



INTERNATIONAL JOURNAL OF CREATIVE RESEARCH THOUGHTS (IJCRT)

An International Open Access, Peer-reviewed, Refereed Journal

Leveraging Machine Learning For Sustainable Investment: Evaluating The Predictive Power Of ESG Metrics On Funding Allocations

Joseph Okpono

Financial Technology and ESG Analyst Researcher,
Department of Accounting and Finance

University of Strathclyde, Glasgow, G1 1XQ, United Kingdom

Abstract - The integration of Environmental, Social, and Governance (ESG) factors into financial modeling has become very crucial, as investors explore investment strategies for sustainable and responsible investment. This study probes how the use of Machine Learning (ML) techniques can be used to predict and allocate funding, based on ESG performance of an organization. The key objective is to evaluate the predictive accuracy of different ML models, in quantitatively forecasting funding allocations using ESG metrics. Dataset such as ESG metrics and financial indicators including revenue and profit were collected from different companies. To improve the model's predictability, feature engineering which involves creating new features that combine ESG metrics with financial indicators to capture complex relationships affecting funding allocations was used. The analysis results indicate that the Random Forest model achieved the highest predictive accuracy, with an R^2 value of 0.8657, demonstrating its robustness in managing complex, non-linear relationships within the dataset. Insights from the Feature Importance Analysis revealed that social and governance-related metrics, such as Social Score Profit and Governance Score Profit, were the most significant predictors of funding received. Both the Random Forest and Gradient Boosting ensemble methods outperformed traditional regression and SVM models in predicting funding allocations based on ESG performance, demonstrating their effectiveness in revealing operational risks and opportunities. The findings from the study highlights the value ML models, such as the ensemble methods, give in guiding investors towards companies with good social responsibility and ethical practices.

Index Terms: ESG metrics; Financial indicators; ESG Performance; Machine Learning; Predictive accuracy; Random Forest

I. INTRODUCTION

1.1 Integration of ESG Factors into Investment Decisions

Integrating Environmental, Social, and Governance (ESG) factors into investment decisions has evolved significantly over the years. Historically, investment decisions were predominantly based on traditional financial metrics such as revenue, profit margins, and earnings per share. However, there has been a growing recognition of the importance of ESG factors in assessing a company's long-term viability and risk profile.

1.1.1 Early Approaches

In the early stages, ESG integration was often ad-hoc, with investors relying on qualitative assessments of corporate responsibility and sustainability (Gupta et al, 2021). For example, ethical investment funds and socially responsible investing (SRI) strategies were among the first to incorporate ESG considerations. These approaches focused primarily on excluding investments in companies involved in controversial activities such as tobacco or firearms.

1.1.2 Modern Practices

Today, ESG integration has become more systematic, and data driven. Investment firms and asset managers use ESG ratings and scores provided by specialized agencies to guide their investment decisions. These ratings are based on a comprehensive evaluation of a company's environmental impact, social practices, and governance structures (Berg et al, 2022). Furthermore, regulatory frameworks in various regions now require disclosure of ESG-related information, enhancing transparency and comparability.

1.2 ESG Metrics and their Impact

ESG metrics are crucial for assessing the sustainability and ethical impact of companies. These metrics provide insights into various dimensions of a company's operations and performance (Peixoto et al, 2022).

1.2.1 Historical Metrics

Traditional ESG metrics included basic indicators such as carbon emissions, waste management practices, and board diversity. Early ESG assessments often relied on self-reported data and qualitative narratives, which were limited in scope and often lacked consistency (Martiny et al, 2024).

1.2.2 Advancements in Metrics

Recent advancements have introduced more sophisticated and standardized ESG metrics. For instance, the Global Reporting Initiative (GRI) and the Sustainability Accounting Standards Board (SASB) provide frameworks for comprehensive ESG reporting. These frameworks help investors evaluate companies based on standardized criteria, improving the reliability and comparability of ESG data (Eccles and Klimenko, 2019). Moreover, metrics now include more granular data, such as detailed greenhouse gas emissions, water usage, and employee diversity statistics, which offer a more nuanced view of corporate sustainability (Kotsiantis, 2007).

1.3 Investor Behavior and ESG Performance

Investor behavior regarding ESG performance has shifted significantly in recent years. This shift reflects a growing recognition of the financial materiality of ESG factors.

1.3.1 Initial Trend

Initially, ESG considerations were often seen as secondary to financial returns. Investors who prioritized ESG factors were typically those driven by ethical or philanthropic motivations (Radzi, 2023). This perspective was supported by early studies that suggested ESG investments might underperform compared to traditional investments (Carvalho et al, 2023).

1.3.2 Current Trends

More recent research and market trends have highlighted the financial benefits of incorporating ESG factors into investment decisions. Studies have shown that companies with strong ESG performance often exhibit lower risk profiles and better long-term financial performance (Friede et al, 2015). For instance, ESG-focused investments have been linked to lower volatility and better risk-adjusted returns (Ashwin Kumar et al, 2016). This shift is driven by increasing evidence that ESG factors can influence financial performance through mechanisms such as improved operational efficiency, enhanced reputation, and better regulatory compliance (Chen, 2023).

1.4 Challenges in Analyzing ESG Data

Analyzing ESG data presents several challenges, primarily due to the complexity and multidimensionality of the data.

1.4.1 Traditional Challenges

Early analyses of ESG data faced issues with data quality and consistency. ESG data was often self-reported and lacked standardized measurement criteria, leading to significant variability in reported metrics (Kotsiantis, 2007). Furthermore, the lack of comprehensive historical data made it difficult to assess long-term trends and impacts.

1.4.2 MODERN CHALLENGES

Despite advancements in data collection and reporting, challenges remain. For instance, the vast volume of ESG data and the need for real-time analysis can overwhelm traditional analytical methods. ESG data often includes qualitative information that is challenging to quantify and integrate with quantitative financial metrics (Jonsdottir et al, 2022). Advanced machine learning techniques are increasingly used to address these challenges by handling large, complex datasets and uncovering hidden patterns in ESG performance (Lee et al, 2022).

1.5 Application of Machine Learning Techniques

Machine learning has emerged as a powerful tool for analyzing ESG data and predicting funding allocations.

1.5.1 Early Techniques

Initially, financial models used linear regression and basic statistical methods to analyze ESG data. These methods provided a preliminary understanding of the relationship between ESG performance and financial outcomes but were limited in their ability to handle complex, high-dimensional datasets (Jorion, 2007).

1.5.2 Recent Advancements

Recent advances in machine learning have enabled more sophisticated analyses. Techniques such as Random Forest, Gradient Boosting, and Support Vector Machines (SVM) can model non-linear relationships and interactions between ESG factors and financial performance (Masood, 2024). For instance, Random Forest can handle large numbers of predictors and capture complex interactions, while Gradient Boosting improves predictive accuracy by combining multiple weak models into a strong ensemble model (Hastie et al, 2009).

1.5.3 Feature Importance Analysis

Machine learning models also facilitate feature importance analysis, which helps identify the most influential ESG metrics for predicting funding outcomes. This analysis supports investors in prioritizing key ESG factors and making more informed investment decisions (Sorathiya et al, 2024).

1.5.4 Predictive Accuracy And Model Evaluation

Ensuring the predictive accuracy of models used for funding allocations is crucial for effective investment decision-making.

1.5.5 Traditional Evaluation Metrics

Historically, model evaluation involved metrics such as R-squared (R^2) and Mean Squared Error (MSE) to assess the fit and accuracy of regression models. These metrics provided a basic measure of model performance but did not capture the full complexity of ESG data (Kutner et al, 2005).

1.5.6 Advanced Metrics

Modern evaluations use a range of metrics to assess model performance more comprehensively. For instance, Root Mean Squared Error (RMSE) provides an interpretable measure of prediction error, while Mean Absolute Error (MAE) offers a direct measure of prediction accuracy (Hodson, 2022). Additionally, ensemble methods such as Stacking Regressors combine predictions from multiple models to improve overall accuracy and generalizability (Lu et al, 2023).

1.7 Research Objectives

This study aims to explore the application of machine learning techniques to predict and allocate funding based on ESG performance. It specifically includes the (1) analysis of how ESG factors influence investment decisions, and (2) evaluation of the predictive accuracy of various machine learning models for funding allocations based on ESG scores.

II. LITERATURE REVIEW

This literature review explores several key theories that provide a robust framework for understanding the relationship between ESG factors and financial outcomes. These theories underpin the methodological approaches used in integrating ESG metrics into investment decisions and leveraging machine learning to analyze complex ESG datasets. The following sections detail each theory (namely, Stakeholder theory, Triple Bottom Line, Modern Portfolio Theory, Resource Based Views, Data Driven Decision Making, and ESG Integration), and its relevance to ESG integration in investment practices.

2.1 Stakeholders Theory

This theory states that organizations should consider the interest, and impact on stakeholders such as investors, employees, customers, suppliers, and the broader community, instead of putting attention solely on shareholder value (Freeman and McVea, 2001). It highlights the importance of including ESG factors in business practices for the purpose of addressing stakeholders' concerns and enhancing corporate sustainability.

2.2 Triple Bottom Line (TBL)

The TBL framework is built on the traditional finance reporting framework, with inclusion of social and environmental considerations, alongside economic, performance, social, and environmental (Correia, 2019). It brings into consideration people, planet, and profit, in corporate organization strategies. This is done by incorporating ESG factors into investment decisions. It highlights the importance of sustainable and responsible business practices in driving, financial performance and risk management.

2.3 Modern Portfolio Theory (MPT)

The Modern Portfolio Theory (MPT) was propagated by Markowitz (1952). It gives a basis for understanding how diversification can enhance and optimize investment returns for a given level of risk. By identifying non-financial risks, and opportunities through the incorporation of ESG factors, in investment decisions, it can enhance risk adjusted returns in a more efficient way that traditional financial metrics might overlook. This will in turn help investors to build more resilient portfolios that can better withstand ESG related risks (Verheyden et al, 2016). The equation for this theory includes the calculation of expected portfolio return as expressed in Equation 2.1, variance (risk) as shown in Equation 2.2, and the optimization process to achieve the efficient frontier.

$$E(R_p) = \sum_{i=1}^n w_i E(R_i) \quad (2.1)$$

where

- $E(R_p)$ = Expected return of the portfolio
- w_i = Weight of the asset i in the portfolio
- $E(R_i)$ = Expected return of the asset i
- Portfolio Variance (Risk)

$$\sigma_p^2 = \sum_{i=1}^n \sum_{j=1}^n w_i w_j \sigma_{ij} \quad (2.2)$$

where

- σ_p^2 = Variance of the portfolio's return
- w_i and w_j = Weights of assets i and j in the portfolio

- σ_{ij} = Covariance between the returns of assets i and j

2.4 Resource Based View (RBV)

According to Barney (1991), the resource-based view of a firm indicates that sustainable competitive advantage evolves, from its unique resources and capabilities. This view places ESG performance as a strategic resource that could help a firm's reputation, operational efficiencies, and regulatory compliance. This view implies that firms that excel, in ESG practices, can create valuable, rare, and non-substitutable capabilities which enhance long term competitive advantages.

2.5 Data Driven Decision Making (DDDM)

According to (Awan et al, 2023), data analytics is valuable in informing and guiding business decisions. Data-Driven Decision Making (DDDM) is used for the application of machine learning techniques to ESG data. It facilitates the processing and analysis of large, complex datasets to give insights to patterns and trends that conventional traditional methods may not provide. The use of Machine Learning algorithm helps in handling multi-dimensional data, and identifying non-linear relationships, which enhances predictive accuracy and decision making.

DDDM Mathematical theory is based on a Linear Regression as shown in Equation 2.3.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n + \epsilon \quad (2.3)$$

where:

- y = Dependent variable (target)
- β_0 = Intercept
- $\beta_1, \beta_2, \dots, \beta_n$ = Coefficients for the predictor variables
- $x_1, x_2, \dots, x_n$ = Predictor variables
- ϵ = Error term

2.6 Support Vector Machine (SVM)

SVM aims to find a hyperplane that separates the data points of different classes

$$\min 1/2 \|w\|^2 \quad (2.4)$$

Subject to: $y_i(w \cdot x_i + b) \geq 1 - \xi_i$

where

- w = Weight vector
- b = Bias
- y_i = Class label of the i-th sample
- x_i = Feature vector of the i-th sample
- ξ_i = Slack variables for misclassification

2.7 Environmental and Social Governance (ESG) Integration

This concept seeks to incorporate ESG factors into financial analysis and investment decision making processes [9]. It shows a holistic approach to assessing, and evaluating corporate performance, with the understanding that ESG factors can impact financial outcomes. This leans towards sustainable and responsible investment, that has ethical considerations as its focus in the quest for optimal financial returns.

III. METHODOLOGY

3.1 Data Collection

The data was made up of ESG scores from different companies. The ESG scores were used to evaluate and assess the company's performance in ESG. The ESG scores give a wide view of a company's sustainability and ethical impact. This study features are Environmental Score, Social Score, Governance Score, Revenue, Profit, and derived metrics such as Revenue to Profit Ratio, and Total ESG Score.

The Environmental Scores encompass the company's impact on the natural environment. These factors are carbon emissions, energy use, waste management, and resource conservation. The social score covers the company's social practices, as it relates to including labor relations, diversity and inclusion, community engagement, and human rights. The Governance score assesses the Governance structure quality of the company. These scores cover board diversity, executive compensation, shareholder rights, and transparency (Ahmad et al, 2023).

The component of the financial metrics includes Revenue and Profit which give a robust view of the company's performance. Revenue in this case is the total income a company generates from its business activities. Profits represent the net income a company makes after expenses have been deducted. To offer insights into a company's operational efficiency and profitability, the Revenue to Profit Ratio is derived (Jayathilaka, 2020). The sum of the ESG provides the Total ESG Score thereby, providing an aggregate measure of a company's overall ESG performance.

3.2 Data Preparation

The study workflow (Fig. 3.1) gives the approach used for the study. Data preprocessing was done to ensure accuracy and reliability of the analysis. The process involves handling any missing values, due to incomplete records or reporting gaps. Imputation techniques were used to estimate missing values, based on available data, or exclusion of records with excessive or unnecessary information. It is important to adequately handle missing data, to avoid biases and inaccuracies in the outcome of the model (Karrar, 2022).

3.2.1 Feature Engineering

Polynomial features expansion was created, to capture the interactions between the variables. Using this feature allows the models, to consider just the linear relationships, between features and the higher-order interactions that may exist. Using this interaction for Environmental and Social scores reveals how a company's environmental initiatives impact its social performance as well as that of its environment. This approach helps the model's ability to capture complex relationships while improving predictive accuracy (Visser et al, 2023).

To ensure equal contribution by all features to the model standardization, the processed dataset was standardized. This standardization involves scaling the features, so that they have a mean of zero and a standard deviation of one. This is an essential step for many machine learning algorithms, which are sensitive to the scale of input data, ensuring that features with larger scales, do not dominate the model training process (Vinay, 2021). This process of data preparation is critical for the subsequent modeling and analysis, thereby ensuring that the dataset is clean, well-structured, and ready for machine learning applications.

3.2.2 Model Training and Evaluation

3.2.2.1 DATA SPLITTING

A structured approach was used to model the training and evaluation. The data was first split into an 80-20 ratio of training and testing sets, this is done to train the models for the evaluation of their performance on unseen data. This helps in assessing the models while also preventing overfitting, which can occur when a model performs well on the training data but does not perform well on the new data (Muraina, 2022).

The standardization of the features ensures equal contribution to the model training process. It involves the transformation of the features, to have a mean of zero and a standard deviation of one. This is an important step for many machine learning algorithms, especially for those that rely on distance measures or gradient descent

optimization, such as Support Vector Machines (SVM) and neural networks. When features are standardized, it ensures that the model training process is not biased towards features with larger scales (Vinay, 2021).

3.2.2.2 Standardization

3.2.2.2.1 HYPERPARAMETER TUNING

Hyperparameter tuning was done using GridSearchCV. This helped to optimize the performance of various regression models. It robustly searches over a specified parameter grid, to find the best combination of hyperparameters for each model. This approach is essential for fine-tuning model performance, and ensuring that the chosen hyperparameters lead, to the best possible results on the validation set (Belete and Manjaiah, 2021).

3.2.2.3 Model Selection and Training

The models considered in this study, include Linear Regression, Random Forest, Gradient Boosting, Support Vector Machine (SVM), XGBoost, Neural Network, and Stacking Regressor (Shrivastav and Kumar, 2022).

3.3 Performance Metrics

Different performance metrics namely, Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2) were used for the evaluation of each model. These metrics provided a robust assessment of model accuracy and reliability. MSE measures the average squared difference between the observed actual outcomes, and the outcomes predicted by the model, with lower values indicating better model performance. RMSE, which is the square root of MSE, offers a more interpretable metric, by being in the same units as the target variable. MAE measures the average absolute errors, thereby providing a direct measure of the model prediction accuracy. R-squared, or the coefficient of determination, indicates the proportion of variance, in the dependent variable that is predictable from the independent variables. The values closer to 1 indicate better model performance (Hodson, 2022).

3.4 Model Evaluation

The Random Forest and Gradient Boosting models, which are known for their high predictive accuracy and ability to handle complex interactions between features were deployed. These models use an ensemble of decision trees to make predictions. They often result in improved performance compared to single models. Hyperparameters such as the number of trees, tree depth, and learning rate (for Gradient Boosting) were tuned using GridSearchCV to achieve optimal results (Mishina et al, 2015).

Support Vector Machines (SVM) with its regression capabilities (SVR), were included for their robustness in handling high-dimensional spaces, and nonlinear relationships. Key hyperparameters such as the kernel type, and regularization parameter are optimized during the tuning process (Awad and Khanna, 2015). Neural Networks, particularly Multilayer Perceptron's (MLP), were also evaluated for their ability to model complex, non-linear relationships. Hyperparameters such as the number of hidden layers, neurons per layer, activation functions, and learning rates were fine-tuned to enhance model performance (Elansari et al, 2023).

The final model, which is the Stacking Regressor, combines predictions from multiple models to improve overall performance. This ensemble method leverages on the strengths of individual models, resulting in better generalization on new data (Lu et al, 2023).

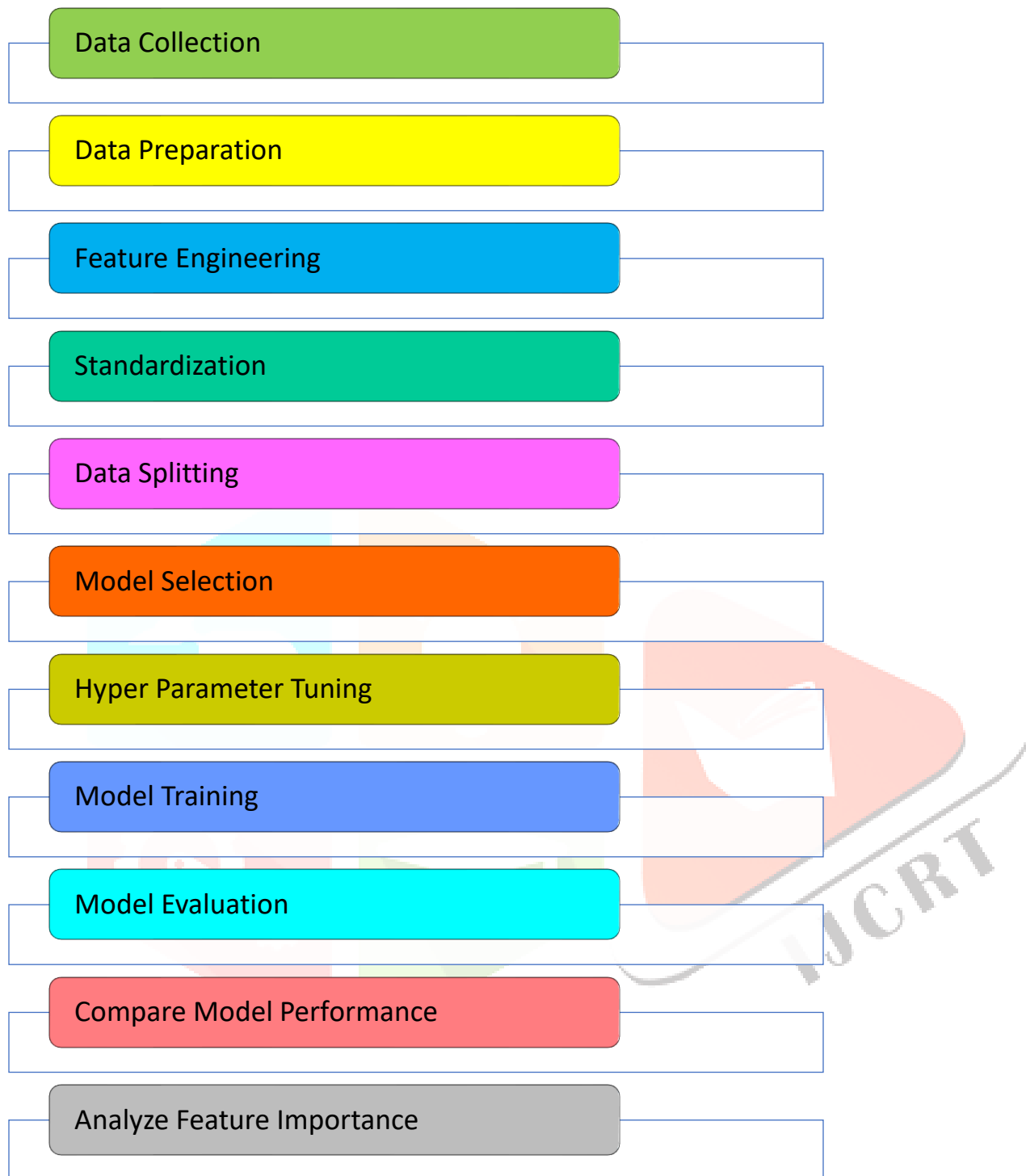


Figure 3.1: Adopted Workflow for ESG Performance-Based Funding Allocation Using Machine Learning Techniques

IV. RESULTS AND DISCUSSION

Several machine learning models were employed in this study, to predict funding allocations based on ESG performance. The performance of each model was evaluated using several metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and R-squared (R^2). Table 4.1 shows the results, which represent varying levels of predictive accuracy among the models. Ensemble methods such as Random Forest, Gradient Boosting, and Stacking Regressor showed better performance, when compared to traditional regression and support vector machine models.

4.1 Model Performance Summary

The Random Forest model gave the highest predictive accuracy with an R^2 value of 0.8657 as shown in Table 4.1., indicating that approximately 86.57% of the variance in the funding received was explained. It got the lowest MSE (1661575.1528) and RMSE (1289.0210), which demonstrates its robustness in handling complex, and non-linear relationships within the data. The Gradient Boosting lagged behind Random Forest, but it performed well by achieving an R^2 of 0.6048, therefore indicating a moderate level of predictive accuracy. The value it got for MSE (4889786.2950), and RMSE (2211.2861) were higher than those of Random Forest, which suggests that it has lower precision in its predictions. XGBoost, which is known for its efficiency and performance, had a ranking of third place with an R^2 of 0.7578. The MSE (2997156.3438) and RMSE (1731.2297) were better than those of Gradient Boosting, but they were not as good as Random Forest. Its advanced regularization techniques contributed to its relatively high accuracy.

The Neural Network model displayed moderate predictive capability with an R^2 of 0.3364. Although neural networks are powerful in modeling non-linear relationships, this model performance suggests the need for more tuning and possibly training of the data. The Stacking Regressor combined predictions from multiple models but did not perform as expected. It had the lowest R^2 value (-0.1950), that indicates poor predictive accuracy. This result outcome suggests that there could be potential issues in the stacking process or the need for better selection, of base models and meta-learners. The Support Vector Machine had the weakest performance, with a negative R^2 value (-0.0152), this means that it performed worse than a simple mean model. Its high MSE (12561755.7903), and RMSE (3544.2567) further illustrates its poor fit to the data.

Table 4.1: The table below summarizes the performance metrics for each model

Model	MSE	RMSE	MAE	R^2
Linear Regression	4652276.210	2156.914	1495.071	0.6240
Random Forest	1661575.150	1289.021	603.8611	0.8657
Gradient Boosting	4889786.295	2211.286	971.9769	0.6048
Support Vector Machine	12561755.790	3544.257	2275.381	-0.0152
XGBoost	2997156.344	1731.230	1096.782	0.7578
Neural Network	8211680.700	2865.603	2278.906	0.3364
Stacking Regressor	14786641.316	3845.340	1768.836	-0.1950

4.2 Feature Importance

The Feature Importance Analysis, from the Random Forest model's shows (Table 4.2) that, Social Score Profit, Profit combined with Total ESG Score, and squared Profit are the most significant predictors of funding received. This insight highlights the importance of social and governance metrics in funding decisions, thereby aligning with recent trends in sustainable investing (D'Amato et al, 2021).

Table 4.2: Top Features Influencing Funding Predictions Based on ESG Performance

Top Features		Score
1.	Social Score Profit (in million \$)	0.167671
2.	Profit (in million \$) Total ESG Score	0.137658
3.	Profit (in million \$)^2	0.133890
4.	Governance Score Profit (in million \$)	0.132746
5.	Environmental Score Profit (in million \$)	0.104062

4.3 Explanation of Key Features and Importance Scores

Table 4.3 is made up of the features, along with their respective importance scores, in predicting funding allocations based on ESG performance. The “Feature's Importance Score” for each of them indicates its relative contribution to the predictive model. Higher scores suggest greater impact on the prediction accuracy.

The feature social score profit (in million \$), with an Importance score of 0.167071, combines a company's social score with its profit, thereby indicating how social responsibility and profitability together influence funding decisions. It has the highest importance score, implying that companies with strong social practices, and high profits are more favored for funding. The profit (in million \$) Total ESG score feature, with an Importance score of 0.137658, combines the company's profit with its overall ESG score, thereby highlighting the influence of a company's total ethical and sustainability performance on funding.

The profit (in million \$) ^2 feature with an Importance score of 0.133890, is the squared profit value which suggests that larger profit values (due to squaring), have a significant non-linear effect on funding predictions. Governance score profit (in million \$) with a feature Importance score of 0.132746, combines the governance score with profit, which indicates that good governance practices, coupled with high profits are critical factors in securing funding. The Environmental score profit (in million \$) feature Importance score of 0.104062, combines the environmental score with profit, showing the importance of environmental practices, and profitability together. The profit (in million \$) feature Importance score of 0.077866, indicates that the pure profit of the company also plays a significant role, but it is less than the combined factors mentioned earlier. The revenue (in million \$) profit (in million \$) feature Importance score of 0.075761, reflecting the combined impact of a company's revenue, and profit on funding decisions.

The Governance score revenue (in million \$) Feature Importance score of 0.025836 (Table 4.3), combines governance score with revenue, and this shows how governance and revenue together affect funding. Social score revenue (in million \$) Feature Importance score of 0.014065, combines social score with revenue, thereby indicating the role of social practices and revenue. The revenue (in million \$) Total ESG Score feature Importance score of 0.013716, combines revenue with total ESG score, showing the impact of overall ESG performance and revenue.

The revenue to profit ratio, which is the interaction between revenue and profit, is considered multiple times in different contexts, emphasizing its importance in various combinations. The squared terms on several features (e.g., profit, revenue to profit ratio), indicates that their non-linear impacts are significant in the model. The lower importance features such as pure ESG scores which is the individual ESG scores and their squared terms (environmental, social, governance), have lower importance when not combined with financial metrics. Features combining ESG scores with other non-financial metrics, (like social score total ESG score) have moderate to low importance.

Table 4.3: Feature Importance in Predicting Funding Allocations Based on ESG Performance

	Features	Importance
17	Social Score Profit (in million \$)	0.167071
31	Profit (in million \$) Total ESG Score	0.137658
29	Profit (in million \$)^2	0.133890
22	Governance Score Profit (in million \$)	0.132746
11	Environmental Score Profit (in million \$)	0.104062
4	Profit (in million \$)	0.077866
26	Revenue (in million \$) Profit (in million \$)	0.075761
21	Governance Score Revenue (in million \$)	0.025836
16	Social Score Revenue (in million \$)	0.014065
28	Revenue (in million \$) Total ESG Score	0.013716
27	Revenue (in million \$) Revenue to Profit Ratio	0.013054
30	Profit (in million \$) Revenue to Profit Ratio	0.013001
10	Environmental Score Revenue (in million \$)	0.012435
3	Revenue (in million \$)	0.011335
25	Revenue (in million \$)^2	0.010081
33	Revenue to Profit Ratio Total ESG Score	0.007157
18	Social Score Revenue to Profit Ratio	0.005875
24	Governance Score Total ESG Score	0.005543
5	Revenue to Profit Ratio	0.005283
12	Environmental Score Revenue to Profit Ratio	0.003882
23	Governance Score Revenue to Profit Ratio	0.003648
32	Revenue to Profit Ratio^2	0.003434
9	Environmental Score Governance Score	0.003166
20	Governance Score^2	0.002797
15	Social Score Governance Score	0.002454
19	Social Score Total ESG Score	0.002266
34	Total ESG Score^2	0.002141
2	Governance Score	0.002048
6	Total ESG Score	0.001938
14	Social Score^2	0.001707
1	Social Score	0.001471
13	Environmental Score Total ESG Score	0.001017
8	Environmental Score Social Score	0.000642
0	Environmental Score	0.000625
7	Environmental Score^2	0.000284

The bar chart in Fig. 4.1 illustrates the importance of various features in predicting funding allocations based on ESG performance, as determined by the Random Forest Regressor model. The features are ranked by their importance scores, which reflect their relative contribution to the model's predictions. The social score profit (in million \$) Feature with the Importance score of 0.167, has the highest importance. It indicates that companies with strong social practices, and high profits are most influential in determining funding allocations. Profit (in million \$) Total ESG Score feature Importance score of 0.138, highlights that the overall ESG performance, along with profitability, is a critical factor for funding decisions. The profit (in million \$)^2 feature Importance score of 0.134, suggests that higher profit levels have a significant, non-linear impact on funding predictions.

Governance score profit (in million \$) feature Importance score of 0.133, indicates that companies with good governance practices and high profits are prioritized for funding. Environmental score profit (in million \$) feature Importance score of 0.104, shows the importance of environmental practices in conjunction with profitability. Profit (in million \$) feature Importance score of 0.078, shows that pure profit alone is a significant factor, although less than the combined metrics above. The revenue (in million \$) profit (in million \$) feature Importance score of 0.076, reflects the combined impact of revenue and profit on funding decisions. Governance score revenue (in million \$) feature Importance score of 0.026, shows the role of governance and revenue together in funding decisions. The social score revenue (in million \$) feature Importance score of 0.014, indicates the role of social practices and revenue. The revenue (in million \$) Total ESG Score feature Importance score of 0.014, highlights the impact of the overall ESG performance and revenue.

Features that combine ESG scores, with financial metrics (profit and revenue), have higher importance scores, suggesting that integrated financial and ESG performance is crucial for funding decisions. The presence of squared terms, (e.g., Profit (in million \$)²) indicates that non-linear relationships are significant in the model. While individual ESG scores are important, their impact is more pronounced when combined with financial metrics. This chart underscores the significance of considering both financial performance and ESG factors together in predicting funding allocations.

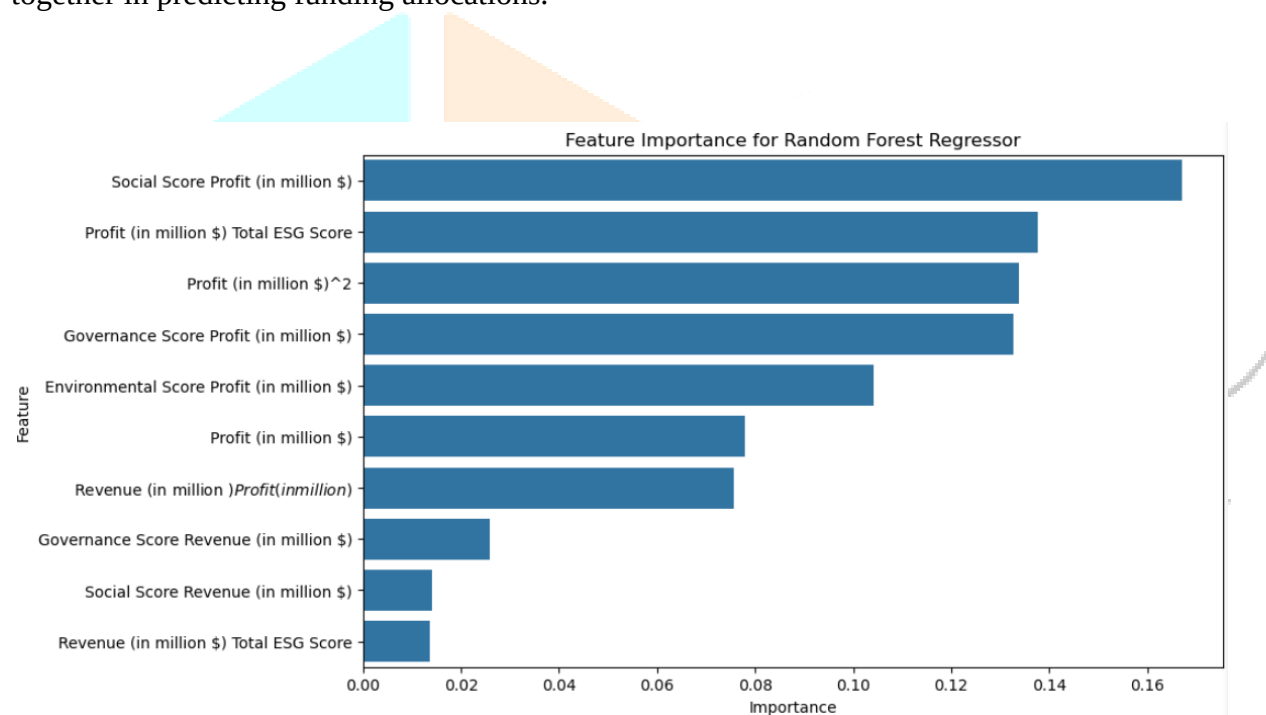


Figure 4.2: Feature Importance for ESG Funding Predictions Using Random Forest Regressor

The scatter plot in Fig. 4.2 compares the actual funding received (x-axis) against the predicted funding received (y-axis) for two different models. The Linear Regression and Random Forest depicted by blue and ground point, respectively on Fig. 4.2, represents a single prediction, with the color indicating the model used. The black dashed line represents the ideal scenario, where the predicted values exactly match the actual values (i.e., a perfect prediction). The points lying on this line indicates perfect predictions. The linear regression blue points represent the predictions made by the Linear Regression model. The scatter of blue points around the dashed line shows the accuracy of the Linear Regression model. Points closer to the line indicate more accurate predictions, while points further away indicate larger errors. The Random Forest green points represent the predictions made by the Random Forest model. The scatter of green points around the dashed line indicates the accuracy of the Random Forest model.

A visual comparison of the distribution of blue and green points shows that the green points (Random Forest), appear to be closer to the dashed line, when compared to the blue points (Linear Regression). This indicates that the Random Forest model generally makes more accurate predictions than the Linear Regression model. On the other hand, there are some points, particularly blue ones, that are distant from the dashed line. These represent

instances where the Linear Regression model's predictions were substantially off from the actual values. The Random Forest model has fewer such outliers, implying better performance in capturing the complex relationships in the data.

The prediction spread in Fig. 4.2 indicates that, for the lower actual funding values (closer to zero), both models show a relatively good fit, with points clustered near the dashed line. While for the higher actual funding values, the Linear Regression model shows a wider spread of predictions, indicating less accuracy. The Random Forest model maintains a closer fit to the dashed line suggesting it handles larger values more effectively. The plot (Fig. 4.2) shows that the Random Forest model provides more accurate and reliable predictions when compared to the Linear Regression model. This is evidenced by the closer alignment of green points, with the dashed line and fewer outliers, particularly for higher funding values.

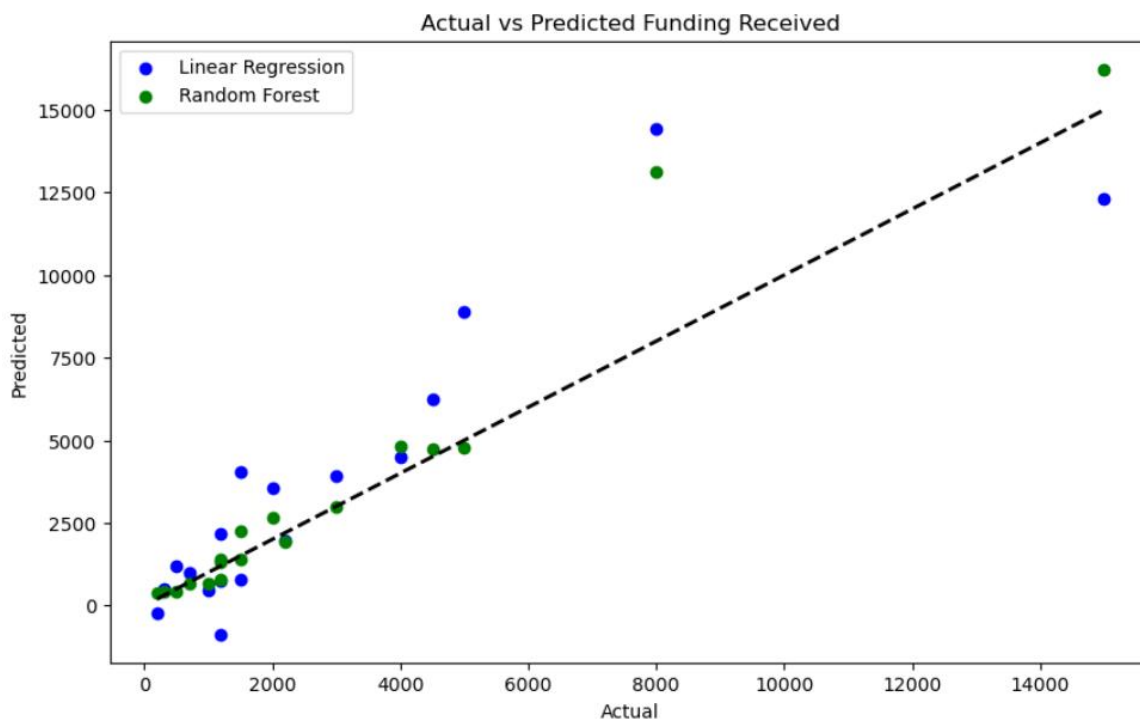


Figure 4.2: Actual vs Predicted Funding Received: Linear Regression vs Random Forest

Figure. 4.3 shows the scatter plot, that compares the actual funding received (x-axis), against the predicted funding received (y-axis), for two different models namely, Gradient Boosting and XGBoost. The various points in the plot represent a single prediction with the color indicating the model used. The black dashed line on the plot represents the ideal scenario where the predicted values exactly match the actual values (i.e., a perfect prediction). The points lying on this line indicate perfect predictions.

The red points represent the predictions made by the Gradient Boosting model. The scatter of these red points around the dashed line (Fig. 4.3) shows the accuracy of the Gradient Boosting model. Points closer to the line indicate more accurate predictions, while points further away indicate larger errors. The purple points represent the predictions made by the XGBoost model. The scatter of these purple points around the dashed line indicates the accuracy of the XGBoost model.

By comparing the distribution of the red and purple points in Fig. 4.3, one can visually assess which model gives more accurate predictions. Both models show a relatively good fit, for lower actual funding values (closer to zero), with points clustered near the dashed line. In the case of the higher actual funding values, there is a noticeable spread, which indicates that both models have larger errors for these predictions. However, there is a visible difference in how they handle higher values. There are a few points, particularly the purple ones, that are

distant from the dashed line. These represent instances where the XGBoost model's predictions were substantially off from the actual values. The Gradient Boosting model has similar outliers, that suggests that it has a slightly poorer performance for higher values. For the lower actual funding values, both models show a relatively good fit with points clustered near the dashed line. The higher actual funding values, for the XGBoost model shows a narrower spread of predictions, thereby indicating better accuracy, when compared to the Gradient Boosting (Fig. 4.3), which maintains a wider spread.

The plot (Fig. 4.3) indicates that both models performed well for lower funding values, but struggle with higher values. The Gradient Boosting model appears to handle higher values slightly better than XGBoost, as indicated by the fewer extreme outliers. This visual comparison helps in understanding the strengths and weaknesses of each model in predicting funding allocations based on ESG performance.

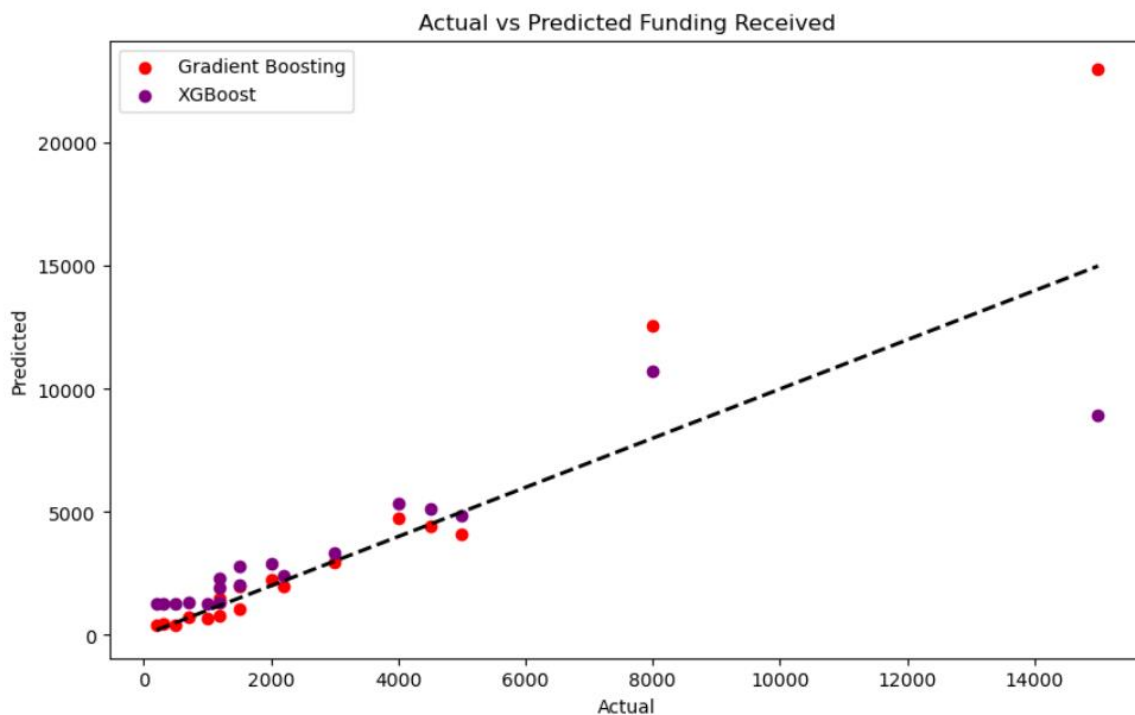


Figure 4.3: Actual vs Predicted Funding Received: Gradient Boosting vs XGBoost

The scatter plot in Fig. 4.4 compares the actual funding received (x-axis), against the predicted funding received (y-axis) for two different models. The Neural Network and Stacking Regressor. The points on the plot represent a single prediction, with the color indicating the model used. The black dashed line represents, the ideal scenario where the predicted values, exactly matches the actual values (i.e., a perfect prediction). Points lying on this line indicate perfect predictions. The orange points represent point predictions made by the Neural Network model. The scatter of orange points around the dashed line shows the accuracy of the Neural Network model. Points that are closer to the line indicate more accurate predictions, while points further away indicate larger errors. The cyan points represent the predictions made by the Stacking Regressor model. The scatter of cyan points around the dashed line (Fig. 4.4) indicates the accuracy of the Stacking Regressor model. A visual comparison of the distribution of orange and cyan points shows that both models have relatively good fit, for lower actual funding values (closer to zero), with the points clustered near the dashed line. For higher actual funding values, there is a noticeable spread, indicating that both models have larger errors for these predictions. However, there are visible differences in how they handle higher values.

There are several points, particularly the cyan ones, that are significantly distant from the dashed line (Fig. 4.4). They represent instances where the Stacking Regressor model's predictions were substantially off from the actual values. The Neural Network model also has outliers, but they are fewer and less extreme, suggesting that it has a slightly better performance for higher values. For the lower actual funding values, both models show a relatively good fit, with points clustered near the dashed line. In the case of higher actual funding values, both models show a wider spread of predictions, indicating less accuracy; especially in the case of the Stacking Regressor, which shows some extreme outliers.

The plot (Fig. 4.4) indicates that both models perform well for lower funding values, but struggle with higher values. The Neural Network model seems to handle higher values, slightly better than the Stacking Regressor, as indicated by fewer extreme outliers. This visual comparison helps in giving us an understanding of the strengths and weaknesses of each model, in predicting funding allocations based on ESG performance.

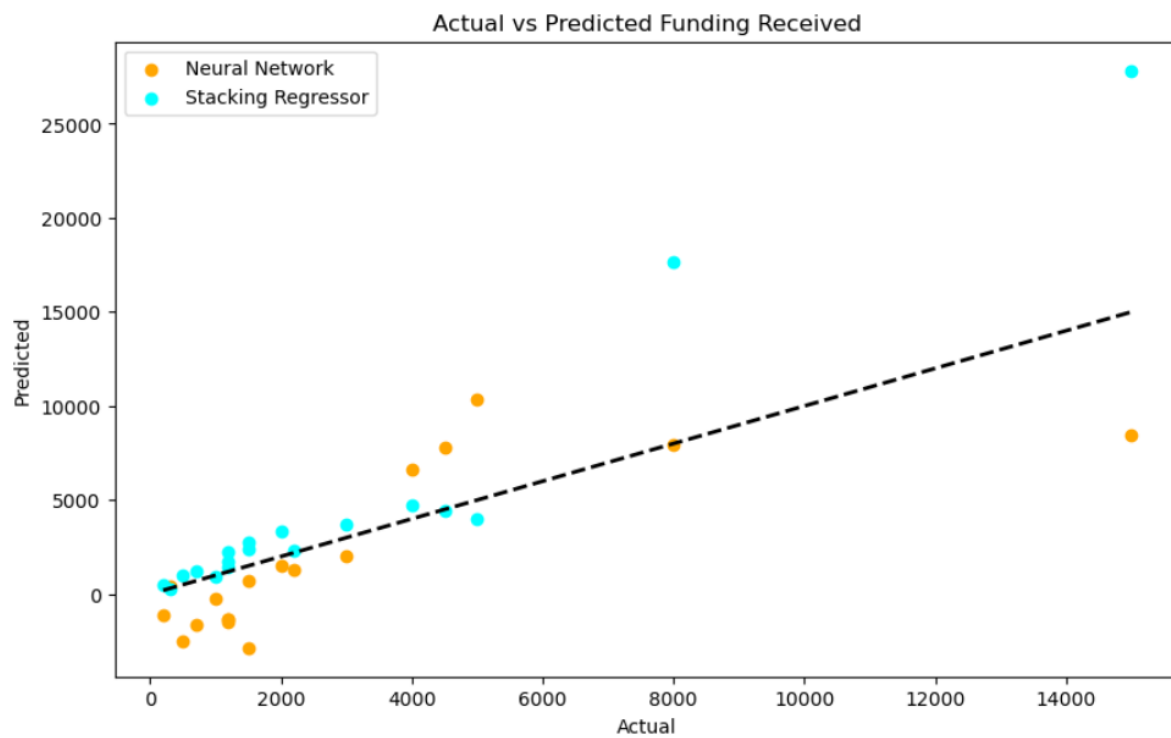


Figure 4.4: Actual vs Predicted Funding Received: Neural Network vs Stacking Regressor

4.4 Discussion

The results from this study reveal significant insights into the performance of various machine learning models in predicting funding allocations based on ESG (Environmental, Social, and Governance) performance. By employing multiple models, the study evaluated their predictive accuracy and highlighted the most important features influencing funding decisions.

4.4.1 Comparative Analysis of Model Performance

In general, the Random Forest model emerged as the best-performing model in this study, with an R^2 value of 0.8657, indicating that it could explain 86.57% of the variance in funding received. This high level of accuracy is consistent with findings in other studies where Random Forest has been shown to excel in handling complex, non-linear relationships in financial and ESG data (Breiman, 2001). Similar studies in ESG-based predictions also favour ensemble methods like Random Forest due to their ability to manage large datasets with numerous variables, and their robustness against overfitting (Berg et al, 2022).

Gradient Boosting, while effective, was less accurate than Random Forest, achieving an R^2 of 0.6048. Gradient Boosting models, such as those used in other financial predictions, often require extensive tuning to reach optimal

performance. XGBoost, another tree-based model, ranked third with an R^2 of 0.7578, reflecting its strong performance in machine learning competitions, where it is frequently used due to its efficient handling of sparse data and its advanced regularization techniques (Chen and Guestrin, 2016).

Neural Networks displayed moderate predictive capability with an R^2 of 0.3364. Neural networks have been widely recognized for their power in modeling non-linear relationships (Goodfellow et al, 2016), but their performance in this study suggests that further tuning and possibly a larger dataset are needed to fully leverage their potential.

The Stacking Regressor and Support Vector Machine (SVM) performed poorly, with negative R^2 values indicating that they were less effective than even a simple mean model. The underperformance of the Stacking Regressor could be attributed to improper model selection or an ineffective meta-learner, which highlights the need for careful configuration in ensemble models (Wolpert, 1992). SVM's poor performance, with an R^2 of -0.0152, aligns with previous findings that SVMs can struggle with large datasets and noisy data, especially when the relationships between variables are non-linear (Cortes and Vapnik, 1995).

4.4.2 Comparison with Similar Studies

In comparison to similar studies, the performance ranking of the models aligns with general trends in the literature. For instance, studies by Athey and Imbens (2017) emphasize the superiority of ensemble methods, particularly Random Forest and Gradient Boosting, in financial predictions due to their ability to capture complex interactions between variables. However, the moderate performance of Neural Networks suggests that while they hold promise, their application in ESG-based financial predictions may require more sophisticated network architectures or larger datasets to realize their full potential.

The importance of feature selection in predicting funding allocations is also consistent with existing research. For example, studies by Kotsiantis (2007) and Guyon and Elisseeff (2003) stress that effective feature selection is crucial in improving model accuracy. In this study, the integration of ESG metrics with financial data (e.g., profit combined with social scores) resulted in higher importance scores, supporting the argument that combining financial metrics with ESG factors leads to more accurate predictions (Chininga et al, 2023).

4.4.3 Key Insights from Feature Importance Analysis

The feature importance analysis in this study underscores the critical role of integrating ESG factors with financial metrics in predicting funding allocations. The most important features, such as the Social Score Profit and the Profit combined with Total ESG Score, highlight how social responsibility and overall ESG performance, when aligned with profitability, are pivotal in funding decisions. This finding corroborates trends in sustainable investing, where investors increasingly prioritize companies with strong ESG performance in addition to financial returns (Eccles and Klimenko, 2019).

The squared terms, such as Profit (in million \$) 2 , emphasize the non-linear impact of profits on funding predictions, which aligns with similar studies that found non-linear relationships between financial performance and ESG factors (Friede et al, 2015). Additionally, the relatively lower importance of pure ESG scores, unless combined with financial metrics, suggests that financial performance remains a significant driver of funding decisions, even in the context of ESG-focused investments.

V. CONCLUSIONS AND RECOMMENDATIONS

The findings from this study lead to several key conclusions:

1. **Ensemble Models for ESG Prediction:** Ensemble methods, particularly Random Forest, are highly effective in predicting funding allocations based on ESG performance. They outperform traditional models like SVM and even advanced methods like Neural Networks, particularly when handling non-linear relationships and complex datasets.
2. **Importance of Integrated Metrics:** The study highlights the importance of combining ESG factors with financial metrics to improve predictive accuracy. Features that combine social scores with profits or overall ESG

scores are more predictive of funding outcomes, reflecting the increasing relevance of integrated financial and ESG performance in investment decisions.

3. Challenges with Neural Networks and SVMs: Neural Networks require extensive tuning and possibly larger datasets to improve their performance in ESG predictions. SVMs, on the other hand, may not be suitable for this type of prediction task due to their sensitivity to large, noisy datasets.

5.1 Recommendations for Future Research

1. Further Exploration of Neural Networks: Future research should focus on optimizing Neural Network architectures for ESG predictions, including experimenting with deeper networks, regularization techniques, and larger training datasets.

2. Refinement of Stacking Regressors: There is a need for more sophisticated selection of base models and meta-learners in stacking approaches. Researchers should explore alternative configurations and tuning strategies to enhance the performance of Stacking Regressors.

3. Expanding Feature Engineering: Continued exploration of non-linear relationships between financial metrics and ESG scores could provide deeper insights into the factors driving funding decisions. Future studies could also investigate the role of emerging ESG factors, such as climate risk or diversity metrics.

By addressing these areas, future studies can build upon the results of this study, leading to even more accurate predictions of funding allocations based on ESG performance.

REFERENCES

- [1] Ahmad, H., Yaqub, M., and Lee, S. H. 2023. Environmental-, social-, and governance-related factors for business investment and sustainability: A scientometric review of global trends. *Environment, Development and Sustainability*, 26: 2965-2987. Available: <https://doi.org/10.1007/s10668-023-02936-2>.
- [2] Ashwin Kumar, N. C., Smith, C., Badis, L., Wang, N., Ambrosy, P., and Tavares, R. 2016. ESG factors and risk-adjusted performance: A new quantitative model. *Journal of Sustainable Finance & Investment*, Oct. 2016. Available: <https://doi.org/10.1080/20430795.2016.1234909>.
- [3] Athey, S., and Imbens, G. W. 2017. The state of applied econometrics: Causality and policy evaluation. *Journal of Economic Perspectives*, 31(2): 3-32, Spring 2017. Available: <https://doi.org/10.1257/jep.31.2.3>. <https://pubs.aeaweb.org/doi/pdf/10.1257/jep.31.2.3>.
- [4] Awad, M., and Khanna, R. 2015. Support vector machines for classification. In *Efficient Learning Machines*, pp. 39-66, Apr. 2015. Available: https://doi.org/10.1007/978-1-4302-5990-9_3. https://www.researchgate.net/publication/300723807_Support_Vector_Machines_for_Classification.
- [5] Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., and Khan, M. N. 2023. Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *IDEAS*, 2023. Available: <https://ideas.repec.org/a/eee/tefoso/v168y2021ics0040162521001980.html>.
- [6] Barney, J. 1991. Firm resources and sustained competitive advantage. *Journal of Management*, 17(1): 99-120. Available: <https://doi.org/10.1177/014920639101700108>.
- [7] Belete, D. M., and Manjaiah, D. H. 2021. Grid search in hyperparameter optimization of machine learning models for prediction of HIV/AIDS test results. *International Journal of Computers and Applications*, 44(1): 1-12. Available: <https://doi.org/10.1080/1206212X.2021.1974663>.
- [8] Berg, F., Kölbel, J. F., and Rigobon, R. 2022. Aggregate confusion: The divergence of ESG ratings. *Review of Finance*, 26(6): 1315-1344. Available: <https://doi.org/10.1093/rof/rfac033>.

- [9] Breiman, L. 2001. Random forests. *Machine Learning*, 45: 5-32. Available: <https://doi.org/10.1023/A:1010933404324>.
- [10] Carvalho, L., Mota, C., and Ramos, P. 2023. Socially Responsible Investment Funds—An Analysis Applied to Funds Domiciled in the Portuguese and Spanish Markets. *Preprints*, Nov. 2023. Available: <https://doi.org/10.20944/preprints202311.1598.v1>.
- [11] Chen, S., Song, Y., and Gao, P. 2023. Environmental, social, and governance (ESG) performance and financial outcomes: Analyzing the impact of ESG on financial performance. *Journal of Environmental Management*, 345: 118829. Available: <https://doi.org/10.1016/j.jenvman.2023.118829>.
- [12] Chen, T., and Guestrin, C. 2016. XGBoost: A scalable tree boosting system. In *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD '16)*, pp. 785-794, Aug. 2016. Available: <https://doi.org/10.1145/2939672.2939785>.
- [13] Chininga, E., Alhassan, A. L., and Zeka, B. 2023. ESG ratings and corporate financial performance in South Africa. *Journal of Accounting in Emerging Economies*, 14(3), Aug. 2023. Available: <https://doi.org/10.1108/JAEE-03-2023-0072/full/html>.
- [14] Cortes, C., and Vapnik, V. 1995. Support-vector networks. *Machine Learning*, 20: 273-297. Available: <https://doi.org/10.1007/BF00994018>.
- [15] Correia, M. S. 2019. Sustainability: An overview of the triple bottom line and sustainability implementation. *International Journal of Strategic Engineering*, 2(1): 29-38. Available: <https://doi.org/10.4018/IJoSE.2019010103>.
- [16] D'Amato, V., d'Ecclesia, R. L., and Levantesi, S. 2021. Fundamental ratios as predictors of ESG scores: a machine learning approach. *Rivista di Matematica per le Scienze Economiche e Sociali*, 44(7): 1-24. Available: <https://doi.org/10.1007/s10203-021-00364-5>.
- [17] Eccles, R. G., and Klimenko, S. 2019. The investor revolution. *Harvard Business Review*, 97: 106-116. Available: <https://www.scirp.org/reference/referencespapers?referenceid=2755951>.
- [18] Elansari, T., Ouanan, M., and Bourray, H. 2023. Modeling of multilayer perceptron neural network hyperparameter optimization and training. *Preprint*, Feb. 2023. Available: <https://doi.org/10.21203/rs.3.rs-2570112/v1>.
- [19] Freeman, R. E., and McVea, J. F. 2001. A stakeholder approach to strategic management. *SSRN Electronic Journal*, Jan. 2001. Available: <https://doi.org/10.2139/ssrn.263511>.
- [20] Friede, G., Busch, T., and Bassen, A. 2015. ESG and financial performance: Aggregated evidence from more than 2000 empirical studies. *Journal of Sustainable Finance & Investment*, 5(4): 210-233. Available: <https://doi.org/10.1080/20430795.2015.1118917>.
- [21] Goodfellow, I., Bengio, Y., and Courville, A. 2016. *Deep Learning*. MIT Press, Cambridge, MA.
- [22] Gupta, A., Sharma, U., and Gupta, S. 2021. The role of ESG in sustainable development: An analysis through the lens of machine learning. In *2021 IEEE International Humanitarian Technology Conference (IHTC)*, Canada, Dec. 2021. IEEE. Available: <https://doi.org/10.1109/IHTC53077.2021.9698939>.
- [23] Guyon, I., and Elisseeff, A. 2003. An introduction to variable and feature selection. *Journal of Machine Learning Research*, 3: 1157-1182. Available: <https://www.jmlr.org/papers/volume3/guyon03a/guyon03a.pdf>.

- [24] Hastie, T., Tibshirani, R., and Friedman, J. 2009. The Elements of Statistical Learning: Data Mining, Inference, and Prediction. 2nd ed., Springer Series in Statistics, Springer. <https://link.springer.com/book/10.1007/978-0-387-84858-7>
- [25] Hodson, T. O. 2022. Root-mean-square error (RMSE) or mean absolute error (MAE): When to use them or not. *Geoscientific Model Development*, 15: 5481-5487. Available: <https://doi.org/10.5194/gmd-15-5481-2022>.
- [26] Jayathilaka, A. K. K. R. 2020. Operating profit and net profit: Measurements of profitability. *Open Access Library Journal*, 7: 1-11, Dec. 2020. Available: <https://doi.org/10.4236/oalib.1107011>. <https://www.scirp.org/journal/paperinformation?paperid=105860>.
- [27] Jonsdottir, B., Sigurjonsson, T. O., Johannsdottir, L., and Wendt, S. 2022. Barriers to using ESG data for investment decisions. *Sustainability*, 14(9): 5157. Available: <https://doi.org/10.3390/su14095157>.
- [28] Jorion, P. 2007. Value at Risk: The New Benchmark for Managing Financial Risk. 3rd ed., McGraw-Hill, New York. Available: <https://www.scirp.org/reference/referencespapers?referenceid=2056015>.
- [29] Karrar, A. E. 2022. The effect of using data pre-processing by imputations in handling missing values. *Indonesian Journal of Electrical Engineering and Informatics (IJEI)*, 10(2): 375-384. Available: <https://doi.org/10.52549/ijeai.v10i2.3730>.
- [30] Kotsiantis, S. B. 2007. Supervised machine learning: A review of classification techniques. *Informatica*, 31: 249-268. Available: [https://datajobs.com/data-science-repo/Supervised-Learning-\[SB-Kotsiantis\].pdf](https://datajobs.com/data-science-repo/Supervised-Learning-[SB-Kotsiantis].pdf).
- [31] Kutner, M. H., Nachtsheim, C. J., Neter, J., and Li, W. 2005. Applied Linear Statistical Models. 5th ed., McGraw-Hill/Irwin, New York. Available: https://users.stat.ufl.edu/~winner/sta4211/ALSM_5Ed_Kutner.pdf
- [32] Lee, O., Joo, H., Choi, H., and Cheon, M. 2022. Proposing an integrated approach to analyzing ESG data via machine learning and deep learning algorithms. *Sustainability*, 14(14): 8745. Available: <https://doi.org/10.3390/su14148745>.
- [33] Lu, M., Hou, Q., Qin, S., Zhou, L., Hua, D., Wang, X., and Cheng, L. 2023. A stacking ensemble model of various machine learning models for daily runoff forecasting. *Water*, 15(7): 1265. Available: <https://doi.org/10.3390/w15071265>.
- [34] Markowitz, H. 1952. Portfolio selection. *The Journal of Finance*, 7(1): 77-91. Available: <https://doi.org/10.2307/2975974>.
- [36] Martiny, A., Tagliatela, J., Testa, F., and Iraldo, F. 2024. Determinants of environmental social and governance (ESG) performance: A systematic literature review. *Journal of Cleaner Production*, 456: 142213. Available: <https://doi.org/10.1016/j.jclepro.2024.142213>.
- [37] Masood, F. 2024. Assessing the impact of machine learning algorithms on portfolio optimization and risk management in the era of sustainable investing. *International Journal of Emerging Multidisciplinaries: Computer Science & Artificial Intelligence*, 3(1): 294. Available: <https://doi.org/10.54938/ijemdcasai.2024.03.1.294>.
- [38] Mishina, Y., Murata, R., Yamauchi, Y., and Yamashita, T. 2015. Boosted random forest. *IEICE Transactions on Information and Systems*, E98.D(9): 1630-1636. Available: <https://doi.org/10.1587/transinf.2014OPP0004>.
- [39] Muraina, I. O. 2022. Ideal dataset splitting ratios in machine learning algorithms: General concerns for data scientists and data analysts. In *Proceedings of the 7th International Mardin Artuklu Scientific Researches Conference*, Mardin, Turkey, Feb. 2022. Available:

https://www.researchgate.net/publication/358284895_ideal_dataset_splitting_ratios_in_machine_learning_algorithms_general_concerns_for_data_scientists_and_data_analysts.

[40] Peixoto, J., Machado, A. de B., and Richter, M. F. 2022. ESG indicator metrics used by organizations to assess the degree of sustainability in companies. *International Journal of Advanced Engineering Research and Science*, 9(9): 589-600. Available: <https://www.researchgate.net/publication/347397366>.

[41] Radzi, H. 2023. An overview of environmental, social and governance (ESG) and company performance. In *Proceedings of the International Conference in Technology, Humanities and Management*, Nov. 2023. Available: <https://doi.org/10.15405/epsbs.2023.11.90>.

[42] Shrivastav, L., and Kumar, R. 2022. An ensemble of random forest, gradient boosting machine, and deep learning methods for stock price prediction. *Journal of Information Technology Research*, 15(1): 1-19. Available: <https://doi.org/10.4018/JITR.2022010102>.

[43] Sorathiya, A., Saval, P., and Sorathiya, M. 2024. Data-driven sustainable investment strategies: Integrating ESG, financial data science, and time series analysis for alpha generation. *International Journal of Financial Studies*, 12(2): 36. Available: <https://doi.org/10.33/ijfs12020036>.

[44] Verheyden, T., Eccles, R. G., and Feiner, A. 2016. ESG for all? The impact of ESG screening on return, risk, and diversification. *Journal of Applied Corporate Finance*, 28(2): 47-55. Available: <https://doi.org/10.1111/jacf.12174>.

[45] Vinay, S. 2021. Standardization in machine learning. *ResearchGate*, Mar. 2021. Available: https://www.researchgate.net/publication/349869617_Standardization_In_Machine_Learning.

[46] Visser, L., Pat-el, R., Lataster, J., Van Lankveld, J., and Jacobs, N. 2023. Beyond difference scores: Unlocking insights with polynomial regression in studies on the effects of implicit-explicit congruency. *Psychologica Belgica*. Available: <https://psychologicabelgica.com/articles/10.5334/pb.1246>.

[47] Wolpert, D. H. 1992. Stacked generalization. *Neural Networks*, 5(2): 241-259. Available: [https://doi.org/10.1016/S0893-6080\(05\)80023-1](https://doi.org/10.1016/S0893-6080(05)80023-1).