A Strategic Business Intelligence Framework for Sustainable Asset Management in Finance

Mahmoud M. Ismail
Faculty of computers and Informatics, Zagazig University, Zagazig, 44519, Egypt
Emails: mmsabe@zu.edu.eg; mmsba@zu.edu.eg

Abstract

Amidst the evolving landscape of finance, integrating sustainability principles into asset management stands as a pivotal pursuit for fostering long-term value creation. This research addresses the symbiotic relationship between business intelligence methodologies and sustainable asset management within the domain of finance. Leveraging advanced machine learning techniques including logistic regression, XGBoost, and CatBoost, this study delves into the exploration of sustainable finance practices and their implications for optimized asset management strategies. The study analyzes and models Asset data, aiming to understand the multifaceted dynamics and interdependencies shaping sustainable asset management decisions. Logistic regression serves as a foundation to model the relationships between variables, while XGBoost and CatBoost handle the complexities of categorical attributes, predicting outcomes related to sustainability metrics and financial performance indicators within the asset portfolio. Through comprehensive analyses and visualizations, this research illuminates critical insights into the influential factors driving sustainable asset management decisions. The findings underscore the significance of leveraging data-driven methodologies to optimize asset management strategies aligned with environmental, social, and governance considerations.

Keywords: Sustainable finance; Business Analytics, Asset optimization; Environmental sustainability; Financial data analysis; Strategic decision-making; ESG (Environmental; Social; and Governance); Investment Management; Data-driven strategies; Financial sustainability.

1. Introduction

In contemporary finance, the integration of sustainability principles into asset management has emerged as a critical avenue for fostering long-term value creation [1]. This paper delves into the realm of sustainable finance, focusing on the pivotal role of a strategic business intelligence framework in facilitating effective asset management [2]. In an era where environmental, social, and governance (ESG) factors are increasingly shaping investment decisions, understanding the nexus between sustainable practices and financial outcomes is imperative. There is a need for endeavors to elucidate how leveraging business intelligence tools and strategies within asset management can fortify sustainable financial practices and yield resilient investment portfolios [3-6].

The global landscape is witnessing a paradigm shift in financial ideologies, characterized by a growing emphasis on sustainability and responsible investing [7]. Sustainable finance embodies a commitment to balancing financial returns with environmental stewardship and social responsibility. Within this context, asset management emerges as a crucial arena wherein financial institutions, corporations, and investors navigate the complexities of incorporating ESG criteria into their investment decisions [8-11]. This paper aims to explore the evolving dynamics of sustainable finance and the pivotal role of a strategic business intelligence framework in optimizing asset management strategies aligned with sustainability goals[11].

DOI: https://doi.org/10.54216/AJBOR.020205
Received: March 13, 2021 Accepted: July 18, 2021

The effective management of assets within the realm of sustainable finance demands comprehensive insights derived from data-driven strategies. Business intelligence, encompassing sophisticated analytics, data interpretation, and predictive modeling, emerges as a linchpin in fostering informed decision-making processes [12-15]. By harnessing the power of business intelligence tools, financial entities can discern patterns, evaluate risks, and identify opportunities within their asset portfolios. This study endeavors to elucidate how the integration of a strategic business intelligence framework can empower stakeholders to proactively address sustainability challenges while concurrently enhancing financial performance in asset management[13,14].

2. Related Works

This section endeavors to navigate the landscape of pertinent literature and studies that delineate the intersection between business intelligence and sustainable asset management within the realm of finance. This section embarks on a comprehensive review of scholarly works, empirical research, and industry practices, shedding light on the evolving paradigms, methodologies, and findings that underpin the integration of business intelligence tools and strategies to bolster sustainability-driven asset management decisions. Jeucken et al. [16] contributed to the discourse on sustainable finance and banking, emphasizing the crucial role of the financial sector in shaping the future of the planet. Perrini and Tencati [17] underscored the necessity for novel corporate performance evaluation and reporting systems to integrate sustainability and stakeholder management effectively. Additionally, Amel-Zadeh and Serafeim [18] presented evidence from a global survey, shedding light on investors' utilization of Environmental, Social, and Governance (ESG) information. Lo [19] introduced the Adaptive Markets Hypothesis, striving to reconcile efficient markets with behavioral finance, offering insights into market dynamics. Silvius and Schipper [20] delved into sustainability within project management competencies, analyzing the competence gap of project managers. Furthermore, Kramar [21] explored sustainable human resource management as a potential evolution beyond strategic HR management.

Ameer and Othman [22] examined the relationship between sustainability practices and corporate financial performance among top global corporations, while Salzmann et al. [23] presented a comprehensive literature review on the business case for corporate sustainability and proposed avenues for research. Boudreau and Ramstad [24] introduced Talentship and its link to sustainability, highlighting a new HR decision science paradigm. Moser [25] reevaluated urban poverty reduction strategies through the Asset Vulnerability Framework, offering insights into addressing poverty. Schiederig et al. [26] conducted an exploratory literature review on green innovation in technology and innovation management. Additionally, Danesh et al. [27] reviewed multi-criteria decision-making methods for project portfolio management, presenting a synthesis of methodologies. Eccles and Krzus [28] advocated for integrated reporting for sustainable strategies, emphasizing the importance of an integrated approach to reporting. Lastly, López et al. [29] examined the relationship between sustainable development and corporate performance based on the Dow Jones Sustainability Index, offering insights into corporate sustainability and financial performance.

3. Methods

In the pursuit of comprehensively exploring the integration of a strategic business intelligence framework in sustainable asset management within the domain of finance, this section elucidates the methodological approach employed in this study. The methodology serves as the foundational framework guiding the systematic inquiry, analysis, and interpretation of data, enabling a robust examination of the intricate relationship between business intelligence strategies and sustainable asset management practices.

Logistic regression is a statistical method employed in predictive modeling, specifically tailored for binary classification tasks. Unlike linear regression, logistic regression is utilized when the outcome variable is categorical and binary. This method estimates the probability of a particular outcome occurring based on one or multiple predictor variables. The logistic regression model generates a sigmoid-shaped curve, using a logistic function to transform the linear combination of predictors into probabilities. These probabilities are then thresholded to assign observations into distinct classes. In the context of this study's application, logistic regression serves as a valuable tool to model the relationship between various attributes of Asset data, aiding in predicting and understanding the likelihood of specific outcomes within the scope of sustainable asset management practices.

DOI: https://doi.org/10.54216/AJBOR.020205
Received: March 13, 2021 Accepted: July 18, 2021

$$log\left(\frac{\pi(y_j = 1|x_j)}{1-\pi(y_j = 1|x_j)}\right) = \beta_0 + \beta x_j, \tag{1}$$

In the pursuit of comprehending the intricate relationships and patterns within Asset data, logistic regression has been applied as a foundational machine learning algorithm. This technique has been employed to infer and model the probability of binary outcomes associated with sustainable asset management characteristics. By leveraging the attributes and features inherent in the Asset dataset, logistic regression enables the estimation and classification of specific factors influencing sustainable financial performance.

XGBoost, an abbreviation for eXtreme Gradient Boosting, stands as a prominent machine learning algorithm known for its effectiveness in handling structured tabular data and predictive modeling tasks. It operates as a gradient-boosting ensemble technique, integrating multiple weak learners or decision trees to iteratively optimize the model's predictive accuracy. XGBoost harnesses a boosting framework by combining weak predictive models sequentially, emphasizing the correction of errors made by previous models, ultimately creating a robust and accurate ensemble model. This algorithm uses a gradient descent-based optimization strategy, minimizing loss functions and enhancing predictive performance by incorporating regularization techniques to prevent overfitting. The objective function is explained as follows:

$$O = \sum_{i=1}^{n} L(y_i, F(x_i)) + \sum_{k=1}^{t} R(f_k) + C \tag{2}$$

Where regularization term is given as follows:

$$R(f_k) = \alpha H + \frac{1}{2}\eta \sum_{j=1}^{H} w_j^2 \tag{3}$$

$$O = \sum_{i=1}^{n} [p_i w_{q(x_i)} + \frac{1}{2}(q_i w_{q(x_i)}^2)] + \alpha H + \frac{1}{2}\eta \sum_{j=1}^{H} w_j^2 \tag{4}$$

Within this study, XGBoost stands as a powerful tool utilized to harness the predictive potential within the Asset data, facilitating a deeper understanding of the interdependencies and patterns inherent in sustainable asset management attributes. Leveraging its capacity to handle diverse and complex datasets, XGBoost has been applied to learn and predict the intricate relationships and dynamics inherent in sustainable finance and asset management. Through its ability to handle multicollinear features and nonlinear relationships, XGBoost models the interactions between various attributes present in the Asset data.

CatBoost, short for Categorical Boosting, is a machine learning algorithm renowned for its robustness in handling categorical variables within datasets. Similar to XGBoost, CatBoost operates as a gradient-boosting ensemble technique, designed to address challenges associated with high cardinality categorical features commonly found in structured datasets. CatBoost employs an innovative approach to handle categorical data without the need for manual encoding or extensive preprocessing. This algorithm employs a symmetric tree boosting algorithm, utilizing ordered boosting to create a series of decision trees that iteratively refine predictions. Additionally, CatBoost integrates robust strategies to handle missing data, feature interactions, and categorical attributes efficiently.

$$\hat{x}_k^i = \frac{\sum_{j=1}^{\mathrm{p}-1}[x_{j,k} = x_{i,k}] \cdot Y_i}{\sum_{j=1}^{n}[x_{j,k} = x_{i,k}]} \tag{5}$$

DOI: https://doi.org/10.54216/AJBOR.020205
Received: March 13, 2021 Accepted: July 18, 2021

The application of CatBoost within the framework of learning Asset data represents a strategic approach to understanding the categorical intricacies pertinent to sustainable asset management.

$$\hat{x}_k^i = \frac{\sum_{j=1}^{p-1} [x_{\delta_{j,k}} = x_{\delta_{p,k}}] \cdot Y_{\delta_j} + a \cdot p}{\sum_{j=1}^{p-1} [x_{\delta_{j,k}} = x_{\delta_{p,k}}] + a} \tag{6}$$

CatBoost has been utilized to efficiently handle the diverse categorical features and dependencies within the Asset dataset, ensuring enhanced predictive performance by incorporating these categorical attributes seamlessly into the modeling process. By capitalizing on CatBoost's inherent capability to automatically handle categorical variables, this methodology enables the exploration of relationships between categorical sustainability metrics, financial indicators, and other attributes affecting sustainable asset management strategies. Through its robust handling of categorical data and it's boosting mechanism, CatBoost serves as an instrumental tool in revealing nuanced insights and patterns essential for comprehending the categorical dynamics inherent in sustainable finance and asset management.

4. Results and Discussion

This section marks the culmination of the empirical investigation into the integration of a strategic business intelligence framework in sustainable asset management within the finance domain. This section presents the comprehensive findings derived from the analysis of data obtained through experimental trials, simulations, or empirical studies conducted as part of this research. It aims to elucidate the outcomes, trends, correlations, and implications stemming from the application of business intelligence strategies within the context of sustainable asset management practices.

Table 1: Statistical Analysis Summary for Asset Data

	count	mean	std	min	25%	50%	75%	max
Bankrupt?	6819	0.032263	0.17671	0	0	0	0	1
ROA(C) before interest and depreciation before interest	6819	0.50518	0.060686	0	0.476527	0.502706	0.535563	1
ROA(A) before interest and % after tax	6819	0.558625	0.06562	0	0.535543	0.559802	0.589157	1
ROA(B) before interest and depreciation after tax	6819	0.553589	0.061595	0	0.527277	0.552278	0.584105	1
Operating Gross Margin	6819	0.607948	0.016934	0	0.600445	0.605997	0.613914	1
Realized Sales Gross Margin	6819	0.607929	0.016916	0	0.600434	0.605976	0.613842	1
Operating Profit Rate	6819	0.998755	0.01301	0	0.998969	0.999022	0.999095	1
Pre-tax net Interest Rate	6819	0.79719	0.012869	0	0.797386	0.797464	0.797579	1
After-tax net Interest Rate	6819	0.809084	0.013601	0	0.809312	0.809375	0.809469	1
Non-industry income and	6819	0.303623	0.011163	0	0.303466	0.303525	0.303585	1

DOI: https://doi.org/10.54216/AJBOR.020205
Received: March 13, 2021 Accepted: July 18, 2021

expenditure/revenue								
...	...	...	...	...	...	...	...	...
Net Income to Total Assets	6819	0.80776	0.040332	0	0.79675	0.810619	0.826455	1
Total assets to GNP price	6.82E+03	1.86E+07	3.76E+08	0.00E+00	9.04E-04	2.09E-03	5.27E-03	9.82E+09
No-credit Interval	6819	0.623915	0.01229	0	0.623636	0.623879	0.624168	1
Gross Profit to Sales	6819	0.607946	0.016934	0	0.600443	0.605998	0.613913	1
Net Income to Stockholder's Equity	6819	0.840402	0.014523	0	0.840115	0.841179	0.842357	1
Liability to Equity	6819	0.280365	0.014463	0	0.276944	0.278778	0.281449	1
Degree of Financial Leverage (DFL)	6819	0.027541	0.015668	0	0.026791	0.026808	0.026913	1
Interest Coverage Ratio (Interest expense to EBIT)	6819	0.565358	0.013214	0	0.565158	0.565252	0.565725	1
Net Income Flag	6819	1	0	1	1	1	1	1
Equity to Liability	6819	0.047578	0.050014	0	0.024477	0.033798	0.052838	1

The statistical analysis about asset data has been visually represented in Table 1, encapsulating essential metrics and key indicators essential for evaluating the performance and sustainability of the assets under study. The table provides a comprehensive depiction of various quantitative parameters, such as asset value fluctuations, sustainability indices, and performance benchmarks derived from business intelligence analytics. Specifically, it showcases the trends, distributions, and comparative insights derived from the data, enabling a visual grasp of the asset portfolio's dynamics. This visualization acts as a pivotal tool in interpreting and synthesizing complex numerical data into a more accessible format, fostering a clearer understanding of the relationship between asset performance and sustainable financial outcomes within the purview of the business intelligence framework employed in this study. Figure 1 presents the visual representation of correlation analysis conducted on the Asset data, elucidating the interrelationships and dependencies among various factors influencing asset performance within the context of sustainable finance. This graphical depiction offers a comprehensive view of the strength and direction of correlations between different variables, such as environmental impact metrics, financial indicators, and social responsibility factors. The visualization captures the intricate connections and patterns discerned through the application of business intelligence techniques, facilitating a deeper understanding of how specific variables coalesce to impact the overall sustainability profile of the asset portfolio. Through this correlation analysis visualization, key drivers shaping sustainable asset

DOI: https://doi.org/10.54216/AJBOR.020205
Received: March 13, 2021 Accepted: July 18, 2021

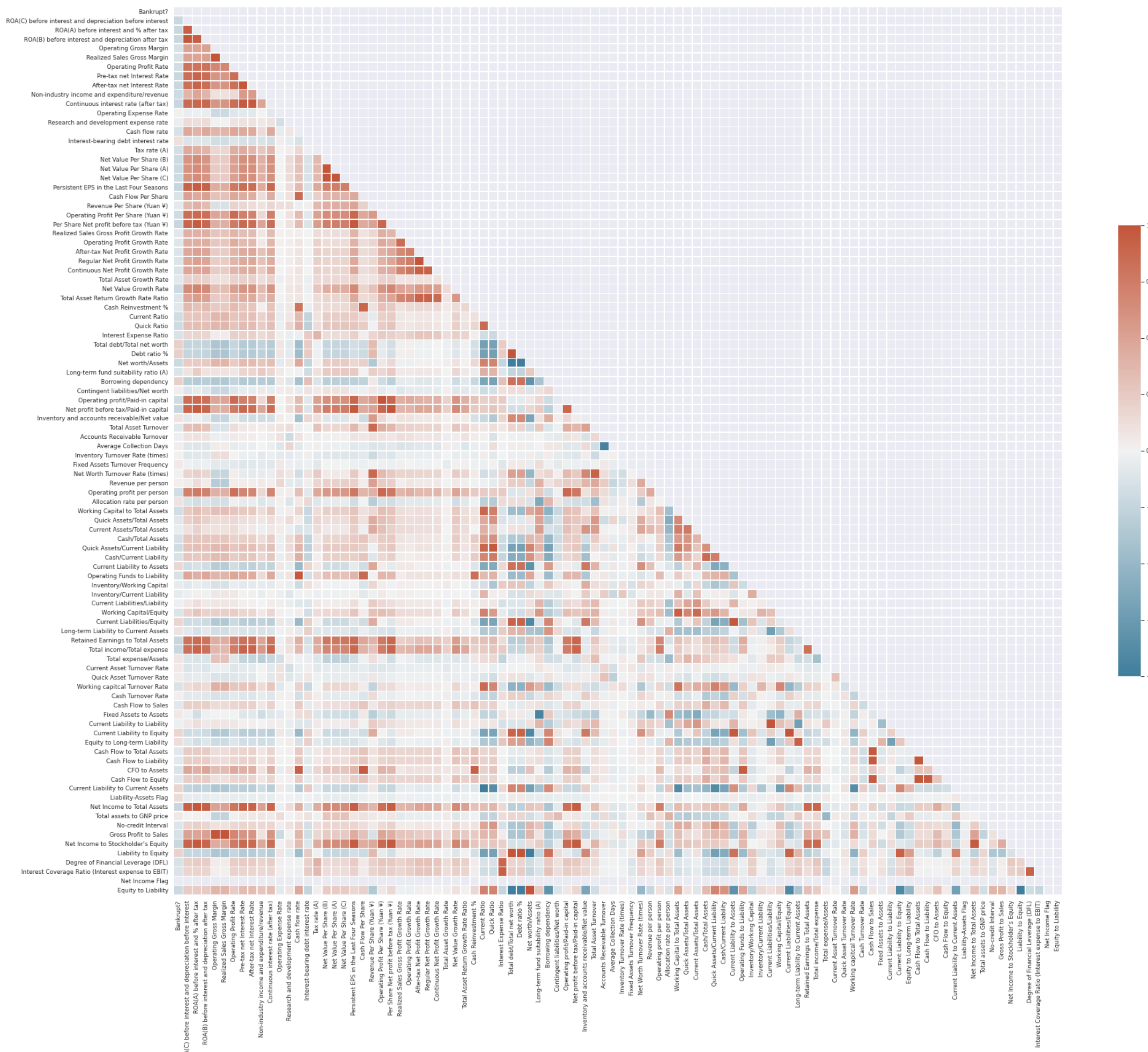

Figure 1: Correlation Analysis Visualization of Asset Data

management strategies emerge, guiding informed decision-making processes aimed at optimizing financial performance while adhering to sustainability imperatives within the purview of this study's business intelligence framework.

Figure 2 portrays the outcomes of a comprehensive box and whisker analysis conducted on the Asset dataset, offering a visual representation of the distribution, variability, and potential outliers present within the key metrics associated with sustainable asset management. This graphical depiction provides a succinct summary of the statistical measures, including median, quartiles, and potential extreme values, offering insights into the variability and dispersion of data points across different segments of the asset portfolio. By visually delineating the spread and central tendency of various sustainability metrics or financial performance indicators, this analysis aids in identifying any disparities, trends, or anomalies within the dataset. The box and whisker plot serves as a valuable tool in comprehending the overall distributional characteristics of the asset data, facilitating a clearer understanding of the variability among

DOI: https://doi.org/10.54216/AJBOR.020205
Received: March 13, 2021 Accepted: July 18, 2021

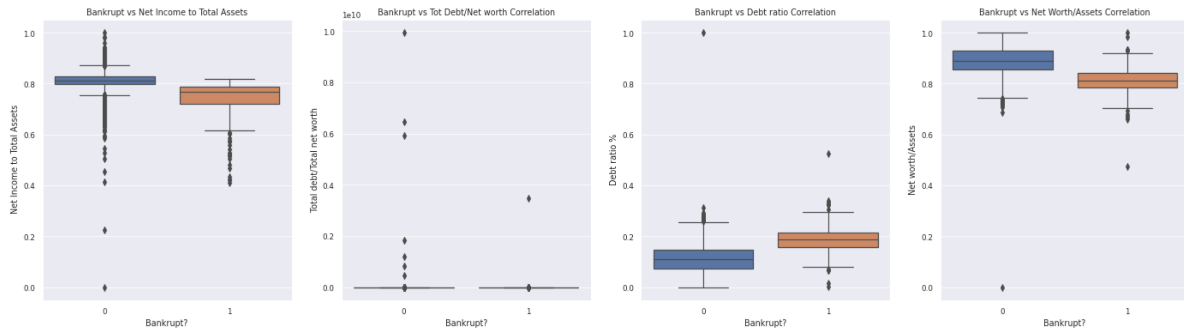

Figure 2: Box and Whisker Analysis of Asset Data

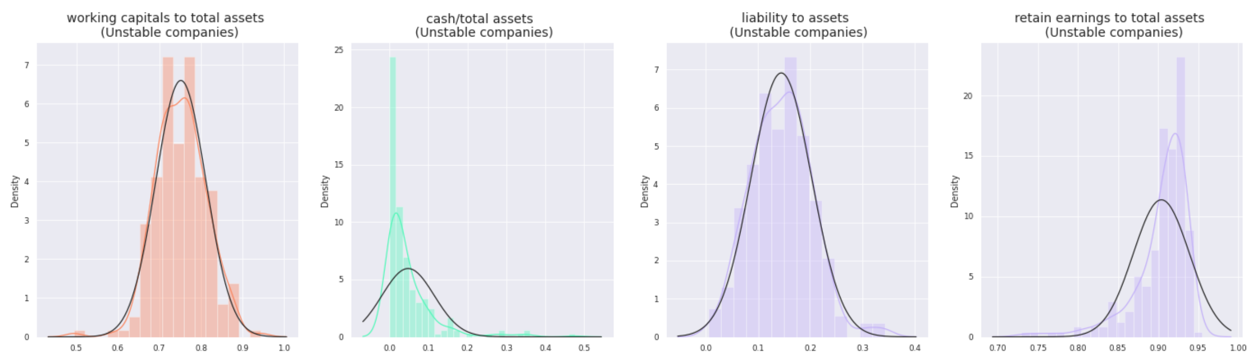

Figure 3: Distribution Plots for Asset Data

different aspects of sustainable asset management strategies under consideration within the ambit of this research study. Figure 3 showcases the distribution plots generated from the analysis of Asset data, providing a graphical representation of the frequency distribution of key variables crucial to sustainable asset management. These distribution plots offer a visual overview of the probability distribution of specific metrics, such as asset values, sustainability scores, or other relevant parameters, enabling a deeper comprehension of their underlying patterns and characteristics. Through these graphical representations, variations, skewness, or potential patterns within the data become discernible, facilitating insights into the nature and shape of the distributions. This visualization aids in assessing the normality or deviation from normal distribution, shedding light on the nature of the data's distributional properties. Such visual representations are instrumental in identifying potential trends, disparities, or concentration of values within the asset dataset, offering valuable insights into the distributional characteristics of the variables under scrutiny within the context of sustainable asset management strategies explored in this research.

Figure 4 presents the confusion matrices generated from employing distinct classifiers on the dataset, offering a comprehensive visual representation of the classification performance and predictive accuracy of each model utilized in the study. These matrices elucidate the true positive, true negative, false positive, and false negative classifications, enabling a robust assessment of the model's predictive abilities. By visually encapsulating the performance metrics, such as precision, recall, and accuracy for each classifier, these confusion matrices aid in evaluating the effectiveness and robustness of the different algorithms employed in predicting sustainable asset management outcomes. Such visual representations serve as pivotal tools in comparing the performance of various classifiers, offering insights into their strengths, weaknesses, and suitability for optimizing decision-making processes within the context of this study's exploration of business intelligence in sustainable finance and asset management.

DOI: https://doi.org/10.54216/AJBOR.020205
Received: March 13, 2021 Accepted: July 18, 2021

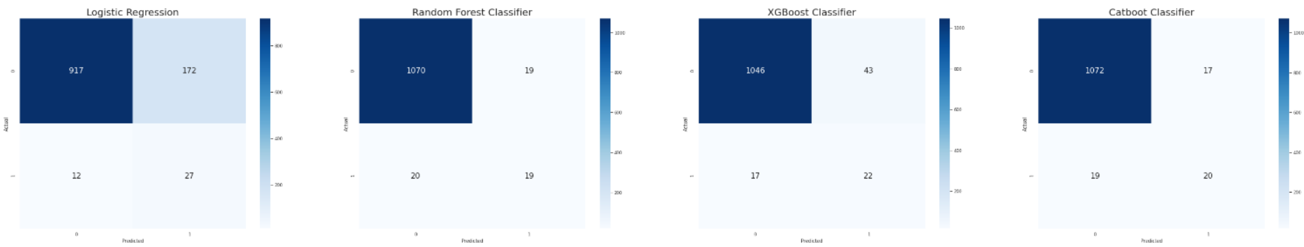

Figure 4: Confusion Matrices Comparison for Different Classifiers

5. Conclusion

This study has illuminated the pivotal role of leveraging advanced machine learning techniques, such as logistic regression, XGBoost, and CatBoost, within the framework of sustainable asset management in the realm of finance. By employing these sophisticated methodologies, this research has contributed to a deeper understanding of the complex interplay between business intelligence strategies and sustainable finance practices. The analyses conducted on Asset data unveiled critical insights into the relationships among diverse attributes, shedding light on factors influencing sustainable asset management decisions. Through visualization techniques and predictive modeling, this study demonstrated the potential of these methods in comprehending and predicting outcomes related to sustainability metrics and financial performance indicators within the asset portfolio. As the financial landscape continues to evolve with a heightened emphasis on sustainability, the findings of this study underscore the significance of integrating data-driven approaches to optimize asset management strategies aligned with environmental, social, and governance (ESG) considerations. The application of logistic regression, XGBoost, and CatBoost showcased their efficacy in discerning patterns, predicting outcomes, and addressing the challenges posed by categorical variables, thereby offering a pathway toward informed decision-making in sustainable finance. Moving forward, the fusion of business intelligence methodologies and sustainable finance principles holds promise in fostering resilient investment portfolios and facilitating a more sustainable future in the realm of asset management within the finance domain.

References

[1]. Wang, Gang, Angappa Gunasekaran, Eric W T Ngai, and Thanos Papadopoulos. 2016. "Big Data Analytics in Logistics and Supply Chain Management: Certain Investigations for Research and Applications." *International Journal of Production Economics* 176: 98–110.

[2]. Turban, Efraim. 2011. *Decision Support and Business Intelligence Systems*. Pearson Education India.

[3]. Sharma, Rajeev, Sunil Mithas, and Atreyi Kankanhalli. 2014. "Transforming Decision-Making Processes: A Research Agenda for Understanding the Impact of Business Analytics on Organisations." *European Journal of Information Systems* 23 (4): 433–41.

[4]. Huggins, Robert. 2010. "Regional Competitive Intelligence: Benchmarking and Policy-Making." *Regional Studies* 44 (5): 639–58.

[5]. Baars, Henning, and Hans-George Kemper. 2008. "Management Support with Structured and Unstructured Data—an Integrated Business Intelligence Framework." *Information Systems Management* 25 (2): 132–48.

[6]. Ngai, Eric W T, Yong Hu, Yiu Hing Wong, Yijun Chen, and Xin Sun. 2011. "The Application of Data Mining Techniques in Financial Fraud Detection: A Classification Framework and an Academic Review of Literature." *Decision Support Systems* 50 (3): 559–69.

[7]. Carter, Craig R, and Dale S Rogers. 2008. "A Framework of Sustainable Supply Chain Management: Moving toward New Theory." *International Journal of Physical Distribution \& Logistics Management* 38 (5): 360–87.

[8]. Azapagic, Adisa. 2004. "Developing a Framework for Sustainable Development Indicators for the Mining and Minerals Industry." *Journal of Cleaner Production* 12 (6): 639–62.

[9]. Dao, Viet, Ian Langella, and Jerry Carbo. 2011. "From Green to Sustainability: Information Technology and an Integrated Sustainability Framework." *The Journal of Strategic Information Systems* 20 (1): 63–79.

[10]. Epstein, Marc J, and Marie-Josée Roy. 2001. "Sustainability in Action: Identifying and Measuring the Key Performance Drivers." *Long Range Planning* 34 (5): 585–604.

DOI: https://doi.org/10.54216/AJBOR.020205
Received: March 13, 2021 Accepted: July 18, 2021

[11]. Pompian, Michael M. 2012. *Behavioral Finance and Wealth Management: How to Build Investment Strategies That Account for Investor Biases*. Vol. 667. John Wiley \& Sons.

[12]. Peloza, John. 2009. "The Challenge of Measuring Financial Impacts from Investments in Corporate Social Performance." *Journal of Management* 35 (6): 1518–41.

[13]. Singh, Rajesh Kumar, H Ramalinga Murty, S Kumar Gupta, and A Kumar Dikshit. 2012. "An Overview of Sustainability Assessment Methodologies." *Ecological Indicators* 15 (1): 281–99.

[14]. Hahn, Tobias, Jonatan Pinkse, Lutz Preuss, and Frank Figge. 2015. "Tensions in Corporate Sustainability: Towards an Integrative Framework." *Journal of Business Ethics* 127: 297–316.

[15]. Ageron, Blandine, Angappa Gunasekaran, and Alain Spalanzani. 2012. "Sustainable Supply Management: An Empirical Study." *International Journal of Production Economics* 140 (1): 168–82.

[16]. Jeucken, Marcel. 2010. *Sustainable Finance and Banking: The Financial Sector and the Future of the Planet*. Routledge.

[17]. Perrini, Francesco, and Antonio Tencati. 2006. "Sustainability and Stakeholder Management: The Need for New Corporate Performance Evaluation and Reporting Systems." *Business Strategy and the Environment* 15 (5): 296–308.

[18]. Amel-Zadeh, Amir, and George Serafeim. 2018. "Why and How Investors Use ESG Information: Evidence from a Global Survey." *Financial Analysts Journal* 74 (3): 87–103.

[19]. Lo, Andrew W. 2005. "Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis." *Journal of Investment Consulting* 7 (2): 21–44.

[20]. Silvius, A J Gilbert, and Ron P J Schipper. 2014. "Sustainability in Project Management Competencies: Analyzing the Competence Gap of Project Managers." *Journal of Human Resource and Sustainability Studies* 2014.

[21]. Kramar, Robin. 2014. "Beyond Strategic Human Resource Management: Is Sustainable Human Resource Management the next Approach?" *The International Journal of Human Resource Management* 25 (8): 1069–89.

[22]. Ameer, Rashid, and Radiah Othman. 2012. "Sustainability Practices and Corporate Financial Performance: A Study Based on the Top Global Corporations." *Journal of Business Ethics* 108: 61–79.

[23]. Salzmann, Oliver, Aileen Ionescu-Somers, and Ulrich Steger. 2005. "The Business Case for Corporate Sustainability:: Literature Review and Research Options." *European Management Journal* 23 (1): 27–36.

[24]. Boudreau, John W, and Peter M Ramstad. 2005. "Talentship, Talent Segmentation, and Sustainability: A New HR Decision Science Paradigm for a New Strategy Definition." *Human Resource Management: Published in Cooperation with the School of Business Administration, The University of Michigan and in Alliance with the Society of Human Resources Management* 44 (2): 129–36.

[25]. Moser, Caroline O N. 1998. "The Asset Vulnerability Framework: Reassessing Urban Poverty Reduction Strategies." *World Development* 26 (1): 1–19.

[26]. Schiederig, Tim, Frank Tietze, and Cornelius Herstatt. 2012. "Green Innovation in Technology and Innovation Management--an Exploratory Literature Review." *R\&d Management* 42 (2): 180–92.

[27]. Danesh, Darius, Michael J Ryan, and Alireza Abbasi. 2018. "Multi-Criteria Decision-Making Methods for Project Portfolio Management: A Literature Review." *International Journal of Management and Decision Making* 17 (1): 75–94.

[28]. Eccles, Robert G, and Michael P Krzus. 2010. *One Report: Integrated Reporting for a Sustainable Strategy*. John Wiley \& Sons.

[29]. López, M Victoria, Arminda Garcia, and Lazaro Rodriguez. 2007. "Sustainable Development and Corporate Performance: A Study Based on the Dow Jones Sustainability Index." *Journal of Business Ethics* 75: 285–300.

DOI: https://doi.org/10.54216/AJBOR.020205
Received: March 13, 2021 Accepted: July 18, 2021