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A Machine Learning Approach to Predict Bankruptcy in Chinese Companies with ESG Integration

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Abstract

In this scholarly investigation, we meticulously assess the effectiveness of Environmental, Social, and Governance (ESG) metrics in predicting financial hardship across a cohort of 3,111 publicly traded companies on the Chinese stock exchange from 2012-2022. This study employs Python software for comprehensive data analysis to process and interpret large datasets efficiently. Our empirical findings robustly validate that incorporating ESG metrics significantly enhances the predictive prowess of our model, thereby elevating precision in discerning instances of financial distress. A striking feature in the process is that the chance of incorrectly identifying the distressed or defaulting firms as sound business enterprises due to the implementation of ESG is impossible.

The foundation of our predictive model, bonded by a strong methodology, includes integrating various tools such as classical statistics methods and state-of-the-art new machine learning models. For a comparative analysis seven machine learning models have been employed, such as Logistic Regression, Decision Trees, Support Vector Machines, Random Forest, Naïve Bayes, AdaBoost, and Gradient Boosting. To interpret the results, three performance parameters have been used which are sensitivity (Se), Area Under the Curve (AUC), and F1 score. Among all the models Random Forest Model stands out as the most stable model, which shows 100% accuracy in all the parameters, with and without the inclusion of ESG Scores. The implications of our work also affect the market scene, making an impact through prospective investors, policymakers, and financial parties affiliated with the forefront companies. Additionally, the present contribution develops the existing literature on distress prediction, as it helps to understand which sustainability factors work best for a comprehensive analysis of the company's problems.

Keywords: Financial distress, ESG indicators, ESG integration, predictive models, bankruptcy prediction, artificial intelligence, machine learning models, Chinese listed companies.

1. Introduction

Financial distress has been a rising concern during crises and disrupts income generation for business organizations (Antunes et al., 2023). Apart from the failing corporate entity, several researchers have discussed the social and economic consequences of corporate failure such as Hafiz et al. (2015); Alaka et al. (2016); Hernandez Tinoco & Wilson (2013); Xu & Zhang (2009); Doumpos & Zopounidis (1999), extend beyond the failing entity to potentially affect interconnected firms. Realizing such profound ramifications reinforces the demanding duty to construct successful bankruptcy predictions to make objective decisions based on reliable information within the global finance arena.

Since the global financial crisis, integrating Environmental, Social, and Governance (ESG) factors into business health has gained momentum. However, there are varying views on how these factors affect the firm's performance (Li et al., 2018; Qureshi et al., 2020). An intensive global endeavor to scale up ESG awareness, adoption, and reporting, precipitated by standards, is an appropriate response to this loss of trust after financial scandals (European Banking Authority, 2021; AEVOAE, 2022).

ESG characteristics are significant when evaluating the outcomes of the bankruptcy prediction models, as the key element of ESG within them has been revealed; thus, ESG factors became more significant in financial risk management. A clear business-level strategy is critical for a firm’s long-term survival and success (Ukko et al., 2019; Bansal & DesJardine, 2014). The elevation of responsibility is determined by the social corporate (CSR) framework and the broader ESG framework highlights the comprehensive scrutiny firms face (Ivascu et al., 2022). Various studies have confirmed that organizations that practice sturdy ESG display liquidity before extreme risks like global pandemics and financial downturns (Lins et al., 2017).

However, beyond the global infatuation with ESG-related challenges, the connection between ESG characteristics and the financial value of prevalent Chinese corporate entities is an under-researched topic, as it may raise concerns given that ESG factors have been commonly known to be integrated with financial performance and market value (Broadstock et al., 2021). This traditional approach of only accounting data proved inefficacious in predicting financial distress and highlights the importance of diversified models that include broader elements (Flannery & Bliss, 2019; Agarwal & Taffler, 2008). The latest studies on this subject matter stress the advantage of the merger of market information, ESG factors, and non-financial data into more reliable forecast models, bearing in mind the critical flaws of models heavily based on accounting data. This evolution tackles the flaws of the conventional models' forecasts for outcomes based on historical data.

This research integrates the ESG indicators with the bankruptcy prediction models which aligns with the global movements on sustainability, and company responsibility, thus enhancing the ability of the models that were used to predict this aspect of the company's sustainable future. Linking corporate strategy and ESG enhances a company's learning and competitive edge (Habib, 2022; Habib & Mourad, 2023). This study continues regarding any analysis that examines the moderating roles of business strategy and ESG procedures regarding a company's likelihood of experiencing financial issues (Bayo-Moriones et al., 2021; Kharub et al., 2019).

The inclusion of ESG variables in the existing bankruptcy prediction models helps to improve the models' performance by considering non-financial information strategic developments and operational vulnerabilities (EmadEldeen, 2024). Integration of machine learning models with the basic solvency assessment and ESG indexes furnish powerful prescriptive capacities, giving a far more detailed perception of the financial failure danger (Zhang, 2024). This integration not only enhances the forecast precision but also contributes to the concept of sustainable investment around the world, which positively impacts investors and policymakers, especially in emerging economies such as China. Besides, enhancing the predictive capacity, this approach offers significant benefits for investors and policymakers in developing countries such as China.

The research seeks to fill in the gaps in the existing literature, where most of the studies are centered on ESG disclosure and risks at the global level (Chiaramonte et al., 2022; European Banking Authority, 2022). This goes beyond the banking sector to incorporate non-financial companies, especially in emerging economies such as China, considering the wider consequences of ESG factors in quickly changing markets. Besides, it also brings the combination of operational research with statistical methods for an accurate bankruptcy prediction model under which ESG elements are found to be comparatively important to the usual economic metrics.

This theoretical perspective views ESG practices as improving information disclosure and stakeholder involvement, which in turn affects the risk profile of the company and financial outcomes (Wu & Shen, 2013). The study emphasizes the crucial role of ESG in improving corporate reputation which affects the costs of capital and cash flows (Azmi et al., 2021). Through the study of the joint influence of business strategies and ESG practices on the likelihood of companies being in financial distress, this research ensures decision-makers and investors by emphasizing the importance of strategic planning integration of ESG.

Although the previous research has not firmly established the relationship between corporate social performance (CSP) and the probability of bankruptcy, the studies conducted by (Cooper & Uzun, 2019), (Boubaker et al., 2020) and (Lin & Dong, 2018) have highlighted beneficial outcomes. The discourse continues regarding the advantages and disadvantages associated with corporate social tesponsibility (CSR) practices, as noted by (Barnett, 2007), (Becchetti et al., 2008), underscoring a notable knowledge gap in comprehending the impact of financial distress on firms' dedication to CSR.

This research focuses on the intricately connected triad of Environmental, Social, and Governance (ESG) risks, financial ratios, and traditional and modern machine learning models for bankruptcy prediction, particularly in emergent economies like China. Due to this, the key purpose is to assess the implementation of one non-financial variable, namely the Environmental, Social, and Governance practices score into the accounting and financial data to enhance the accuracy and reliability of the existing models for bankruptcy prediction. Our research aims to equip decision-makers, policy-makers, regulators, investors, and stakeholders with better financial risk management tools, while at the same time advocating for sustainable businesses.

In addressing the challenges associated with understanding the impact of ESG factors on the predictability of bankruptcy among non-financial firms, this study emphasizes the need for a more nuanced integration of ESG considerations into financial distress prediction models. In doing so, this study proposes a more subtle approach of incorporating ESG considerations into the traditional financial distress prediction models. It seeks to unravel the complexities involved in such integration and to illuminate the pathways through which ESG risks can influence a firm's financial stability. The research is vital in assisting managers and investors to make informed decisions on profitability, sustainability, and risk conditions for companies operating in volatile markets in terms of ESG performance.

Moreover, the study also advocates critically looking at the techniques being employed in merging ESG scores into the existing models and trying to develop new ways which may better explain the financial implications of such a company's ESG practices. The given research will endeavor to bring the discourse on sustainable finance to a new level, encouraging a shift towards more responsible investment strategies that integrate both financial and non-financial risk factors. Generally, this research outlines the role of ESG metrics in predicting the bankruptcy models in developing countries, beside this contribution, it underlines the effect of ESG factors on the financial future of companies trading in emerging economies.

2. Literature Review

The inclusion of environmental, social, and governance (ESG) metrics as a factor of financial distress detection models goes beyond simply assessing corporate well-being and sustainability. The synthesis of the literature review's salient points from different studies to ascertain the effect of the integration of ESG on the predictability of bankruptcy in Chinese companies is provided using machine learning for a high level of accuracy. Research in CSR, CSP, and ESG literature has evolved historically through different stages, thereby revealing the secret inclination toward financial success (Broadstock et al., 2021; Lins et al., 2017). The inclusion of ESG factors in the bankruptcy models reflects a deeper recognition of the many facets that contribute to financial total that usually leads to a much more stable financial architecture.

Previous literature has repeatedly shown a strong link between strong ESG practices and financial performance, implying that good management of ESG concerns improves creditworthiness and market valuation (McWilliams et al., 2006; Aslan et al., 2021; Garcia & Orsato, 2020). This relationship indicates that it is the effective ESG strategy that developed sustainability as the main operating concept in the originations. Correlating ESG score factors with financial attributes offers a base for a close examination and a tool to study individual firms' distinctness and all factors around them. This approach helps to improve the accuracy of financial distress models by taking into account the specific drivers of non-performing loans (Habib, 2023).

The inclusion of Environmental, Social, and Governance (ESG) criteria into financial distress prediction models, researchers, and practitioners can create more complete tools for forecasting financial crisis, so supporting more stable and sustainable economic systems (Campbell et al., 2008). Recent work has underlined how well ESG criteria predict financial crisis and bankruptcy risk. (Zhao et al., 2018; Cooper & Uzun, 2019) emphasized the impact of Corporate Social Responsibility (CSR) on bankruptcy, particularly for large firms that benefit from stakeholder considerations. Additionally, Singh, (2023) also showed that compared to non-ESG companies, ESG-sensitive companies have fewer financial difficulties.

Moreover, the Citterio & King (2023) study stands out as the first to use ESG variables in a model to foresee bank financial crises, therefore underlining the increasing necessity of applying ESG criteria to increase bank stability. The research unequivocally shows how ESG criteria are included in financial distress prediction models not only enhances forecast accuracy but also displays a better knowledge of the several influences of ESG elements on financial stability. Including ESG criteria helps academics create more strong models that fairly forecast financial crisis, so supporting sustainable financial practices all around.

The research theories related to the financial crises provide a full framework for understanding the causes and manifestations of corporate bankruptcy. Usually, these concepts depend on the knowledge that bankruptcy is the outcome of a declining financial condition that may be discovered by means of many indicators and financial ratios rather than a sudden event. Altman's Z-score model is among the key studies in this field, who designed to forecast bankruptcy within two years. To get a score reflecting the probability of bankruptcy, the model aggregates five separate financial ratios including liquidity, profitability, leverage, solvency, and activity. This study allows one to modify the Altman Z-score model to incorporate ESG elements as extra variables. Governance scores, for example, can be used as a proxy for management quality a crucial element of the original Z-score model (Chhillar & Lellapalli, 2022; Sagita & Nugraha, 2022; Qurriyani, 2014).

Several approaches can be taken into consideration to customize these financial theories especially for this study. Direct inclusion of ESG elements into the new study helps to change already existing financial distress models. Environmental risk, for instance, could be considered in asset valuation changes; social scores could affect computations of human expenses or litigation risks. Alternatively, composite indicators combining financial information with ESG ratings can be created to offer a more complete picture of a company's situation and bankruptcy sensitivity. Moreover, a longitudinal study of how variations in ESG scores correlate with conventional financial distress signals over time can help one determine whether ESG factors are leading, lagging, or coincidental markers of financial distress (Bargagli-Stoffi et al., 2023; Chhillar & Lellapalli, 2022; Chen et al., 2020).

From a theoretical standpoint, integrating ESG factors into financial distress models aligns with the broader movement toward sustainable and responsible investing. Empirical findings suggest that ESG risks, as determined by ESG scores, can have a significant impact, especially during periods of financial crisis. The COVID-19 epidemic has underlined even more the need of including ESG criteria into risk management since studies have indicated that good ESG performance helps to create market resilience during crises. Including ESG factors into financial distress models would help to give a more complete knowledge of a company's financial situation and bankruptcy susceptibility as the demand in socially responsible investments keeps rising.

Advanced statistical and machine learning methods help the model to better understand the patterns among the financial indicators and ESG factors and get highly accurate predictions. The smart approach used by the mentioned practice is meant to show the relationship between financial health and the broader impacts of sustainability (Citterio & King, 2023). The Institutional Difference Hypothesis (IDH) held that the institutional environment in which the firm operated was the determinant of the efficiency of CSP in emerging economies. These insights should be considered strategically in situations where businesses may choose short-term monetary gains over long-term sustainability investments (Grygiel-Tomaszewska & Turek, 2021).

Studies revealed the negative relation between CSR involvement and the chances of a financial crisis, indicating the influence of the CSR on increase of the organization's reputation; operational efficiency, and stakeholder trust. This relationship thus results in good financial health and a decrease in the occurrence of individual cases of bankruptcy (Altman & Hotchkiss, 2010; Nguyen et al., 2020). The characteristic of ESG reporting that is open and honest improves a firm quality and value offer, respectively. It makes companies reinforce their good reputation, discover new operational levels, and reduce risks. Empirical data shows that ESG performance leads to financial system stability and resilience (Lin & Dong, 2018; Igbinovia & Agbadua, 2023). The mediating link among board independence, CSR, and bankruptcy risk suggests governance is a fundamental component in optimizing CSR as a competitive endowment. Another difficult feature of the CSR impact on financial stability subject is the function of moral imperative (Javed et al., 2020).

This study highlights the importance of including ESG components into financial failure prediction models and the role of advanced machine learning techniques in enhancing its predictions with more precision. In the realm of Chinese companies and emerging economies, researchers and practitioners have the potential to develop more robust models that accurately capture the intricate nature of corporate financial well-being. This can be achieved by incorporating environmental, social, and governance (ESG) factors and employing a sophisticated methodology that takes into account company-specific variables. This comprehensive analysis highlights the significant impact of incorporating environmental, social, and governance (ESG) factors in promoting sustainability and financial stability in the global financial landscape.

3. Data and Methodology

As for the data of the study, it encompasses 3,111 publicly listed companies in the exchange markets of China during 2012-2022. The data set Table. 1 include financial ratios, and accounting ratios together with the Environmental, Social, and Governance (ESG) score sourced from Data Stream Thomson Reuters' Refinitiv Eikon. We augment our distress prediction analysis and introduce important financial parameters majorly comprising the financial statement data. In crafting this study, it was important to include a diverse list of financial ratios which included Profitability, Liquidity, Activity, cash flow, and Leverage/Solvency ratios based on the enlightening framework developed by Domicián et al., (2023). In addition to the conventional ones, we smoothly interwove among the other models Logistic Regression, Decision Trees, Support Vector Machines, Random Forest, Naïve Bayes, AdaBoost, and Gradient Boosting supported by the ESG rating figures. Notably, in this research, the financial data and ESG scores were extracted from Refinitiv Eikon Data Stream which helped build a robust and comprehensive platform for analysis.

Table 1: Final Financial Ratios Dataset

Variable Name	Abb.	Formula
ESG Score	ESG	Environmental, Social, and Governance
Net Profit Margin	P1	Net Income / Net Sales X 100
Operating Profit Margin	P2	Operating Profit / Net Sales X 100
A BSIC Earning Power (BEP)	P7	EBIT / Avg Total Assets
Return on Capital Employed (ROCE)	P8	EBIT / Total Assets - Total Current Liabilities
Current Ratio	L1	Current Assets / Current Liabilities
Cash to Current Liabilities	L3	Cash + Cash Equivalents / Current Liabilities
No. of Days in Inventory	AC2	Avg Inventory / CGS X 365 (DIO)
No. of Days in Receivables	AC4	Avg Accounts Receivables / Revenue X 365 (DSO)
No. of Days in Payable	AC6	Avg Account Payable / CGS X 365 (DPO)
Debt to Asset Ratio	S2	Total Debt / Total Assets
WC / TA	X1	Working Capital / Total Assets
RE / TA	X2	Retained Earnings / Total Assets
MC / TL	X4	Market Capitalization/Book Value of Liabilities
Ln (ASSETS) / TA	X5	Log of Total Assets / Total Assets
EBIT / TA	X3	EBIT / Total Assets
Ln (ASSETS) / GNP	O1	Log of Total Assets / Gross National Product
TL / TA	O2	Total Liabilities / Total Assets
CL / CA	O4	Current Liabilities / Current Assets
NI / TA	O5	Net Income / Total Assets
INTWO	O7	INTWO = 1 If Net Income was negative for the last three years, 0 otherwise
OENEG	O8	OENEG = One if total liabilities exceed total assets, zero otherwise
CHIN	O9	CHIN = $\frac{NI_t - NI_{t\_1}}{\lvert NI_t \rvert + \lvert NI_{t\_1} \rvert}$ Where NIt and NIt_1 is the Net Income for the most recent and the preceding year, respectively

3.1 Methodology

In delineating the framework for analysis, the Z-score was selected as the dependent variable, capturing the particular indicator used to establish business financial distress. A well-known measure, the Z-score is used to assess the solvency risk of a business to indicate by how many standard deviations the profits need to decline to make equity negative. This concept has been examined by different scholars including, (Laeven and Levine, 2009), (Delis & Staikouras, 2011), and (Chiaramonte and Casu, 2017). We calculate the means and standard deviations of ROAs for each of the rolling five-year periods. Z-Score can be calculated as;

$$Z - Score = \frac{(\mathrm{ROA}) + (\frac{Equity}{Total} Assets)}{\sigma(ROA)} \qquad (1)$$

The Z-score is standardized to '0' if the firm 'i' encounters financial difficulties during the period 't' and '1' otherwise. Due to the absence of a universal threshold differentiating healthy firms from distressed ones, we meticulously apply our model using equation no.2.

$$D_{i,t} = \beta_0 + \beta_1 X_{i,t-1} + \varepsilon_{i,t-1} \qquad (2)$$

$D_i = 0$ otherwise and $D_i = 1$ if the observation falls within the nth percentile of the Z-score's statistical range. Xi is a vector of predictor variables from the previous year, whereas ε_i represents the error term following a normal distribution with a mean of zero.

The study adopts a multifaceted approach due to the lack of consensus on the optimal model for predicting financial distress. It employs diverse methodologies, including statistical methods, Logistic Regression (LR) and artificial intelligence techniques, Decision Trees (DT), Support Vector Machines (SVM), Random Forests (RF), Naïve Bayes, AdaBoost, and Gradient Boosting. This approach accounts for challenges in parameter identification and the complexity associated with AI techniques. Subsequently, the model is employed for predicting the occurrence of financial distress:

$$\widehat{D}_i = \hat{\beta}_0 + \hat{\beta}_1 X_i \qquad (3)$$

Equation (3) models the likelihood of financial distress $\widehat{D}_i$ Based on X attributes, they are impacting the binary classification of firms. A '0' is typically assigned for predicted probabilities < 0.5, and '1' otherwise. Recognizing potential inefficiency in this method, we adopt the mean F-score (Fs) metric from established research (Serrano-Cinca & Gutiérrez-Nieto, 2013); (Le & Viviani, 2017). The optimal threshold is determined by maximizing the mean of the harmonic means of sensitivity (Se) and positive predictive value (ppv), as well as specificity (Sp) and negative predictive value (npv), following the provided formula for (Fs).

$$F_s = max \left(\frac{Se \times ppv}{Se + ppv} + \frac{Sp \times npv}{Sp + npv}\right) \qquad (4)$$

The term "sensitivity" refers to the rate at which valid positive results are identified. The "positive predictive value" (ppv) measures the proportion of firms correctly anticipated as being in default (or healthy). The "negative predictive value" (npv) refers to a percentage of companies accurately identified as being in good financial standing (or in default). Lastly, "specificity" reflects the rate at which accurate negative results are identified. This approach facilitates the identification of the optimal threshold where a balance is achieved in minimizing both Type I and Type II errors. A heightened F-score signifies the model's enhanced capability to mitigate inaccurate classifications.

4. Data Analysis

4.1 Descriptive Statistics

Descriptive statistics, encompassing key measures such as the mean, and, standard deviation (SD) have been computed for the sample. Table. 2 shows a statistical summary (mean and standard deviation) for various financial ratios categorized under profitability, solvency, liquidity, activity, and cash flow ratios for a dataset of 3,111 firms. These metrics are critical for assessing the financial health and risk of bankruptcy among firms, specifically within the context of Chinese companies. A mean ESG score of approximately 34 suggests that, on average, firms in this sample perform at a moderate level regarding their ESG commitments and practices. Also, profit margins such as the net profit margin (P1) and operating profit margin (P2) have average values of 6.325% and 7.809% respectively. These show that on average, companies can convert a small percentage of their sales into profits, but this varies a lot. The average values for other ratios such as the current ratio (L1) and cash to current liabilities (L3) are about 1.992 and 1.797 respectively, and companies can pay their short-term obligations with their short-term assets and cash holdings. A higher standard deviation means that the data is spread out more around the mean, which means that there are big differences in the financial performance of the companies. For instance, the standard deviations for the net profit margin (P1) and the operating profit margin (P2) are very high at 76.147 and 77.340 respectively. This shows the extreme variability in profitability among the companies, which means that while some are highly profitable, others may be operating at a loss. The inventory, receivables, and payables days (AC2, AC4, AC6) also have high standard deviations, which means that there is a big difference in the way the inventories and financial operations are managed across the companies.

The particular indicators such as O7, although mostly zero, show the variability which indicates that a few companies have had consistent losses over the years. This ratio is different from the ratios like the ratio of Ln (Assets) to Total Assets (X5), which have no variability at all, thus, showing the consistent measurement or scale across all companies.

Table 2: Descriptive Statistics

Variable Name	Variables	Mean	Std. Deviation
ESG Score	ESG	33.788	16.518
Net Profit Margin	P1	6.325	76.147
Operating Profit Margin	P2	7.809	77.340
Basic Earning Power (BEP)	P7	0.075	0.108
Return on Capital Employed (ROCE)	P8	0.111	1.723
Current Ratio	L1	1.992	2.141
Cash to Current Liabilities	L3	1.797	2.969
No. of days in Inventory	AC2	133.425	229.327
No. of Days in Receivables	AC4	109.704	125.580
No. of Days in Payable	AC6	131.822	290.375
Debt to Asset Ratio	S2	0.233	0.179
WC/TA	X1	0.172	0.237
RE/TA	X2	0.206	0.368
EBIT/TA	X3	0.067	0.105
MC/TL	X4	10.336	31.706
Ln (ASSETS)/TA	X5	0.000	0.000
Ln (ASSETS)/GNP	O1	3.266	0.657
TL/TA	O2	0.453	0.204
CL/CA	O4	0.849	0.740
NI/TA	O5	0.047	0.103
INTWO	O7	0.029	0.415
OENEG	O8	0.003	0.051
CHIN	O9	0.103	0.304

4.2 Evaluation of Performance Measures

Initially, we evaluate model predictive performance, accounting for the presence or absence of an ESG score. Subsequently, we quantitatively compare each predictor's overall improvement in predictive efficiency. Noteworthy is that while all approaches display adequate accuracy, machine learning models surpass individual classifiers.

The table. 3 compares the models' confusion matrix and performance metrics, incorporating and excluding the ESG score. These parameters relate to forecasting data not present in the original sample, revealing that incorporating the ESG score enhances the predictive capacity of the models.

Table 3: ESG-based Prediction Models: Performance and Comparison

Methods	Performance measures (%) with ESG			Performance measures (%) without ESG		
	F1-score	Se	AUC	F1-score	Se	AUC
Logistic Regression	100	100	100%	97.56	100	95%
Decision Tree	97.44	95	100%	97.44	95	100%
Random Forest	100	100	100%	100	100	100%
Naïve Bayes	95.24	100	99%	97.56	100	100%
SVM	97.56	100	100%	95.00	95	99%
AdaBoost	94.74	90	100%	100.00	100	100%
Gradient Boosting	97.44	95	100%	97.44	95	100%

Results highlight varied performance with and without ESG considerations, emphasizing the impact of environmental, social, and economic factors on prediction accuracy. The table. 3 displays the key accuracy metrics, including sensitivity (Se), Area Under the Curve (AUC), and F1 score.

Results from Table. 3, show that incorporating ESG factors significantly impacts machine learning models for bankruptcy prediction. Decision Tree, Random Forest, Ada Boost, and Gradient Boosting excel without considering ESG. ESG variables affect different algorithms, causing modest metric reductions for SVM and Naïve Bayes. For Logistic Regression, the value of AUC is significantly reduced when ESG is excluded from the ratios. Adding the ESG score enhances prediction accuracy, with AUC varying between 5 (Logistic Regression) and 1 point (SVM), and F-score reaching a maximum of 2.44 and 2.56 points for SVM and Logistic Regression, respectively.

Logistic Regression shows perfect F1-score (100%) and AUC (100%). Without ESG suggests the model rarely makes incorrect predictions and a high F1-score (97.56%) and AUC (95%), though a slightly reduced slight drop in F1-score. Decision Tree, with ESG, shows a high F1-score (97.44%) and perfect AUC (100%) and without ESG indicating that ESG factors do not significantly affect the Decision Tree's ability to classify bankrupt firms, indicating consistent performance regardless of ESG inclusion. Random Forest performs perfectly with and without ESG factors, showing that the Random Forest is highly effective in predicting bankruptcy and does not falsely predict bankruptcy for non-bankrupt firms. It suggests a robust model that is not dependent on ESG factors. The ESG F1-score (100%) and AUC (100%), which indicate a robust model for both scenarios, indicate that it is not significantly dependent on ESG factors for this dataset.

Naïve Bayes with ESG, exhibit a high F1-score (95.24%). It has a very high AUC (99%) and a slightly reduced F1-score (97.56%) but a perfect AUC (100%) without ESG. SVM shows good predictive ability with a slight risk of false alarms (predicting bankruptcy when there is not one) and a high F1-score (97.56%) with perfect AUC (100%) with ESG. It shows a slight decline in the model's predictive accuracy without ESG, with a reduced F1-score (95.00%), and a slight decrease in AUC (99%). AdaBoost, with ESG, exhibits a Lower F1-score (94.74%) but a perfect AUC (100%). Without ESG, it shows perfect F1-score (100.00%) and AUC (100%), though this perfection may warrant scrutiny for potential overfitting. F1-score improves to perfect without ESG, though this might not translate to real-world performance as the model might be overfitting. Gradient Boosting with ESG shows a high F1-score (97.44%) and perfect AUC (100%). Without ESG, it shows the same F1-score as with ESG (97.44%) and perfect AUC (100%), showing stability. It performs slightly worse without ESG regarding the F1 score but retains the same AUC.

Including ESG factors generally improves the accuracy of predictions for most methods, particularly noticeable in the Logistic Regression and SVM methods. Random forest stands out as the most stable model. Random forest is the standout model with perfect scores across all measures, both with and without ESG factors. This suggests that the model is particularly well-suited for bankruptcy prediction in this context and is robust to including or excluding ESG factors. The significant values suggest the importance of ESG factors in the prediction models, and they highlight the strengths and potential weaknesses of each model in the specific context of bankruptcy prediction for Chinese firms.

Though the overall incrementation is minuscule, if ESG is to be integrated during the classification, it helps significantly minimize Type II errors. This decrease desensitizes overclassifying distressed firms with apparently healthy companies which will reduce wrong options on the direction of distressed firms. When using the model for predicting the firm's default, the matter of false negatives has to be kept to the minimum, and the occurrence of false positives is secondary (Poghosyan & Čihak, 2011); (Cole & White, 2012).

It has been established that incorporation of ESG factors involves improvement in the accuracy of the model and stability of the model especially in cases relating to bankruptcy prediction. The most contemporary works promoting the integration of ESG factors in the financial model will improve the model's sparsity and reduce the likelihood of type II errors, which is highly critical in financial distress prediction (Cohen, 2023). This aligns with other works indicating that Logistic Regression models benefit from the implementation of ESG factors for consideration as it boosts the models' predictive ability (De Lucia et al., 2020). Logistic Regression models have been proven effective in estimating early signs of business failure (Vukčević et al., 2024).

In the same way, Support Vector Machine (SVM) models engage the highest informative scores insofar as they comprise the ESG factors, these factors constituting the key determinants of the given models (D'Amato et al., 2024). Algorithms such as Decision Tree models generally appear to be immune to variations in the inclusion of ESG factors. Setting that into context, recent studies reveal that decision trees are stable on predictive tasks (Natekin & Knoll, 2013). In contrast, the Random Forest models give promising and stable results for bankruptcy prediction, and based on recent works, it can be stated that the Random Forest algorithm is particularly efficient in FD prediction (Escrig-Olmedo et al., 2019). Random Forest is a robust model for the classification of bankruptcy probabilities (Hamdi et al., 2024).

As for the AdaBoost model, while ESG factors' inclusion indicated a higher potential of overfitting, future research should investigate if its performance correlates with real scores with a perfect result (Hernandez-Perdomo et al., 2019). Also, gradient-boosting models are more stable and resistant to overfitting, and it was observed that ESG factors affect them less, proving the models' insensitivity to such factors (Park & Oh, 2022). Hence, the impact of this observation is backed by literature identifying Gradient Boosting as robust in predictive work (Zheng et al., 2022).

In general, the incorporation of ESG factors boosts the reliability of the models in classifying firms that are likely to face financial distress and thereby unearths those firms that should be considered for the prevention of bankruptcy (Cohen, 2023). Therefore, the role of ESG considerations in enhancing the predictive models explained by employing Logistic Regression and SVM is as follows which goes a long way in enhancing the performance metrics which in turn caused a reduction in the Type-II errors in the case of bankruptcy prediction. When several models were tested, the results showed that although models may differ in their degree of sensitivity to the ESG factors, it can be concluded that ESG integration improves the performance of the models thereby helping in providing better financial distress predictions.

4.3 ROC Curve

The ROC curve visually represents a binary classification model's performance across different decision thresholds by plotting sensitivity against 1 - specificity. The Area Under the Curve (AUC) quantifies the model's ability to distinguish between positive and negative instances, with a higher AUC indicating better performance. The evaluation of models through the analysis of the Area Under the Curve (AUC) is given below in Figures 1 & 2.

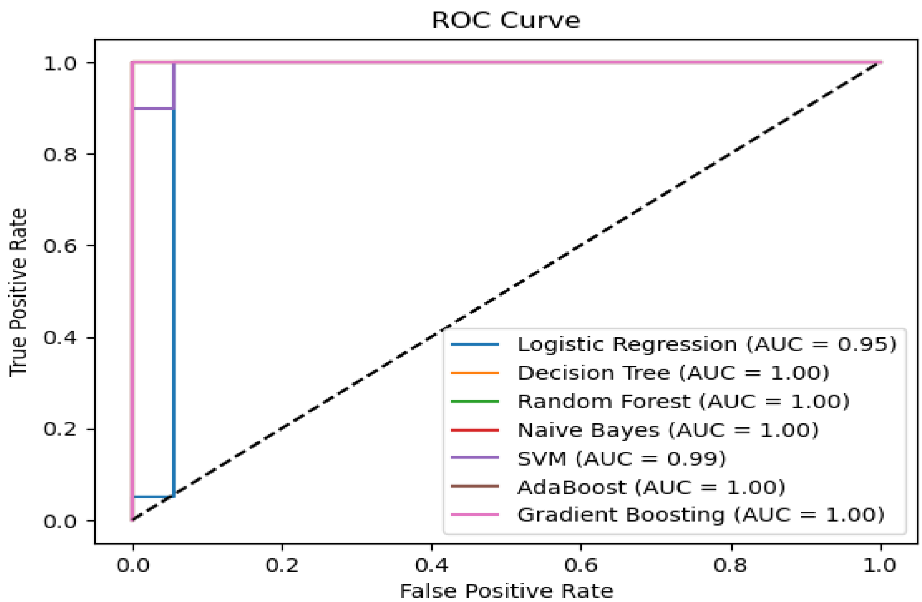

Figure 1: ROC Curve (without integrating ESG Score)

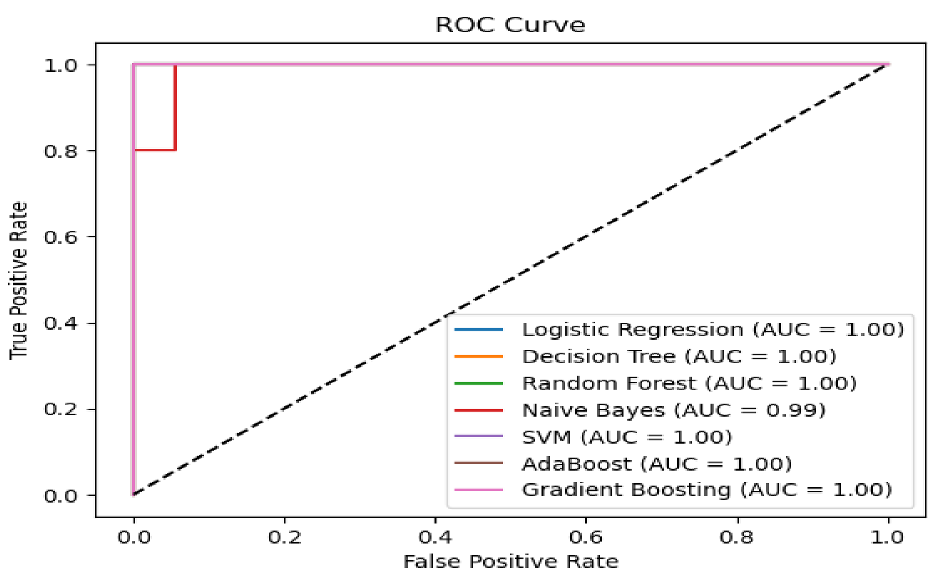

Figure 2: ROC Curve (with integrating ESG Score)

Random Forest performs exceptionally well in both scenarios, showcasing its robustness in bankruptcy prediction. Logistic regression remains to have better results in the Se criterion, while the AUC varies dramatically without ESG as a factor. The SVM and the Naïve Bayes models show little of a change in their performance metrics with the incorporation of ESG.

The findings show not only the complexity but also the particular effect of ESG factors on the prediction performance of the different models. Models like Random Forest and AdaBoost cut robust options because of the soundness of their results across various criteria. This underpins the concerns of selecting an appropriate model by considering the different evaluation goals, for instance, accuracy, sensitivity, or AUC, since informed decisions on bankruptcy prediction must be the outcome.

5. Discussion and Recommendations

This paper introduces a first-of-its-kind approach that incorporates Environmental, Social, and Governance (ESG) indicators into various types of prediction models to forecast bankruptcy. The idea lying at the core of our research brings about the innovative features of the incorporation of Environmental, Social, and Governance (ESG) factors especially in the reduction of the likelihood of misclassifying entities that are financially weak. Furthermore, this is a crucial problem that carries deep implications for different players, for instance, financial analysts, investors, and policymakers who can depend on its framework for estimating and resolving financial distress. The outcomes highlight the importance of measuring ESG with the process of bankruptcy prediction, which allows for making the financial environment more durable and enduring.

ESG models, such as Random Forest and AdaBoost, have shown themselves to be both robust and consistent performers in both metrics, whether or not ESG factors were included, which indicates their nature in predicting bankruptcy. Logistic Regression demonstrated a high level of accuracy of sensitivity, but the AUC value was then significantly changed when ESG factors were removed. Also, SVM and Naïve Bayes as well prove to have changes in performance metrics by the inclusion of ESG factors. The above inferences make us to understand that ESG factors are tailor-made for different machine learning models and as such the inclusion of ESG metrics is a surety for the improvement of the bankruptcy prediction system.

These insights underscore for policymakers and regulators that a rise in the transparency and disclosure of the ESG metrics enriches the existing literature on bankruptcy by providing valuable insights into the role of sustainability indicators. Thus, a holistic approach that is multi-purpose can be adopted that help in the process of decision-making and financial risk management. The study emphasizes on the need for integrating ESG factors in the strategic planning process and policy formulation, highlighting their importance in building a sturdier and environmentally conscious financial system. The financial analysts and the potential investors will also be benefited by taking into consideration ESG as the key factor of risk profile of a firm, and this will influence their investment decisions and risk assessment. Our approach's interconnectedness and dynamic nature underline its relevance and applicability for many scenarios in decision-making in the dynamic financial realm.

Thus, the study presented herein reveals several limitations. The findings of the present research can be used to remove or at least minimize the impact of these limitations in further studies. One weakness is a potential heterogeneity of both, the ESG data quality and its availability to employ in the model across regions and industries. Furthermore, regarding the approach, it is apparent that further enhancement of the methods of machine learning algorithms of higher levels and data analysis approaches can be applied. For this research, it is suggested that future research ought to estimate the nature of the causality between ESG incorporation into business operations and bankruptcy, establish the impact that certain ESG factors have on the prevalence of bankruptcy, and also analyze the possible usage of ESG forecasts within different types of industries and geographical locations. Thus, there is an opportunity for deriving more ESG-relative predictive variables and refining those common with the application of machine learning techniques.

Moving to the practical contributions, this study offers a logical model for interpreting the findings, which aims to serve as a practical guide to the stakeholders in enriching the procedures of financial risk evaluation and decision-making. Upon the consideration of ESG factors, it becomes easy for firms to face risks and avoid techniques that may lead to business distress thus promoting sustainable growth. These findings can help in the creation of policies, when implemented, and will enhance on the reporting of ESG information. It asserted that these models can help standardize investment by investors and even dealers as well as financier analysts, thereby helping to bring positive changes to the improvement of the soundness of the financial globe.

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