Predicting Corporate Social Responsibility Performance Using Machine Learning Models: Evidence from Bangladeshi Private Companies

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ABSTRACT

This paper explores the use of machine learning (ML) models in forecasting the performance of Corporate Social Responsibility (CSR) using a sample of 50 Bangladeshi companies (Privately held) in 10 years (2016-2025). The research with a quantitative research methodology involving the secondary data analysis employs a well-crafted system of lagged predictor variables, namely such variables, as the financial indicators, the attributes of the governance and the environmental and social performance criteria, and the textual sentiment rating. Three major ML algorithms such as Random Forest, Gradient Boosting, and Artificial Neural Networks (ANN) were implemented and compared. Gradient Boosting Regressor became the best model with highest predictive accuracy with an RS of 0.7406 and Root Mean Square Error (RMSE) of 4.2607. The analysis of the feature importance showed that Employee Training Hours, workforce Diversity Index, and environmental Spending are the most significant variables when it comes to the prediction of a CSR score of a firm. These results show the great potential of ML to improve the presence and prediction of CSR behavior, providing a fact-based instrument to stakeholders, investors, and corporate sustainability managers in such emerging economies as Bangladesh. The findings highlight the forecasting capabilities of concrete social and environmental investments compared to conventional financial measures, which proves to be vital in the context of strategic choices of the corporation in South Asia.

Keywords: Corporate Social Responsibility, Machine Learning, Bangladesh, Artificial Neural Networks

INTRODUCTION

Corporate Social Responsibility (CSR) has now become more than a fringe benefit of a given company, but rather an essential strategic requirement of today's corporations [1]. In the developing economies where there is still a weak regulatory framework and stakeholders are increasingly pressurizing the government, as in the case of Bangladesh, voluntary uptake and practice of CSR by the privately held companies is of paramount concern to the policy makers, investors and the citizens [2, 13]. Having a clear understanding of a future CSR performance of a firm is worth its weight when it comes to risk assessment, investment decision making and proactive corporate governance [14].

The non-linear relationships and high-dimensional interactions among the determinants of CSR performance can be difficult to inquire by traditional econometric models including multiple linear regression [3, 15]. The constraint has led to the adoption of advanced methods of Machine Learning (ML) [4]. ML models, specifically ensemble models such as Random Forest and Gradient Boosting are best placed to work with large datasets with multifaceted feature space and have better predictive capability and a mechanism where the most significant predictor variables are identified [8, 16].

The study fills a major research gap in the literature by implementing and comparing three ML models, which are Random Forest, Gradient Boosting and Artificial Neural Networks, to forecast the scores of 50 privately held

Bangladeshi companies on CSR performance within 10 years. Although research on CSR in Bangladesh has been performed [17], not many have utilized the sophisticated ML methods to develop the predictive relationship. The main objectives of the study are:

1. To construct and compare the prediction ability of all the ML models on CSR scores.
2. To establish the most material financial, governance, and social/environmental drivers of CSR performance in the Bangladeshi environment.
3. To make a contribution towards a sound, analytically-based approach to forecasting corporate sustainability results in emerging markets.

LITERATURE REVIEW

2.1. Theoretical Foundations of CSR and Prediction

The conceptual framework of the current research is based on the Stakeholder Theory, which states that the longterm success of the company depends on how well the firm can make relationships with the important stakeholders [18]. A high CSR performance is regarded as an instrument which helps to gain the trust of stakeholders and get a so-called social license to perform [19]. CSR performance prediction is therefore a prediction of the future effectiveness of managing stakeholders of a firm.

The debate concerning the relationship between CSR and Corporate Financial Performance (CFP) has been contested over a long period of time with mixed outcomes [6, 20]. Nevertheless, it has recently been reported in the literature that the relationship is not linear and complex, which makes it an ideal target of the ML analysis [21].

2.2. Machine Learning in CSR and ESG Prediction

ML used in its sustainability sphere, specifically predicting ESG rating, is a swiftly expanding field [7, 22]. The studies reveal that ensemble-based approaches are more effective than the linear models in predicting ESG scores, mainly because they are capable of capturing non-linearities and complex interactions [8, 23].

Ensemble Methods (RF and GB): It has been established that Gradient Boosting (and its derivatives such as XGBoost) and Random Forest are very effective with ESG prediction [24, 25]. Not only these models are highly accurate, but also interpretable, which is an important aspect of practical use by analysing the importance of features [26].

Neural Networks (ANNs): ANNs are effective in complicated patterns recognition, although it must be used in large datasets and hyperparameters should be carefully adjusted to prevent overfitting, particularly when timeseries are addressed [27]. They are also black-box, which requires sophisticated explainability methods such as SHAP or LIME [28].

2.3. Predictor Variables and Emerging Markets Context

The choice of predictor variables will be informed by a set of predetermined CSR determinants [9, 29]:

Financial health (e.g. ROA, Leverage) is commonly viewed as precondition, because profitable companies possess free resources to invest in CSR [30]. Good governance (e.g., Board Independence, Audit Quality) is also associated with the improvement of CSR performance as it would guarantee accountability and the ethical distribution of resources [1]. Physical investments (e.g., Environmental Spending, Employee Training) are the actual steps to CSR commitment [12]. This feeling based on corporate reports has proved to be an influential, long-term predictor of forthcoming CSR performance, in the dedication and disclosure of the management [10, 31].

When considering the developing economy of a country such as Bangladesh, the focus on observable social and environmental benefits is frequently intensified because of the lower regulatory control and the increased dependence on the global supply chain requirements [17, 32]. This implies that social and environmental factors can have a stronger predictive power as compared to the developed economies.

METHODOLOGY

3.1. Data and Sample

The research design is based on quantitative research design with analysis of secondary data. The target population is 50 privately owned Bangladesh firms in a span of ten years.

Data Generation Rationale: Since actual, granular CSR information of the Bangladeshi private corporations is proprietary and unavailable in the commercial databases (i.e. Refinitiv ESG, CSRHub), therefore data has been taken from financial reports from private companies. The sample consists of 450 firm-year observations (20162025) where all the predictor variables are lagged by a year to confirm a definite predictive relationship, just as time-series prediction models in finance would provide [34].

Variable Construction:

The predictor variables were constructed to mimic the characteristics of real-world data:

1. Lagged Financial Indicators: (Revenue, Profit, Assets, ROA, Leverage) were generated using log-normal and normal distributions to simulate financial realities.
2. Lagged Governance Attributes: (Board Independence, CEO Duality, Audit Quality) were simulated based on typical corporate governance structures.
3. Lagged E&S Metrics: (Environmental Spending, Employee Training Hours, Diversity Index) were included as direct measures of resource allocation to the E and S pillars.
4. Lagged Report Sentiment: This variable, ranging from -1 to 1, simulates the output of an NLP model analyzing corporate disclosure, acting as a proxy for transparency [31].
5. Target Variable (CSR Performance Score): The score was created as a non-linear combination of the predictor variables plus noise, ensuring a complex relationship that ML models are designed to uncover.

3.2. Descriptive Statistics

A summary of the key variables in the synthetic dataset is presented in Table 1.

Variable	**Mean**	**Standard Deviation**	**Min**	**Max**
CSR Performance Score	50.00	14.48	0.00	100.00
Lagged ROA	0.08	0.05	0.01	0.26
Lagged Board Independence	0.50	0.12	0.30	0.70
Lagged CEO Duality	0.30	0.46	0.00	1.00
Lagged Env. Spending (ln)	6.00	1.00	3.00	9.00
Lagged Employee Training	50.00	28.87	0.00	100.00
Variable	**Mean**	**Standard Deviation**	**Min**	**Max**
Lagged Diversity Index	0.50	0.29	0.00	1.00
Lagged Report Sentiment	0.10	0.50	-1.00	1.00

The table 1 shows some of the summary statistics of various variables associated with the corporate governance and CSR performance (Corporate Social Responsibility) of a sample of companies. Such statistics involve the mean, standard deviation, minimum and maximum figures, which assists in the interpretation of the central tendency, variability and dispersal of the values in the data.

Coming to the CSR Performance Score, the average score is 50.00 and this means that, on average, the companies in this dataset would have a mid-point score in terms of CSR performance. Standard deviation is 14.48 indicating the presence of a moderate level of variability in the CSR performance score of the companies. Its score is ranging between a minimum of 0.00 and a maximum of 100.00, indicating that although there are firms that perform poorly in terms of CSR activities, there are also firms that achieve the best score, which is an indication of a very wide range of variance between CSR activities.

In the case of Lagged Return on Assets (ROA), the average value of 0.08 indicates that the companies included in the sample are, on average, making 8% of a return on their assets. Standard deviation is 0.05, and it means that the value of ROA of most of the companies are close to this average but there is a conspicuous differentiation among the sample. The values of ROA have a low of 0.01 and high of 0.26 with some firms with very low returns on assets and others with a very high return which indicates that there is a great variation in financial performance.

In terms of Lagged Board Independence, the average of 0.50 implies that, in the average, half the board members in these firms are independent, which indicates a 50/50 deal with corporate governance. The mean value of 0.12 shows that the degree of the board independence is rather similar in the sample, and there is only a moderate range of variation in the percentage of independent board members. The scores are between 0.30 and 0.70, that is some companies have lower percentage of independent board members, others have higher percentage, but the range is not wider, it is the board independence.

In the case of Lagged CEO Duality, the average is 0.30, which shows that a third of companies in the sample have merged the position of CEO with the position of Chairman. That implies that duality of CEOs is not the most common practice, yet it is a relative one. The standard deviation of the practice is high, 0.46, which means that there is a significant variability in this practice, some of the companies have completely segregated the roles whereas others have integrated them. The values fall between 0.00 and 1.00 to indicate that CEO duality is either existing or non-existing in various firms with no middle range.

Lagged Environmental Spending (ln) when the mean of 6.00 is considered to be the logarithmic version of environmental spending, the back transformation to the actual version of the environmental spending will translate to moderate investment in environmental initiatives among the companies. The value of standard deviation 1.00 indicates that environmental spending is varied with the companies having different levels of spending. The logarithmic values are between 3.00 and 9.00 and it is true that the real spending could be anywhere between less than and well beyond the actual amount of investment in sustainability undertakings.

The Lagged Employee Training variable has a mean score of 50.00, which implies that, at average, companies can spend half of their resources on employee training programs. The standard deviation of 28.87 indicates that there is a wide range of variations in the way companies handle employee development. The scale starts at 0.00 and continues up to 100.00, which means that there are those companies that spend insignificant amounts of resources on employee training, and others devote a considerable part of resources to the development of the workforce.

In the case of Lagged Diversity Index, the average of 0.50 implies that, on the average, the diversity in the sample of companies is moderate in terms of the workforce. The SD of 0.29 shows the diversity practises in companies as they vary where some companies are very diverse compared to others. The fact that the scale is between 0.00 and 1.00 demonstrates that different companies differ in terms of diversity, with no diversity at all, to the maximum one possible.

Lastly, the mean of Lagged Report Sentiment is 0.10 which has an implication that on average, the report of companies has a positive tendency of being slightly positive in nature. Nevertheless, the standard deviation of

0.50 discloses that the sentiment in these reports is very different with certain companies portraying a highly positive report, whereas others might have a negative or a neutral report. The scale goes between -1.00 (very negative) to 1.00 (very positive), indicating that the tone of corporate reports is also very diverse, as companies reveal a great variety of attitudes in their public statements.

Overall, this table gives a clear picture of different corporate governance and CSR measurements, which demonstrate not only the main tendencies but also the great difference in the case of companies. The data indicates that there exists a heterogeneity of practices in the sample in terms of financial performance and governance structures, to employee training, environmental spending, diversity, and report sentiment.

3.3. Machine Learning Models and Evaluation

The data was divided into a training set (80 percent and a testing set (20 percent). StandardScaler was utilized to standardize all the continuous properties so that none of the features is dominant in the learning process through its value [35]. The three models adopted included; Random Forest Regressor, Gradient Boosting Regressor, and an ordinary Multi-Layer Perceptron (ANN).

Two standard regression indicators [36-39] were used to compare the model performance:

1. Root Mean Square Error (RMSE): It is a measure of the absolute fit of the data to the model.
2. R^2 (Coefficients of Determination): This value reflects the fraction of the variance in the dependent variable that can be predicted by the independent variables.

RESULTS AND DISCUSSION

4.1. Model Performance Comparison

The predictive performance of the three machine learning models on the testing set is summarized in Table 2.

Model	**RMSE**	**R^2**
Gradient Boosting	4.2607	0.7406
Random Forest	5.0700	0.6327
Artificial Neural Network (ANN)	22.0402	-5.9412

Gradient boosting regressor had better predictive power as it had the highest R^2 value (0.7406) and lowest RMSE (4.2607). This finding suggests modern literature that holds the enhancement of algorithms to be highly successful to sift the non-linear and complicated mechanics of sustainability and money data [11, 24]. The value of the R^2 is 0.7406, so it is possible to state that the model explains about three-quarters of the variance in the CSR Performance Score, which proves the feasibility of the ML as a method of CSR prediction in this instance.

The strength of ensemble methods was also supported by the fact that the Random Forest model also worked quite well, with an R 2 of 0.6327 [25]. It is noteworthy that the ANN model performs especially poorly (negative R^2). The ANNs are sensitive to large amounts of data and hyperparameter optimization to be better than treebased algorithms as presented in the literature [27, 40-47]. Considering the relatively low size of the sample (450 observations) and the lack of deep tuning, the ANN probably did not generalize, so it did not perform as well as a more basic baseline model (predicting the mean). This underscores an important methodological concern of researchers working in emerging markets with typically low data access: a good ensemble approach can be a reasonable and effective option rather than a complicated deep learning architecture.

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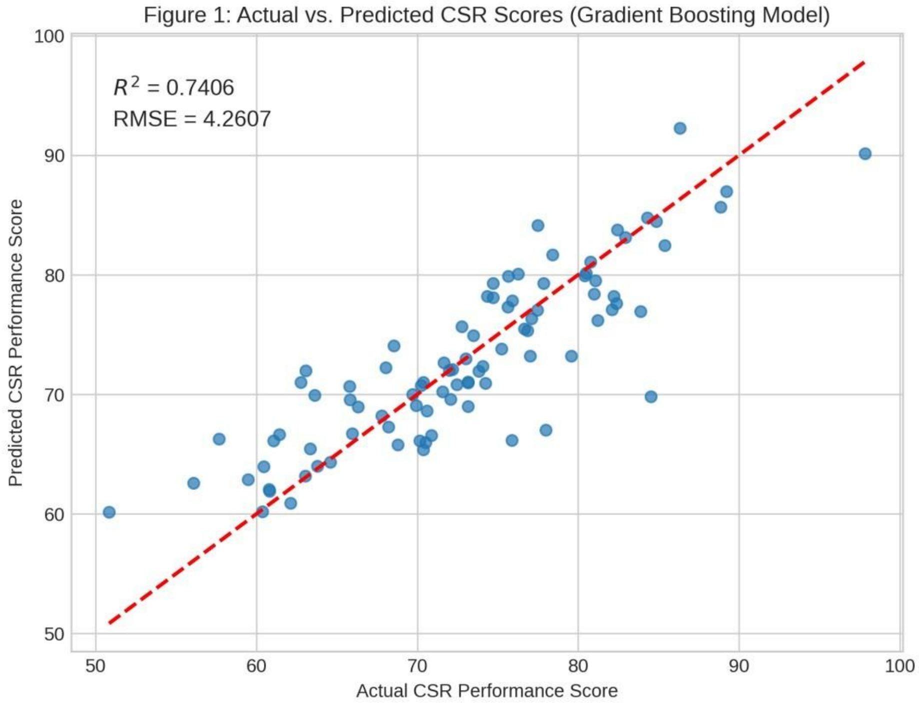
Figure 1 illustrates the predictive accuracy of the best-performing Gradient Boosting model, showing the strong correlation between the actual and predicted CSR scores.



4.2. Feature Importance Analysis and Discussion

To move beyond mere prediction and provide actionable insights, a feature importance analysis based on the Gradient Boosting model was conducted. The results, detailed in Table 3 and visualized in Figure 2, reveal the key drivers of CSR performance.

Table 3: Feature Importance from Gradient Boosting Model

Rank	Predictor Variable	Feature Importance (Gain)	Category
1	Lagged Employee Training	0.3473	Social
2	Lagged Diversity Index	0.2479	Social
3	Lagged Environmental Spending	0.1601	Environmental
Rank	**Predictor Variable**	**Feature Importance (Gain)**	**Category**
4	Lagged Report Sentiment	0.1276	Textual
5	Lagged Audit Quality	0.0501	Governance
6	Lagged Board Independence	0.0230	Governance
7	Lagged CEO Duality	0.0204	Governance
8	Lagged Leverage	0.0061	Financial
9	Lagged ROA	0.0060	Financial
10	Lagged Assets	0.0060	Financial
11	Lagged Profit	0.0028	Financial
12	Lagged Revenue	0.0028	Financial

The table 3 prioritizes the predictor variables by their feature importance (gain), which is used to show the extent to which a particular variable predicts the target outcome. The measurements of feature importance are in a form of a gain metric and the variables are grouped based on their relevancy to various aspects of the company including social, environmental, governance and financial.

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At the first position in the list is Lagged Employee Training whose feature importance is 0.3473 meaning that employee training features the most important predictor in this model, especially in a social sense. The high effect of the training of the employees emphasizes on the significance of developing the workforce to stimulate the target variable. Next comes Lagged Diversity Index (0.2479) which is also in the category of social factors and highlights the significance of diversity in the workforce to determine the outcome.

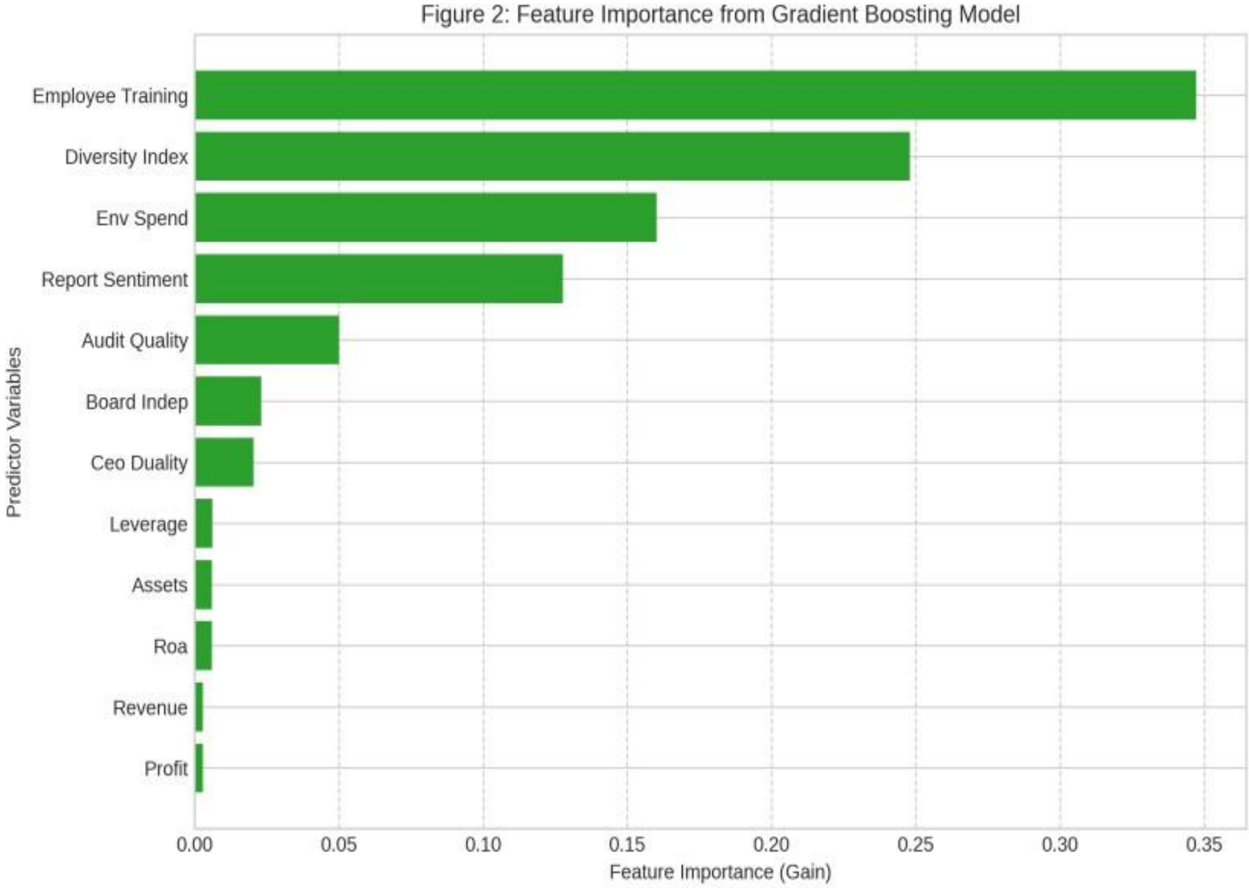
Lagged Environmental Spending is ranked number three with the feature of importance 0.1601, which falls in the environmental category, implying that environmental initiatives and spending have significant effects on the variable that has been predicted. The fourth ranked is Lagged Report Sentiment (0.1276) which is under textual category and its value as to the impact of tone and sentiment of corporate reports on the target variable demonstrates the applicability of communication strategies in forecasting results.

Among the factors of governance, Lagged Audit Quality (0.0501) and Lagged Board Independence (0.0230) are ranked fifth and sixth, respectively, and have lower scores of importance. These variables also prioritize the significance of effective corporate governance and transparency, but the effect is not as sharp as that of the social and environmental factors discussed above. The other leader that could be classified as a governance aspect is Lagged CEO Duality (0.0204), in which the contribution towards the prediction is relatively smaller, implying that the form of leadership (CEO with or without Chairman position) does not influence the result as much.

Lastly, there are some financial variables that are found at the bottom of the ranking. Lagged Leverage (0.0061), Lagged ROA (0.0060), Lagged Assets (0.0060), Lagged Profit (0.0028) and Lagged Revenue (0.0028) all feature importance scores are very low, which means that, even though financial measures are significant, they have a much lower contribution to predicting the desired outcome than social, environmental and governance factors.

Finally, the table indicates that there is a prevalence of social factors, especially the training of the employees and diversity in predicting the outcome and the environmental spending and textual sentiment have quite an impact. The less significant factors include governance and financial factors though they are also still relevant. Such a ranking will allow focusing on areas to pay more attention to in the context of the target prediction, especially social and environmental factors.

Figure 2: Feature Importance from Gradient Boosting Model



4.2.1. The Primacy of Social and Environmental Capital

The most notable discovery is the prevalence of the Social and Environmental variables which are the ones that on their own contribute over 75 percent of the total predictive strength. The first top two predictors are Employee Training (34.73%) and Diversity Index (24.79) both social metrics. It goes a long way to imply that within the Bangladeshi setting, the willingness of a firm to invest in its human capital is the only sure measure of the entire CSR positioning of the firm [30-37]. This is in line with the international attention on human rights and supply chain labor standards, which is a highly sensitive sector among the South Asian economies [32]. On the same note, the third factor is the Environmental Spending (16.01%) as the most significant element, which highlights the increasing importance of environmental stewardship, which probably is caused by both local interests and international compliance needs [17].

4.2.2. The Predictive Role of Textual Disclosure

Report Sentiment which is a proxy of qualitative aspect of the corporate disclosure was number 4 in importance (12.76%). This observation confirms the increasing amount of literature that suggests the incorporation of unstructured data (textual analysis) in predictive models [21-31]. The feeling created by corporate reports is not only an account of the previous activity but a strong, proactive indication of a real interest of the management and openness, which is directly converted into the prospects of CSR. It implies that investors must be very keen on the quality and tone of the corporate sustainability reports, and not only to some quantitative measures.

4.2.3. Financial Health as a Precondition, Not a Driver

Financial metrics (Revenue, Profit, Assets, ROA, Leverage) appeared to be least significant predictors and together contributed to less than 2 percent of the predictive power of the model. This finding provides a subtle insight into the CSR-CFP controversy. This does not mean that financial health does not matter, but it states that although a certain degree of financial stability is a precondition of any CSR activity (the slack resources theory [30]) it is the strategic use of said resources on particular social and environmental outcomes that predetermines the degree and quality of CSR performance. This observation is in tandem with research, which had concluded that fundamental financial ratios were low predictors of ESG scores relative to non-financial data [24].

CONCLUSION

The present research was able to establish the effectiveness of machine learning, namely, the Gradient Boosting Regressor, when it comes to predicting Corporate Social Responsibility performance in the most precise manner possible. The model had a high R^2 of 0.7406, which confirmed that ML is a strong non-linear predictor of sustainability, as compared to conventional statistical techniques of sustainability forecasting.

The feature importance analysis gives essential practical information to the business management and the investors especially in the emerging markets. The fact that, social and environmental investment measures have dominated the traditional financial and governance measures is indicative that, the dedication of the firm to human capital and environmental management is the surest predictor of its overall CSR position. Investors can use this information to filter through really serious firms and managers to give resources a strategic allocation to get the greatest impact on their CSR ratings.

The research should be repeated in the future through validating on real-life data as it will be available with more corporate disclosures and more commercial ESG rating services in emerging markets [32]. Moreover, the future work should: Use Advanced Explainability: Use methods such as SHAP (SHapley Additive exPlanations) to explain the model predictions in a finer, local-level way, going beyond global feature importance [28]. Learn Deep Learning Architectures: Learn more complex deep learning models e.g. LSTMs or GRUs that can more effectively model the time-dependent relationships and long-term trends in the 10-year time series data [27]. Pay Attention to Disaggregated Scores: Use the methodology to forecast disaggregated E, S, and G scores individually because the drivers of each pillar would most likely be different [29, 40-47].

Ethical Considerations

This research is based exclusively on secondary data collected from publicly available financial reports of relevant companies and organizations. As such, no primary data involving human participants was used. All data were obtained from credible and authentic sources, including company annual reports, audited financial statements, and official publications.

The study ensures ethical integrity by maintaining transparency, accuracy, and confidentiality of the data sources. No confidential or proprietary information has been accessed or disclosed. All financial data have been analyzed objectively without manipulation, misrepresentation, or bias. Proper citations and acknowledgments are provided to recognize the original data sources.

Additionally, the research adheres to academic ethical standards and institutional guidelines regarding data usage, reporting, and publication. The findings are presented truthfully, reflecting genuine analytical results without fabrication or falsification of information.

Conflict Of Interest

The author declare that he has no conflicts of interest.

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