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Abstract

Environmental, Social, and Governance (ESG) considerations have become integral to corporate strategy, investor decision-making, and regulatory oversight. ESG violations—such as environmental harm, governance failures, and social misconduct—pose substantial reputational, financial, and legal risks. This study develops a machine learning-based framework for the early detection of ESG policy violations using the World Benchmarking Alliance's Nature Benchmark dataset (2022–2024), covering 816 firms across more than 20 industries. To address the pronounced class imbalance inherent in ESG violation data, the Synthetic Minority Over-sampling Technique (SMOTE) is applied. Three classification models—Logistic Regression, Decision Tree, and Random Forest—are evaluated. The Random Forest model demonstrates the most robust performance, achieving a superior balance between accuracy and recall. Model interpretability is ensured through feature importance measures and SHAP values, which identify key ESG dimensions and industry-specific drivers associated with violations. Overall, the findings highlight the effectiveness of combining ensemble learning, resampling techniques, and explainable machine learning to support scalable and proactive ESG risk assessment.

Keywords: *ESG, ESG violations, sustainability analytics, machine learning, Random Forest, SMOTE, SHAP*

JEL Codes: *C38, C45, G17, Q56*

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The authors acknowledge the academic guidance and feedback received during the presentation of this paper at academic forums. Any remaining errors are solely the responsibility of the authors.

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INTRODUCTION

Environmental, Social, and Governance (ESG) factors have emerged as critical indicators of corporate sustainability, ethical conduct, and long-term value creation. As regulators, investors, and other stakeholders place increasing emphasis on ESG performance, the ability to anticipate and mitigate ESG violations has become a central challenge for firms. Such violations can result in reputational damage, financial losses, and regulatory sanctions, underscoring the importance of early risk identification.

This study applies machine learning techniques to predict ESG policy violations using historical ESG performance data. By leveraging structured ESG scores, rankings, and industry-level indicators, the research develops an early warning framework capable of identifying firms and sectors that are particularly vulnerable to ESG non-compliance. In addition, the study emphasizes model interpretability to ensure that predictive outcomes can be translated into actionable insights for policymakers, investors, and corporate decision-makers.

DATA AND METHODOLOGY

Data source

The dataset is obtained from the World Benchmarking Alliance's Nature Benchmark public dataset for the years 2022–2024. The Nature Benchmark evaluates how firms manage their environmental impacts and contribute to biodiversity protection. The sample consists of 816 companies across more than 20 industries.

Variable Construction and Preprocessing

A binary target variable, ESG_Violation, is constructed based on assessment outcomes. Firms classified as "Unmet" are coded as 1 (violation), while others are coded as 0. ESG scores, governance indicators, and industry classifications are used as explanatory variables.

Missing numerical values are imputed using median values, while categorical variables are imputed using modal values. Categorical features are label-encoded, and numerical variables are standardized.

Handling Class Imbalance

Given the imbalanced distribution of ESG violations, SMOTE is applied to the training data to synthetically oversample the minority class. This improves the model's ability to detect violations without excessively biasing predictions toward the majority class.

Model Development

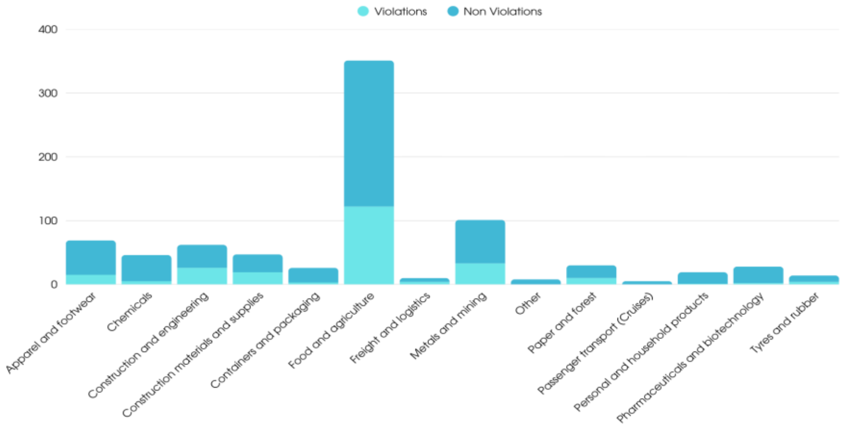
Three supervised learning models are estimated: Logistic Regression, Decision Tree, and Random Forest. Hyperparameter tuning for the Random Forest model is conducted using grid search with cross-validation. Model performance is evaluated using accuracy, precision, recall, F1-score, and AUC-ROC metrics.

RESULTS AND DISCUSSION

Industry wise distribution of ESG Violations

The industry-wise distribution of ESG violations (Fig.1) reveals significant sectoral heterogeneity. Food and Agriculture records the highest number of violations (122), followed by Metals and Mining (33), and Construction and Engineering (26). These sectors are particularly exposed to environmental degradation, labor rights issues, and governance challenges. Mid-tier industries such as Construction Materials and Supplies, Apparel and Footwear, and Paper and Forest show moderate levels of violations, while Pharmaceuticals and Biotechnology, Personal and Household Products, and Passenger Transport exhibit relatively low ESG non-compliance.

Figure 1: Industry wise ESG Violations



Source: World Benchmarking Alliance, Nature Benchmark Dataset (2022–2024)

Note: The figure shows the count of firms classified as ESG violators (below the 30th percentile of total ESG scores) across industries.

Model Performance Comparison

Three models—Logistic Regression, Decision Tree, and Random Forest—are evaluated using accuracy, precision, recall, F1-score, and AUC-ROC metrics (Table 1). Accuracy reflects overall predictive correctness, while recall is particularly important for identifying ESG violations, where false negatives are costly. Precision captures the reliability of positive predictions, and AUC-ROC measures overall discriminatory power.

Table 1: Model Performance Metrics

Model	Accuracy	Precision (Class 0)	Recall (Class 0)	F1-Score (Class 0)	AUC-ROC
Logistic Regression	0.59	0.23	0.62	0.34	0.65
Decision Tree	0.63	0.27	0.67	0.38	0.71
Random Forest	0.64	0.27	0.67	0.38	0.71

Source: Author's computation

Note: Metrics are reported for the test dataset after applying SMOTE to the training data.

Confusion Matrix Analysis

The confusion matrix (Table 2) analysis indicates that the Random Forest model identifies a larger share of ESG-compliant and non-compliant firms compared to the other models. Although false positives and false negatives remain due to class imbalance, the ensemble structure of Random Forest improves robustness relative to single-tree and linear models.

Table 2: Confusion Matrix-Random Forest Model

	Predicted Negative	Predicted Positive
Actual Negative	2342	1154
Actual Positive	6362	10816

Source: Author's computation

Note: Rows indicate actual class labels, while columns represent predicted class labels.

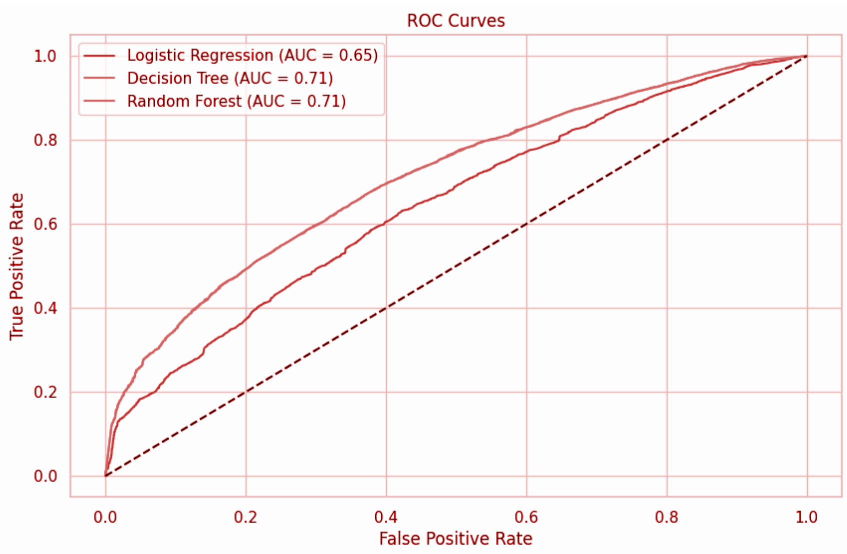
ROC Curve Analysis

ROC curve analysis (Fig.2) illustrates the trade-off between the true positive rate and false positive rate across different classification thresholds. Both Random Forest and Decision Tree models achieve an AUC of approximately 0.71, indicating moderate discriminatory power, while Logistic Regression records a lower AUC of 0.65.

Impact of SMOTE on Model Performance

The application of SMOTE significantly improves recall for the minority class across all models by generating synthetic ESG violation samples. While this enhances the detection of violations, it introduces a precision–recall trade-off. Overall, Random Forest achieves the most balanced performance, making it the preferred model for ESG violation prediction.

Figure 2: ROC Curves for Machine Learning Models



Source: Author's computation

Note: The diagonal line represents random classification; curves farther from the diagonal indicate better performance.

CONCLUSION

This study develops a machine learning-based framework for the early detection of ESG policy violations using the World Benchmarking Alliance's Nature Benchmark dataset. By comparing Logistic Regression, Decision Tree, and Random Forest models, the analysis demonstrates that ensemble methods—particularly Random Forest—provide superior predictive performance in identifying ESG violations. The application of SMOTE effectively mitigates class imbalance, improving recall for high-risk firms, while explainability tools such as feature importance measures and SHAP values enhance the transparency and interpretability of model predictions.

The findings underscore the presence of significant sectoral heterogeneity in ESG risk, with industries such as Food and Agriculture, Metals and Mining, and Construction exhibiting a higher incidence of violations. From a policy and managerial perspective, the proposed framework offers a scalable and data-driven approach to proactive ESG risk monitoring and compliance assessment. Future research may extend this work by incorporating real-time disclosures, textual data, and sentiment analysis to further improve predictive accuracy and support timely ESG interventions.

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