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Ouattara Kifory(Author) *Universite Jean Lorougnon Guede*	**Renewable Energy, CO_2 Emissions, and Human Capital as Déterminants of Per Capita Income in ECOWAS: Evidence from GMM and Quantile Regression**

Abstract

This study investigates the impact of Renewable energy consumption, carbon dioxide (CO_2) emissions, and human capital on per capita income in ECOWAS countries over the period 1990–2023. Employing both the Generalized Method of Moments (GMM) and quantile regression techniques, the analysis accounts for heterogeneity across different income distributions and addresses potential endogeneity issues. Empirical findings reveal that human capital has a consistently positive and significant effect on per capita income across all models. This underscores its critical role in driving sustainable economic development and improving resilience in West African economies. In contrast, renewable energy consumption exhibits a generally negative impact on income, which may reflect issues of low energy efficiency, insufficient infrastructure, or poor integration of renewable energy into productive sectors. The effect of CO_2 emissions is mixed: while GMM results show a negative association with per capita income, quantile regressions particularly around the median suggest a positive relationship. This apparent contradiction points to potential non-linear dynamics and the possibility that moderate emissions may be correlated with industrial activity and growth at certain income levels. These findings imply that one-size-fits-all energy policies may not be effective for the ECOWAS region. Instead, a differentiated strategy is needed one that fosters greater investment in human capital and improves the efficiency and integration of renewable energy sources. Additionally, environmental policies must account for the nuanced relationship between emissions and economic performance. This paper contributes to the literature on sustainable development by offering new insights into the complex interplay between energy, environment, and economic growth in Sub-Saharan Africa.

Keywords: Renewable energy, Human capital, CO_2 emissions, GMM, Quantile regression

Mark Lokanan(Author) *Royal Roads University, BC, Canada* **Sana Ramzan(Co-Author)** *Royal Roads University*	**Exploring the Role of Strain Theory in Enhancing Financial Distress Prediction Models**

Introduction

Foreseeing financial challenges is essential for developing efficient financial strategies and aiding stakeholders in decision-making. It allows organizations to identify financial issues early and implement actions to mitigate risks, thereby protecting them from potential systemic threats (Lokanan & Ramzan, 2024). These disruptions become particularly noticeable during economic downturns, as financially struggling firms can hurt other companies and destabilize industrial sectors (Dinh et al., 2021). An increasing number of studies reveal a significant link between financial difficulties and earnings manipulation, suggesting that distressed firms frequently distort financial reports to uphold investor perceptions of credit reliability and competitive advantage (Habib et al., 2013; Lokanan & Ramzan, 2024; Ranjbar & Farsad Amanollahi, 2018; Valaskova et al., 2021). In financial distress situations, management incentives might shift towards concealing poor performance through accounting manipulations, leading to unlawful actions that damage stakeholder confidence (Habib et al., 2013; Hajek & Henriques, 2017; Lau et al., 2022). Consequently, market participants typically view optimistic earnings projections from distressed companies with skepticism due to increased concerns regarding bias and misrepresentation (Hajek & Henriques, 2017; Lau et al., 2022).

Although earnings management and fraud are distinct ideas, the literature shows a notable correlation between financial distress and the manipulation of financial statements (Lokanan & Ramzan, 2024; Perols, 2011; Perols & Lougee, 2011). Additionally, earlier studies show that financial distress occurs when companies experience pressure due to high debt levels, low liquidity, or adverse market conditions, often pushing them toward criminal actions (Dinh et al., 2021; El Madou et al., 2024;

Farooq & Qamar, 2019; Lokanan & Ramzan, 2024). These elements correspond with the tenets of strain theory, a crime and deviance concept suggesting that pressure and stress from societal structures can trigger criminogenic behavior. Consequently, financial challenges may be regarded as a type of organizational stress that could result in inaccurate financial reporting. While strain theory has been applied in fraud prediction models, its use remains limited in financial distress prediction models (Donegan & Ganon, 2008; Lokanan, 2019; Ramzan & Lokanan, 2025). Therefore, the current gap in the financial distress prediction scholarship highlights the need for further research to more effectively bridge theoretical frameworks with practical prediction methodologies for identifying early indicators of distress to identify criminogenic behavior as the multifaceted and interrelated complexity of fraud makes it difficult to single one directional theory that accounts for all instances of fraud (Cooper et al., 2013; Lokanan, 2015, Morales et al., 2014; Ramzan & Lokanan, 2024). While the link between financial distress and earnings manipulation is increasingly recognized, the application of criminological theories beyond the widely adopted Fraud Triangle by Cressey remains limited in financial distress prediction models. Indeed, critics have pointed out that despite the accounting profession's (e.g., The American Institute of Certified Public Accountant (AICPA)) rapid embrace of Cressey's fraud triangle, the broader criminology literature has largely been underutilized in accounting research, thereby hindering its potential to enrich fraud accounting scholarship to detect, investigate and deter fraud (Donegan & Ganon, 2008; Cooper et al., 2013; Lokanan, 2015; Morales et al., 2014; Ramzan & Lokanan, 2024; Ramzan & Lokanan, 2025). The literature gap underscores the need for further research to bridge theoretical frameworks with practical prediction methodologies more effectively.

Despite decades of empirical research on financial distress prediction, many traditional statistical models, such as discriminant analysis and logistic regression, continue to exhibit limitations in handling high-dimensional, imbalanced, and non-linear financial datasets (Al Ali et al., 2023; Apergis et al., 2019; Ramzan & Lokanan, 2024; Wang et al., 2018). While these models remain theoretically grounded, their rigid assumptions often limit their generalizability across contexts, especially in turbulent financial conditions or evolving regulatory environments (Elhoseny et al., 2025; Yu & Li, 2023). In response, a growing body of scholarship has turned to machine learning as a complementary paradigm, offering advanced capabilities for pattern recognition, feature interaction modeling, and dynamic risk identification (Farooq & Qamar, 2019; Qian et al., 2022; Lokanan & Ramzan, 2024; Lokanan & Sharma, 2025). Yet, despite these advances, critical gaps persist, particularly in integrating theories of misconduct with algorithmic prediction tools. Most machine learning based financial distress models optimize for statistical performance metrics (e.g., accuracy, recall) (Carmona et al., 2022; Figlioli & Lima, 2022), often overlooking the organizational and systemic drivers that influence firm-level manipulation and failure (Ramzan & Lokanan, 2024; Ramzan & Lokanan, 2025). Hence, the current study addresses this shortcoming by embedding Merton's strain theory within a machine learning framework, thereby moving beyond predictive accuracy toward theoretically informed classification of financial distress and earnings manipulation.

Drawing on a dataset of NYSE- and NASDAQ-listed firms from 2015 to 2024, this paper introduces a model that integrates three components: machine learning classifiers for robust pattern detection, Beneish M-Score to capture signals of earnings manipulation, and financial, market, and governance variables aligned with the pressures articulated in strain theory (Donegan & Ganon, 2008; Lokanan, 2015; Ramzan & Lokanan, 2025). The central research question guiding this study is: How can machine learning algorithms, in conjunction with the Beneish M-Score and strain theory variables, improve the predictive accuracy and theoretical interpretability of financial distress and earnings manipulation among publicly listed U.S. firms?

One of the core objectives of this study is to evaluate and compare the effectiveness of resampling techniques, SMOTE, ADASYN, and SMOTE-Tomek, across multiple machine learning models. Such a comparison advances methodological understanding of how class balancing strategies interact with classifier learning dynamics, particularly in shaping the recall–precision trade-offs that are critical in regulatory and audit settings (Hou et al., 2025). The resampling methods adopted in this study are deliberately chosen for their documented efficacy in improving AUC while addressing the significant class imbalance inherent in financial distress datasets, where the minority (distressed) class is often underrepresented, leading to biased model predictions (Hou et al., 2025; Lokanan & Ramzan, 2024; Lokanan & Sharma, 2025). Beyond methodological contribution, this research showcases theoretical depth by empirically validating Merton's strain theory at the organizational level, thereby reinforcing that earnings manipulation is not solely the result of opportunism, but of structural constraints and goal–performance misalignments. The integration of strain theory allows for a clearer, criminologically informed understanding of why firms manipulate financial statements, particularly under institutional, market and governance pressures (Cooper et al., 2013; Morales et al., 2014; Ramzan & Lokanan, 2024; Sehgal et al., 2021; Tron et al., 2022). In summary, this study bridges a critical gap between criminological theory and quantitative analytics in accounting and finance research. By embedding criminological constructs into predictive modelling workflows, it not only improves model performance but also deepens our understanding of the institutional and organizational conditions that give rise to financial distress and fraudulent reporting.

The remainder of this paper is structured as follows: Section 2 explains the tenets of strain theory and how these propositions devise the theoretical framework governing the foundation of this research study, Section 3 reviews the existing research on the use of machine learning in financial distress prediction, Section 4 details the experimental design incorporating the data science process which includes data collection, data integration and transformation, exploratory data analysis, data visualization, model building and model assessment. Section 5 discusses the results and offers a complete analysis of the findings. Finally, Section 6 concludes the study, discussing its limitations and future directions for further research.

Literature Review

Machine Learning for Financial Distress Prediction

Predicting financial distress through machine learning techniques has seen a significant surge in research interest, resulting in a substantial body of literature exploring the capabilities of various machine learning algorithms in accurately forecasting financial distress and bankruptcy. Carmona et al. (2022) exemplify this approach by applying the XGBoost algorithm to identify key predictors of financial distress and corporate failure among French firms. Their model achieved an area under the receiver operating characteristic curve (AUC) of 96.44% and an accuracy rate of 87.43%, making a significant contribution to the literature by demonstrating how the interpretability of XGBoost can enhance financial distress prediction. Figlioli and Lima (2022) have also made notable contributions by developing a robust prediction score to forecast corporate distress and recovery. Their approach incorporates financial and economic predictors, resulting in a more rigorous prediction score compared to the classic Altman Z-Score. The outcomes were noteworthy, with the prediction score achieving an AUC of 92.31%, outperforming the Z Score, which attained an AUC of 67.18%. Qian and colleagues (2022) conducted a comprehensive study that applied eight benchmark machine learning models to determine the most effective model for predicting financial distress. Notably, gradient-boosting decision trees outperformed all other models, achieving recall and F1 values of 82.85% and 81.14% in one dataset, and 79.51% and 77.65% in the other. These findings underscore the effectiveness of machine learning algorithms in predicting financial distress.

Malakauskas and Lakstutiene (2021) ventured into financial distress prediction by employing binomial classifiers in a separate study. The authors used logistic regression, artificial neural networks, and random forest techniques and made intriguing observations. Their findings indicated that artificial neural networks outperformed the other classifiers, achieving the highest AUC value of 62%. However, after integrating new variables into the initial dataset, the random forest exhibited superior performance, earning the highest AUC value of 68%. Sehgal et al. (2021) engaged in a study focused on identifying the primary microeconomic factors contributing to financial distress in the Indian corporate sector. In this context, they crafted a concise distress prediction model that harnessed observable financial predictors and employed various classification techniques. Support vector machines surpassed artificial neural networks and the logit model by achieving a remarkable 83.60% predictive accuracy. The study by Jiang and Jones (2018) embraced TreeNetÒ, a commercial machine learning technique, to predict corporate financial distress in China. Impressively, TreeNetÒ exhibited an accuracy of 94.74% in predicting distress (Type I error) and 94.85% in predicting healthy firms (Type II error), firmly establishing its effectiveness in accurately evaluating the financial status of companies. Collectively, these studies highlight the intensifying research focus on utilizing machine learning algorithms for predicting financial distress in firms while underscoring the effectiveness of these models in achieving this objective, underscoring the nascent, non-commercialized nature of the industry.

Ensemble learning has garnered growing attention in recent scholarship as a promising avenue for predicting and detecting financial distress. Ensemble learning, a machine learning technique, involves amalgamating predictions from multiple individual models, known as base learners or weak learners, to enhance accuracy and robustness (Mousavi & Lin, 2020). Ensemble learning models, such as random forest, gradient boosting, and extreme gradient boosting, have garnered considerable recognition for their ability to elevate prediction accuracy and model resilience (Tang et al., 2020; Tron et al., 2022). These ensemble learning models are particularly advantageous when individual models may exhibit limitations or biases, as they can effectively mitigate these shortcomings by capitalizing on the diversity of the constituent models (Carmona et al., 2022; Tang et al., 2020; Tron et al., 2022). Bagging methods, exemplified by the random forest, and boosting techniques, including gradient boosting and XGBoost, stand out as two prominent forms of ensemble learning that are frequently employed in scholarly research (Bragoli et al., 2022; Carmona et al., 2022; Ding et al., 2023; Huang et al., 2017; Jabeur et al., 2021; Qian et al., 2022; Tang et al., 2020; Tron et al., 2022; Zhao et al., 2023). Bagging entails the simultaneous independent learning of homogeneous weak learner models, combining their outputs to establish an average model. Ensemble approach enhances prediction accuracy, mitigates concerns about overfitting, and strengthens the model's overall performance and stability (Mousavi & Lin, 2020). Conversely, boosting, founded on homogeneous weak learners, diverges in its approach compared to bagging. Boosting emphasizes models' sequential and adaptive learning, enhancing the learning algorithm's predictive capabilities (Mousavi & Lin, 2020).

Recent literature in financial distress prediction increasingly emphasizes the application of ensemble learning methods, particularly Random Forest, XGBoost, and CatBoost, due to their favorable performance metrics across diverse datasets. For example, Huang et al. (2017) report an AUC of 77.2% for Random Forest when forecasting financial distress. Similarly, Tron et al. (2022) find that Random Forest outperforms logistic regression, achieving an ROC area of 93.57%. Boosting techniques also demonstrate strong predictive capabilities. Carmona et al. (2022) apply XGBoost to a sample of French firms and report an AUC of 96.44% and an accuracy of 87.43%. Bragoli et al. (2021) identify XGBoost as the top-performing model in their study, with a classification accuracy of 89.73% in detecting bankruptcies. Lokanan and Ramzan (2024) found that artificial neural networks (ANN) outperformed other classifiers, achieving 98% accuracy in predicting financial distress among TSX-listed firms. The use of RFECV and bootstrapped CART enhanced model stability. Hence, the study highlights the effectiveness of machine learning techniques, particularly ANN, for financial health monitoring. Zhao et al. (2023) observe that Extreme Gradient Boosting maintains an AUC above 90% consistently over five years, suggesting model stability across time. In a related study, Jabeur et al. (2021) demonstrate that CatBoost achieves an AUC of 99.4% for a one-year prediction horizon and performs well in multi-year forecasting. Other studies, including Qian et al. (2022) and Tang et al. (2020), report that gradient boosting decision trees yield strong recall, F1-scores, and accuracy levels between 75% and 90% across various data contexts.

While ensemble learning methods such as Random Forest, XGBoost, and CatBoost have demonstrated strong performance across multiple studies, their superiority is not universal and is often contingent on dataset characteristics, resampling strategies, and evaluation metrics. The evidence reviewed in this study suggests that ensemble models tend to perform well in predicting financial distress, particularly when handling high-dimensional and imbalanced datasets (Carmona et al., 2022; Lokanan & Ramzan, 2024). However, their effectiveness must be interpreted within the constraints of overfitting risks, sensitivity to synthetic data, and reduced interpretability compared to linear models, due to the black box characteristic of machine learning algorithm (Carmona et al., 2022; Hajek et al., 2022; Yu and Li, 2023). For instance, while models such as XGBoost achieved higher F1-scores and AUCs in this analysis, gains in recall were sometimes accompanied by reductions in precision, underscoring trade-offs that must be carefully considered depending on application context (Carmona et al., 2022; Hajek et al., 2022; Hou et al., 2025). Hajek and his supporting authors (2022) prefer higher recall (catching fraud) even if it increases false positives, arguing that the business cost of missing fraud is higher.

Recent advances in machine learning have demonstrated considerable potential in predicting financial distress, with ensemble models such as Random Forest, XGBoost, and CatBoost consistently delivering strong performance metrics across diverse datasets. Studies show that these algorithms excel particularly when applied to high-dimensional, imbalanced data, often achieving AUC scores above 90%. However, much of this literature remains focused on technical optimization, with limited attention to the broader institutional and structural contexts in which distress occurs. Financial, market, and governance indicators, while used as predictors, are often treated as isolated inputs rather than reflections of deeper organizational strain. To address this limitation, the current study integrates machine learning with a criminological lens, drawing on Merton's strain theory to provide a more theoretically grounded interpretation of predictive results. The usage of the framework enables a richer understanding of how systemic pressures, such as performance expectations, capital constraints, and governance failures, may contribute to earnings manipulation and financial collapse. Embedding predictive analytics within such a framework not only enhances model interpretability but also supports more targeted regulatory interventions. The next section elaborates on strain theory as a conceptual foundation for linking data-driven predictions to the structural antecedents of corporate misconduct.

Theoretical Framework

Strain theory of crime

The present study investigates corporate crime using Merton's (1938) strain theory. Developed initially within sociology to explain crime and deviance, the theory has since become a valuable framework for understanding corporate misconduct, particularly fraudulent accounting practices within organizations (Erickson et al., 2006; Lokanan, 2015; Lokanan et al., 2019). The theory's core proposition asserts that discrepancies between society's objectives and the available means to attain them can propel individuals or organizations to engage in criminal activities. The study sets out to scrutinize the applicability of Merton's strain theory within corporate crime, aiming to identify profound insights from the performances enacted by organizations when grappling with the insurmountable challenge of reconciling societal and corporate goals while concurrently appeasing the multifaceted expectations of numerous stakeholders (Erickson et al., 2006; Herdjiono & Kabalmay, 2021; Lokanan et al., 2019). Organizations often require assistance in overcoming roadblocks to achieving their objectives, primarily due to constraints stemming from limited resources and opportunities (Merton, 1938). As Merton posited, this strain can drive organizations toward deviant or illicit actions as a desperate means of achieving their otherwise elusive goals (Merton, 1938). Numerous studies have since bolstered this foundation, affirming the notion that when organizations are under relentless pressure to realize their aspirations, they may resort to unlawful paths, including cooking the books to bolster their profits, improve their financial positions, and safeguard their standing within the corporate world (Erickson et al., 2006; Lokanan, 2015; Lokanan et al., 2019; Pathak & Munde, 2019; Ramzan & Lokanan, 2025). A telling example is Lokanan's (2019) elucidation of how the unyielding pressure on banks to meet market expectations became a source of financial strain, ultimately leading to the manipulation of LIBOR rates. Such a case illustrates how the relentless pursuit of goals can create profound strain, resulting in acts of criminogenic behavior.

Within this landscape, corporate crime emerges as a coping mechanism, both for individuals and the organizations they represent, aimed at mitigating the overwhelming strain that accompanies the quest for unattainable goals (Erickson et al., 2006; Herdjiono & Kabalmay, 2021; Ramzan & Lokanan, 2025). The quest to attain a comprehensive understanding of the underlying causes of corporate crime assumes paramount importance, as it holds the potential to empower organizations and governments alike, enabling them to craft more efficacious measures for the prevention and detection of fraudulent activities (Gupta & Mehta, 2024; Lokanan, 2015; Lokanan et al., 2019; Morales et al., 2014; Ramzan & Lokanan, 2025). By invoking Merton's (1938) strain theory, this study seeks to illuminate the challenges of achieving objectives within high-pressure organizational environments. Hence, Merton’s (1938) theory explains how unethical actions can emerge as coping mechanisms in the pressure faced by distressed firms. The study aims to improve understanding of the key factors that drive corporate crime and to offer insights that can help develop more effective strategies for preventing and detecting distressed organizational conditions that may lead to fraudulent activities. By conducting a detailed study of the relationships among financial, market, and corporate governance pressures, this study aims to provide valuable insights that may help companies and governments create more effective strategies to identify distressed firms and prevent criminogenic behavior.

Exploring the Strain Dimensions

Lack of Opportunities

Strain theory suggests that institutional constraints and barriers, which block legitimate paths to achieving desired goals, can create pressure on individuals or organizations to engage in illicit activities to reach those goals (Agnew, 1992; Agnew, 2009; Merton, 1938). Illicit behavior can occur in various contexts when people or organizations face limited opportunities. These constraints may lead to the manipulation of financial statements in organizations, particularly during uncertain economic times (Donegan & Ganon, 2008). Companies often employ criminogenic practices in desperate attempts to achieve their goals during cyclical economic downturns and corporate financial crises (Lokanan et al., 2019; Lokanan, 2015; Morales et al., 2014). Research shows that financially distressed companies commit deception to maintain a positive image and prevent stock depreciation (Bragoli et al., 2022; Figlioli & Lima, 2022; Huson et al., 2004; Sehgal et al., 2021). Management may use deceptive accounting practices to save earnings and avoid write-offs amid desperate financial times (Campbell et al., 2015; Gupta & Mehta, 2024; Lokanan, 2015). When facing severe financial challenges, the pursuit of objectives can lead individuals to engage in unethical and fraudulent behavior, particularly if the company's financial stability is uncertain. Consequently, strain theory offers an important perspective for comprehending the illicit behaviors of distressed companies that could be susceptible to financial statement fraud.

Strain to Achieve Financial Goals

While traditional financial indicators provide crucial insights into corporate health, a comprehensive understanding and prevention of fraudulent accounting practices can be significantly enhanced by contextualizing distress situations within broader criminology research. Such an interdisciplinary approach offers novel insights into the underlying causes of misconduct and provides additional tools for effective detection and prevention. During financial distress, companies frequently feel pressured to project an image of stability, worrying that disclosing their actual financial status may foster distrust among investors, creditors, and clients, potentially leading to a decline in their financial health. The constant pressure to display optimism may drive organizations to engage in deceptive practices. During periods of intense financial distress, companies face significant challenges in achieving their financial goals due to ineffective strategies and overwhelming debt. These obstacles significantly reduce cash flow, restrict profitability, and impede operational performance (Bragoli et al., 2022; Carmona et al., 2022; Figlioli & Lima, 2022). As a result, substantial changes to recovery strategies become necessary (Figlioli & Lima, 2022; Lokanan, 2015). Financial distress often tempts stakeholders to bypass regulations in order to maximize profits, prompting potential manipulation of financial reports to present a false picture of financial success (Beasley et al., 2000; Lokanan, 2015). Struggling organizations may struggle to meet their debt obligations, leading them to engage in fraudulent practices to secure additional financing or artificially inflate their financial statements, which creates a misleading portrayal of their creditworthiness (Carmona et al., 2022). Merton's strain theory suggests that when conventional avenues face constraints, individuals and organizations may resort to illicit means in their pursuit of financial goals (Herdjiono & Kabalmay, 2021; Lokanan, 2015; Lokanan et al., 2019; Ramzan & Lokanan, 2025). Financial distress impacts financial performance, reputation, relationships with suppliers and customers, and overall business strategy (Figlioli & Lima, 2022; Lokanan et al., 2019). Under such challenging circumstances, management and stakeholders face the daunting task of safeguarding the organization's reputation and fulfilling its obligations (Beasley et al., 2000; Figlioli & Lima, 2022; Herdjiono & Kabalmay, 2021; Lokanan, 2015). Consequently, organizations may manipulate financial records when encountering adversities, attempting to portray the achievement of their desired financial goals through deceptive means.

Strain to Achieve Market Goals

Beyond financial aspects, an organization's performance is closely linked with qualitative variables, including market trends and relationships with other corporate entities (Bragoli et al., 2022; Figlioli & Lima, 2022). Organizations must achieve market objectives as they strive to attract and satisfy investors, shareholders, creditors, and stakeholders. Failing to meet these expectations can generate substantial internal tension. Organizations in financial distress often experience significant pressure to satisfy market and investor expectations, particularly when past financial statements have portrayed strong financial performance (Figlioli & Lima, 2022). In such situations, some may resort to fraudulent practices to conceal their difficulties, maintain an appearance of stability, and secure additional investment or acquisition opportunities. Management teams face the significant challenge of simultaneously addressing financial and market goals to reinforce their organization's position, enhance its reputation, and strengthen its brand. Research indicates a strong correlation between financial distress and the pressure to meet market expectations, including growth, enterprise value, and market capitalization (Bragoli et al., 2022; Donegan & Ganon, 2008; Sehgal et al., 2021). Such a relationship can increase pressure on managers to engage in unethical practices, including manipulating accounting records to present stronger market performance (Lokanan, 2015; Morales et al., 2014). Such pressures can manifest as intense internal strain; for instance, in the case of Qwest, evidence indicated that subordinates genuinely feared the repercussions of not meeting or exceeding earnings targets (Donegan & Ganon, 2008), directly contributing to the 'strain to achieve market goals' and potentially leading to manipulative accounting practices. The fierce competition among managers to gain recognition, credibility, and influence in the market through illegitimate means may raise suspicions among stakeholders about an organization's practices (Kothari, 2010). Consequently, cultivating a positive market image becomes a significant incentive for organizations to engage in fraudulent accounting practices while they grapple with the formidable challenges of achieving their business objectives.

Strain to achieve governance goals

Organizational entities with complex or poorly designed governance structures are more vulnerable to involvement in fraudulent activities. The establishment of robust corporate governance frameworks, characterized by independent boards and vigilant audit committees, holds the promise of preventing deceptive financial reporting and forestalling its occurrence (Mousavi & Lin, 2020; Nasir et al., 2019; Rostami & Rezaei, 2022). Robust corporate governance mechanisms can potentially deter managerial misconduct, particularly within financially distressed firms (Tron et al., 2022; Viana et al., 2022). Financially troubled organizations often have weak corporate governance structures, which are susceptible to the influence of top-tier management that may prioritize their interests over the organization's welfare (Tron et al., 2022). These weakened structures might encompass inadequate internal controls and the appointment of less qualified board and audit committee members (Nasir et al., 2019; Rostami & Rezaei, 2022; Tron et al., 2022). The pressure that financially imperils firms in achieving their governance objectives increases the probability of fraudulent activities (Crisóstomo et al., 2020; Herdjiono & Kabalmay, 2021; Luo et al., 2020; Mousavi & Lin, 2020; Viana et al., 2022). A robust corporate governance structure fosters adequate internal controls within the organization, thereby serving as a predictor of financial distress and financial statement fraud (Nasir et al., 2019; Tron et al., 2022). However, an evidence research gap exists regarding the comprehensive analysis of corporate governance factors as indicators of a company's financial distress, as current scholarship treats governance indicators as secondary variables rather than as core components within predictive models, leaving a gap in both theory and application. Given the inverse relationship between robust corporate governance and fraud, these factors warrant serious consideration in predicting financial distress (Luo et al., 2020; Mousavi & Lin, 2020; Tron et al., 2022). Hence, the oversight and monitoring of corporate governance mechanisms assume pivotal significance in predicting and preventing financial distress. Figure 1 illustrates how the theoretical framework below guides the study's analysis of the dynamics of distress and fraud in the context of diverse organizational goals and their associated pressures. Hence, the current study uses Merton's strain theory to explain the link between competing objectives and unethical actions taken to achieve them during distressed situations.

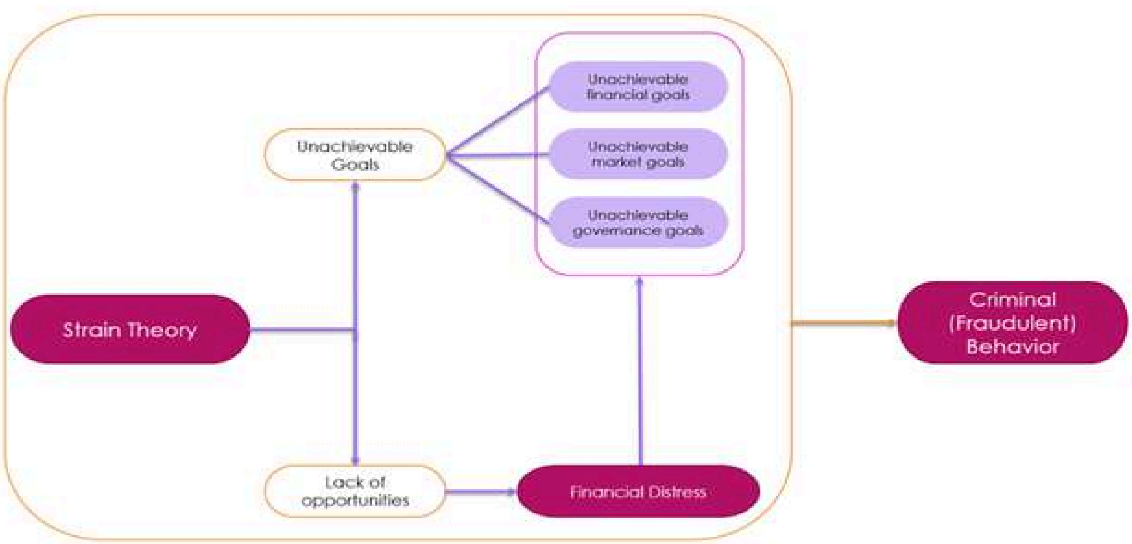

Figure 1: Theoretical Framework

Drawing from the preceding literature, this study aims to predict financial distress and identify earnings manipulation by modeling the relationship between financial distress and its determinants expressed as:

Financial Distress = f(financial, market, governance indicators) *(1)*

In this formulation, the functional form of f may be additive, where each factor contributes independently, or synergistic, where the presence of one factor amplifies the effect of another. The formulation guides the investigation of potential associations by allowing empirical testing of how these dimensions jointly or separately correspond with variations in financial distress, while avoiding premature causal claims.

Methodology

Machine learning, as a quantitative methodology, relies on statistical modelling and computational algorithms to extract patterns and insights from data (Lokanan & Ramzan, 2024). The current study employs classification-based machine learning techniques to predict financial distress and detect earnings manipulation among NYSE and NASDAQ-listed firms, using the Beneish M Score as a binary classification variable. Prior research supports the utility of such predictive models in identifying early warning signs of distress and fraudulent financial reporting (Lokanan & Ramzan, 2024; Sun et al., 2014; Zhao et al., 2023). The effectiveness of a machine learning model depends on several key factors: the selection of training and testing data, relevant input features, the choice of classification algorithms, and performance evaluation metrics (Lokanan & Ramzan, 2024). The paper constructs a predictive model that integrates financial, market, and governance variables, along with the Beneish M Score, to identify significant predictors and classify firms at risk of financial distress, as illustrated in Figure 2. The novelty of this method is by integrating corporate governance variables with traditional distress indicators and the Beneish M Score, a risk score, as core predictive features, directly into the machine learning predictive framework, rather than treating them as secondary control variables. The model provides a clearer picture of distress risk by capturing not only the firm's financial and market profile but also its governance structure and potential for earnings manipulation within corporate financial reporting.

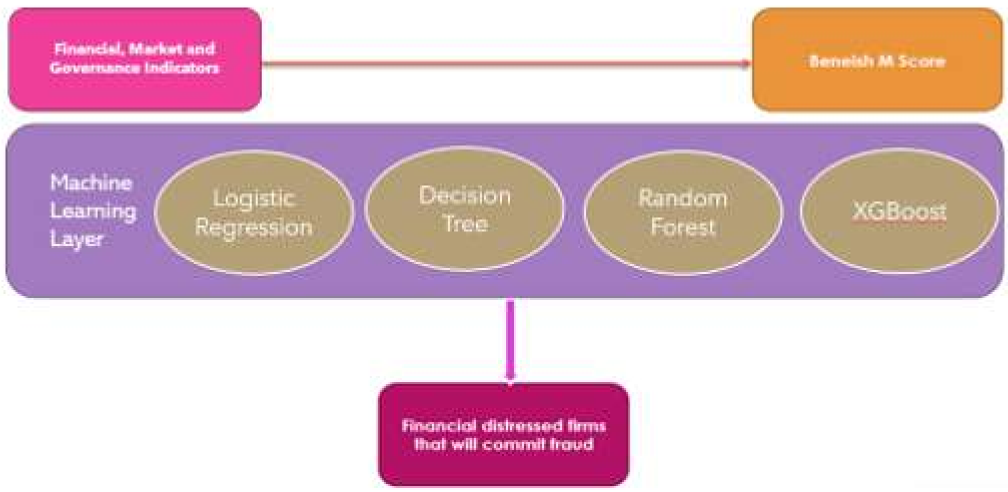

Figure 2: Predictive Model Flowchart

Data Collection

The study draws on a multi-dimensional sample dataset of 1,308 publicly traded companies listed on the NYSE and NASDAQ, two of the world's largest stock exchanges, sourced from the Bloomberg Terminal, a financial analytics systems. NYSE and NASDAQ-listed firms offer a high-quality, diverse, and well-regulated data environment that is ideal for empirical research, due to the exchanges' comprehensive disclosure requirements, broad sectoral coverage, and global economic relevance. The selection process employed stringent screening protocols to eliminate organizations with inadequate disclosures. The choice of sample size was determined by the availability of comprehensive variables for these firms, ensuring the reliability and external validity of the model's predicted outcomes within the context of the U.S. financial markets. The 1308 companies incorporated in this study are part of various industries, including finance, technology, healthcare, consumer goods, and industrials, ensuring the inclusion of sectoral diversity and strengthening the robustness of this study's analysis. The dataset used in this study contains 13,081 rows and 45 columns, totaling 5,886,445 data cells.

The dataset comprises annual financial, market, and corporate governance indicators from 2015 to 2024. A ten-year data span (2015–2024) was selected to reduce the risk of overfitting to the characteristics and anomalies of any single year, as supported by prior studies on financial distress prediction (Carmona et al., 2022; Lokanan & Ramzan, 2024; Lokanan & Sharma, 2025). Utilizing a multi-year dataset enables a more comprehensive understanding of firm behavior across varying economic conditions and market cycles. Notably, the inclusion of data from 2023 and 2024 allows the study to capture the lingering impacts of the COVID-19 pandemic, particularly regarding heightened institutional and organizational pressures (Ding et al., 2023; Lokanan & Ramzan, 2024).The financial variables encompass profitability, liquidity, solvency, and efficiency ratios as these variables are well-established reliable indicators of financial distress in the literature, whereas the non-financial variables comprise market and corporate governance variables that are effective predictors of financial distress. Financial indicators in this study establish a benchmark for evaluating model performance against prior studies and investigate the synergic effects of these variables when combined with non-financial predictors such as corporate governance metrics and the Beneish M-Score.

Variable Measurements

Independent variables

The independent variables in this study encompass a comprehensive set of financial predictors widely recognized in the literature as proxies for organizational strain that may lead to financial distress and earnings manipulation (Abdullah, 2021; Bao et al., 2015; Ding et al., 2023; Dinh et al., 2021; Huang et al., 2017; Mousavi & Lin, 2020; Wang et al., 2018; Zhao et al., 2023). While these financial metrics are well-established in distress prediction models, this research extends beyond their isolated use. Studies indicate that financial factors may not be sufficient to identify misstatements accurately, but they become relevant when combined with non-financial variables (Dinh et al., 2021; Gupta & Mehta, 2024; Jiang & Jones, 2018; Nasir et al., 2019), such as market and governance variables. The primary objective is to evaluate the predictive utility of these variables alongside market and governance predictors of strain within a machine learning framework. These combined variables serve as critical inputs for the machine learning models, enabling the identification of complex patterns, interactions, and early warning signals that may lead to financial distress or manipulative financial reporting.

Profitability ratios

Numerous studies highlight the significance of profitability ratios in evaluating a company's financial stability and distress levels (Carmona et al., 2022; Figlioli & Lima, 2022; Jabeur et al., 2021). Research indicates that diminished profitability, assessed using metrics such as return on assets and net profit margin, is significantly associated with an increased risk of financial distress, thus proving the significance of these ratios as early warning systems and risk assessment (Liu et al., 2023; Lokanan & Ramzan, 2024; Sun et al., 2014, 2023). Sehgal et al. (2021) determined that a support vector machine utilizing return on capital employed achieved an accuracy of 83.3%. Moreover, research also indicates that incorporating profitability metrics, alongside liquidity and leverage ratios, enhances the accuracy of financial distress prediction models when employing modern data mining and statistical techniques (Geng et al., 2015; Hassan et al., 2024). Specific research indicates that profitability may influence the impact of other financial ratios, such as sales growth and activity ratios, on distress outcomes (Figlioli & Lima, 2022a; Gupta & Mehta, 2024; Lokanan & Ramzan, 2024) . Several studies assert that maintaining robust profitability is crucial for mitigating the risk of financial difficulties; however, the strength of this association may vary among sectors and circumstances. Therefore, utilizing machine learning techniques in conjunction with profitability ratios enhances prediction accuracy, hence providing stakeholders with valuable information for decision-making.Table 1: Profitability ratios used in this study

Variable Code	Variable Description
IS_EBIT	Earnings Before Interest and Taxes
NET_INCOME	Net Income
IS_OPER_INC	Operating Income
RETURN_ON_ASSET	Return on Assets
RETURN_COM_EQY	Return on Common Equity
PROF_MARGIN	Profit Margin
GROSS_MARGIN_ADJUSTED	Adjusted Gross Margin
RETURN_ON_INV_CAPITAL	Return on Invested Capital
IS_EPS	Earnings Per Share
WACC_NET_OPER_PROFIT	Weighted Average Cost of Capital on Net Operating Profit

Liquidity ratios

Financial distress prediction models often utilize liquidity ratios, such as the current ratio, quick ratio, and cash ratio, to assess a company's ability to meet its short-term obligations. However, their forecasting capabilities vary across industries and contexts, and recent studies have yielded mixed findings on their effectiveness (Jabeur et al., 2021; Lokanan & Ramzan, 2024). Liquidity ratios, in conjunction with other metrics such as profitability and debt, are frequently utilized in financial distress models (Carmona et al., 2022; Gupta & Mehta, 2024; Jabeur et al., 2021). Few studies indicate that liquidity ratios are effective in distinguishing between distressed and non-distressed enterprises, particularly when financial metrics are used (Hassan et al., 2024; Lokanan & Ramzan, 2024). Liquidity ratios exhibit a significant negative correlation with financial distress in numerous instances, where increased liquidity is associated with a diminished probability of distress (Bukhori et al., 2022; Gupta & Mehta, 2024). However, in some sectors, liquidity measures alone do not consistently predict financial challenges effectively; profitability and leverage ratios hold greater significance (Bukhori et al., 2022; Carmona et al., 2022; Gupta & Mehta, 2024; Jabeur et al., 2021).

Table 2: Liquidity ratios used in this study

Variable Code	Variable Description
WORKING_CAPITAL	Working Capital
CUR_RATIO	Current Ratio
QUICK_RATIO	Quick Ratio
BS_CUR_LIAB	Current Liabilities
BS_CUR_ASSET_REPORT	Current Assets Reported on Balance Sheet
CF_CASH_FROM_OPER	Cash Flow from Operating Activities
BS_CASH_NEAR_CASH_ITEM	Cash and Near Cash Items

Solvency ratios

Solvency ratios, such as the debt-to-equity and interest coverage ratios, are vital predictors of a firm's long-term financial stability. Solvency ratios evaluate a company's ability to fulfill its long-term obligations, distinguishing between distressed firms and solvent ones. According to the financial distress prediction scholarship, lower solvency ratios (indicating higher leverage or debt burden) are associated with a greater likelihood of distress or bankruptcy (Ding et al., 2023; Gupta & Mehta, 2024). However, the strength of this relationship can depend on the industry and the economic environment (Ding et al., 2023). Prior research consistently identifies these metrics as strong predictors of financial distress (Abdullah, 2021; Bukhori et al., 2022; Farooq & Qamar, 2019; Hassan et al., 2024; Jiang & Jones, 2018; Malakauskas & Lakstutiene, 2021). Recent machine learning models also rank solvency ratios among the top predictors of distress (Dinh et al., 2021; Gupta & Mehta, 2024). Moreover, studies also indicate that solvency ratios are most effective when used in conjunction with liquidity, profitability, and efficiency ratios, as models combining these ratios tend to exhibit higher predictive accuracy (Bukhori et al., 2022; Ding et al., 2023; Dinh et al., 2021; Lokanan & Ramzan, 2024). Overall, solvency ratios remain foundational in the early detection of financial distress.

Table 3: Solvency ratios used in this study

Variable Code	Variable Description
BS_TOT_ASSET	Total Assets
BS_TOT_LIAB	Total Liabilities
SHORT_AND_LONG_TERM_DEBT	Short and Long Term Debt
TOTAL_ASSETS_SEQUENTIAL_GROWTH	Sequential Growth in Total Assets
BS_NET_ASSET_VALUE_PER_SHARE	Net Asset Value per Share
PX_TO_TANG_BV_PER_SH	Price to Tangible Book Value per Share
BS_PURE_RETAINED_EARNINGS	Pure Retained Earnings
NET_FIX_ASSET_TURN	Net Fixed Asset Turnover

Market and Economic Variables

Market and economic variables provide forward-looking insights into a firm's financial health and the broader economic environment. Enterprise value, sales growth and market capitalization are frequently used to capture investor sentiment and firm value (Bao et al., 2015; Ding et al., 2023; Dinh et al., 2021; Wang et al., 2018). Declining enterprise value or market capitalization often precedes financial distress, signaling a reduction in market or investor confidence. Studies show that economic downturns significantly increase the likelihood of firm failures (Dinh et al., 2021). Integrating market data improves model responsiveness to real-time shifts in risk. Moreover, market-based variables outperform some accounting metrics in dynamic settings. Recent research combines firm-level market signals with macroeconomic trends to create robust models for predicting financial distress (Apergis et al., 2019; Wang et al., 2018). These predictors enhance early warning systems by capturing external pressures and influences. Overall, market and economic variables complement traditional financial ratios in forecasting financial distress.

Table 4: Market variables in this study

Variable Code	Variable Description
TOT_MKT_VAL	Total Market Value
HISTORICAL_MARKET_CAP	Historical Market Capitalization
SALES_REV_TURN	Sales Revenue Turnover
SALES_GROWTH	Sales Growth
CHG_PCT_1YR	1-Year Percentage Change
RETURN_ON_INV_CAPITAL	Return on Invested Capital
CURR_ENTP_VAL	Current Enterprise Value
PE_RATIO	Price to Earnings Ratio
PX_TO_SALES_RATIO	Price to Sales Ratio
PX_TO_BOOK_RATIO	Price to Book Ratio
PX_TO_TANG_BV_PER_SH	Price to Tangible Book Value per Share
BOOK_VAL_PER_SH	Book Value per Share

Governance variables

Incorporating governance variables such as board size, audit committee composition, and ownership structure into financial ratios improves predictive accuracy compared to relying solely on financial data. The enhancement stems from selecting the most relevant governance attributes and combining them with key financial ratios (Liang et al., 2020; Mousavi & Lin, 2020; Tron et al., 2022), thereby addressing the inherent limitations of using only financial features (Wang et al., 2018). Research indicates that inadequate governance frameworks frequently precede financial crises due to insufficient oversight and risk management (Mousavi & Lin, 2020; Tron et al., 2023). Tron and their co-authors (2023) assert in their research that governance variables, including CEO renewal and stability, enhance the accuracy of the Random Forest technique. Despite their importance, numerous governance variables are inadequately employed in machine learning models for forecasting financial distress (Mousavi & Lin, 2020). Consequently, more sophisticated frameworks that integrate governance variables with traditional financial variables are necessary, as their inclusion will continually enhance model performance and reduce the misclassification of distressed enterprises.

Table 5: Governance variables in the study

Variable Code	Variable Description
NUMBER_OF_DIRECTORS_ON_BOARD	Number of Directors on Board
INDEPENDENT_DIRECTORS	Independent Directors
SHS_HLD_BY_EXECS_PCT_OF_OUTSTDG	Shares Held by Executives as % of Outstanding Shares
AUDITORS_OPINION	Auditor's Opinion
CEO_DUALITY	CEO Duality
TOT_COMP_AW_TO_CEO_EQUIV	Total Compensation Awarded to CEO (Equiv.)
BOARD_SIZE	Board Size
PCT_INSIDER_SHARES_OUT	Percentage of Insider Shares Outstanding

Dependent Variable

The dependent variable employed in this study is the Beneish M-Score, a statistical model designed to identify the likelihood of earnings manipulation based on eight distinct financial ratios (Beneish et al., 2012). Increasingly, scholars have recognized its potential as an indirect measure of financial distress, given that firms under strain often resort to manipulative accounting practices to conceal their actual financial position (Lokanan & Ramzan, 2024). Empirical evidence supports the robustness of the M-Score in detecting financial irregularities and signaling distress-related behaviors (Aviantara, 2023; Beneish et al., 2012). Unlike traditional metrics such as the Altman Z-score, which rely heavily on the accuracy of financial data, the M-Score evaluates the reliability of financial disclosures, thereby enhancing this study's model validity (Aviantara, 2023; Lokanan & Ramzan, 2024). In the context of machine learning applications, its inclusion has been shown to improve classification performance when combined with financial predictors. Furthermore, Beneish and Vorst (2022) advocate for cost-sensitive evaluation criteria of M-Score, reinforcing the score's practicality as a predictive tool. For the purpose of this study, the M-Score is operationalized as a binary indicator where scores below -2.22 are coded as '0' to denote non - manipulators, while scores above this threshold are coded as '1' to represent potential manipulators. The dichotomous framework facilitates the identification of distress through the lens of financial reporting integrity, positioning the M-Score as both a diagnostic marker of manipulation and a leading indicator of financial vulnerability.

$$y = \begin{cases} 0 & non\ distressed \\ 1 & distressed \end{cases} \tag{2}$$

Machine Learning Workflow

Figure 3 illustrates the end-to-end machine learning pipeline utilized to construct a robust classification model for detecting financial manipulation. The workflow begins with data importation and cleaning, ensuring the dataset is free from missing values and inconsistencies. The workflow is followed by exploratory data analysis to understand the distributions and relationships of the variables. Feature engineering and selection are then performed to identify the most predictive variables. The data is preprocessed by handling outliers and standardizing the features to bring them to a standard scale. After preprocessing, the dataset is partitioned into training and testing subsets to evaluate generalization performance. Multiple classification algorithms, including Logistic Regression, Decision Trees, Random Forest and XGBoost suggested by the financial distress scholarship, are trained on the training data, hence being systematically tested and evaluated. The models are then evaluated on the test data using metrics such as accuracy, confusion matrix, and classification reports. The final step involves making predictions on unseen data based on the tuned model.

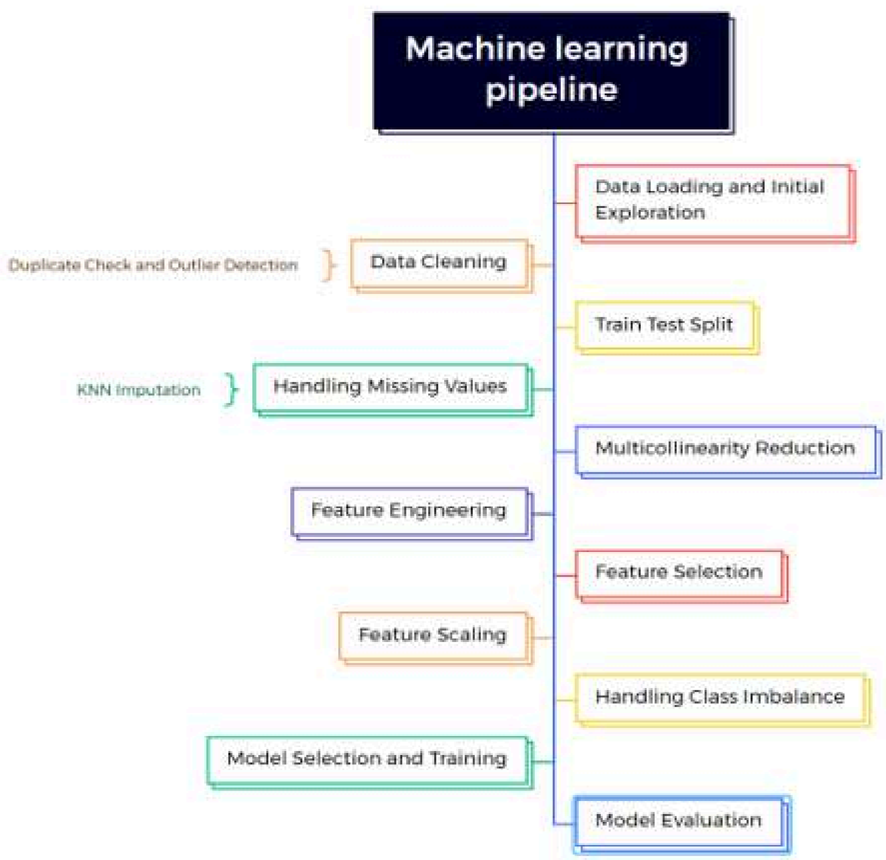

Figure 3: Machine Learning Workflow

Exploratory Data Analysis

The dataset demonstrates considerable heterogeneity in financial characteristics across firms. Variables such as TOT_MKT_VAL (mean = 18,681.22; std = 31,022.88) and BS_TOT_ASSET (mean = 10,750.88; std = 16,289.22) reflect highly skewed distributions with extreme values at the upper tail (max values exceeding 300,000), indicating the presence of large-cap firms in a broader population of smaller firms. Similar variability is observed in SALES_REV_TURN and IS_EBIT, reinforcing a wide dispersion in firm size and profitability. Many features exhibit high positive skewness (e.g., PE_RATIO = 52.63, SALES_GROWTH = 11.56, NET_FIX_ASSET_TURN = 12.34), and extreme kurtosis values (e.g., PROF_MARGIN = 410.30, PX_TO_TANG_BV_PER_SH = 139.05), suggesting long right tails and the presence of outliers or extreme events. These distributions violate the normality assumption, which can adversely affect statistical inference and model stability if not transformed or properly handled. Ratios such as CURRENT_RATIO (mean = 2.11) and QUICK_RATIO (mean = 2.37) suggest that most firms maintain a healthy liquidity buffer. However, extremely high maximum values (e.g., CUR_RATIO = 10.90) hint at potential inefficiencies or cash hoarding by a few firms. Profitability metrics such as RETURN_ON_ASSET and RETURN_COM_EQY show low average returns (mean = 0.04 and 0.93 respectively), with a widespread and negative skew, suggesting distressed or loss-making firms in the dataset. Governance features such as BOARD_SIZE (mean = 9.52), INDEPENDENT_DIRECTORS (mean = 7.91), and CEO_DUALITY (mean = 0.49) suggest moderate board independence, with CEO duality present in nearly half of the firms. These features may have predictive value in distress modeling, particularly in light of agency theory and prior literature on governance inefficiencies (Nasir et al., 2019; Tron et al., 2022). The binary MSCORE variable (mean = 0.1521) indicates that approximately 15.2% of firms are flagged as potentially manipulating earnings, serving as a key target variable or classification label. The clear class imbalance suggests that resampling is essential for supervised learning tasks. Therefore, the dataset is non-normal, highly skewed, and contains extreme values, requiring robust preprocessing. Missing data handling, especially for financial ratios and executive ownership variables, is crucial. Feature scaling and outlier treatment are necessary for model generalization. Moreover, the diversity of financial metrics (liquidity, profitability, leverage, governance) offers rich multi-dimensional features for machine learning models but also requires dimensionality reduction or regularization.

Data Cleaning and Preprocessing

Prior to conducting exploratory data analysis, the dataset was checked for duplicate columns to ensure data integrity, and no data points were identified. Categorical variables, such as AUDITORS_OPINION and CEO_DUALITY, were encoded into numerical formats to facilitate analysis. The target variable, MSCORE, was separated from the feature matrix, and non-predictive attributes such as the YEAR column was removed to avoid data leakage. Missing values in the target variable were assessed, with a total of 885 rows containing NaN values. These rows were excluded prior to outlier detection to ensure that the modelling process was based solely on valid observations. Hence, the preprocessing step reduced the dataset from 13,081 to 12,196 observations across 43 features.

Outliers were detected using the Z-score technique with a threshold of ±3 (Salgado et al., 2016; Chikodili et al., 2021). The Z-Score method calculates the standardized score for each feature and flags rows containing any feature value exceeding the threshold (Lokanan & Ramzan, 2024). Observations beyond this range were excluded to prevent distortion of model training and mitigate the influence of extreme values on classification outcomes. Although such anomalies may occasionally signal financial distress, their inclusion risks introducing noise that undermines model stability and generalizability (Hajek & Henriques, 2017; Salgado et al., 2016). Emphasis was placed on the M-score to systematically identify financially distressed firms, enabling the model to prioritize statistically valid indicators over outlier-driven values (Hajek et al., 2022; Lokanan & Ramzan, 2024). Eliminating extreme values supported the preservation of data integrity and enhanced the model's ability to focus on reliable predictors of financial instability. Therefore, out of the 12,196 records, 1,693 outliers (13.88%) were identified and removed. The remaining dataset consisted of 10,503 observations with no missing values in the target variable.

Train and Test Split

After the removal of outliers and missing target variables, the dataset was partitioned into training and testing subsets. A stratified random sampling approach was employed to maintain the original class distribution of the binary target variable, *MSCORE*. The data was split using a 75:25 ratio, with 7,877 samples allocated to the training set and 2,626 to the testing set. A fixed random seed (random_state=42) was applied to ensure reproducibility of the split. Following the stratified split, the class proportions remained consistent across both subsets. In the training set, 6,679 instances (84.8%) were classified as non-distressed (*MSCORE = 0*) and 1,198 (15.2%) as distressed (*MSCORE = 1*), yielding a class imbalance ratio of approximately 5.58:1. The testing set followed a similar distribution, with 2,226 non-distressed and 400 distressed cases, corresponding to a 5.57:1 ratio.

Handling Missing Values

The training and testing datasets were evaluated for missing values, where the training set contained 29,242 missing entries, while the testing set included 9,761 entries. A feature-wise analysis revealed several variables with non-negligible proportions of missing data. To maintain data quality and avoid bias in imputation, variables with more than 40% missing values were removed prior to further processing (Lokanan & Ramzan, 2024; Zhang, 2019). Specifically, two features, *BS_NET_ASSET_VALUE_PER_SHARE* (99.9% missing) and *SHS_HLD_BY_EXECS_PCT_OF_OUTSTDG* (100% missing), were excluded from both sets. Following this removal, the training and testing sets retained 41 features each. The missing values were imputed using the K-Nearest Neighbors (KNN) method, with the number of neighbors set to k = 5, allowing for the estimation of missing entries based on the closest observed values in the feature space.The KNN algorithm estimates missing values based on the Euclidean distance between instances in the feature space, preserving the multivariate structure of the data (Holman & Glas, 2005; Lokanan & Ramzan, 2024; Little et al., 2024). The imputation model was trained on the cleaned training set and then applied to the testing data. After imputation, all remaining missing values were resolved, yielding a complete dataset suitable for model development. A total of 13,497 missing values in the training set and 4,509 in the testing set were imputed using the KNN method. The final datasets consisted of 7,877 observations in the training set and 2,626 in the testing set, each with 41 fully populated features.

Multicollinearity Reduction

Multicollinearity among predictor variables was assessed and addressed through a two-stage process. First, Pearson correlation analysis was conducted on the training dataset to identify feature pairs with high linear correlation, defined by an absolute correlation coefficient of 0.70 or greater (Lokanan & Ramzan, 2024). The step identified 43 pairs of highly correlated features, suggesting redundancy in the dataset, as shown in Figure 4.

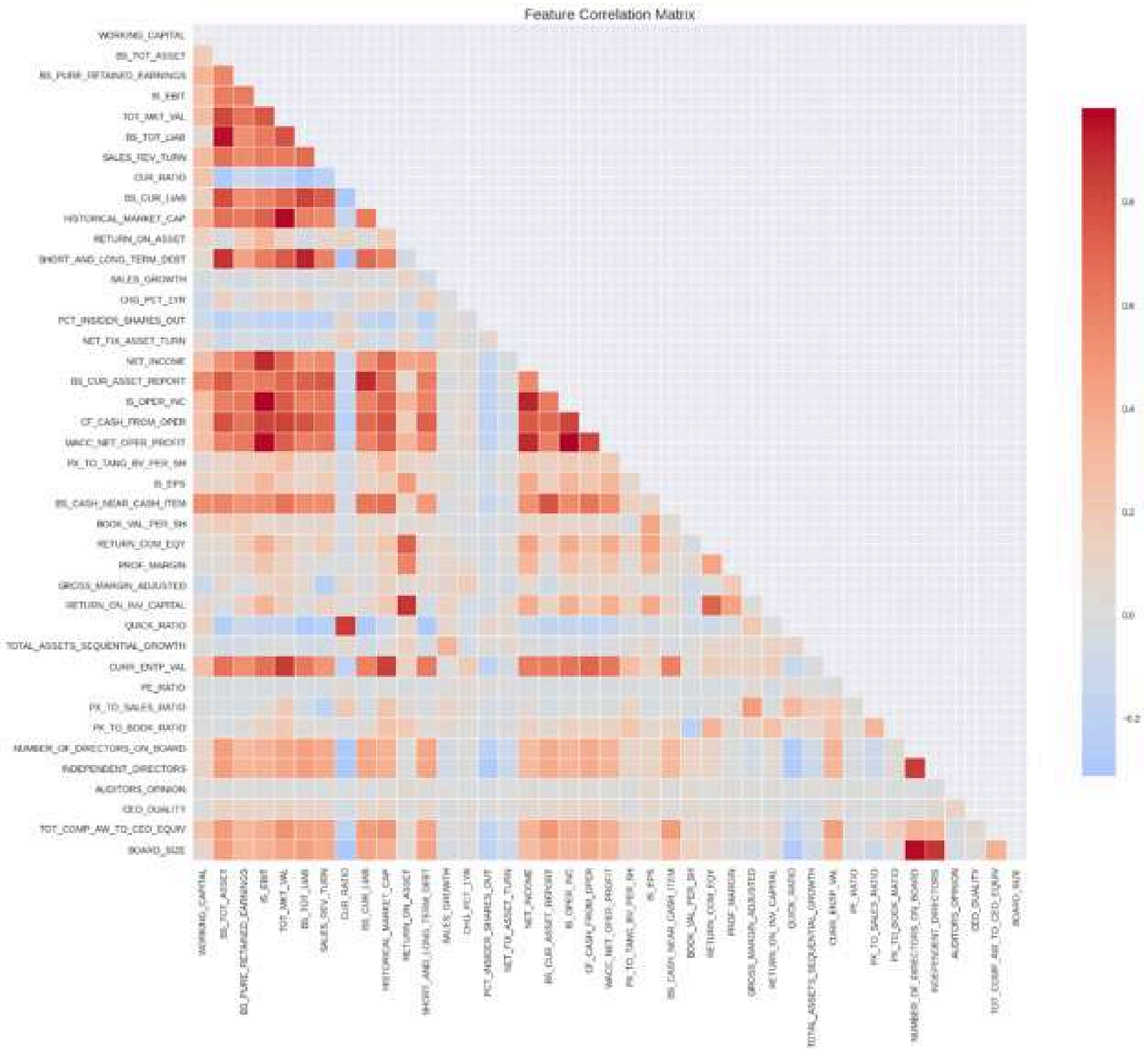

Figure 4: Heatmap for highly correlated features

To reduce this redundancy, one feature from each highly correlated pair was removed based on lower variance, retaining the more informative of the two. A total of 18 features were removed through this method. The resulting feature set was then subjected to Variance Inflation Factor (VIF) analysis to identify multicollinearity not captured by pairwise correlations. VIF was calculated for each remaining variable, with a threshold of VIF > 10 used to indicate problematic multicollinearity. Two features, AUDITORS_OPINION (VIF = 36.04) and INDEPENDENT_DIRECTORS (VIF = 23.51), initially exceeded this threshold. An iterative removal process was employed, beginning with the feature exhibiting the highest VIF. After removing AUDITORS_OPINION, the remaining features all exhibited acceptable VIF scores below the cutoff. Following correlation and VIF-based filtering, the total number of features was reduced from 41 to 22, effectively eliminating redundant or collinear variables. The final datasets included 7,877 observations and 22 features in the training set, and 2,626 observations and 22 features in the testing set. By refining the feature set to exclude redundant and highly correlated variables, the model was trained on more distinct and informative inputs, thereby enhancing interpretability and improving generalization performance.

Feature Engineering

The feature engineering process of this studywas informed by foundational theories and empirical evidence derived from the financial distress scholarship (Liang et al., 2020; Wang et al., 2018; Zhao et al., 2023). To enhance the explanatory power of the model and incorporate domain-specific insights, additional features were engineered using standard financial ratio formulations. The engineered features were designed to capture key dimensions of a firm's performance, including liquidity, profitability, leverage, efficiency, market valuation, growth, governance, and financial stability. These aspects of accounting status have been frequently used by previous studies to enhance the predictive signal within the dataset, especially in the context of class imbalance and firm-level heterogeneity (Wang et al., 2018; Zhao et al., 2023). Among the candidate variables, only one engineered feature, SALES_GROWTH_ABS, was retained, as other computed features relied on variables previously removed during multicollinearity reduction. The new feature represents the absolute value of sales growth, capturing magnitude regardless of direction, and was added to both training and testing sets. The final training and testing datasets each included 23 features, with one new variable, SALES_GROWTH_ABS, successfully integrated. Post-processing validation confirmed that both datasets were free of missing or infinite values.

Feature Selection

In the feature selection process, univariate feature selection was performed using the SelectKBest method with F-test values derived from ANOVA as the scoring function to find the optimal feature subset, reduce dimensionality, noise, and improve prediction accuracy (Liang et al., 2020; Lokanan et al., 2019; Lokanan & Ramzan, 2024, Zhang, 2019). The individual relationship of each predictor and target variable is evaluated using this method, where features are ranked based on their statistical significance. The approach emphasized features with the strongest univariate association with financial distress, striking a balance between performance and interpretability (Liang et al., 2020; Zhang, 2019; Zhao et al., 2023). A range of values for the number of features to retain *k* was tested: 10, 15, 20, 25, 30, 35, 40, 45, and 50. For each *k*, a logistic regression model was evaluated using five-fold cross-validation, with the F1-score as the performance metric. The value of *k* yielding the highest average F1-score was selected as optimal. The results identified k = 20 as the optimal number of features for machine learning modelling. Hence, the feature selection process derives the optimal feature subset that will lead to successful model development.

Feature Scaling

For feature scaling, standard scaling was applied to standardize the range of all selected input variables and ensure comparability across features, preventing certain features from disproportionately influencing model performance (Lokanan & Ramzan, 2024; Singh & Singh, 2020). In the standardization procedure applied in this model, each financial metric was transformed to achieve a mean of zero and a standard deviation of one (Farooq & Qamar, 2019; Lokanan et al., 2019; Lokanan & Ramzan, 2024). Subsequently, the mean was subtracted from each observed value, and the result was divided by the corresponding standard deviation. The transformation can be expressed mathematically as:

$$x' = \frac{x - \mu}{\sigma}$$

StandardScaler was fitted on the training dataset and subsequently applied to the test set to avoid data leakage, ensuring consistency in transformation across both datasets. The dimensions of the datasets remained unchanged, with 7,877 observations and 20 features in the training set and 2,626 observations and 20 features in the test set. Descriptive statistics before and after scaling demonstrated successful transformation. For example, the CUR_RATIO feature originally had a mean of 2.10 and standard deviation of 1.45, which were standardized to approximately 0.00 and 1.00, respectively. Hence, the scaling process preserves the relative structure and variability of each feature, as shown for CUR_RATIO in the Figure 5 below, while aligning them to a common scale suitable for machine learning algorithms.

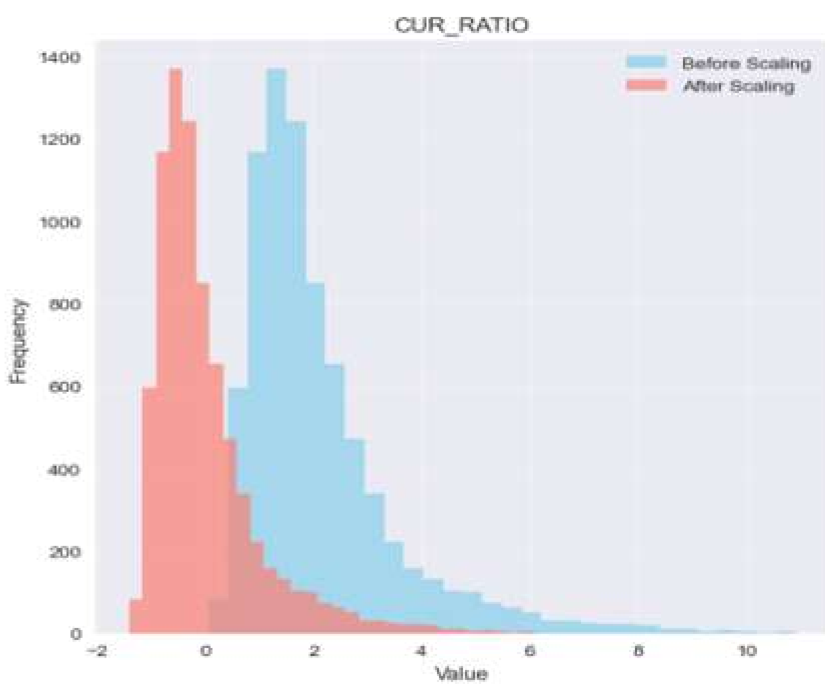

Figure 5: Standardization of CUR_RATIO

Handling Class Imbalance

Class imbalance poses a significant challenge in financial distress prediction, where most firms are categorized as non-distressed. The training dataset exhibited a pronounced class imbalance, with 84.8% of observations labeled as non-distressed and only 15.2% as distressed, yielding a ratio of approximately 5.58:1. Three established resampling techniques, Synthetic Minority Over-sampling Technique (SMOTE), Adaptive Synthetic Sampling (ADASYN) and SMOTE-Tomek Links, were applied to mitigate the adverse effects of this imbalance on model performance by augmenting minority class through synthetic sample generation or cleaning boundary instances. SMOTE remains one of the most widely adopted oversampling techniques, synthesizing new samples by interpolating between minority class neighbors (Lin et al., 2013; Mujahid et al., 2024; Nguyen et al., 2024). The method is particularly effective when the minority class forms a dense and learnable structure. ADASYN extends this concept by generating more synthetic samples in regions where the minority classes are harder to learn (Mujahid et al., 2024). SMOTE-Tomek, a hybrid method, combines SMOTE with Tomek Links to remove ambiguous samples near class boundaries after oversampling, further cleaning the dataset (Mujahid et al., 2024; Nguyen et al., 2024). Each technique was applied to the training split to ensure comparability across models. The resulting class distributions were nearly balanced across all three resampling techniques, effectively mitigating the bias introduced by class imbalance, as shown in Table 6. However, it is essential to note that while oversampling reduces bias toward the majority class, it may increase the risk of overfitting, especially if synthetic examples fail to capture actual data variation (Lin et al., 2013; Mujahid et al., 2024; Nguyen et al., 2024; Sun et al., 2014). To preserve generalizability, each resampled dataset was processed separately in downstream model development (Lin et al., 2013). The modular approach enabled a comparative evaluation of their impact on model performance metrics, such as F1-score and AUC, and how different sampling strategies interact with various classifiers.

Table 6: Resampling Results

Method	Total Samples	Class 0	Class 1	Ratio
Original	7877	6679	1198	5.58:1
SMOTE	13358	6679	6679	1.00:1
SMOTETomek	13264	6658	6658	1.00:1
ADASYN	13504	6679	6656	1.00:1

Hyperparameter tuning

Table 7 presents the parameters used to fine-tune the machine learning models employed in this study. The hyperparameter tuning phase of the study employed a GridSearchCV strategy to optimize the performance of machine learning algorithms trained on a wide range of hyperparameter settings. For instance, Logistic Regression was tuned over a grid of regularization strengths (*C*), penalty types (*l2*), and solvers (*newton-cg*), while tree-based models such as Decision Trees and Random Forests were tuned using parameters like max_depth, min_samples_split, and min_samples_leaf. XGBoost models incorporated additional controls such as learning_rate and subsample to fine-tune ensemble behavior and regularization (Carmona et al., 2022; Lokanan & Ramzan, 2024). GridSearchCV approach is a grid-based hyperparameter tuning approach that is computationally intensive and exhaustively evaluates model performance across defined parameter combinations using 5-fold cross-validation (Lokanan & Ramzan, 2024). The approach used F1 score as an evaluation metric to handle the class imbalance in the dataset due to its capacity to harmonize precision and recall, which are essential in detecting the minority (distressed) class (Lin et al., 2013; Lokanan et al., 2019; Lokanan & Ramzan, 2024; Sun et al., 2014). During this process, the hyperparameters were manually optimized through a targeted calibration process, which facilitated a deeper understanding of the individual and combined effects of each parameter on the model's predictive performance. Therefore, the hyperparameter tuning process allowed for both optimization and a deeper understanding of the modeling process, particularly relevant in the context of financial distress prediction, where regulatory and decision-making transparency are critical.

Table 7: Hyperparameter tuning

Algorithms	**Predictive modeling with GridSearchCV**
Logistic Regression	"C": 100, "penalty": l2, "solver": "newton-cg", "max_iter": 100
Decision Trees	"max_depth": 12, "splitter": "best", "min_samples_leaf": 4, "max_features": sqrt
Random Forest	"n_estimators": 100, "max_features": sqrt, "max_depth": 6, "max_leaf_nodes": 6
XGBoost	"max_depth": 3, 4, 5, 6, "learning rate": 0.01, 0.1, 0.2, "n_estimators": 100, 200, 300

Algorithms Used

Logistic Regression

Logistic regression is one of the most widely applied classification methods in financial distress prediction due to its effectiveness, interpretability, and suitability for binary outcomes (Chen, 2011; Zizi et al., 2021). It models the probability that a firm will experience financial distress, making it ideal for distinguishing between distressed and non-distressed entities (Lokanan & Ramzan, 2024; Lokanan

& Sharma, 2022). The model estimates the likelihood of an outcome using a logistic function, where each predictor is associated with a coefficient derived from training data (Chen, 2011; Lokanan & Sharma, 2022; Lokanan & Ramzan, 2024; Zizi et al., 2021). The transparent structure of this algorithm enables easy interpretation of how individual financial variables influence distress risk, providing critical insights for regulators and decision-makers (Chen, 2011; Zizi et al., 2021). Despite the rise of complex machine learning techniques, logistic regression remains competitive, especially in longer-term forecasting scenarios, often outperforming advanced models in predictive accuracy (Hajek & Henriques, 2017; Lokanan & Ramzan, 2024; Perols, 2011). Therefore, the algorithm's computational simplicity, combined with extensibility and strong empirical performance, solidifies logistic regression's position as a foundational model in the financial analytics domain. The mathematical equation of logistic regression is represented in Equation 2:

$$y = \frac{e^{(b_0 + b_1 * x)}}{(1 + e^{(b_0 + b_{1*x})})}$$

where,
y is the predicted output,
b_0 is the bias or intercept term,
and b_1 is the coefficient for the single input value (x).

Decision Trees

Decision tree algorithms have become increasingly prominent in financial distress prediction due to their capacity to model complex, nonlinear relationships inherent in financial data. Their rule-based structure offers high interpretability, enabling stakeholders such as regulators, investors, and corporate managers to clearly trace and understand model outcomes (Liu et al., 2023; Qian et al., 2021). Unlike traditional linear models, decision trees can uncover complex interactions among financial variables, enhancing predictive power. Empirical studies have shown that decision trees, and their ensemble extensions such as random forests and gradient boosting, often achieve superior accuracy, particularly in short-term forecasting horizons (Chen, 2011; Liu et al., 2023; Qian et al., 2021). Moreover, these models inherently perform feature selection, ranking variables by importance, and adapt to imbalance datasets, a common issue in financial distress modeling, which aids both performance and transparency (Liu et al., 2023; Qian et al., 2021). In practice, the decision paths derived from trees offer actionable insights for policy and risk management. As a result, decision tree models serve not only as accurate predictors but also as interpretable decision-support tools in financial analysis. The mathematical equation for decision trees is as follows:

$$\hat{y} = \sum_{j=1}^{J} c_j \,.\, I(x \in R_j)$$

where,

is the predicted output,

I is the total number of terminal (leaf) nodes,

c_j is the predicted value (constant) assigned to region R_j, typically the mean or majority class of training samples in that leaf.

is an indicator function that equals 1 if the input vector x falls into region $R_{j,}$ and 0 otherwise,

and R_j are disjoint regions (leaves) created by recursive binary splits on feature values.

Random Forest

Random Forest has emerged as a leading machine learning method for financial distress prediction due to its consistent accuracy, resilience, and practical interpretability (Huang et al., 2017; Malakauskas & Lakstutiene, 2021). Leveraging an ensemble of decision trees, it effectively captures nonlinear interactions among financial variables that traditional statistical models often overlook as the algorithm "generates a collection of decorrelated trees (random forest) based on multiple simulations of the actual training sample" (Bragoli et al., 2022; Breiman, 2001; Jabeur et al., 2021). Empirical research consistently shows that Random Forest outperforms methods such as logistic regression, support vector machines, neural networks and Naïve Bayes across diverse datasets and economic environments (Huang et al., 2017; Liu et al., 2023; Malakauskas & Lakstutiene, 2021; Mousavi & Lin, 2020). The model's ROC has reached as high as 93% in some studies, demonstrating its superiority in both classification performance and stability (Lokanan & Ramzan, 2024; Tron et al., 2023). The model's robustness stems from its resistance to overfitting, making it well-suited for high-dimensional, imbalanced financial data (Chen, 2011; Huang et al., 2017; Liu et al., 2023). Therefore, this dual capacity for performance and interpretability enhances its suitability for credit risk analysis, regulatory oversight, and early warning systems. The mathematical equation for Random Forest is represented in Equation 3:

$$\hat{y} = \frac{1}{T}\sum_{t=1}^{T} f_t(x)$$

where,

is the final predicted output of Random Forest,

T is the total number of decision trees in the forest,

$f_t(x)$ is the prediction made by the t^{th} decision tree in the ensemble,

and x is the input feature vector.

XGBoost

XGBoost has emerged as a preferred machine learning algorithm for financial distress prediction due to its use of regularization to prevent overfitting, parallel computation and robustness across complex financial datasets (Ding et al., 2023; Jabeur et al., 2021; Liu et al., 2021; Qian et al., 2022). As a gradient boosting framework, XGBoost efficiently mines patterns in high-dimensional data and exploits features that are relevant to the target variable, providing a structured view of feature importance, due to its state of art tree based ensemble nature (Bragoli et al., 2022; Carmona et al., 2022; Ding et al., 2023; Zhao et al., 2023). Its ability to address imbalanced class distributions through cost-sensitive learning and resampling strategies enhances its performance in detecting rare but critical instances of financial distress (Jabeur et al., 2021). Empirical evidence shows that XGBoost frequently outperforms traditional models such as logistic regression and other ensemble methods like Random Forest in accuracy, precision, and recall (Ding et al., 2023; Jabeur et al., 2021). The algorithm's adaptability allows it to serve as an effective early warning system, identifying at-risk firms before distress materializes and scalability and efficiency in computation make it ideal for large-scale financial datasets (Carmona et al., 2022; Qian et al., 2022). Consequently, XGBoost stands out as a reliable, accurate, and interpretable tool in predictive financial analytics.

$$\hat{y}_i = \sum_{k=1}^{K} f_k(x_i), \quad f_k \in \mathcal{F}$$

where,

is the predicted output for the ith observation,

K is the total number of trees in the ensemble,

$f_k(x_i)$ is the prediction made by the k^{th} regression tree for input x_i,

and is the space of all possible regression trees (i.e., CARTs – Classification and Regression Trees).

Performance Measures

To evaluate the predictive power and robustness of the machine learning models, this study employed a suite of performance metrics that go beyond traditional statistical predictors. These include accuracy, precision, recall, F1 score, and the AUC, each offering comprehensive insights into model behavior across balanced and imbalanced datasets (Lin et al., 2013; Lokanan & Sharma, 2022; Mujahid et al., 2024). The performance of a classifier is measured using confusion matrices and classification reports. Accuracy serves as the baseline measure, capturing the proportion of correctly predicted instances over the total sample size. Although widely used, accuracy may offer a misleading assessment in the presence of class imbalance, where high scores can obscure poor classification of minority classes (Géron, 2019; Sekar, 2022). Precision measures the proportion of correctly predicted positive cases out of all positive predictions made. It is particularly critical in contexts where false positives incur high costs, offering insights into the model's discriminatory accuracy for the positive class (Lokanan & Sharma, 2022). Recall, or sensitivity, evaluates the model's ability to identify actual positive instances, with an emphasis on minimizing false negatives. A high recall indicates strong coverage of the target class and is essential in financial applications where failing to detect distress can have severe consequences (Géron, 2019; Lokanan & Sharma, 2022). F1 Score integrates both precision and recall into a single metric, calculated as the harmonic mean of the two. It balances the trade-off between false positives and false negatives, making it highly effective for evaluating models under imbalanced class distributions (Sekar, 2022). AUC captures the model's capacity to distinguish between classes across varying decision thresholds. AUC values range from 0 to 1, where higher scores indicate superior ranking ability of the classifier, especially in cases where the distribution of class labels is skewed (Géron, 2019; Lokanan & Sharma, 2022). Together, these metrics offer a comprehensive evaluation of model performance, addressing not only overall predictive accuracy but also the model's ability to generalize across diverse and imbalanced financial datasets. The performance metrics used in this paper are shown in Table 8:

Table 8: Model evaluation metrics

Metric	CV
Accuracy	$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Number\ of\ Samples}$
Precision	$Precision = \frac{True\ Positives}{True\ Positives + False\ Positives}$
Recall	$Recall = \frac{True\ Positives}{True\ Positives + False\ Negatives}$
F1	$F_1 = 2 * \frac{Precision * Recall}{Precision + Recall}$
Area under the ROC curve	$\int_0^1 TPR(FPR)d(FPR)$

Results

Results from Machine Learning

To rigorously evaluate the predictive capacity of financial distress classifiers under class imbalance, the study tested four supervised machine learning algorithms: Logistic Regression, Decision Tree, Random Forest and XGBoost. Each model was assessed across three resampling techniques, including SMOTE, ADASYN, SMOTETomek, and the original sample. The performance was evaluated using standard classification metrics, including accuracy, precision, recall, F1-score, and the AUC, with a focus on F1-score and AUC due to their reliability in imbalanced classification tasks.

The models trained on the ORIGINAL (unbalanced) training data exhibit patterns typical of highly imbalanced classification problems. All models achieved high accuracy scores, ranging from 0.83 (Decision Tree) to 0.86 (Logistic Regression), as shown in Table 9 below. However, this high accuracy masks a critical deficiency in identifying the minority class, evidenced by the uniformly low recall scores. The Random Forest model, although achieving the best precision (0.83), suffers from the poorest recall (0.0375), resulting in the lowest F1-Score (0.0718). The results of the original data confirm that ensemble models, such as Random Forest, tend to favour stability and majority patterns, leading to conservative predictions, which is great for precision, but risky for recall. Moreover, XGBoost demonstrated the highest recall (0.2525) and the highest F1-Score (0.35) among the models using the ORIGINAL data. Furthermore, XGBoost achieved the best AUC-ROC score (0.77), indicating superior discriminative power, even when faced with significant class imbalance. The consistently low recall across all models on the ORIGINAL data highlights that passive learning on imbalanced datasets fails to capture the minority signals associated with financial distress, leading to a high rate of false negatives.

Table 9: Performance evaluation metrics on original data

Model	**Accuracy**	**Precision**	**Recall**	**F1-Score**	**AUC-ROC**
Logistic Regression	0.86	0.65	0.16	0.25	0.75
Decision Tree	0.83	0.40	0.19	0.26	0.62
Random Forest	0.85	0.83	0.04	0.07	0.76
XGBoost	0.86	0.58	0.25	0.35	0.77

Logistic Regression models showed substantial improvement in recall and F1-score, due to the application of resampling techniques. The combination of Logistic Regression with SMOTE (SMOTE-LR) emerged as the best-performing technique in the study. SMOTE-LR achieved the highest F1 score of 0.45, and recall jumped from 0.16 to 0.63, demonstrating the strong capability of the model in identifying distressed firms. The combination of Logistic Regression with SMOTETOMEK (SMOTETOMEK-LR) maintained nearly identical performance to SMOTE-LR, with a F1 score of 0.45 and a recall of 0.63. The combination of Logistic Regression with ADASYN (ADASYN-LR) achieved the highest recall score (0.66) across all models and resampling techniques, confirming its aggressive generation of synthetic minority samples. However, this high recall came with a notable trade-off, where accuracy dropped for this model to 0.74 and precision fell to 0.32, the lowest among the Logistic Regression models. Hence, the pattern aligns with prior findings in the literature that emphasize the cost of achieving high recall in imbalanced classification leads to increased false positives and reduced overall precision (Lokanan & Ramzan, 2024).

Additionally, Decision Trees and Random Forest models also saw substantial increases in recall and F1-score under resampling, although the F1 values remained lower as compared to Logistic Regression and XGBoost, as shown in Table 10. The combination of Decision Tree and SMOTE (SMOTE-DT) achieved a recall of 0.48 and a F1 score of 0.35, a significant improvement over the original F1 of 0.26. The combination of Random Forest and SMOTE (SMOTE-RF) achieved an improved recall score of 0.59 from the original recall score of 0.038. While this dramatically improved its predictive power, the resulting F1-Score of 0.40 of Random Forest across all resampling strategies, which suggests that even with balanced data, the model remained relatively conservative compared to Logistic Regression, reinforcing the notion that ensemble models favor stability and may struggle with minority class sparsity. Moreover, XGBoost consistently achieved accuracy above 0.84 across all resampling methods, while Logistic Regression, Decision Trees, and Random Forest ranged between 0.72 and 0.76, indicating that XGBoost utilized the synthetic features more effectively while maintaining robustness. The combination of XGBoost and SMOTE (SMOTE-XGBoost) achieved an F1score of 0.41, slightly below Logistic Regression but considerably higher than Decision Trees and Random Forest. The combination of XGBoost and SMOTETOMEK (SMOTETOMEK-XGBoost) achieved the highest F1 score of 0.41. Therefore, XGBoost demonstrated stable performance across the resampling methods, indicating its ability to capture complex patterns while maintaining accuracy. In contrast, Logistic Regression showed a greater decline in accuracy when recall was prioritized. Hence, based on the overall analysis, the SMOTE-LR is identified as the overall optimal choice based on the F1-Score (0.45). In the context of financial distress prediction, while the SMOTE-LR model is mathematically the best balanced model, its Precision (0.35) may still be considered too low by auditors who must balance investigation costs against risk. Conversely, its Recall (0.63) suggests a meaningful improvement in identifying risk compared to the highly precise, yet functionally useless, Random Forest model on the ORIGINAL data (Recall 0.038, Precision 0.83).

Table 10: Model performance summary table

Model	Accuracy	Precision	Recall	F1_Score	AUC_ROC	CV_F1_Score
SMOTE-LR	0.77	0.35	0.63	0.45	0.75	0.68
SMOTE-DT	0.73	0.28	0.48	0.35	0.67	0.73
SMOTE-RF	0.73	0.30	0.59	0.40	0.73	0.68
SMOTE-XGB	0.85	0.49	0.35	0.41	0.74	0.91
SMOTETOMEK-LR	0.77	0.35	0.63	0.45	0.75	0.68
SMOTETOMEK-DT	0.74	0.28	0.48	0.36	0.67	0.73
SMOTETOMEK-RF	0.73	0.30	0.58	0.40	0.73	0.68
SMOTETOMEK-XGB	0.84	0.48	0.36	0.41	0.75	0.92
ADASYN-LR	0.74	0.32	0.66	0.43	0.75	0.65

ADASYN-DT	0.69	0.26	0.57	0.36	0.67	0.73
ADASYN-RF	0.72	0.29	0.60	0.39	0.73	0.66
ADASYN-XGB	0.84	0.47	0.35	0.40	0.73	0.91

Collectively, these results underscore the effectiveness of resampling in improving sensitivity to the minority class, particularly for logistic regression models. However, they also reaffirm the trade-offs between recall and precision, which are central to algorithmic performance in high-stakes domains such as financial distress prediction. Moreover, Figure 6 provides a comparative visual analysis of the F1-Scores across four machine learning models (Decision Tree, Logistic Regression, Random Forest, and XGBoost) under four different resampling strategies (Original, SMOTE, SMOTETomek, and ADASYN). The heatmap reveals that Logistic Regression models achieved the highest F1-scores across all resampling techniques, particularly with SMOTE and SMOTETomek, indicating that linear classifiers significantly benefit from synthetic minority oversampling. The heatmap also showcased that XGBoost and Random Forest performed consistently well, especially with SMOTETomek and SMOTE, reinforcing the ensemble models' robustness and capacity to generalize with the aid of sampling. However, both models underperformed on the original imbalanced dataset and outperformed after resampling due to enhanced class balance. The resampling procedure allowed the model to better learn decision boundaries for the minority (distressed) class, thereby increasing recall without compromising precision. Interestingly, the Decision Tree model lagged behind in all configurations, particularly on the original and ADASYN datasets, likely due to its high variance and susceptibility to noise, including the synthetic examples generated.

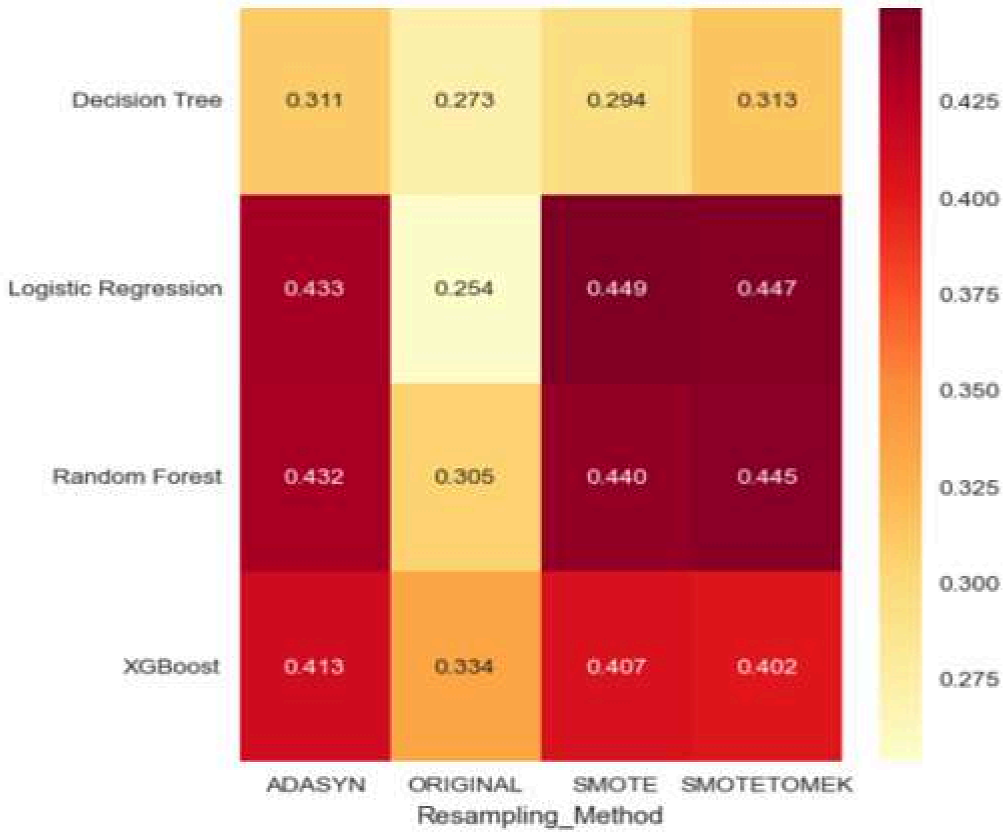

Figure 6: Heatmap comparing model performance based on F1 score

When considering the model performance comparison using AUC-ROC, as shown in Figure 7, the ensemble methods outperformed other models, where XGBoost consistently achieved the highest AUC-ROC scores across all resampling methods, peaking with SMOTETOMEK and SMOTE, indicating its robust discriminative ability even under class imbalance conditions. Random Forest followed closely, with AUC values just below those of XGBoost. Notably, the performance variation across resampling methods was minimal, reflecting the stability of the ensemble model. Logistic Regression exhibited moderate AUC scores across all techniques, reaffirming its sensitivity but relatively lower specificity when compared to ensemble methods. Decision Trees showed the weakest performance, with AUC values consistently under 0.65, particularly struggling with ADASYN and SMOTETOMEK, likely due to overfitting on synthetic samples.

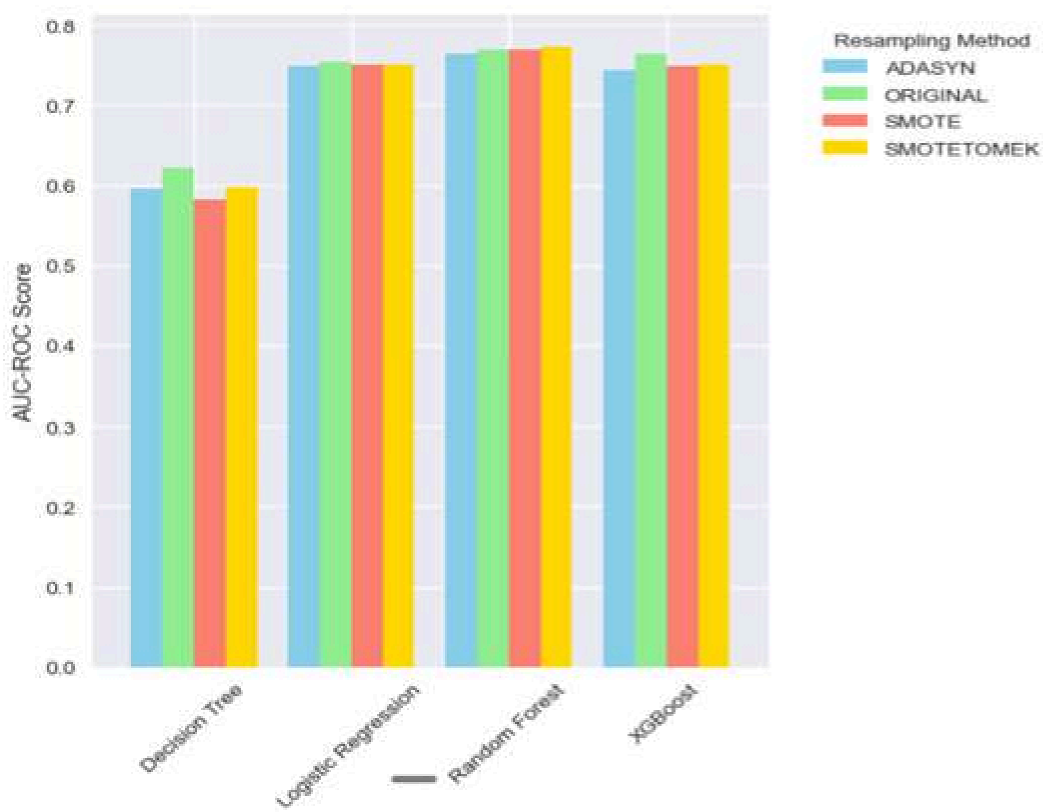

Figure 7: Bar plot comparing model performance based on AUC-ROC score

Feature Importance Analysis

The feature importance rankings derived from the Random Forest model trained on the SMOTETomek-resampled dataset provide valuable insights into the structural predictors of financial distress, as shown in figure 8. Among the top-ranked features, TOTAL_ASSETS_SEQUENTIAL_GROWTH, SALES_GROWTH, and SALES_GROWTH_ABS emerged as dominant, collectively accounting for nearly 30% of total model importance. These variables reflect temporal growth dynamics and firm expansion trajectories, suggesting that anomalously high or declining asset and revenue growth rates serve as early warning indicators of financial instability, consistent with prior studies linking aggressive growth strategies to earnings manipulation and distress risk.

Governance-related features such as INDEPENDENT_DIRECTORS and TOTAL_COMP_AW_TO_CEO_EQUIV also demonstrated notable predictive power, affirming the relevance of board independence and executive compensation alignment in identifying governance-induced strain. Liquidity and profitability indicators, CUR_RATIO, GROSS_MARGIN_ADJUSTED, and RETURN_COM_EQY, further reinforce that operational and financial efficiency play a central role in distress prediction. Lastly, market-based and ownership variables, including WORKING_CAPITAL and PCT_INSIDER_SHARES_OUT, round out the top contributors, highlighting that capital structure and insider activity hold predictive relevance in financial risk modeling. Overall, the feature importance distribution aligns with strain theory's emphasis on financial, governance, and market pressures, reinforcing the multidimensional nature of distress mechanisms.

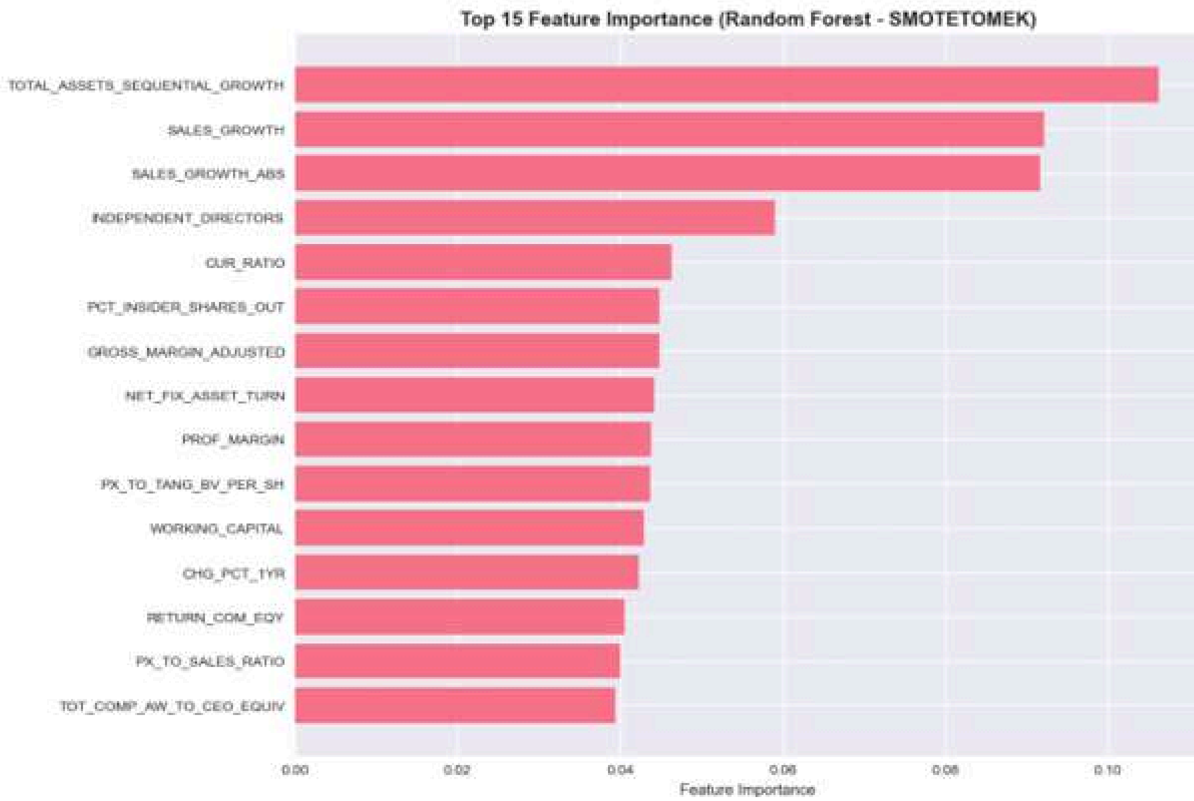

Figure 8: Feature importance ranking

Discussion

Where possible in this sectin, say your findings either corroborate or is contrary to the findings of XXX…you need to show the relevance of the literature review and theory.

The observed patterns among the distressed firms listed on the NYSE and NASDAQ provide empirical validation for Merton's strain theory as a robust framework for understanding the antecedents of financial distress and earnings manipulation among publicly traded firms. Rather than viewing financial distress solely through quantitative indicators, this research situates it within systemic and organizational pressures. The findings corroborate with the literature and show that financial, market, and governance strains are closely tied to structural pressures that manifest in observable patterns of corporate misconduct, including fraudulent accounting practices (Cooper et al., 2013; Lokanan, 2015; Morales et al., 2014; Ramzan & Lokanan, 2024; Ramzan & Lokanan, 2025).

Firstly, the observation that distressed firms exhibit lower profitability, constrained liquidity, and elevated financial leverage aligns directly with the "strain to achieve financial goals" tenet of strain theory (Donegan & Ganon, 2008; Ramzan & Lokanan, 2025). Descriptive statistics confirm these vulnerabilities: metrics such as RETURN_ON_ASSET and RETURN_COM_EQY show low central tendencies (means of 0.04 and 0.93, respectively), while highly skewed distributions in liquidity indicators such as CUR_RATIO suggest the presence of firms either experiencing or masking financial instability. These constraints limit legitimate paths to performance recovery, intensifying pressure on management. Hence, the findings of this study corroborate with prior literature on financial distress and fraudulent reporting stating that internal pressure is shown to be a primary driver of unethical behavior (Carmona et al., 2022; Lokanan, 2019).

Secondly, market features such as TOTAL_ASSETS_SEQUENTIAL_GROWTH and SALES_GROWTH were among the most influential predictors of manipulation. Their prominence reinforces the idea that distress signals embedded within financial ratios are both diagnostic and predictive of manipulation risk. The striking finding that fraudulent firms reported significantly higher average sales growth (83.97%) compared to non-fraudulent ones (7.20%) highlights the strain to uphold market image and institutional expectations. While seemingly counterintuitive, the elevated sales growth likely reflects revenue inflation, a common strategy to boost perceived performance and meet investor demands. Such organizational pressures, especially when prior performance sets high benchmarks, create systemic constraints that incentivize manipulation. Moreover, the high importance of SALES_GROWTH_ABS and PX_TO_SALES_RATIO in feature rankings confirms that these inflated metrics are likely artificially enhanced to maintain market confidence, consistent with revenue inflation strategies. The findings of this study corroborate with Donegan and Ganon (2008), Figlioli and Lima (2022), Ramzan and Lokanan (2025), Sehgal et al. (2021), and Lokanan (2019), all of which emphasize how institutional demands for growth and enterprise value can compel management toward unethical accounting practices. Therefore, the study empirically links institutional and performance-related pressures to concrete instances of financial manipulation, showing how systemic constraints drive such outcomes.

Thirdly, the prevalence of weak corporate governance structures, evidenced by inadequate audit opinion oversight, lower board independence and CEO duality, in firms classified as manipulators provides strong support for the argument that structural weaknesses in governance create conditions of strain. Feature importance rankings also highlight governance variables such as Independent Directors (importance = 0.0591) and CEO Compensation (0.0394), confirming their central role in fraud detection. The findings corroborate with prior scholarship asserting that robust governance frameworks are crucial for preventing deceptive financial reporting (Nasir et al., 2019; Tron et al., 2022). The study's results indicate that when organizations are under pressure to achieve governance objectives, pre-existing weaknesses in oversight mechanisms can enable or amplify unethical financial behavior. Moreover, the finding addresses an existing research gap identified in the literature, where governance variables are often treated as secondary control factors rather than core components within predictive models (Lokanan & Ramzan, 2024; Nasir et al., 2019). By integrating these governance factors as primary predictive features, the study moves beyond mere correlation to highlight their enabling role in the manifestation of strain-induced misconduct.

In summary, the results demonstrate that financial, market, and governance dimensions serve as separate but interconnected sources of strain. Financial strain involves constraints such as declining cash flow, debt commitments, and covenant risks that limit legitimate options for recovery (Bragoli et al., 2022; Carmona et al., 2022). Market strain originates from goal–performance gaps caused by previous growth targets and investor expectations, which lead to revenue inflation to maintain a positive image (Donegan & Ganon, 2008; Sehgal et al., 2021). Governance strain is rooted in weak oversight, including limited independence of the board and ineffective audits, which reduce detection chances and facilitate manipulation (Nasir et al., 2019; Tron et al., 2022). Among these, market and governance strains are most prominent in the findings, highlighting the importance of institutional pressures and governance capacity as key factors in misconduct (Lokanan, 2015; Lokanan et al., 2019; Sehgal et al., 2021). The study's findings extend Merton's strain theory at the organizational level by tracing how structural constraints and goal–performance gaps channel firms toward earnings manipulation.

Beyond its theoretical contributions, this study also offers methodological advances by integrating machine learning techniques, the Beneish M-Score, and strain theory predictors into a unified framework. Each component addresses a known limitation in financial distress prediction, where machine learning models enhance classification accuracy and capture nonlinear relationships overlooked by traditional statistics (Carmona et al., 2022; Qian et al., 2022); the Beneish M-Score adds a fraud-detection dimension, signaling potential manipulation that often precedes or coincides with distress (Beneish et al., 2012; Aviantara, 2023); and strain theory provides structural indicators of financial, market, and governance pressures that ground prediction in criminological theory (Lokanan, 2015; Ramzan & Lokanan, 2025). When combined, these elements create a model that is not only statistically rigorous but also theoretically informed, moving beyond accuracy metrics to explain why firms under institutional constraints may inflate performance. The integrated approach strengthens early warning systems by linking predictive power with explanatory depth, addressing a gap in existing scholarship where financial, governance, and criminogenic factors are often analyzed in isolation.

The comparative use of SMOTE, ADASYN, and SMOTE-Tomek Links, across four distinct supervised learning algorithms: Logistic Regression, Decision Tree, Random Forest, and XGBoost, represents another methodological contribution by moving beyond the common reliance on a single oversampling method. Prior research has often relied on a single resampling technique, typically SMOTE, without exploring how different methods interact with model-specific learning dynamics

(Hou et al., 2025; Mujahid et al., 2024; Nguyen et al., 2024). By comparing multiple combinations, this study addresses a critical gap in the literature and offers a granular understanding of how oversampling affects model behavior, particularly in terms of recall–precision tradeoffs. The findings reveal that while resampling significantly improves recall and F1-scores, particularly for logistic and ensemble models, the magnitude and nature of improvements are model-dependent. The findings of this study corroborate with prior studies (Lin et al., 2013; Sun et al., 2014) that highlight the risk of synthetic boundary distortion and increased false positive rates with aggressive oversampling.

The comparative analysis revealed distinct patterns in how resampling techniques interacted with classifier architectures. Logistic Regression exhibited the greatest improvement from resampling, with both SMOTE and SMOTETomek elevating the F1-score and recall, indicating a heightened sensitivity to minority-class instances. However, this gain came at a cost, as models like ADASYN-LR, while achieving the highest recall, experienced noticeable declines in precision and accuracy, underscoring the trade-off between identifying distressed firms and minimizing false positives. In contrast, Decision Trees showed only moderate performance gains under resampling, limited by their susceptibility to variance and noise amplification, especially from synthetic samples. Although SMOTE improved the F1-score, Decision Trees remained the least robust across sampling techniques. Random Forest initially favored precision over recall on the imbalanced dataset but responded positively to resampling while increasing recall and F1.

Nevertheless, the model retained a conservative classification bias, suggesting that ensemble bagging methods, while stabilized by averaging, are less flexible in adapting to class-boundary shifts induced by synthetic data. Among all classifiers, XGBoost demonstrated the most consistent and balanced performance across resampling methods. F1-scores remained stable (0.40–0.41) and AUC-ROC scores exceeded 0.74 in all cases. Unlike Logistic Regression, which traded off precision and accuracy to enhance recall, XGBoost preserved overall model robustness, maintaining accuracy above 0.84 even in resampled scenarios. Hence, the findings suggest that the XGBoost's framework effectively integrates synthetic samples without significant overfitting or performance degradation. Taken together, these results underscore that the effectiveness of resampling is inherently model-dependent. While Logistic Regression benefit most in terms of sensitivity, ensemble methods such as XGBoost offer superior generalization and class-discriminative power under imbalance conditions.

The choice of resampling method significantly influences downstream decisions in high-stakes domains like audit, regulation, and financial supervision, where the balance between recall and precision is ethically consequential (Carmona et al., 2022; Hou et al., 2025; Lokanan & Ramzan, 2024). High recall, as seen in SMOTE-LR and ADASYN-LR, enables early detection of distressed firms, but may overwhelm systems with false positives, leading to resource misallocation and reduced trust in automated surveillance tools. Nevertheless, several scholars, such as Hajek et al. (2022), argue that in fraud detection, higher recall is preferred despite the rise in false positives, as the cost of missing fraudulent cases outweighs the consequences of investigating false alarms. Conversely, high precision models such as Random Forest on the original dataset (Precision = 0.83, Recall = 0.04) may appear performant but are functionally ineffective, as they fail to flag the very instances of concern. Moreover, the results reinforce findings from Qian et al. (2022) and Sehgal et al. (2021) that oversampling must be interpreted contextually, especially in financial data where minority class signals may represent genuine distress or fraud. Over-reliance on numerical metrics without theoretical grounding, such as strain theory, may lead to misguided model optimization. For instance, a high recall model may detect many distressed firms, but without understanding the underlying drivers of manipulation, regulatory or audit interventions may remain superficial.

Conclusion

In conclusion, the study proposes and validates an integrated machine learning framework that combines traditional financial distress predictors, the Beneish M-Score, and strain theory–derived indicators to improve the detection of financial distress and earnings manipulation among NYSE- and NASDAQ-listed firms. By situating these predictors within ensemble learning methods such as Random Forest and XGBoost, the study responds to recent literature emphasizing the trade-offs between accuracy, interpretability, and class imbalance correction in financial datasets. The integration of strain-based structural pressures with algorithmic models provides not only predictive gains but also theoretical grounding, addressing concerns raised in prior research that machine learning approaches often optimize accuracy at the expense of explanatory depth. In bridging quantitative financial analytics with theory-driven indicators, the framework advances both methodological rigor and practical applicability in forensic accounting and financial regulation.

The incorporation of strain theory represents an important theoretical contribution to financial distress prediction. Grounding the analysis in structural pressures rather than relying solely on financial ratios or algorithmic outputs provides a framework for explaining why misconduct may arise under conditions of constraint. The triadic strain dimensions, financial, market, and governance, were included in the feature set based on this framework, however, their predictive strength varied across algorithms and sampling strategies. Some models ranked these dimensions highly and showed performance gains, while others produced weaker results, reflecting the complexity of linking theory-driven indicators to machine learning outputs. Situating model performance within the structural logic of strain theory strengthens interpretability and enhances the relevance of predictive systems for forensic accounting and financial regulation.

From a methodological standpoint, this research advanced the field by integrating and comparatively evaluating multiple resampling techniques (SMOTE, ADASYN, and SMOTE-Tomek Links) within a comprehensive machine learning pipeline. The study confirms that no single model–resampling combination dominates across all metrics, as indicated by the literature (Hou et al., 2025). The effectiveness of oversampling is contingent on model architecture, class imbalance severity, and tolerance for Type I versus Type II errors. Among all combinations, SMOTE-LR emerged as the most balanced in terms of recall and F1-score, while XGBoost with SMOTETomek demonstrated the strongest AUC-ROC performance and model stability. Therefore, practitioners and researchers must select models not solely based on peak metrics, but on contextual trade-offs and domain-specific costs of misclassification. The comparative framework introduced in this study thus offers a reproducible, data-driven approach for handling class imbalance in financial distress prediction, moving the field beyond single-technique reliance and toward a holistic evaluation of model behavior, ethical implications, and operational relevance.

In summary, this study underscores that financial distress is not merely a numerical anomaly but a complex social and criminology phenomenon. By integrating Merton's strain theory, this research moves beyond mechanistic algorithmic fitting to provide a profound, theory-driven understanding of *why* specific structural organizational patterns emerge as indicators of corporate failure and earnings manipulation. The synthesis of this criminology theory with advanced machine learning methods marks a promising path toward developing more robust, interpretable, and ethically informed early warning systems for regulators, investors, and auditors, ultimately improving early detection of earnings manipulation and enhancing the interpretability for regulatory audits

Limitations and Future Directions

Nonetheless, this study is not without limitations. First, while the Beneish M-Score is a widely accepted proxy for earnings manipulation, it remains a statistical estimate and not a confirmed indicator of fraud. The inherent noise may have constrained the model's ability to achieve higher classification scores. Second, the dataset, although large and diverse, may still miss important variables such as managerial intent, internal pressure, or macroeconomic shocks, which could further elucidate the strain mechanisms. Despite the advances in predictive modeling, a persistent challenge facing accounting researchers lies in obtaining access to the comprehensive data required to empirically test hypotheses related to macro- and micro-coercion, perceived organizational strain, and the influence of legitimate or corrupt social support systems . Future research endeavors should strive to incorporate more granular qualitative data to elucidate these complex criminologenic mechanisms further. Future research should also explore hybrid models that integrate textual analysis of corporate disclosures or auditor reports to capture qualitative dimensions of strain. Additionally, recursive feature selection and model explainability tools may help isolate non-linear interactions between financial and governance indicators that are currently underexplored. Furthermore, the study did not incorporate nested cross-validation, which could have provided a more robust estimate of generalization performance. Hence, future work could incorporate Bayesian optimization or evolutionary algorithms to explore high-dimensional hyperparameter spaces more efficiently.

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<table>
<tr>
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<td>Minimal Setting Stroke Unit in a Sub-Saharan African Public Hospital</td>
</tr>
</table>

INTRODUCTION

Stroke is a leading cause of death and disability worldwide (1). Good outcome in brain arteries occlusions is conditioned by early recanalization to prevent ischemic neuronal loss under the "time is brain" paradigm. To that aim, Healthcare policies in high income countries (HIC) underwent important structural modifications to allow as many patients as possible to benefit from recanalization therapy based on effective triage by advanced brain imaging and referral centers (2). This approach rely on both expansive imaging and endovascular intervention technique but has proved cost-effective to prevent death and disability from stroke in HIC (3). In recent years, the burden of stroke has moved from HIC to LMIC that now host 75 % of stroke mortality and 81 % of stroke-related disability (4). In low to middle income countries (LMIC), acute brain imaging facilities or stroke treatment referral centers are neither accessible nor affordable for the vast majority of the population (5) and most efforts to alleviate stroke burden are, therefore, based on primary prevention to control and limit risk factors (6, 7). Death and neurological deterioration after ischemic strokes are related to cerebrovascular complications due to lack of recanalization during the first hours (8) but can be attributed to medical complications in approximately 50 % of cases afterwards, mainly inhalation pneumonia, cardiac and thromboembolic diseases (9). These complications are partly prevented by acute surveillance in stroke units (SU). SU, in acute stroke management, consistently showed significant reduction of stroke burden and mortality, even in the earliest trials done when access to CT brain scanning was available for only a few patients which suggests that SU may contribute to stroke care in settings without easy access to brain imaging facilities (10).

In this work, we aim to assess the effect of a minimal setting SU on stroke mortality and medical complications in Conakry, Guinea, Ignace Deen public referral hospital that has no brain imaging facilities.

METHODS Local Setting

Guinea is a Sub-Saharan country of almost 12,000,000 inhabitants with an estimated medical doctor density of 7/100 000 inhabitants. Guinea is among the poorest countries in the world, ranking 171/192 based on the international money fund gross domestic product estimates. Healthcare system is pyramidal with the three national hospitals (Donka, Ignace Deen and Sino-Guinean) located in the capital, Conakry, of which only the Sino-Guinean is equipped with a computer tomography. According the World Health Organization data, two third of healthcare costs are supported by the patients and are therefore inaccessible to more than 40% of the population. In that context, cost-effectiveness has to be carefully balanced for patients to yield benefits from health intervention.

Method

At Ignace Deen Hospital, a minimal setting stroke unit of three *acute* beds, separated from the other Neurology ward thirty beds, has been equipped in 2017 with heart rate, blood pressure and blood oxygen saturation monitoring and portable oxygen concentrator. There, patients are evaluated every 4 h, for clinical parameters, body temperature and National Institute of Health Stroke Score (NIHSS) by a dedicated stroke team that consists of five senior neurologists, eight neurologists in training, seven nurses, and three physiotherapists. Standard procedure, adapted from the American stroke association guidelines on *In-Hospital Management of acute stroke: General Supportive Care* (11) (For details, see **Addendum**), were implemented for fever, pneumonia and decubitus complication prevention. When patients are stabilized, they are transferred to *non-acute* beds in the neurology ward. Ignace Deen Neurology ward is keeping a stroke registry since 2015 of which clinical characteristics are recorded, based on the world health organization ''STEPS" (12) approach. Mortality at 28 days, Modified Rankin Scale (MRS) at 28 days when available and in-hospital pneumonia, urinary tract infections, sores and venous thromboembolism rates of admitted stroke patients after the installation of a minimal stroke unit during a 12 months period (January-December 2018, POST) were extracted and compared to stroke patients admitted before the stroke unit creation (January-December 2017, PRE). Patients included all had Brain CT during hospitalization that were realized at the medical imaging center, *Caisse Nationale de Sécurité Sociale*, a facility independent from Ignace Deen hospital located at 500 meters from the hospital.

Comparisons between the proportions were performed with respect to qualitative and quantitative variables. Proportions were compared between groups by Fisher exact test. MannWhitney test was performed to compare numeric variables in the two groups. Statistical significance was set after correction for multiple comparisons (13) using a Bonferroni correction at $p < 0.004$.

The local Ethics Committee of Ignace Deen Hospital (Comité National d'Ethique pour la Recherche en Santé, CNERS) approved the study, but waived the need for informed consent as only anonymous and operational monitoring data were collected and analyzed.

RESULTS: (SUMMARIZED IN TABLE 1)

Three hundred and sixty-nine patients were included in the stroke registry after the installation of the SU (POST) and were compared to the three hundred and eighteen patients admitted for stroke when the SU did not exist (PRE). PRE and POST patients were comparable in term of age (61 ± 14 vs. 60 ± 14.8 years, $p = 0.24$), sex (56 vs. 50% males, $p = 0.09$), High blood pressure rates (76.7 vs. 79%, $p = 0.44$), stroke subtype (ischemic in 72 vs. 78% of cases, $p = 0.05$), NIHSS (11 ± 4 vs. 11 ± 4, $p = 0.85$)

and time from stroke onset to SU admission (93 ± 70.6 vs. 92.3 ± 59.1 h, $p = 0.9$). Diabetes was more frequent in the PRE group (19 vs. 9%, $p < 0.001$).

Mortality was significantly lower in the POST group (7.2 vs. 22.3%, $p < 0.0001$) as well as medical complications (4.1 vs. 27.7%, $p < 0.001$) with lower pneumonia rate (3.3 vs. 14.5%, $p < 0.001$), urinary tract infections (UTI) (2.3 vs. 12.2%, $p < 0.001$) and sores (6.6 vs. 0.8%, $p < 0.001$). A trend for higher MRS in stroke survivors was found in the POST compared to the group (3.39 ± 1.05 vs. 2.92 ± 0.94, $p = 0.007$).

DISCUSSION

This study compared stroke mortality and main medical complications in a Sub-Saharan public hospital without brain imaging facilities, before and after the onset of a minimal setting stroke unit. In that context, surveillance of stroke patients in a minimal setting SU led to significantly lower mortality and main medical complications.

TABLE 1 | Comparison of PRE and POST cohort clinical characteristics, outcome and complication.

	PRE STROKE (n = 318)	POST STROKE (n = 361)	p–value
Age (years)	61 ± 14	60 ± 14,8	0.24
Males (%, n)	56 (178)	50 (178)	0.09
High Blood pressure (%, n)	76.7 (243)	79 (285)	0.44
Diabetes (%, n)	19.8 (63)	9.2 (33)	<0.0001
Ischemic stroke (%, n)	71.4 (227)	78 (281)	0.05
NIHSS	11± 4	11± 4	0.85
Death (%, n)	22.3 (71)	7.2 (26)	<0.0001
Stroke onset to admission (hours)	93 ± 70.6	92.3 ± 59.1	0.9
Complications (%, n)	27.7 (88)	4.2 (26)	<0.0001
Pulmonary infections	14.4 (46)	3.3 (12)	<0.0001
UTI	12.6 (40)	2.3 (10)	<0.0001
TE	0.9 (3)	0.3 (1)	0.88
Sores	6.6 (21)	0.8 (3)	<0.0001
MRS of stroke survivors	2.92 ± 0.94 (n = 227)	3.39 ± 1.05 (n = 249)	0.007

NIHSS, national institute of health stroke scale; SU, stroke unit; UTI, urinary tract infection; TE, thrombo-embolic. MRS, modified rankin scale ranging from 0 (no symptoms) to 6 (death), >3: unable to walk unassisted.

Our cohort matches the characteristics of prior reports in Sub-Saharan Africa in term of age, sex, high blood pressure and diabetes prevalence as well as in term of ischemic stroke proportion (13–15). The twenty-two percent mortality rate in Conakry stroke patients before the setting of the SU corresponds to the rates reported in the InterStroke study that pooled data from Mozambique, Nigeria, South Africa and Sudan and those from smaller series from Cameroon (13) and Congo (14) which suggests that our studied population is representative of SubSaharan LMIC stroke epidemiology. The stroke severity of our cohort, reflected by the NIHSS, is lower than the in high income countries stroke trials that validated thrombolysis where mean NIHSS was of 14 (16) and five points lower than the mean NIHSS retrieved from a meta-analysis of the mechanical thrombectomy trials (17). This relatively lower stroke severity can be explained by the fact that, in Guinea, most severe cases probably failed to reach the hospital due to the lack of hospital accessibility in terms of distance, cost and medical transportation means. Indeed, a survey realized at Ignace Deen Neurology ward in 2014 revealed that only 2% of stroke patients arrived in ambulance, 46 % came by public transportation, 27 % by personal car while the rest had to find other means. This lack of accessibility is also reflected by the time elapsed between the stroke onset and the admission in the SU closing to 4 days. These facts combined with the lack of money to sustain the high healthcare costs associated to severe diseases in Guinea suggest that an important part of the severe stroke cases remained and/or died at home or died underway. Paradoxically, the long time between stroke onset and SU admission is also likely to explain the efficiency of the SU on stroke mortality in Conakry. Indeed, stroke death in the first week is mostly accounted by acute cerebrovascular complications such as hemorrhagic conversion of the ischemic brain tissue or cerebral herniation due to edema of around the necrotic zone (8, 9). The patients hospitalized in Ignace Deen SU had for most of them, already survived the first days and were entering the period after stroke onset where medical complications are responsible for an important proportion of supplementary deaths. Pathological studies found that stroke deaths after the first week were, respectively, due to pulmonary embolism in 30%, inhalation bronchopneumonia in 27% and cardiac disease in 37% of autopsied cases (9). In our PRE group, this reality is well-reflected by the rates of main stroke medical complications such as bronchopneumonia, urinary tract infections and sores that are corresponds to the range of previous report in western countries, even in term of thromboembolic complications (18). However, while infections and sores are easily diagnosed and managed in medical contexts with few ancillary exams available, the 0.9% rate for thromboembolic complications probably underestimates the prevalence of such complication in LMIC settings, due to a diagnosis bias related to the lack of access to ventilation/perfusion scintigraphy or pulmonary arteries computed tomography angiography. Accordingly, the number of diagnosed thromboembolic complications was too low for statistical comparisons. Similarly, underlying cardiac diseases and complications could not be reliably recorded in our population for lack of technical means and are therefore missing from this report, an important caveat as deaths from cardiac affections accounts for a substantial proportion of delayed stroke deaths. The reported effect of the SU on stroke mortality in the Conakry context is likely to be related to the better prevention, detection and treatment of infectious and immobility complications at a time where medical complications are the main providers of increased mortality in stroke survivors. That fact also explains why SU care failed to improve the mean functional stroke disability outcome assessed by the MRS in POST compared to PRE: higher proportion of fragile and severely disabled patients were prevented to die from stroke complications by SU care, therefore increasing the mean

MRS of stroke survivors in POST. This hypothesis is corroborated by the observed fall in bronchopneumonia, urinary tract infections and sores rates in the POST compared to the period prior to the SU onset. These results, obtained in a LMIC with no advanced brain imaging facilities accessibility, emphasizes the benefits of SU on death from stroke regardless of advanced brain imaging facilities accessibility and parallels findings obtained in HIC at a time when brain computed tomography was not yet a standard of care (19–21). In line with our study, in those seminal studies, one of the main effect of SU was to reduce the rate of stroke medical complications, mainly pneumonia, sores and venous thrombo-embolic diseases (19). Our report suggests that in contexts with low healthcare means and accessibility, SU could play a significant role in reducing stroke death and dependency. Especially in LMIC that now harbor the majority of the world stroke death and disability, public healthcare policies that enforce SU settings may prove highly effective in reducing disability-adjusted life years lost to stroke. SU spreading in LMIC may lead to more effective prevention of death and dependency from stroke than the development of single referral centers dedicated to recanalization therapy when patients struggle to pay the most basic healthcare interventions and arrive at the hospital several days after the stroke onset.

SUMMARY

Minimally equipped stroke units significantly reduce stroke mortality and main medical stroke complications in SSA and may constitute the base of stroke care regardless of advanced brain imaging accessibility.

ADDENDUM

Acute stroke care procedures:

- Supplemental oxygen
    - In case of decreased level of consciousness
    - To maintain blood oxygen saturation >94%
- Blood pressure control
    - If blood pressure(BP) is above 220/120 in the first 24 h: BP is lowered by 15%.
    - If BP is above 140/90 and the patient neurologically stable: antihypertensive therapy is started.

– Temperature

- Temperature above 38°C is treated by antipyretic and its cause looked for.
- Clinical pneumonia and urinary tract infections are treated by antibiotics when suspected.

– Glucose

- Blood Glucose levels are monitorized and insulin given to maintain the glycemia between 140 and 200 mg/dL.

– Dysphagia

- All stroke patients are clinically assessed: one tea spoon of water is given at the patient with his head in anteflexion. If coughing or alterations of mental state: no oral food for 24 h, then re-test: if coughing occurs, liquid and nutriments are given by nasogastric tube.

– Deep vein thrombosis and sore prophylaxis

- Regular patient mobilization and turning
- Regular skin assessment and maintenance of good skin hygiene.

DATA AVAILABILITY

The datasets generated for this study are available on request to the corresponding author.

AUTHOR CONTRIBUTIONS

All authors listed have made a substantial, direct and intellectual contribution to the work, and approved it for publication.

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<table>
<tr><td>Ali Raza(Author)
Imran Idrees College of Pharmacy</td><td>The Role of Drug Inspectors in Strengthening Pakistan's Healthcare System: A Career Perspective from a Final-Year Pharm-D Student</td></tr>
</table>

Abstract

This research paper highlights the role of drug inspectors in Pakistan's healthcare system, addressing their core responsibilities, qualifications, legal framework, challenges, and the scope for Pharm-D students. As a final-year Pharm-D student at Imran Idrees College of Pharmacy (affiliated with the University of the Punjab), I, Ali Raza, have carried out extensive research on the recruitment, training, and real-world responsibilities of drug inspectors. The aim of this paper is to provide a deep understanding of how this role contributes to public health, along with a personal reflection on my ambition to join this noble profession.

Introduction

The drug regulatory system plays a critical role in ensuring the quality, safety, and efficacy of medicines. In Pakistan, drug inspectors serve as frontline regulators who enforce drug laws and monitor pharmaceutical practices. With a growing population and increasing demand for healthcare services, the role of drug inspectors has become more crucial than ever. As a finalyear pharmacy student aspiring to become a drug inspector, I have explored the multi-faceted responsibilities of this profession through legal documents, recruitment advertisements, field interviews, and regulatory guidelines.

Objectives of the Study

- To understand the official roles and duties of drug inspectors in Pakistan
- To explore the recruitment and qualification process for the role
- To identify current challenges and gaps in the system
- To assess the future prospects for pharmacy graduates in this field
- To present a personal perspective as a future healthcare professional

Literature Review

Research shows that drug inspectors in Pakistan are governed by the **Drug Act of 1976**, **DRAP Act 2012**, and **Punjab Drug Rules 2007**. According to official job postings by the **Punjab Public Service Commission (PPSC)**, eligibility criteria include a Pharm-D or equivalent degree from an HEC-recognized university. Literature from the **Pakistan Pharmacists Association** and various academic journals highlight the shortage of trained inspectors, lack of digital monitoring systems, and need for regulatory reforms.

Roles and Responsibilities

As per the Drug Act 1976 and DRAP guidelines, a Drug Inspector performs the following:

- Inspect medical stores, pharmacies, and drug manufacturers
- Collect drug samples for laboratory analysis
- Ensure that only registered medicines are sold
- Take legal action against violations such as expired drugs, unregistered outlets, or spurious medicines
- Monitor storage conditions and license renewals
- Submit periodic reports to health departments

These duties require both technical knowledge and legal awareness, making the role suitable for qualified pharmacists.

Qualification & Recruitment Process

To become a drug inspector in Pakistan, the common requirements are:

- **Pharm-D or BPharmacy** (from HEC-recognized university)
- **Registration with the Pharmacy Council**
- **Basic knowledge of drug laws and pharmacology**
- **Selection through competitive exams like PPSC, FPSC, SPSC, etc.**
- **Medical fitness and character verification**

In recent advertisements by PPSC, Drug Inspector posts are highly competitive, with thousands of applicants applying for limited seats.

Challenges in the Current System

Despite their critical role, drug inspectors in Pakistan face several challenges:

- Shortage of staff relative to the number of pharmacies
- Political interference in fieldwork
- Outdated inspection tools and paperwork
- Inadequate training programs post-recruitment
- Legal loopholes exploited by unlicensed sellers
- Limited digital reporting and drug tracking systems

Addressing these challenges requires updated laws, digital infrastructure, and capacity building.

The Need for Reform

To ensure medicine safety and public health, Pakistan must:

- Increase the number of drug inspector posts based on district population
- Introduce smart inspection tools and mobile apps
- Provide refresher trainings and certifications
- Launch public awareness campaigns about legal drug dispensing
- Collaborate with DRAP and international agencies for global practices

Scope for Future Pharmacists

As a Pharm-D student, I believe this profession offers:

- A direct role in public health improvement
- Legal and scientific exposure
- Career stability and government benefits
- Opportunities for growth within regulatory bodies
- Respect in the pharmaceutical and healthcare communities

My long-term goal is to serve as a drug inspector in Punjab, ensuring quality medication reaches the public and contributing to the regulatory system of Pakistan.

Conclusion

Drug inspectors are the silent guardians of our health system. Their work ensures that patients receive safe and effective medicines. For aspiring pharmacists like me, this role represents more than a job — it's a mission to protect lives. With proper reforms and support, we can strengthen this vital profession and improve healthcare delivery across Pakistan.

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