ISSN 2776-8007

Anomaly Detection in Corporate Balance Sheets for Financial Risk Assessment Using Isolation Forest from 2020 to 2023

Khabib Adi Nugroho[1,*], Turino[2]

[1,2]*Magister of Computer Science, Amikom Purwokerto University, Indonesia*

(Received: March 10, 2025; Revised: April 14, 2025; Accepted: July 31, 2025; Available online: September 14, 2025)

Abstract

This study aims to evaluate corporate financial risk by analyzing changes in balance sheet accounts from 2020 to 2023 using anomaly detection methods. Employing the Isolation Forest algorithm with a 5% contamination rate, we identified a consistent 3,264 anomalies each year out of a total of 65,296 entries, focusing on key accounts, including Accumulated Depreciation (61 anomalies), Additional Paid-In Capital (17 anomalies), Accounts Payable (9 anomalies), and Accounts Receivable (6 anomalies). These anomalies highlight areas of potential financial risk associated with asset valuation, capital structure, and cash flow management. The steady presence of anomalies suggests underlying, possibly systemic factors influencing financial stability. Findings indicate that significant fluctuations in Accumulated Depreciation and Additional Paid-In Capital may impact the company's asset valuation and investor perceptions, while irregularities in Accounts Payable and Accounts Receivable suggest short-term liquidity risks. Recommendations include regular monitoring of high-risk accounts, trend analysis to identify cyclical patterns, and examining correlations with macroeconomic conditions to understand root causes. Future research should explore advanced anomaly detection models and integrate real-time detection capabilities to enhance proactive financial risk management. This study demonstrates the effectiveness of anomaly detection in identifying critical financial risks, supporting improved decision-making and corporate resilience.

Keywords: Anomaly Detection, Balance Sheet Analysis, Corporate Financial Stability, Financial Risk Assessment, Isolation Forest Algorithm

1. Introduction

In today's volatile economic landscape, assessing financial risk is essential for corporate decision-making and long-term sustainability. Financial instability can emerge from various factors, including changes in asset valuation, fluctuations in capital structure, and variations in short-term liabilities [1]. These factors may go undetected without in-depth analysis, exposing companies to potential financial risk. As balance sheet accounts provide insights into a company's financial health, detecting unusual changes within these accounts can reveal early signs of instability and highlight areas requiring closer scrutiny [2]. Traditional financial analysis often relies on ratios and trend analysis to evaluate risk; however, these methods may not effectively capture irregular patterns in data [3]. Anomaly detection offers an advanced, data-driven approach by identifying unusual values that deviate from expected trends. This method is particularly relevant in identifying hidden risks within extensive financial data, where patterns of variability may signal potential threats to financial stability [4]. While previous studies have utilized conventional financial ratios and basic statistical methods to analyze financial risk, these approaches are limited in their ability to detect anomalies within complex financial datasets [5]. Research on using advanced anomaly detection techniques, particularly machine learning-based models, in corporate financial analysis is still limited [6]. There is a need for more sophisticated methods that can dynamically and accurately detect deviations in financial accounts over time, providing early warnings of financial instability. Additionally, while many studies have focused on predictive risk models, few have explored anomaly detection specifically within balance sheet accounts, despite their critical role in reflecting a company's overall financial health [7].

Machine learning has introduced several powerful methods for anomaly detection, with Isolation Forest emerging as one of the leading approaches due to its effectiveness in isolating outliers in multidimensional data. Isolation Forest

***Corresponding author: Khabib Adi Nugroho (23ma41d018@students.amikompurwokerto.ac.id)**
DOI: https://doi.org/10.47738/ijaim.v5i3.107

works by randomly partitioning data points and quickly isolating anomalies, making it particularly suited for high-dimensional datasets common in financial analysis [8]. Unlike traditional statistical outlier detection methods, Isolation Forest is computationally efficient and scales well with large datasets, making it feasible for use in corporate financial settings. Recent research has demonstrated the algorithm's effectiveness in fraud detection and cybersecurity. Yet, its application in financial risk assessment, particularly at the corporate balance sheet level, remains underexplored. This study applies the Isolation Forest algorithm to analyze potential financial risks across a company's balance sheet accounts over four years (2020-2023). By setting a 5% contamination rate, the algorithm identifies anomalies in key accounts, including Accumulated Depreciation, Additional Paid-In Capital, Accounts Payable, and Accounts Receivable. Each account plays a critical role in maintaining financial stability, and significant anomalies within them could indicate underlying risks. The objectives of this research are twofold: first, to detect and quantify anomalies in balance sheet accounts, thereby identifying areas of potential financial risk; and second, to analyze these anomalies to understand the broader implications for asset valuation, liquidity, and equity stability. By employing anomaly detection, this study seeks to provide a more nuanced view of financial risk that can complement traditional methods and enable proactive risk management.

2. Literature Review

2.1. Traditional vs. Machine Learning Approaches in Financial Risk Assessment

Anomaly detection has gained significant attention as a tool for identifying irregularities within large datasets, with applications across fields such as fraud detection, cybersecurity, and finance. In the context of financial risk assessment, anomaly detection techniques offer a data-driven approach to identifying unusual patterns that may signal potential financial instability. This review discusses existing approaches in financial risk assessment, highlights the limitations of traditional methods, explores recent advancements in anomaly detection for financial applications, and reviews related work on the application of machine learning techniques in finance. Financial risk assessment traditionally relies on financial ratios and trend analysis to evaluate corporate stability. Ratios such as liquidity, solvency, and profitability ratios have long been used to gauge a company's financial health, as noted by Altman [9]. Studies have shown the effectiveness of ratio analysis in providing a snapshot of financial performance and identifying general trends in stability or decline, as noted by Beaver [10]. However, ratio-based methods often fail to capture unusual fluctuations within individual accounts and are limited in addressing complex, multidimensional financial data.

Additionally, these methods are retrospective, providing insights based on historical data rather than proactive alerts of emerging risks. Another traditional approach is statistical outlier detection, where financial data points are identified as anomalies based on predefined thresholds. While this method is straightforward, it lacks flexibility and fails to account for the intricate relationships between different financial variables, especially in dynamic environments where the thresholds for "normal" can shift over time [11].

With the advent of machine learning, anomaly detection has advanced significantly, enabling the development of algorithms that automatically learn patterns in data and detect deviations. Machine learning models such as Support Vector Machines (SVM). According to Jäkel et al., they have been used in anomaly detection, offering a more robust approach than traditional statistical methods [12]. These models identify outliers based on data distribution and distance metrics, making them suitable for large datasets. However, their performance can be limited in high-dimensional data and may require intensive computation, especially with large corporate financial datasets. Isolation Forest, introduced by Liu, Ting, and Zhou, has emerged as one of the most effective algorithms for detecting anomalies in high-dimensional data [13]. Unlike other machine learning techniques, Isolation Forest isolates anomalies by recursively partitioning data points. This algorithm works on the principle that anomalies are few and distinct from normal observations, making them easier to isolate through random partitioning. This property makes Isolation Forest particularly efficient and scalable, which is advantageous in financial data analysis where datasets are typically extensive and contain numerous variables. Isolation Forest has demonstrated strong performance in various applications, such as fraud detection, but its use in financial risk assessment remains limited [14]. Some studies have explored its application in credit risk scoring, where the algorithm helps identify unusual patterns in credit applications that may indicate high default risk, according to Chatterjee et al. [15]. Yet, few studies have specifically applied Isolation Forest to balance sheet data to assess financial stability, representing a gap in the current literature.

Several studies have applied anomaly detection and machine learning techniques within financial domains, particularly in fraud detection and credit scoring. For instance, Phua et al. reviewed various machine-learning approaches for fraud detection, highlighting the effectiveness of anomaly detection models, such as Neural Networks, SVMs, and Decision Trees [16]. Likewise, Ghosh and Reilly showed that artificial neural networks could detect fraudulent transactions in real-time, paving the way for anomaly detection models in financial applications. Although these methods are effective, their application in corporate finance, specifically for balance sheet analysis, has been relatively sparse [17]. In corporate finance, the use of machine learning has been mainly limited to predictive modeling and time-series forecasting for profitability and stock price prediction. For instance, Zhang et al. applied Long Short-Term Memory (LSTM) networks to predict corporate financial distress, demonstrating the value of deep learning in financial applications [18]. However, the specific focus on anomaly detection within balance sheet accounts remains underexplored. Notably, Tsai et al. implemented an anomaly detection model for corporate credit scoring but did not extend the approach to detailed account-level analysis [19]. This study builds on previous work by applying Isolation Forest directly to corporate balance sheets, an approach that has not been extensively addressed in existing literature.

2.2. Research Gap and Contribution to Financial Risk Assessment

Despite advances in machine learning, the application of anomaly detection to corporate financial analysis, particularly at the balance sheet level, is still underdeveloped. Existing studies primarily focus on fraud detection and credit scoring but do not address the broader implications of anomalies within balance sheet accounts. Furthermore, while studies on financial stability have traditionally relied on aggregate financial indicators, a detailed, account-level analysis using machine learning techniques could offer more granular insights into corporate risk factors. This study addresses this gap by applying Isolation Forest to balance sheet accounts over four years, identifying anomalies that may indicate potential risks related to asset valuation, equity structure, and cash flow. By focusing on accounts such as Accumulated Depreciation, Additional Paid-In Capital, Accounts Payable, and Accounts Receivable, this research provides a novel perspective on financial risk assessment. It demonstrates the potential of Isolation Forest as a tool for proactive risk management, offering a more dynamic and nuanced approach compared to traditional financial analysis. In summary, this literature review underscores the need for advanced anomaly detection methods in corporate financial analysis, highlighting Isolation Forest as a promising approach. Through this study, we aim to contribute to the field of financial risk assessment by demonstrating how anomaly detection can enhance traditional risk analysis, enabling companies to identify and mitigate risks before they escalate.

3. Methodology

This study employs the Isolation Forest algorithm to detect financial risks within corporate balance sheet accounts from 2020 to 2023. The dataset includes annual values for key accounts such as Accumulated Depreciation, Additional Paid-In Capital, Accounts Payable, and Accounts Receivable, collectively reflecting the company's financial health. Each account serves a specific function: Accumulated Depreciation indicates asset valuation stability; Additional Paid-In Capital shows changes in shareholder equity; Accounts Payable and Accounts Receivable signal short-term liquidity and cash flow management. Together, these accounts offer insights into potential financial risks and areas requiring more intensive monitoring, as illustrated in figure 1.

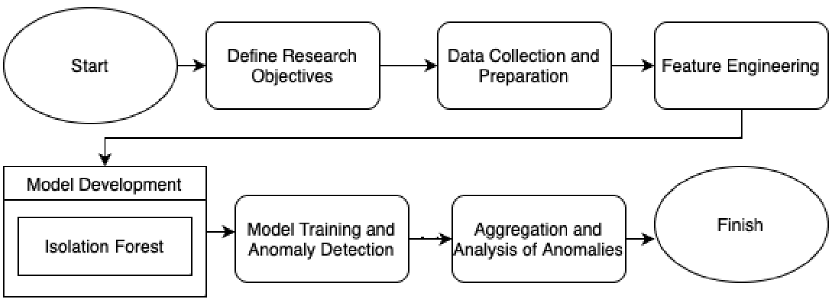

Figure 1. Research Methodology

ISSN 2776-8007

The data preprocessing involved handling missing values, normalizing values to ensure a uniform scale, and calculating year-over-year percentage changes to capture significant fluctuations in account values over time. This percentage change was calculated using the formula:

$$Change_t = \frac{Value_t - Value_{t-1}}{Value_{t-1}} \times 100 \tag{1}$$

Note: where $Value_t$ represents the current year's account value and $Value_{t-1}$ the previous years. These additional features enhance the model's ability to detect significant deviations in account values.

Isolation Forest, the chosen algorithm, is well-suited for anomaly detection in high-dimensional datasets. It isolates anomalies by recursively partitioning data and identifying points with unusually short paths. Anomalies, which differ significantly from normal data, tend to have shorter paths, making them easier to isolate. Each data point receives an anomaly score, $s(x,n)$, where x which is the point and n the number of samples [20]. This score is calculated as follows:

$$s(x,n) = 2^{-\frac{E(h(x))}{c(n)}} \tag{2}$$

Note: where $E(h(x))$ is the average path length for x, and $c(n) \approx 2\ 1\text{n}\ (n-1) + 0{,}5772$, representing the average path length in a binary search tree. A higher score signifies as higher likelihood of being an anomaly.

After training the Isolation Forest model on normalized data with a 5% contamination rate, anomaly scores, and labels were generated, allowing the identification of accounts deviating from expected values. Anomalies were then aggregated by account and year, enabling the study to pinpoint accounts with recurring anomalies and evaluate the associated risks. High-risk accounts, such as Accumulated Depreciation and Additional Paid-In Capital, showed consistent anomalies, suggesting underlying issues in asset valuation and capital management. Accounts affecting liquidity, like Accounts Payable and Accounts Receivable, indicated potential cash flow risks due to significant variability.

In summary, the Isolation Forest model systematically identified financial risks within corporate balance sheets by flagging unusual account values. By integrating normalization, year-over-year change calculations, and anomaly detection, the methodology enabled early detection of potential risks, supporting proactive financial management. This approach allows companies to monitor critical accounts closely and respond to risks before they escalate.

4. Results and Discussion

4.1. Result

This study aims to evaluate corporate financial risk potential by analyzing changes in balance sheet accounts from 2020 to 2023 using anomaly detection methods. The Isolation Forest algorithm was applied to the financial data with a contamination rate of 5%, implying that approximately 5% of the data is assumed to contain unusual or anomalous values. The anomaly detection results are summarized in table 1, which shows the total number of entries and the number of anomalies detected for each year.

Table 1. Anomalies Detected per Year

Year	Total Entries	Anomalies Detected
2020	65,296	3,264
2021	65,296	3,264
2022	65,296	3,264
2023	65,296	3,264

As observed in table 1, the number of detected anomalies remains consistent each year. Out of a total of 65,296 entries in each period, 3,264 entries were identified as anomalies, or approximately 5% of the data, in line with the contamination level set within the algorithm. This consistency in anomaly counts suggests that unusual variations in financial accounts occur steadily from year to year, potentially indicating sustained impacts from internal or external factors influencing the financial data.

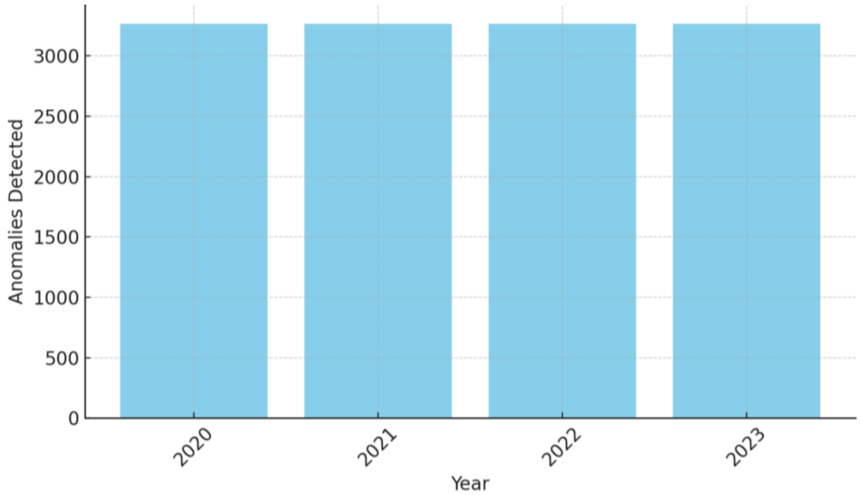

Figure 2. Anomalies Detected per Year

Figure 2. illustrates the consistency in the number of anomalies detected from 2020 to 2023, with each year showing 3,264 anomalies out of the total data analyzed. Furthermore, the distribution of anomalies by account type was analyzed to identify accounts with larger fluctuations that could heighten risk potential. Table 2 presents the number of detected anomalies for each account classified within the balance sheet (BS). The analysis results reveal that the Accumulated Depreciation account has the highest number of anomalies, with a total of 61 cases identified as anomalies. This condition may reflect instability in the valuation of corporate assets, potentially influenced by shifts in accounting strategies or long-term asset price fluctuations.

Table 2. Distribution of Anomalies in Accounts with the Highest Anomaly Counts

Account Name	Account Type	Anomalies Detected
Accumulated Depreciation	BS	61
Additional Paid-In Capital	BS	17
Accounts Payable	BS	9
Accounts Receivable	BS	6
Allowance for Doubtful Accounts	BS	1

The Additional Paid-In Capital account analysis revealed 17 anomalies, suggesting significant changes in capital structure or shareholder contributions. These fluctuations can impact corporate equity and influence investor perceptions. Similarly, the 9 anomalies in Accounts Payable suggest variability in short-term liabilities, likely due to changes in supplier payment policies or vendor relations, potentially affecting cash flow. The 6 anomalies in Accounts Receivable indicate possible collection delays, raising liquidity risk, while the single anomaly in Allowance for Doubtful Accounts may represent an isolated risk event. Anomalies in these key accounts indicate financial instability, particularly in asset, equity, and liability management. Variability in Accumulated Depreciation may lead to inaccuracies in asset valuation, while fluctuations in Additional Paid-In Capital affect capital structure and perceived stability. To address these findings, regular monitoring of accounts with high anomaly rates is recommended. Further trend analysis is needed to determine seasonal or cyclical patterns, and correlations with external factors should be evaluated to identify underlying causes. Routine monitoring and in-depth analysis will help the company detect financial risks earlier and take effective mitigation actions.

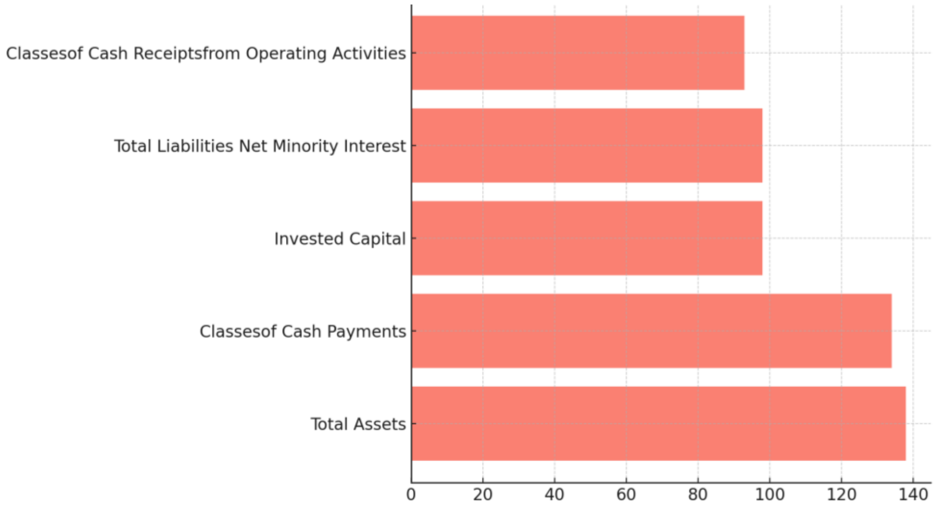

Figure 3. Distribution of Anomalies in Accounts with the Highest Anomaly Counts

Figure 3. displays accounts with the most anomalies, such as Accumulated Depreciation and Additional Paid-In Capital. These accounts exhibit larger fluctuations and may require closer attention in risk evaluation.

4.2. Discussion

The anomaly detection results highlight critical areas in the company's financial accounts that may contribute to heightened financial risk. The consistent number of anomalies detected each year (3,264 anomalies annually from 2020 to 2023) suggests that unusual changes are recurring within the data. This consistency points to ongoing, possibly systemic factors, both internal and external, influencing the company's financial reporting. Significant anomalies were found in key accounts, such as Accumulated Depreciation and Additional Paid-In Capital, indicating potential issues in asset valuation and capital structure. High levels of anomalies in Accumulated Depreciation suggest possible instability in asset management, as fluctuations in depreciation methods or rates could distort the book value of assets and, consequently, the company's overall valuation. Such volatility might arise from changes in accounting policies or fluctuating asset prices, which may warrant management's attention to ensure accurate financial representation. In Additional Paid-In Capital, the detection of anomalies implies shifts in capital injections or structural changes in equity. These fluctuations can affect corporate equity and influence investor perceptions, potentially impacting the company's stock price and overall valuation. Effective management of this account is essential for maintaining a stable capital structure that reassures shareholders and attracts future investment.

The Accounts Payable and Accounts Receivable accounts also demonstrated notable levels of anomalies, suggesting variability in short-term liability and collection practices. High variability in Accounts Payable may reflect changes in supplier relationships or payment policies, potentially affecting liquidity and cash flow management. If these anomalies indicate delayed payments to suppliers, it could strain vendor relationships, impacting the company's supply chain. Similarly, anomalies in Accounts Receivable hint at collection delays, which can raise liquidity risks and hinder operational stability if prolonged. A singular anomaly in Allowance for Doubtful Accounts could represent an isolated risk, possibly due to an unexpected event affecting the estimation of uncollectible receivables. While less frequent, this anomaly underscores the importance of regularly reviewing credit policies and customer payment histories to preemptively address potential collection issues. Given these findings, regular monitoring of accounts with high anomaly rates is crucial to detect early signs of financial instability. Further, an analysis of trend patterns especially in accounts with frequent anomalies could reveal whether cyclical or seasonal factors contribute to these variations. Examining correlations with macroeconomic factors, such as economic downturns, policy changes, or company-specific events, would provide additional insight into the causes behind these fluctuations. Ultimately, proactive measures in financial monitoring, combined with in-depth trend analysis, will enable the company to identify and manage financial risks more effectively. This approach not only strengthens financial reporting accuracy but also contributes to greater financial stability, enhancing the company's resilience against both foreseeable and unexpected financial challenges.

5. Conclusion

This study utilized anomaly detection methods to evaluate potential financial risks within a company's balance sheet accounts from 2020 to 2023. By applying the Isolation Forest algorithm, we identified consistent anomalies in key accounts, notably in Accumulated Depreciation, Additional Paid-In Capital, Accounts Payable, and Accounts Receivable. These findings highlight areas of financial variability that may indicate underlying risks in asset management, capital structure, and cash flow stability. The recurring nature of anomalies each year suggests ongoing factors influencing financial stability, with specific accounts showing fluctuations that could impact the company's valuation and operational liquidity. For example, significant anomalies in Accumulated Depreciation raise concerns about accurate asset valuation, while irregularities in Additional Paid-In Capital suggest potential changes in capital structure. Accounts Payable and Accounts Receivable anomalies further indicate potential risks in short-term financial management and cash flow. To address these risks, regular monitoring of high-risk accounts is recommended, along with trend analyses to uncover any cyclical patterns. Additionally, exploring correlations with external factors such as economic conditions or policy changes could enhance understanding of the root causes behind these anomalies. Proactive measures in financial oversight will enable the company to respond to potential risks more swiftly, reinforcing its financial resilience and stability.

Future research could expand on this study by exploring different anomaly detection methods, such as deep learning-based autoencoders, which may capture more complex patterns in financial data. Additionally, incorporating predictive modeling to assess the impact of detected anomalies on long-term financial outcomes would offer valuable insights into the risks associated with specific accounts. Further, examining how external macroeconomic factors, such as inflation, interest rates, or market trends, influence the occurrence of anomalies could provide a deeper contextual understanding. Another promising avenue for future work is integrating real-time anomaly detection into financial monitoring systems, allowing companies to identify and respond to risks as they emerge. These advancements in methodology and application would greatly enhance the utility of anomaly detection in proactive financial risk management.

6. Declarations

6.1. Author Contributions

Conceptualization: K.A.N., T.; Methodology: K.A.N., T.; Software: K.A.N.; Validation: T.; Formal Analysis: K.A.N.; Investigation: K.A.N.; Resources: T.; Data Curation: K.A.N.; Writing – Original Draft Preparation: K.A.N.; Writing – Review and Editing: K.A.N., T.; Visualization: K.A.N.; All authors have read and agreed to the published version of the manuscript.

6.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

6.4. Institutional Review Board Statement

Not applicable.

6.5. Informed Consent Statement

Not applicable.

6.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

[1] I. Cairó and J. Sim, "Market power, inequality, and financial instability," *J. Econ. Dyn. Control*, vol. 164, pp. 104875, 2024, doi: https://doi.org/10.1016/j.jedc.2024.104875.

[2] P. Behr, W. Wang, and S. Adasi Manu, "Bank's balance sheet management as a bargaining tool: Evidence from Brazilian labor strikes," *Emerg. Mark. Rev.*, vol. 59, no. March, pp. 101094, 2024, doi: https://doi.org/10.1016/j.ememar.2023.101094.

[3] Y. Zhou, C. Xie, G.-J. Wang, Y. Zhu, and G. S. Uddin, "Analysing and forecasting co-movement between innovative and traditional financial assets based on complex network and machine learning," *Res. Int. Bus. Financ.*, vol. 64, no. January, pp. 101846, 2023, doi: https://doi.org/10.1016/j.ribaf.2022.101846.

[4] H. Zha, S. Ruan, and W. Li, "The characteristics of the new dual-cycle development pattern and systemic financial risk based on TVP-SVAR and MS-VAR model analyses," *Heliyon*, vol. 10, no. 15, pp. 1–12, 2024, doi: https://doi.org/10.1016/j.heliyon.2024.e34943.

[5] F. Cao and X. Guo, "Automated financial time series anomaly detection via curiosity-guided exploration and self-imitation learning," *Eng. Appl. Artif. Intell.*, vol. 135, no. September, pp. 108663, 2024, doi: https://doi.org/10.1016/j.engappai.2024.108663.

[6] W. Hilal, S. A. Gadsden, and J. Yawney, "Financial Fraud: A Review of Anomaly Detection Techniques and Recent Advances," *Expert Syst. Appl.*, vol. 193, no. May, pp. 1-34, 2022, doi: https://doi.org/10.1016/j.eswa.2021.116429.

[7] I. Bhattacharya and A. Mickovic, "Accounting fraud detection using contextual language learning," *Int. J. Account. Inf. Syst.*, vol. 53, no. June, pp. 1–17, 2024, doi: https://doi.org/10.1016/j.accinf.2024.100682.

[8] E. Marcelli, T. Barbariol, D. Sartor, and G. A. Susto, "Active Learning-based Isolation Forest (ALIF): Enhancing anomaly detection with expert feedback," *Inf. Sci. (Ny).*, vol. 678, no. September, pp. 121012, 2024, doi: https://doi.org/10.1016/j.ins.2024.121012.

[9] E. I. Altman, "Financial ratios, discriminant analysis and the prediction of corporate bankruptcy," *J. Finance*, vol. 23, no. 4, pp. 589–609, 1968, doi: 10.2307/2978933.

[10] W. H. Beaver, "Financial Ratios as Predictors of Failure," *J. Account. Res.*, vol. 4, pp. 71–111, 1966, doi: 10.2307/2490171.

[11] V. Hodge and J. Austin, "A Survey of Outlier Detection Methodologies," *Artif. Intell. Rev.*, vol. 22, no. 2, pp. 85–126, 2004, doi: 10.1023/B:AIRE.0000045502.10941.a9.

[12] F. Jäkel, B. Schölkopf, and F. A. Wichmann, "Generalization and similarity in exemplar models of categorization: Insights from machine learning," *Psychon. Bull. Rev.*, vol. 15, no. 2, pp. 256–271, 2008, doi: 10.3758/PBR.15.2.256.

[13] F. T. Liu, K. M. Ting, and Z.-H. Zhou, "Isolation Forest," *in 2008 Eighth IEEE International Conference on Data Mining*, 2008, pp. 413–422. doi: 10.1109/ICDM.2008.17.

[14] A. Safari, M. Sabahi, and A. Oshnoei, "ResFaultyMan: An intelligent fault detection predictive model in power electronics systems using unsupervised learning isolation forest," *Heliyon*, vol. 10, no. 15, pp. 1–13, 2024, doi: https://doi.org/10.1016/j.heliyon.2024.e35243.

[15] P. Chatterjee, D. Das, and D. B. Rawat, "Digital twin for credit card fraud detection: opportunities, challenges, and fraud detection advancements," *Futur. Gener. Comput. Syst.*, vol. 158, no. September, pp. 410–426, 2024, doi: https://doi.org/10.1016/j.future.2024.04.057.

[16] S.-H. Li, D. C. Yen, W.-H. Lu, and C. Wang, "Identifying the signs of fraudulent accounts using data mining techniques," *Comput. Human Behav.*, vol. 28, no. 3, pp. 1002–1013, 2012, doi: https://doi.org/10.1016/j.chb.2012.01.002.

[17] Ghosh and Reilly, "Credit card fraud detection with a neural-network," *in 1994 Proceedings of the Twenty-Seventh Hawaii International Conference on System Sciences*, 1994, pp. 621–630. doi: 10.1109/HICSS.1994.323314.

[18] X. Zhang, X. Liang, A. Zhiyuli, S. Zhang, R. Xu, and B. Wu, "AT-LSTM: An Attention-based LSTM Model for Financial Time Series Prediction," *IOP Conf. Ser. Mater. Sci. Eng.*, vol. 569, no. 5, pp. 1–8, 2019, doi: 10.1088/1757-899X/569/5/052037.

[19] C.-F. Tsai, K.-L. Sue, Y.-H. Hu, and A. Chiu, "Combining feature selection, instance selection, and ensemble classification techniques for improved financial distress prediction," *J. Bus. Res.*, vol. 130, no. June, pp. 200–209, 2021, doi: https://doi.org/10.1016/j.jbusres.2021.03.018.

[20] T. Liu, Z. Zhou, and L. Yang, "Layered isolation forest: A multi-level subspace algorithm for improving isolation forest," *Neurocomputing*, vol. 581, no. May, pp. 127525, 2024, doi: https://doi.org/10.1016/j.neucom.2024.127525.