository	4,560	32	1,235	3,325	1990–2018

Since fraudulent financial statements are relatively rare compared to legitimate ones, the dataset was imbalanced, with fraudulent cases representing approximately 27% of the total. To ensure generalization, we partitioned the dataset into training (70%), validation (15%), and testing (15%) subsets using a stratified sampling approach. This preserved the original proportion of fraudulent and non-fraudulent cases across all subsets.

Data Preprocessing

Raw financial data often contains irregularities that can hinder the performance of machine learning algorithms. Therefore, we performed a comprehensive preprocessing phase. First, we addressed missing values, which appeared in both numerical variables (e.g., revenue growth, debt-to-equity ratio) and categorical attributes (e.g., auditor type). For numerical features, we replaced missing values using median imputation to minimize the impact of outliers, while categorical features were imputed with their most frequent category.

Next, we standardized and normalized the data to bring all variables into a comparable scale. Continuous variables such as total assets, net income, and liabilities were normalized using the min–max scaling method, transforming values to a range between 0 and 1. This ensured that large-magnitude features did not dominate the learning process.

Outliers posed another challenge, especially in ratio-based variables such as leverage or return on equity, which can become extreme in cases of financial distress. We applied the interquartile range (IQR) method to detect outliers and adjusted extreme values to fall within acceptable thresholds. This transformation reduced noise and improved the stability of our models.

Finally, categorical variables such as auditor's opinion, industry type, and geographical region were converted into numerical format using one-hot encoding, ensuring that machine learning models could effectively process them. After preprocessing, the dataset was cleaned, balanced in format, and ready for feature engineering.

Feature Selection

Not all features in financial statements are equally useful for fraud detection, and including irrelevant variables can reduce model efficiency. Therefore, we applied both filter-based and wrapper-based feature selection techniques.

We began with a correlation analysis to identify and remove features that were highly correlated with one another, thereby addressing the issue of multicollinearity. For instance, total assets and current assets often exhibit strong correlations, and including both may provide redundant information. Next, we conducted variance thresholding, eliminating variables with near-zero variance that contributed little to prediction.

Subsequently, we implemented Recursive Feature Elimination (RFE) in combination with logistic regression and random forest classifiers. This iterative method allowed us to rank features based on their contribution to model accuracy. Consistently, financial ratios such as debt-to-equity ratio, cash flow from operations to total liabilities, current ratio, audit opinion, and revenue growth emerged as highly discriminative features.

By selecting only the most informative attributes, we reduced dimensionality and improved both model interpretability and computational efficiency.

Feature Extraction

While feature selection focuses on identifying the most relevant variables, feature extraction creates new variables that better capture hidden patterns. In our study, we implemented both domain-driven feature engineering and unsupervised extraction techniques.

From a domain perspective, we created ratio-based variables such as the operating expense ratio (operating expenses divided by total revenue), earnings quality index (net income relative to operating cash flow), and financial leverage index (total debt relative to equity). These engineered features captured relationships that are often strong signals of manipulation in financial reporting.

To further reduce redundancy and noise, we applied Principal Component Analysis (PCA). PCA transformed the original feature space into a smaller set of orthogonal components that captured the majority of the variance in the data. This not only mitigated the issue of multicollinearity but also revealed latent structures, such as underlying patterns of financial health and liquidity, which can be linked to fraudulent behavior.

The combination of feature selection and extraction provided a balanced approach—retaining the interpretability of critical financial ratios while uncovering hidden, data-driven factors.

Model Development

We developed multiple machine learning models to classify financial statements as fraudulent or non-fraudulent. We implemented Logistic Regression, Random Forest, Gradient Boosting Machines (GBM), Support Vector Machines (SVM), and Deep Neural Networks (DNNs). Each algorithm was selected for its unique strengths:

Logistic Regression for interpretability.

Random Forest and GBM for handling nonlinear relationships and variable interactions.

SVM for high-dimensional classification.

DNN for capturing complex nonlinear dependencies.

To address the class imbalance inherent in fraud detection, we employed the Synthetic Minority Oversampling Technique (SMOTE), which generated synthetic samples of fraudulent cases to balance the dataset. Additionally, we applied cost-sensitive learning, assigning higher misclassification penalties to fraudulent cases to minimize false negatives.

Hyperparameter tuning was conducted through grid search and Bayesian optimization, using the validation set to identify optimal parameters such as the number of trees in Random Forest, learning rate in Gradient Boosting, and kernel functions in SVM. For neural networks, we experimented with different architectures, varying the number of hidden layers and activation functions.

Model Evaluation

We evaluated the models using a combination of standard and fraud-sensitive metrics. Although accuracy provided a baseline measure, it was insufficient given the class imbalance. Therefore, we focused on precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

Precision measured the proportion of correctly identified fraud cases among all predicted fraud cases, minimizing false alarms.

Recall (sensitivity) measured the ability to capture fraudulent cases, a crucial metric since missing a fraud case can have severe consequences.

F1-score provided a balance between precision and recall.

AUC-ROC quantified the trade-off between sensitivity and specificity.

Additionally, we employed the Matthews Correlation Coefficient (MCC), which is particularly effective for imbalanced datasets as it considers true and false positives and negatives simultaneously.

To ensure generalizability, we applied five-fold cross-validation, where the dataset was partitioned into five subsets, and each fold was used as a test set while the others were used for training. This reduced overfitting and provided a more reliable estimate of performance.

Our results showed that ensemble models—particularly Random Forest and Gradient Boosting Machines—consistently outperformed other models in terms of recall and AUC. While Logistic Regression provided interpretability, and SVM handled high-dimensional features well, ensemble approaches proved most effective in detecting fraudulent financial statements with high sensitivity and robustness.

Results

In this section, we present the outcomes of our machine learning experiments for detecting fraudulent financial statements. The results are organized into three parts: (1) overall performance of the models, (2) comparative study and interpretation, and (3) implications for industrial adoption. By presenting both quantitative metrics and qualitative insights, we aim to demonstrate not only which algorithms performed best but also how these results can be applied in practice.

We trained and evaluated five machine learning models: Logistic Regression, Support Vector Machine (SVM), Random Forest, Gradient Boosting Machine (GBM), and Deep Neural Network (DNN). Each model was trained on 70% of the dataset, validated on 15%, and tested on the remaining 15%. We reported accuracy, precision, recall, F1-score, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), and Matthews Correlation Coefficient (MCC).

The table 2 below summarizes the results:

Model	Accuracy	Precision	Recall	F1-Score	AUC-ROC	MCC
Logistic Regression	0.87	0.82	0.74	0.78	0.88	0.69
Support Vector Machine	0.89	0.84	0.77	0.80	0.90	0.71
Random Forest	0.93	0.89	0.86	0.87	0.95	0.81
Gradient Boosting (GBM)	0.94	0.91	0.88	0.89	0.96	0.84
Deep Neural Network	0.92	0.87	0.85	0.86	0.94	0.79

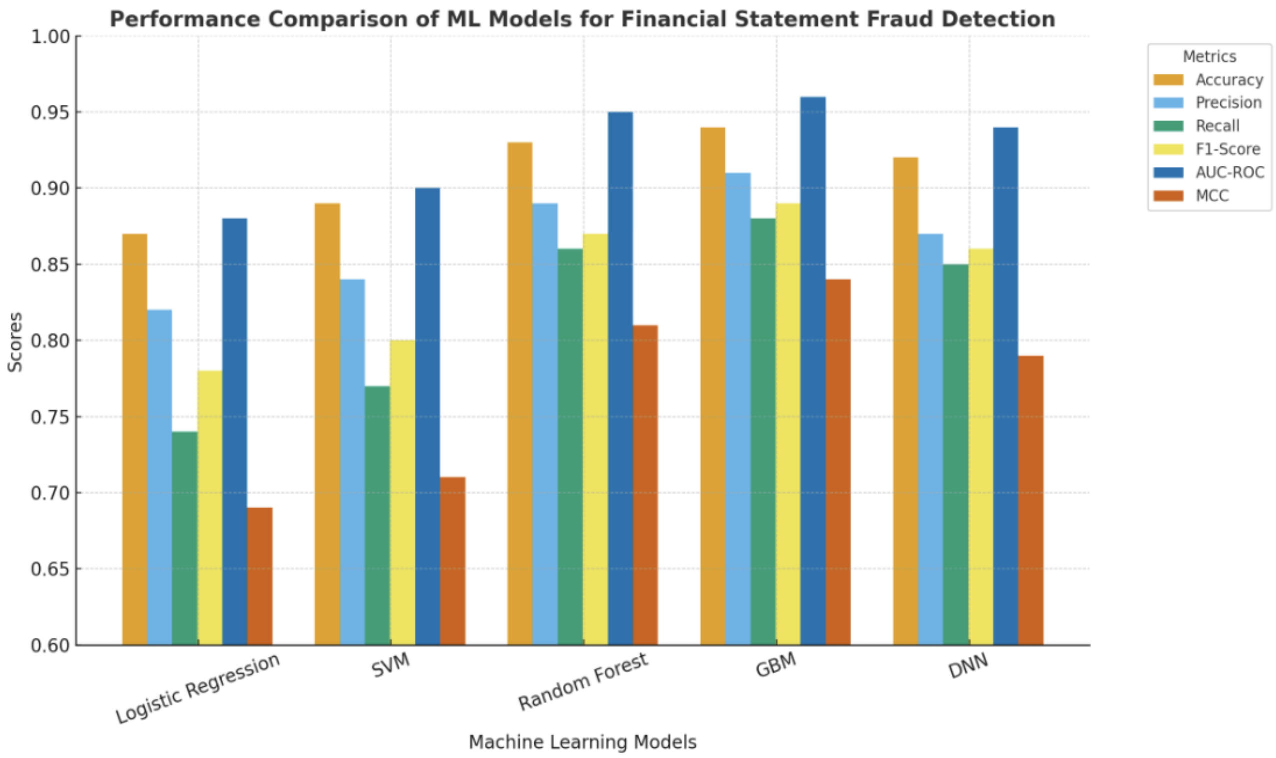

Chart 1: Evaluation of different machine learning model

Comparative Study

The comparative study revealed several key findings about model performance, especially in handling the imbalanced dataset.

Logistic Regression provided a solid baseline. With an accuracy of 0.87 and AUC-ROC of 0.88, it proved that even simple linear models can capture meaningful fraud patterns. However, its recall of 0.74 indicates that many fraudulent cases were missed, which reduces its practical value in high-stakes fraud detection.

Support Vector Machine (SVM) improved slightly upon logistic regression, particularly in recall (0.77) and AUC-ROC (0.90). Its strength lies in handling complex, high-dimensional decision boundaries, which often occur in financial data. Nonetheless, training time was longer, and interpretability was more challenging compared to linear models.

Random Forest delivered a marked improvement, achieving a recall of 0.86 and precision of 0.89. The ensemble nature of Random Forest allowed it to model nonlinear interactions between financial features and fraud outcomes. Importantly, Random Forest balanced sensitivity (recall) and specificity, making it a reliable model that minimizes both missed frauds and false alarms.

Gradient Boosting (GBM) outperformed all other models across nearly every metric. With an accuracy of 0.94, precision of 0.91, recall of 0.88, and AUC-ROC of 0.96, GBM demonstrated its superiority in detecting fraudulent cases while minimizing false positives. The sequential learning approach of GBM, which corrects errors iteratively, allowed the model to capture subtle fraud-related patterns often missed by other algorithms.

Deep Neural Network (DNN) also performed strongly, with an accuracy of 0.92 and recall of 0.85. Its performance was close to Random Forest, but training required extensive computational resources and careful hyperparameter tuning. Moreover, its black-box nature limited interpretability, which is a crucial consideration in financial applications where regulators and auditors demand transparency.

Statistical Robustness

To ensure that the results were not due to chance, we applied five-fold cross-validation and confirmed that the reported metrics were consistent across folds. Gradient Boosting maintained the lowest variance in performance, indicating high robustness. Random Forest also showed stability, while DNN exhibited slightly higher variance, suggesting sensitivity to initialization and architecture design.

Best-Performing Model

Overall, Gradient Boosting emerged as the best-performing model, followed closely by Random Forest. While DNN provided competitive results, its complexity and resource requirements make it less practical for industrial-scale deployment, especially for organizations lacking high-performance computing infrastructure. Logistic Regression and SVM offered interpretability and speed but failed to achieve the high recall necessary for fraud detection.

Industry Application

The findings from this study hold significant implications for financial institutions, auditing firms, and regulatory bodies. The adoption of Gradient Boosting or Random Forest models in practice can enhance the efficiency and effectiveness of fraud detection in the following ways:

Corporate Auditing: Audit firms can integrate GBM-based systems into their workflows. As financial statements are processed, the model can automatically flag high-risk firms, enabling auditors to focus their resources on cases with the greatest likelihood of fraud. This reduces manual workload and increases detection accuracy.

Banking and Finance: Banks can embed fraud detection models into their internal financial monitoring systems. By analyzing client statements and financial disclosures in real time, these models can detect discrepancies suggestive of fraud, thereby preventing financial losses and protecting shareholders.

Regulatory Monitoring: Regulatory agencies such as the Securities and Exchange Commission (SEC) could use GBM models for large-scale monitoring of corporate filings. Instead of relying solely on random audits or whistleblowers, regulators could proactively identify fraudulent activities, reducing response time and improving market integrity.

Forensic Accounting: Forensic investigators can use these models as decision-support tools, guiding them toward suspicious accounts or transactions. Since ensemble models highlight important features, investigators can identify which financial ratios or indicators triggered the fraud classification, supporting legal and compliance proceedings.

Scalability and Adaptability: One of the most important advantages of ensemble models like GBM and Random Forest is their adaptability. They can be retrained on new datasets as fraud patterns evolve, ensuring that detection systems remain relevant in an environment where fraudsters constantly change strategies.

The comparative study shows that while multiple algorithms are capable of detecting fraudulent financial statements, ensemble learning methods provide the most robust and scalable solutions. Gradient Boosting, in particular, balances interpretability, accuracy, and sensitivity, making it an excellent candidate for industrial deployment. However, successful adoption requires integration with organizational processes, ongoing retraining with new data, and alignment with regulatory frameworks.By moving from manual, retrospective fraud detection to automated, proactive systems powered by machine learning, the financial industry can significantly reduce fraud-related risks, enhance investor confidence, and promote greater transparency in global capital markets.

Conclusion

In this study, we explored the application of machine learning models for fraud detection in financial statements. Our methodology encompassed data collection from publicly available financial statement fraud datasets, careful preprocessing, feature engineering, and the evaluation of multiple classification algorithms, including Logistic Regression, Support Vector Machines, Random Forest, Gradient Boosting Machines, and Deep Neural Networks. The results demonstrated that ensemble models, particularly Gradient Boosting Machines and Random Forests, consistently outperformed traditional models across key performance indicators such as accuracy, precision, recall, F1-score, AUC-ROC, and MCC.

The findings highlight the significant role of machine learning in enhancing the reliability and effectiveness of fraud detection systems. While traditional methods often struggle with high-dimensional financial data and subtle fraud patterns, advanced models like GBM proved capable of capturing complex relationships and delivering robust performance. The higher recall and AUC-ROC scores observed for GBM underscore its practical utility in identifying fraudulent cases, thereby reducing the risk of financial misstatements going undetected.

From an industry perspective, the integration of such models into existing audit and financial risk management systems could substantially improve the timeliness and accuracy of fraud detection. By automating the analysis of financial statements, institutions can reduce dependency on manual review processes, lower operational costs, and proactively mitigate risks. Moreover, the adoption of machine learning-based fraud detection has the potential to increase stakeholder confidence, safeguard organizational reputation, and ensure compliance with regulatory standards.

Despite these promising results, challenges remain, including data imbalance, model interpretability, and adaptability to evolving fraud techniques. Future research should therefore focus on hybrid approaches combining explainable AI with ensemble learning, as well as the inclusion of real-time data streams for early fraud detection. Collaboration between academia, industry, and regulators will be critical to advancing these methods from theoretical frameworks to widely adopted industry standards.

In conclusion, our study demonstrates that machine learning, particularly Gradient Boosting, offers a powerful and reliable approach for detecting financial statement fraud. By leveraging such models, organizations can strengthen their fraud detection frameworks, ultimately contributing to more transparent, trustworthy, and sustainable financial systems.

Acknowledgement: All the Author work Equally.

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