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Predictive Modelling for Esg Risk Levels in S&P 500 Companies: Empowering Informed Investment Decisions

Dr. Yashodhan K. Karulkar, Dr. Christine D'lima (Corresponding Author) *, Atharva Hardikar, Anushka Rajurkar, Prathamesh Raut
MPSTME, NMIMS University

ABSTRACT

ESG is significant because in the world of Finance and investments, as several socially conscious investors, use ESG criteria to screen and take informed decisions related to long-term investments in a corporation. ESG metrics are not usually part of mandatory financial reporting, though companies are increasingly making disclosures in their reports. This paper studies the fundamental role of ESG factors in corporate performance evaluation, in particular companies within the S&P 500 index. The research paper is focused on developing a predictive model and its capability to evaluate and predict the ESG risk levels given a wide dataset sourced from Kaggle using advanced machine learning methods. The methodology includes exhaustive data preparation, exploratory data analysis, feature engineering, and the application of several classification algorithms such as Random Forest, Decision Tree, and Naïve Bayes. Model evaluation metrics using accuracy, precision, recall, F1-score, and AUC-ROC were applied to ensure the robustness and reliability of the prediction. The main finding of this analysis is the potential data leakage when the "ESG Risk Percentile" feature was removed and it improved the balance in the model. This contribution will underline the importance of including ESG consideration within investment practices and derive useful insights for investors and stakeholders. These findings underline the practical value of ESG risk analysis to drive more sustainable and ethical business practices, hence leading to more informed and resilient investment decisions.

Keywords:-ESG, risk analysis, Machine Learning, S&P 500, Sustainable investing

I. INTRODUCTION

ESG is an abbreviation for environmental, social, and governance factors commonly used in the world of trade and finance. The ESG is a particularly valuable framework for strategic investors, retail investors and asset management companies to comprehend how an organization is managing risks and opportunities related to environmental, social, and governance criteria (also called ESG factors in business context).

In the fast-evolving financial landscape, investors seek much more than classic conventional numbers in making investment calls. [21; 3] ESG considerations, within the sustainability and ethical impact of businesses, have rapidly become vital variables for other investors. ESG risk analysis extends way beyond the scope of traditional financial analysis in producing a full overview of company operations, hence influencing stakeholder decisions. [22; 37]. This introduction will discuss why ESG is a screening metric for the stock-picking process and its impact and importance.

The term 'ESG investing' has attracted a lot of consideration from investors as an investment value chain that integrates environmental, social, and governance considerations to achieve a more sustainable and responsible investment portfolio. Such an approach has the potential to improve the risk-return profile and hence advance the long-term financial performance of a portfolio substantially. This information is related to the environmental dimension of the company through how it affects the planet by its carbon footprint, waste, and competence in managing resources. The social dimension relates to how a business deals with its relationships with stakeholders like customers, employees, suppliers, and communities. Governance comprises of the company's leadership, executive compensation, audit, internal control, and rights of shareholders.

There are numerous benefits to introducing ESG considerations into choices of investments. Businesses with a high ESG score tend to manage their risks better, are more transparent, and have greater efficiency in the delivery of services, thus experiencing less idiosyncratic risks and higher long-term performance [2; 31]. For instance, firms with healthy ESG practices have a low likelihood of catastrophic incidents, such as fraud or environmental disasters, which hurt their stock prices and overall valuation [14]. Moreover, ESG-related data can act as an early alarm mechanism to pinpoint some important risk and opportunity factors that are otherwise not identifiable by conventional financial analysis [16]. ESG becomes a primary screening metric for stock selection, and dual advantage derives therefrom: firstly, identification of businesses that are not only financially viable but also committed to sustainable and ethical practices. This alignment allows a company to experience better reputation, customer loyalty, and regulatory compliance—factors crucial for long-term success. Furthermore, the integration of ESG criteria will reduce risks from bad corporate practices that can seriously harm investors through unexpected controversies and possible regulatory penalties [1; 2; 35].

The S&P 500 index is composed of some of the largest and most powerful companies in the United States, providing a rich source of information to help one study the relationship of ESG factors to financial performance and risk profiles. Our study utilizes the dataset among the companies in the S&P 500. Since these lessons are on the leaders, in general, they apply across a wide range of companies, industries and markets. The methods of machine learning classification will be applied to predict the levels of ESG risk, and from thereon, further deepen valuable insights into the role ESG plays in shaping informed investment decisions. As we crisscross the ESG-inspired landscape, it becomes vividly apparent that ESG integration is not some fad but a material paradigm shift toward more responsible and resilient investing. This paper elucidates how ESG metrics can be practically transformed into value when companies embed durable and ethical business practices, as drawn through our in-depth analysis of the S&P 500 index companies.

II. LITERATURE REVIEW

Over the last few years, ESG has gained a lot of attention in terms of becoming one of the major trends in developing corporate strategies and investment decisions. The shifts towards sustainable and responsible business conduct are most vividly perceived in the widespread integration of ESG into companies' and investors' decisions. [8; 14; 32]. The issue is increasingly realized not only as a means to promote sustainability but also to provide better financial performance and risk management.

Long-term studies have already shown that companies rated as high ESG are likely to indicate better financial performance and reduced risk, arising from improved profitability, risk management, and reduced cost of capital. Giese et al. set up three key transmission channels through which ESG factors impact financial performance: the cash flow channel, the idiosyncratic risk channel, and the valuation channel. Their study showed that companies with higher ESG ratings displayed better financial performance, therefore making a strong case for the ESG factor in affecting equity risk, valuation, and performance. Another study provides an overview of the mixed yet probably positive impact of ESG factors on company performance. This research portrays that ESG investments do come with high costs, but there is a significant upside related to improved reputation and risk management [2; 27; 34].

There are several studies in the literature that support the positive relationship between ESG performance and firm value. For instance, the study of CSR practices in Korean firms showed a significant positive impact on market value, especially in chaebols—large family-owned business conglomerates—due to better governance practices [3; 30]. This is further supported by Schramade's work on the integration of ESG factors into valuation models via the Value-Driver Adjustment approach, which shows that ESG factors can have a huge effect on target prices and, therefore, investment decisions, proving financial materiality [4]. All in all, this also confirms the results of Wan et al.'s bibliometric analysis, which provides a holistic perspective of the evolution of ESG research, outlining major hotspots and trends [5; 21]. According to the study, it has been portrayed that ESG research substantially happens to be focused on linking ESG performance to financial outcomes, corporate governance, and sustainable investing. Methodologically, Aydoğmuş et al. used panel data fixed effects models studies that examine the impact of ESG scores on firm value and profitability.

The influence of ESG in emerging markets remains somewhat more obscure, often because of varying institutional conditions and structures of governance. Second, ESG frameworks applied within the context of a multinational and an emerging market are fraught with complexities that need nuanced approaches, taking into consideration local conditions and the views expressed by stakeholders [8; 22; 28]. A recent study into the Indian market has shown a considerable positive correlation between ESG performance and financial performance, hence giving support to the view that good ESG practices help in the enhancement of firm value even in emerging economies [7; 28].

The role of ESG in risk management is more crystal clear in controversial industries. The power generation sector in China was researched by Zhao et al. [16; 29], while studies on CSR in controversial sectors have also shown that sound ESG practices aid in mitigating risks, enhancing resilience, and yielding better long-term financial performance. In particular, this is consistent with the broader literature highlighting the importance of ESG factors in reducing volatility and firm-specific risks. Another trend is the incorporation of ESG factors with advanced technologies like artificial intelligence. In his paper, Lim argues how AI can help drive ESG disclosure, governance, and investment decisions by implying that AI techniques could contribute immensely to the practice of sustainable finance [9].

Different studies emphasize the linkage of ESG practices with a number of related policy implications. Research into the impact of ESG disclosures in the airline industry and among FTSE350 UK firms drives home the need for regulatory support and standardized ESG metrics in case studies for improved transparency and comparability [19]. These findings are also replicated in a study on public enterprises in Europe, which advocates policy frameworks that will propel firms toward sustainable practices and better ESG reporting [20; 33].

ESG practices can also be an important factor in the reduction of firm risk, especially in firms engaged in high-risk industries. For instance, a study conducted in the area of CSR in controversial industries that include alcohol, tobacco, and gambling indicates that firms with higher CSR levels are associated with lower stock price volatility and firm-specific risk [17]. This is attributed to CSR's positive impact on the firm's reputation and stakeholder relationships that can buffer against negative events and regulatory scrutiny. More importantly, the role of ESG in strengthening financial performance can be seen transcending industries. For example, governance activities are found to have a positive influence on firm value in the airline industry, thus standing in support of the stakeholder theory. It also, however, identified that firm size and age might moderate the relationship between ESG activities and financial performance.

Existing literature furthermore emphasizes the contribution of ESG factors as value drivers and a source of long-term risk. For instance, the paper "Valuing ESG: Doing Good or Sounding Good?" critically examines the value implications of incorporating ESG criteria into corporate and investment decision-making [4; 11]. The authors argue that, although ESG practices can potentially improve growth and profitability, the relationship between ESG and financial performance is nuanced at best and sometimes even contradictory. This is further supported by an in-depth review provided by Liang and Renneboog, which investigates the integration of CSR and ESG issues into the corporate management process and financial decision-making. They emphasize mixed evidence of a direct link between ESG practices and the increase in profitability, which underlines better ESG measurement and reporting practices [12; 27; 40].

The future research directions bring out the need for more harmonized methodologies and measures so that studies can be comparable. There is a need to extend further research within specific industries and in developing economies so that how sustainability practices will impact financial performance can be understood. Moreover, further research is required in terms of the integration of advanced technologies along with ESG factors to enhance their reliability and effectiveness [13; 21]. A huge bulk of literature pertaining to ESG emphasizes that this aspect significantly affects financial performance, risk management, and corporate governance. The integration of the factors in ESG into the investment strategies, therefore, pertains very strongly to the promotion of sustainability and ensuring long-term financial stability. Of necessity, therefore, ESG requires continued research and policy support to further its understanding and practice in a diverse range of economic contexts [19; 24].

In sum, the literature emphasizes the role of ESG in driving sustainable and profitable business practices. Several studies have shown that companies that demonstrate good ESG practices generally perform better financially, handle their risks quite well, and enjoy reputational benefits. However, ESG integration benefits are not homogeneous across markets and industries. Thus, the local conditions and stakeholder perception must be factored into the approach. Finally, due to continuous changes in ESG, further research is required in the standardization of ESG metrics, sector-specific impact research, and playing out the role of advanced technologies in fanning out sustainability and financial performance [23; 25; 26].

III. OBJECTIVES

In this study, we delve deep into the ESG ratings of the S&P 500 listed companies, providing an exhaustive investigation covering descriptive statistics, exploratory data analysis, and predictive modeling. It is only through analyses of this dataset that one may unlock potential value for modern investing in the behavior of the ESG factors. These are our three major objectives:

Objective 1: Understanding ESG Rating Distribution
Analyze the distribution of ESG ratings across the S&P 500 companies to identify trends and patterns.

Objective 2: Assessing the Impact of ESG Ratings on Company Reputation
Investigate how ESG ratings influence the public perception and reputation of companies within the S&P 500.

Objective 3: Predicting ESG Risk Levels Using Machine Learning

Develop a predictive model that can accurately forecast ESG risk levels based on various company-specific and external factors.

By achieving these objectives, we hope to demonstrate the practical value of ESG analysis in the investment process, promoting a more sustainable and responsible approach to investing.

IV. METHODOLOGY AND DATA SOURCE

1. Data Source

We sourced the data for this research from Kaggle. The dataset we have used is called "S&P 500 ESG Data," containing complete ESG ratings for companies in the S&P 500 list. The dataset contains different measures—environmental, social, and governance concerns—hence, respective in-depth research for each company's ESG performance. The shape of the dataset is (503, 15), meaning that the dataset features contain 503 rows or, in other words, companies and 15 features. These 15 features include Symbol, Name, Address, Sector, Industry, Full-Time Employees, Description, Total ESG Risk Score, Environment Risk Score, Governance Risk Score, Social Risk Score, Controversy Level, Controversy Score, ESG Risk Percentile, and ESG Risk Level. Some of the more relevant features are:

- Environmental Risk Score: A measure of a company's eco-liability and impact, reflecting its commitment to planet protection.
- Governance Risk Score: The assessment of the transparency, ethics, and quality of corporate governance, affecting long-term viability.
- Social Risk Score: This score can quantify a firm's societal contributions regarding employee welfare, diversity, and community engagement.
- Controversy level: An intelligently determined measurement going from "Low" to "High," assessing public or judicial controversies that are somehow associated with this company.
- Controversy Score: Quantitatively expresses the intensity of controversies and gives insight into reputational risk.
- ESG Risk Percentile: The overall ESG risk score of the organization as compared to other organizations.

2. Methodology

1. **Data Collection and Preparation:**
   The data set was downloaded from Kaggle and loaded into a Python environment for analysis. Initial data exploration gave a rough insight into the dataset structure and content. This step checked, among other things, if there were any null values and the distribution of some variables in the dataset. Missing values have been detected and treated appropriately: Categorical attributes, including 'Controversy Level' and 'ESG Risk Level', are imputed to be 'Unknown'. Missing values in the 'Full-Time Employees' column were imputed using the median value after converting the column into numerical format. Rows with missing ESG scores are dropped to ensure the integrity of the analysis. Z-Scores were implemented to identify if there was anything worth noting in terms of an outlier and it reported that there were none to address.
2. **Descriptive Statistics:**

Descriptive statistics were used to summarize the dataset's key properties, such as measures of central tendency (mean, median) and dispersion (standard deviation, variance) for each ESG indicator.

	Total ESG Risk score	Environment Risk Score	Governance Risk Score	Social Risk Score	Controversy Score
count	430.000000	430.000000	430.000000	430.000000	403.000000
mean	21.533721	5.739767	6.725116	9.070465	2.007444
std	6.889176	5.092421	2.208085	3.657924	0.793283
min	7.100000	0.000000	3.000000	0.800000	1.000000
25%	16.400000	1.800000	5.300000	6.700000	1.000000
50%	21.050000	4.050000	6.100000	8.900000	2.000000
75%	26.000000	8.950000	7.675000	11.200000	2.000000
max	41.700000	25.000000	19.400000	22.500000	5.000000

Fig 1.1 Descriptive Statistics

3. Exploratory Data Analysis (EDA):

EDA was used to identify patterns, correlations, and insights in the dataset. This included investigating the relationships between various ESG elements and financial performance measures.

4. Feature Engineering:

Relevant features were chosen and designed for predictive modelling. This involved developing new features based on existing data, such as integrated ESG scores and weighted averages of various ESG components.

Data Leakage and Feature Importance:

The first data exploration indicated that when the default RandomForestRegressor feature importance technique was applied to the initial study, the "ESG Risk Percentile" feature dominated the importance by around 99.56%. This is indicative of a possible problem with data leakage, which means information that should not spill into the model under training but inadvertently does so, leading to an optimistic estimation of performance. Here are some steps that I took to prevent this:

Feature Elimination: The feature "ESG Risk Percentile" has been removed from the dataset to prevent data leakage.

Model retraining: The new model was retrained without the dominant feature, which increased the mean squared error (MSE) and root mean squared error (RMSE), meaning that it was less accurate but more balanced.

Evaluation: It would prevent data leakage and make the model more balanced and reliable by removing a dominating feature. This was important to make sure that the predictive analysis would be robust.

The features used as input in the model are: Sector, Industry, Full Time Employees, Environment Risk Score, Governance Risk Score, Social Risk Score, and Controversy Level.

5. Predictive Modelling:

The machine learning categorization technique was applied to predict the level of ESG risk. The prediction models included Decision Tree, Random Forest, and Naive Bayes. The process then split the dataset into two categories: the training set and the testing set to check the model performance.

Decision Tree: A simple model in predicting the ESG risk levels for companies within the S&P 500 based on their respective ESG scores. This is a model that helps to classify companies using their environmental, social, and governance (ESG) scores. This type of model divides the data into branches according to feature values; for example, an environmental risk score or governance practice. Each of the nodes in the tree represents a decision based on those features, and at the leaves, we see classification. The good thing about this model is that it yields a clear and interpretable path of decisions, making it pretty understandable which factors mostly affect ESG risk levels.

Random Forest: This will be used to improve the predictive strength of the ESG risk level. The model constructs several multiple decision trees by using different subsets of data and attributes in each. Then, each tree makes its prediction, and the final ESG risk level is determined by aggregating the votes from all the trees in an ensemble way. This ensemble method generally reduces the overfitting risk that an individual decision tree can have and therefore provides more accurate and stable predictions. Random Forest proves particularly effective for the complexity and high dimensionality of ESG data to ensure a model generalizes well on new data.

Naive Bayes: Another method that has been used for predicting ESG risk levels is Naive Bayes. It is a probabilistic model that applies Bayes' theorem and makes the assumption that all the features are conditionally independent given the class label. The weak naive assumption aside, Naive Bayes performs fairly well in practice, especially with large datasets. It is efficient when used to predict ESG risk because it acts on features that are in the environmental, social, and governance scores by computing the probability that a company belongs to each grade of risk. So it would be a good starter classifier for an initial classification task: simple and effective and serving as a good base to which more complicated models, such as Random Forest, could be compared. Naive Bayes works really well when you need to make very quick and easy-to-understand predictions, especially where the relationship among the features is not that complex.

6. Model Evaluation:

Model performance was assessed using criteria such as accuracy, precision, recall, F1-score, and Area Under the Receiver Operating Characteristic Curve (AUC-ROC).

Confusion matrices were utilized to illustrate the classification models' performance in forecasting ESG risk levels.

The best-performing model was chosen based on evaluation indicators and then further evaluated to explain the findings.

We hope that by carrying out the research in a structured manner, an in-depth analysis of ESG risk levels can be provided for S&P 500 companies, and the role of ESG in current investment practices might be effectively highlighted.

V. FINDINGS AND DISCUSSION

1. Exploratory Data Analysis Findings

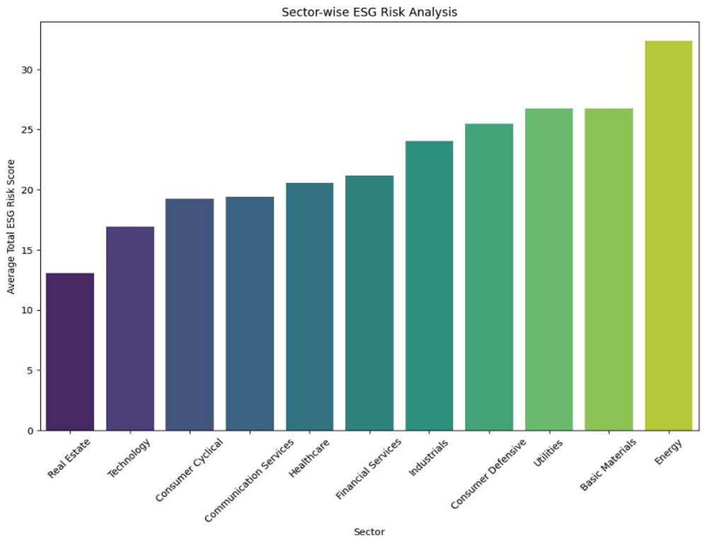


Fig 1.2 Sector- wise ESG Risk Analysis

The analysis gives some valuable insights for better-informed investing decisions. Most significantly, it has been found that the sectors with lower average ESG risk scores are real estate, technology, and consumer cyclical, with scores of 13.1, 16.9, and 18.8, respectively. These scores suggest they might be safer options for ESG-conscious investors. On the other hand, the ones that have higher-than-average ESG risks are energy, utilities, and basic materials, scoring 33.15, 27.75, and 27.42, respectively. This means, by consequence, that the investments in these industries might go into deeper ESG-related scrutiny and consequent fluctuations. In this context, data reveal to be an effective screening device for a priori decision-makers.

In one respect, it indicates that a lower average ESG risk score is better from the point of view of a more responsible industry with regard to environmental, social, and governance issues. In another respect, the industries with higher average ESG risk scores urge a finer and more careful detailed approach. Within such higher-risk sectors, this can be an opportunity for investors to find companies operating within the general trends of the sector but managing to be effective in the field of ESG risk management. In a sense, this sector-specific ESG risk breakdown acts as a strategic roadmap for both risk-averse and risk-tolerant investment strategies by guiding investors through the complexities of ESG investing.

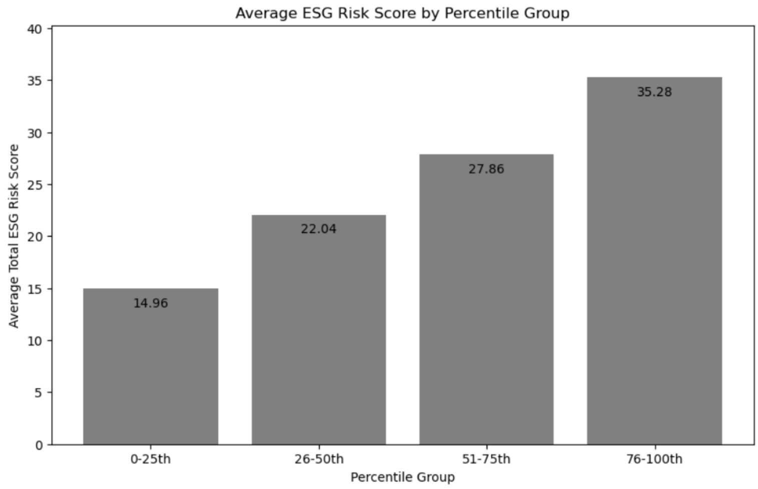


Fig 1.3 Average ESG Risk score

The result shows that the firms with scores in the 0-25th percentile range average 14.8 in ESG risk scores, signifying relatively low ESG risks. One assurance that will likely act as a cushion to investors is that such a low level of risk is associated very often with long-term sustainability and regularity adherence. In contrast, the average ESG risk score for companies in the 76-100th percentile group is much higher, at about 36.5, with increased risks that could lead to more scrutiny by regulators and loss of reputation by investors. Such stratification makes it possible for investors and decision-makers to customize their investments according to the level of risk they are willing to take and achieve the ESG goals—thus easy to pick through and select investments matching their individual needs.

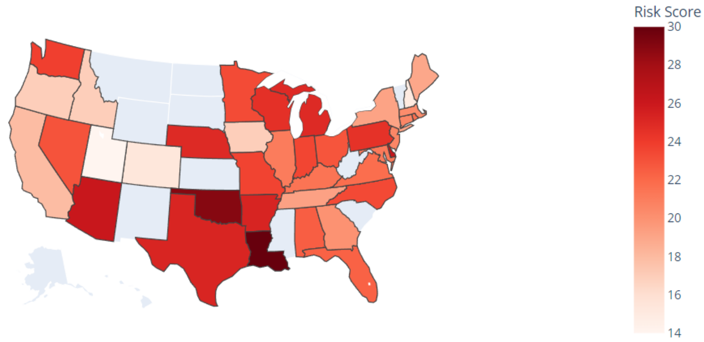


Fig 1.4 Risk Score- heat map showing ESG risk rankings among states

The heat map shows large variances in ESG risk rankings among states. States in the central and southern areas, such as Louisiana and Texas, have higher ESG risk rankings. This suggests that for companies Headquartered in these locations the ESG issues may be severe. Further, investments in such firms may not be financially viable. States on the Northeast and West Coast, such as California and New York, have lower ESG risk scores, indicating better ESG management and maybe more severe rules or business practices.

The trends seen in individual states may also reflect the dominating industries in those areas. For example, states with a strong presence in the energy and utilities sectors may have higher ESG risk scores due to the inherent issues these companies confront.

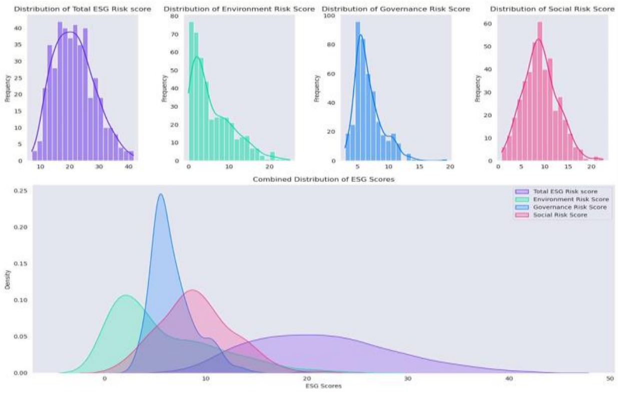


Fig 1.5 Distribution of ESG Scores- Total ESG Risk scores, Environment Risk Scores, Government Risk scores and Social Risk scores.

The distribution is roughly normal, with most organizations scoring 10 to 30, suggesting moderate ESG risk. A few outliers with high ratings raise potential red signals for investors.

Environmental Risk Score: Scores are substantially biased towards the lower end, with the majority of organizations scoring between 0 and 10, suggesting effective environmental risk management. The extended tail of higher scores identifies some corporations that pose significant environmental hazards.

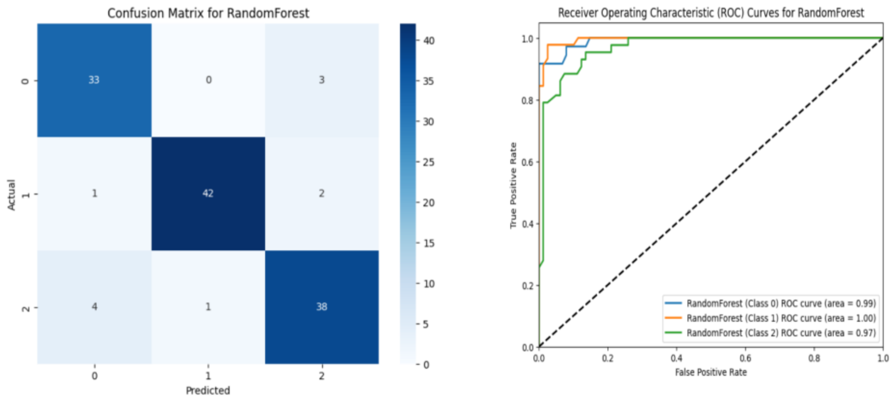
Governance Risk Score: Scores range generally from 0 to 5, showing effective governance practices. However, a few higher ratings indicate that certain organizations may have governance difficulties affecting their ESG performance.

Social Risk Score: Scores are slightly weighted downward, with most corporations scoring between 5 and 15, indicating moderate social risks. Outliers with higher ratings indicate issues in areas such as employee relations and community impact.

The combined density map demonstrates that environmental risks are generally well-managed, governance risks are consistently low, and social risks are more diverse. This emphasizes the need for businesses to focus more on strengthening their social responsibility initiatives.

2. Predictive Modelling Results

1. Random Forest Classifier

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Classification Report for RandomForest:

              precision    recall  f1-score   support

        High       0.87      0.92      0.89        36
         Low       0.98      0.93      0.95        45
      Medium       0.88      0.88      0.88        43

    accuracy                           0.91       124
   macro avg       0.91      0.91      0.91       124
weighted avg       0.91      0.91      0.91       124
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Fig 1.6 Classification report for random Forest

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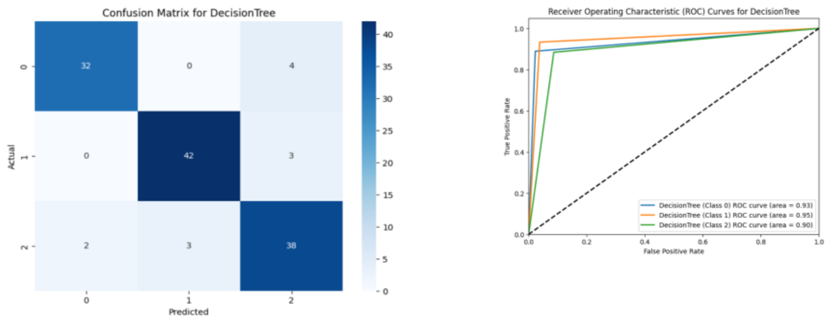
The confusion matrix shows that the model is very good at correctly classifying instances across all risk categories. It performs especially well in identifying high-risk cases, correctly identifying 33 out of 36. This indicates that the model is effective in distinguishing between different levels of ESG risk.

The ROC curves also demonstrate the model's strong performance, with AUC values near 1.00 for all classes, showing it has excellent discriminatory power. This means the model can reliably tell apart high, medium, and low ESG risks, which is essential for accurate risk assessment.

The classification report gives detailed performance metrics, showing high precision, recall, and F1-scores across all categories. For high-risk cases, the model achieves a precision of 0.87, a recall of 0.92, and an F1-score of 0.89. The scores for low-risk and medium-risk categories are similarly high, with a precision of 0.98 for low-risk and both recall and F1-score at 0.88 for medium-risk. The overall accuracy of 0.91 further highlights the model's reliability.

2. Decision Tree Classifier



Classification Report for DecisionTree:

	precision	recall	f1-score	support
High	0.94	0.89	0.91	36
Low	0.93	0.93	0.93	45
Medium	0.84	0.88	0.86	43
accuracy			0.90	124
macro avg	0.91	0.90	0.90	124
weighted avg	0.90	0.90	0.90	124

Fig 1.7 Classification report for Decision tree

The confusion matrix shows that the Decision Tree model accurately classifies most instances in each risk category. For high-risk companies, it correctly identifies 32 out of 36 cases, highlighting the model's capability in pinpointing high-risk firms. Similarly, the model performs well for low-risk and medium-risk categories, correctly classifying 42 out of 45 and 38 out of 43 instances, respectively.

The ROC curves indicate strong performance, with high area under the curve (AUC) values for each class. The high-risk category (Class 0) has an AUC of 0.93, the low-risk category (Class 1) has an AUC of 0.95, and the medium-risk category (Class 2) has an AUC of 0.90. These AUC values suggest that the Decision Tree model is very effective at distinguishing between different levels of ESG risk.

The classification report provides a breakdown of performance metrics, showing high precision, recall, and F1-scores for all categories:

- For high-risk companies, the model achieves a precision of 0.94, a recall of 0.89, and an F1-score of 0.91.
- For low-risk companies, the precision, recall, and F1-score are all 0.93.
- For medium-risk companies, the model has a precision of 0.84, a recall of 0.88, and an F1-score of 0.86.

3. Naïve Bayes

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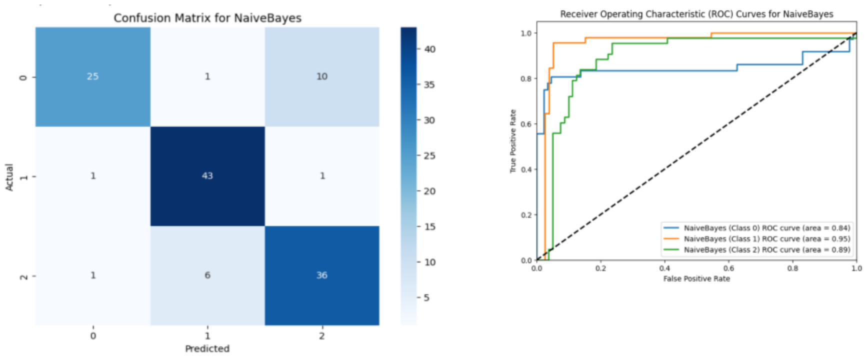

Classification Report for NaiveBayes:

	precision	recall	f1-score	support
High	0.93	0.69	0.79	36
Low	0.86	0.96	0.91	45
Medium	0.77	0.84	0.80	43
accuracy			0.84	124
macro avg	0.85	0.83	0.83	124
weighted avg	0.85	0.84	0.84	124

Fig 1.8 Classification report for Naïve Bayes

The decision tree does a good job of classifying instances, correctly identifying 25 out of 36 for the 'High' risk class, 43 out of 45 for the 'Low' risk class, and 36 out of 43 for the 'Medium' risk class. However, the Naive Bayes model doesn't perform as well in comparison, particularly when looking at the area under the curve (AUC) in the ROC curve. For the 'High' risk class, the Naive Bayes model's precision, recall, and F1-score are 0.93, 0.69, and 0.79, respectively, showing that it struggles more with accurately identifying high-risk instances.

This discrepancy in performance can be attributed to the inherent assumptions made by the Naive Bayes algorithm, particularly the assumption of feature independence. In real-world scenarios, especially in the context of ESG risk assessment, the relationships between environmental, social, and governance factors are complex and interdependent. The Naive Bayes model struggles to capture these intricate interactions effectively, which impacts its overall performance.

VI. LIMITATIONS

1. **Sector-specific variations:** The impact of ESG risks is different for each sector; the research might not particularly consider sector-specific idiosyncrasies in their approach and hence may deliver very generic findings, not applicable across all sectors.
2. **Model Complexity and Interpretability:** Complex machine learning models, like Random Forest, may be somewhat hard to read. Such models are quite accurate but a bit obscure in terms of being understood through the full process of the decisions made, so they limit the actionable insights for stakeholders.
3. **Geographic Scope:** The study is primarily based on S&P 500 companies located within the US. This places a geographical limitation and restricts the applicability of conclusions for other firms operating under different regulatory frameworks and market conditions in countries worldwide.
4. **Static Analysis:** This analysis uses a snapshot of ESG scores and financial performance data. It does not take into account changes in time, the dynamic character of ESG practices, or their long-term effects on firm success.

These limitations suggest areas for future research, such as incorporating more diverse datasets, exploring sector-specific ESG impacts, and employing methods to enhance model interpretability.

VII. CONCLUSION

This study emphasizes the significance of ESG factors in today's investment considerations, most notably among S&P 500 companies. When including ESG ratings as part of traditional financial research, we are enabled to create a much broader and more complete picture of a company's sustainability and ethical policies, both of which are ever more recognized in importance for long-term financial performance and risk management [32; 39].

Our analysis revealed sector-specific significant differences in average ESG risk scores. The real estate, technology, and consumer cyclical sectors displayed lower average ESG risk scores of 13.1, 16.9, and 18.8, respectively. These sectors reflect an environment that is far less risky for a careful ESG investor. On the other hand, Energy, Utilities, and Basic Materials have the highest average ESG risks, with scores of 33.15, 27.75, and 27.42, respectively, which means a higher potential for regulatory issues and reputational risks. These results indicate that sector-specific ESG assessments should be part of the investment strategies, meaning that the decision on ESG factors should be approached in a more advanced way by investors.

Our predictive analysis, in which we applied the models of machine learning, Random Forest, Decision Tree, and Naive Bayes, was programmed to correctly identify the levels of ESG risk. The confusion matrix shows how varied the levels of accuracy are—the Decision Tree model shows 93.02% of predicting the categories of ESG risk. Thus, the accurate prediction of the ESG risk levels can help shareholders, stakeholders, investors, and promoters to make better decisions. An ESG risk profile analysis for a company helps the shareholders and stakeholders verify that their investment is in line with their ethical principles and environmental objectives. Predictive models help to show the investor potential risks or opportunities that the standard financial analysis could not reveal. A genuine understanding by the senior management and leaderships of such administrations can bring about an augmentation in terms of corporate governance and transparency. It also brings about a move to more sustainable business practices. In conclusion, such practices increase investor confidence as well as profitability in the long run.

Incorporating ESG considerations into investment decisions exemplifies a shift to responsible and sustainable investing. The capability to determine the levels of ESG risk effectively arms all concerned parties with the right instruments to navigate through the complex ESG-based environment, therefore making the financial world a better place sustainably and ethically. In this study we have presented the importance of ESG issues in defining the future of investment strategies. Further, vigilant consideration of such issues have the potential to create both financial performance and social benefit.

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