

An Efficient Predicative Approach of ESG Invest Scoring Using Random Forest Algorithm

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Abstract. Environmental, social, and governance (ESG) factors are considered while making business and investment choices. Human capital and climate change are causing firms to re-evaluate their focus away from conventional financial gains. Investors are drawn to socially responsible investments due to a shift in global attitudes toward sustainability and the availability of environmental, social, and governance (ESG) indicators. The strategic value of ESG measures has been researched extensively for private organisations, but less attention has been paid to public corporations. The use of quantitative methodologies for improving and standardising ESG grading, as well as for building ESG portfolios, is neglected, despite the fact that ESG-driven portfolios currently represent a significant and rising share of global assets under management. Deep learning is used to develop an ESG investment score prediction algorithm in this article. The ESG score is analysed and predicted using a random forest learning algorithm in the suggested system.

Keywords: Machine learning, ESG core Prediction, Random Forest, Data analysis, Firm performance.

1. Introduction

The volumes of investors' funds funneling into sustainable investments rise every year with no decline being insight. In 2020, more than 51 billion USD of new funds were channeled into sustainably acting companies, more than double the amount in 2019 [1]. Consequently, the demand for data for non-financial due diligence is not lagging. The most widely spread approach in performing the ESG evaluation leans on the independent rating agencies. By assessing and diligently evaluating the indicators relating to environmental impact, social endeavors, and corporate governance, the ESG rating agencies plug the data into their methodologies and evaluation models. The results usually come out in a single score or a rating [2].

As sustainability-related data is generally qualitative and difficult to compare, results vary. As of 2019, there are 500 ESG scores, 100 ESG awards, and 120 optional ESG disclosure requirements [3]. Different data suppliers assess and evaluate ESG differently due to a lack of universal standards. When comparing the sustainability ratings of five market-leading ESG rating companies, they observed an average correlation value of 0.61 [4]. While academic literature explains some of these discrepancies, such as data quality and gathering techniques, scoring models and methodology vary. As investors pay for ESG scores, unlike credit scoring, where corporations pay for their scores, the riddle of ESG rating discrepancies remains [5].

With increasing numbers of investors and funds currently incorporating environmental, social, and governance (ESG) as an investment strategy, ESG investing has contributed to the country's economic growth and development. The environment covers topics such as climate risk, natural resources, pollution, and waste, as well as environmentally related investment opportunities, social issues including labor issues and product responsibilities, threats such as information security, issues related to corporate stakeholders, and governance, including matters related to the quality and effectiveness of the board of directors. ESG is a data analysis tool for identifying and developing sustainable investments. In particular, ESG data is often classified as "non-accounting" information because it reflects an essential factor to measure a company's performance without revealing it in financial reports [6].

Predicting company financial performance has always been a matter of significant interest and a challenging problem for academic scholars and industry practitioners [7]. Typically, in the practical

process of evaluating and predicting a firm future performance, using a set of financial measures or various indicators has been a traditional yet practical approach for decision-makers. More specifically, firms are quantified by economic indicators that describe their current business condition based on past observations to induce a statistical or mathematical model. Nevertheless, merely using financial ratios as predictors has not accurately predicted future financial performance. Thus, a further request for accurately identifying critical features to predict the future performance of companies has been an emerging stream of finance and industrial research, exceptionally promptly for effectively making the business strategic decisions or investment decision making [8].

Although attention in ESG has grown quickly, there is no absolute index, and agencies use different rating methods. Lack of absolute standards causes turmoil for both businesses and investors, hence ESG professionals are desired [9]. Machine learning and deep learning algorithms evaluate ESG, but obtaining datasets is difficult. Available environmental quantitative datasets include carbon data [10]. Collecting and standardizing social and governance data is problematic.

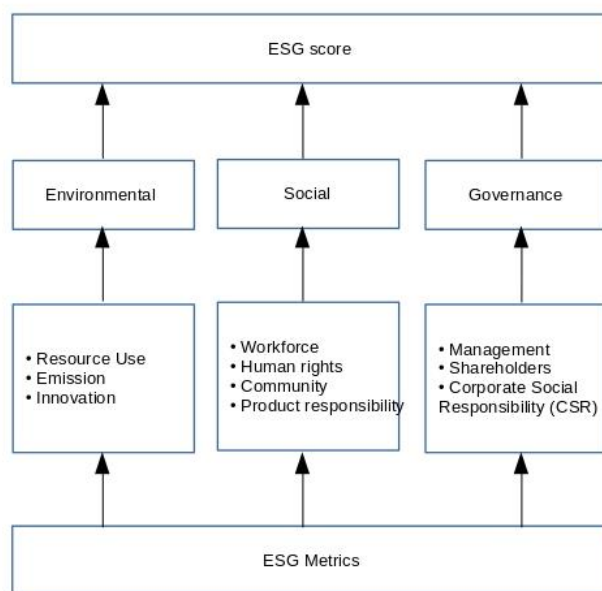


Figure 1. ESG score evaluation process

This research uses machine learning and deep learning to analyze ESG data. Random forest predicted each dataset's ESG score. This research examines and analyses social and governance datasets using deep learning random forest algorithms. Second, proposing a technique for forecasting ESG scores or rankings.

This article's remaining sections are as follows: Section 2 reviews ESG studies and data. Section 3 describes the paper's ESG prediction algorithm. Section 4 shows each experiment's accuracy score (RMSE) and mean absolute error (MAE) (MAE). Section 5 addresses the study's main results and limitations that will be addressed in future research. Section 6 summarizes the research.

2. Literature Review

De Lucia et al. [11] employed a mixed method combining machine learning (ML) procedures and inferential (i.e., requested calculated relapse) model. The previous estimated the precision of ROE and ROA on numerous ESG and other financial standards and satisfies target #1. A causal connection between ESG speculation decisions and ROA and ROE might be tried, as can the level of any such affiliation. The inferential investigation satisfies target #2. The outcomes suggested that ML successfully predicts ROA and ROE and illustrate, utilizing the arranged calculated relapse model, the presence of a positive connection between ESG rehearses and the monetary measurements.

De Franco et al. [12] planned an AI technique that finds connections between's ESG highlights and monetary exhibitions for organizations in a wide venture universe. The calculation included regularly refreshed sets of decides that map areas inside the high-layered space of ESG elements to abundance bring conjectures back. Their examination introduced new experiences in the rising area of monetary writing that examinations the connection between ESG behaviour and the economy. The ESG profile of a company definitely contains some type of alpha, as we demonstrate, but only through the application of substantial, non-linear approaches such as machine learning can this alpha be obtained.

Lee et al. [13] suggested incorporating AI into the five ESG experiments. They also analysed governance and social statistics using NLP algorithms to forecast a company's ESG rankings. Every experiment reached the goal for accuracy, RMSE, and MAE. Also examined ESG data using multiple algorithms, according to the results. The study focused adversarial attacks on ESG datasets and provides ways to identify them.

Hong et al. [14] used machine learning to analyse organisation predictions that businesses could enhance M&A success to promote sustainable growth. AdaBoost was used to train numerous weak classifiers (decision trees) to create a strong decision-making model with 215,160 deal activity. 10-fold cross validation using the AdaBoost model produced 80.1% accuracy. We observed that M&A prediction features change based on sustainable development. For robustness, an SVM model yielded equivalent results. By analysing cross-border M&A decision-making features, their research aimed to further machine learning in ecosystem studies.

D'Amato et al. [15] examined how balance sheet components impact ESG rankings for publicly listed companies. Using a Random Forest method, they explored how structural data affects STOXX 600 ESG scores. Balance sheet data helps explain ESG rankings. ESG investments were influenced by environmental, social, and governance concerns in diverse areas of the global economy. Asset managers that evaluate and manage ESG risks were focusing on sustainable and responsible financing. Monetary Institutions and Rating Agencies formulated an ESG score to unveil environmental, social, and administration (CSR) models. CSR/ESG appraisals are famous, in spite of the fact that their precision was questioned. Resource chiefs may not necessarily believe that markets sufficiently cost environment gambles into corporate qualities. In these cases, ESG evaluations offer a critical instrument in the organization's gathering pledges process or on the offers' return.

Krappel et al. [16] introduced a heterogeneous ensemble approach to predict ESG scores using basic data. The CatBoost and XGBoost ensemble members form the basis of the model. The presented approach would enable the generation of first ESG scores in a cost-effective and scalable manner, given the availability of fundamental data to the general public (also for companies without sustainability reporting). At 54% of the variance in ratings (R^2), they were able to explain that with their technique and surpassed previous work.

Sokolov et al. [17] deployed deep learning for natural language processing to automatically transform unstructured text input into ESG ratings (NLP). The authors demonstrated how to use natural language processing (NLP) to uncover ESG concerns in social media. The authors discussed how existing NLP could be employed to construct algorithmic skills for processing ESG-relevant documents by using deep-learning models to learn broad representations of text data, which can subsequently be applied to different ESG tasks. The authors explored how NLP models could be employed to aggregate ESG scores and how to develop completely or semi-autonomous ESG scoring systems.

Zhang et al. [18] presented SRI portfolio creation methods incorporating a twofold screening technique utilizing AI forecast and a drawn out worldwide least difference (GMV) model (or expanded most extreme Sharpe proportion (MSPR) model). Models incorporate stock screening and resource portion. To adjust the monetary and ESG objectives of SRI financial backers, a drawn out GMV model (or expanded MSPR model) used to calculate stock capital allocation ratios. They analysed the models on China's A-share market. The empirical findings revealed that presented models outperformed existing models in annualized return, ESG score, and Sharpe ratio.

Chen et al. [19] used ESG scholar data to construct an algorithmic trading technique and a machine learning method to estimate a company's ESG premium and collect ESG alpha. First, they build an ESG investing universe and apply feature engineering on Microsoft Academic Graph ESG scholar data. The academic data-based ESG alpha method captures ESG premium better than conventional financial metrics (1,443.7%).

Raman et al. [20] analyzed company revenue call transcripts for ESG tendencies. Using a small corporate sustainability reporting dataset, a pre-trained language model was fine-tuned. Using a novel distant-supervision approach, the semantic information within that classification model was employed to conferencing transcript sentences. Extensive empirical analysis of the developed transfer learning approach revealed their efficacy. In the last 5 years, 15% of earnings calls included ESG, indicating that ESG was essential to corporate strategy.

3. Proposed Methodology

This section will introduce the proposed random forest based ESG score predictor architectures used in this study. Random forest algorithm based deep learning model is used in this work. The objective of this examination is to foresee the score of ESG information. 0 is the least conceivable ESG score; 100 is the most noteworthy conceivable ESG score; and 15 of the other 186 special measurements are all in the scope of 0 to 100. Consequently their demonstrating might be portrayed as a relapse issue. R2 (coefficient of assurance) and MAE (mean outright blunder) were utilized to examine execution in the relapse task, with MSE filling in as the misfortune capability for the models. The excess 171 downright measurements were viewed as in the characterization setting with cross-entropy being the misfortune capability and the exactness and the F1 score used as assessment measurements.

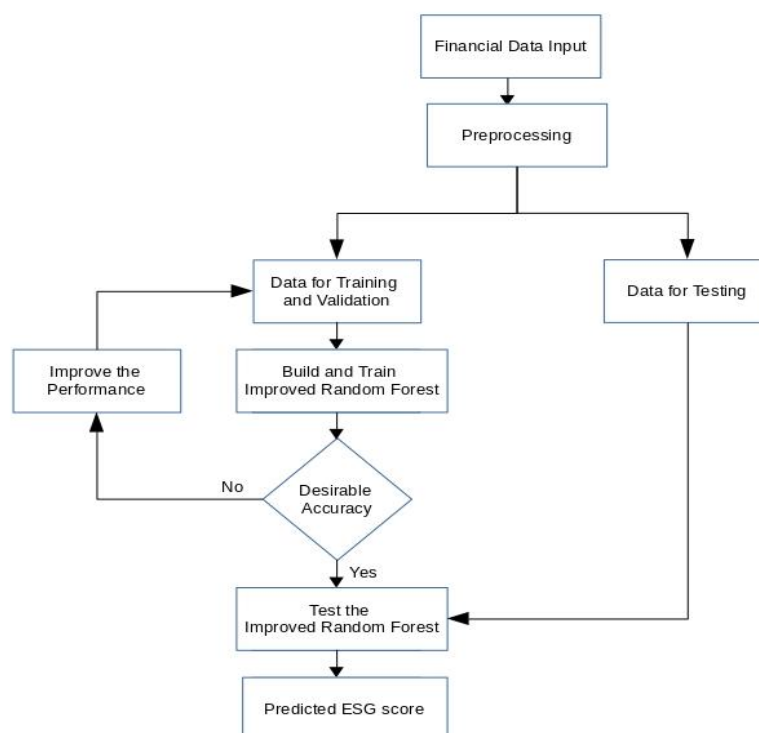


Figure 2. Architecture of the Proposed ESG score prediction system

3.1 Preprocessing

Data preprocessing converts raw data into an understandable format. Real-world data is sometimes insufficient, inconsistent, missing particular behaviours or patterns, and inaccurate. This might lead to poor data collecting and poor data-based models. Preprocessing data solves such issues. Machines understand 1s and 0s, not language, images, or videos. So showing a presentation of all our photos

and expecting machine learning to learn from it won't work. In Data Preprocessing, the data is encoded to make it simpler for the computer to interpret. The algorithm can now comprehend data features. Real-world data is incomplete, noisy, and inconsistent. There may be missing or irrelevant data. Data cleansing handles this. Data cleaning techniques fill in missing numbers, smooth out noise, and detect outliers. Dirty data confuses the model.

Data Preprocessing includes Data Cleaning/Cleaning. Missing data is prevalent. Missing values may have occurred during data collection or due to a data validation rule. If the whole row is NaN, it's worthless. So, drop these rows/columns immediately. Or if more than 65% of a row/column is missing, discard it. If a row or column repeats, maintain the first occurrence. So machine learning algorithms don't favour or prejudice a certain data item. Basic interpolation methods can fill in missing values if only a small percentage is missing. Missing data are usually filled up by the feature's mean, median, or mode.

Machines can't understand noisy data. Poor data collection, entry errors, etc. might cause it. Noise in a financial dataset could impact results. The noise can deviate the min-max value of a dataset. This could affect the accuracy of the prediction. The Gaussian preprocessing steps were applied on the financial dataset. Through this preprocessing, we could avoid the potential danger of incomplete data and errors in the data, which is significant to improve the accuracy of the prediction.

3.2 Random Forest Algorithm

RF is an assortment of relapse trees (CART) prepared by packing and irregular variable choice. RF tree improvement utilizes recursive dividing, similar to CART. In recursive dividing, the cut-point and parting variable depend on the learning test dispersion. Truck is an unsound student on the grounds that a slight change in learning information could influence the underlying cut-point or parting variable and the entire tree structure. RF evades CART's unsteadiness by anticipating utilizing a few trees. Involving many trees for expectation diminishes each tree's unsteadiness. Joining trees with extraordinary variety would supplement the flimsiness of each tree since CART is a fair-minded indicator that is temperamental yet precise by and large. Combining comparable trees wouldn't compliment their instability since they might both be unstable. Random forest models predictions and behaviour using decision trees. It has several decision trees that classify random forest data. Random forest takes the instance with the most votes as the prediction.

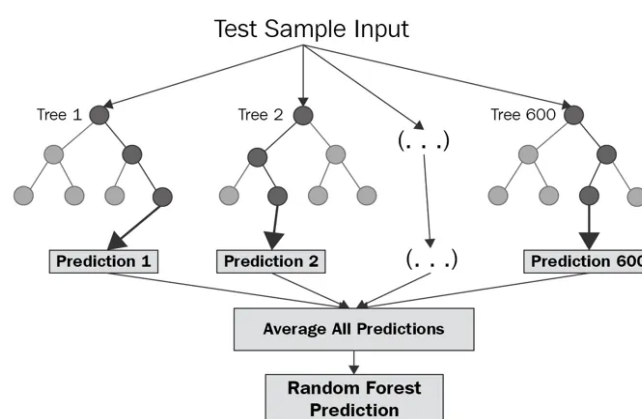


Figure 3. Random Forest prediction system

Random forest technique predicts using unpruned random forest regression trees. Regression trees, which shouldn't be pruned, employ bootstrap sampling. The optimum splitting feature uses optimal tree nodes. Random sampling reduces regression tree correlation and variance. It enhances forest tree prediction. Bootstrapping enhances tree independence.

Random forest models are difficult to evaluate from a biological perspective without variables (features). The naive method assigns variables' value depending on how often they appear in the sample. It's easy to do, but the cost-cutting and accuracy-boosting advantages are redundant.

Permutation importance measures prediction accuracy when out-of-bag variables are reprocessed. Permutation importance is better than naive, but more costly. Due of random forest's inability to interpret predictions from a biological standpoint, the strategy depends on the naive, mean decrease impurity, and permutation importance techniques. Three techniques support multiple-category predictor variables.

To make a prediction at a new point x :

$$\hat{f}_{rf}^B(x) = \frac{1}{B} \sum_{b=1}^B T_b(x) \quad (1)$$

The random forest estimate (15.2) approximates the expectation

$$\hat{f}_{rf}(x) = E_{\emptyset} T(x; \emptyset) = \lim_{B \rightarrow \infty} \hat{f}(x)_{rf}^B \quad (2)$$

Permutation importance and mean decrease impurity are bias-free for continuous predictor variables with a same number of categories. Variable selection is biased. Subsampling without replacement and random forest should be utilised to prevent it. Oblique random forests employ oblique splits instead of node splits for choices. Oblique woodlands have several exceptional features. First, they can separate distributions using a single multivariate split that includes deep axis-aligned divides. Second, they reduce decision tree bias for plotted limitations. Using oblique splits to separate related classes is simpler and more efficient than using axis-aligned divides.

Random forest classifier uses prediction trees. Every tree in the random forest depends on independent random vectors with comparable distribution. Originally built for machine learning, the classifier has acquired favour in remote-sensing because to its accuracy. It accomplishes the needed speed and parameterization. The random forest classifier bootstraps random samples where the highest-voted prediction is chosen. Individuality of the trees is crucial. These features ensure each tree's identity. First, each sample tree training employs random subsets of initial training data. The optimal split is then determined using randomly selected tree node features. Trees grow without limitations and shouldn't be removed. Random forests (neural networks) evaluate variable relevance. It handle missing data well. The most common variable in a node replaces missing values. Random forests give the most efficient classification. Random forest can accommodate thousands of variables. It can balance data sets when a class is infrequent. Fast variable handling makes the approach suitable for complex tasks.

3.3 ESG score prediction

Random Forest is used to determine variable significance for each ESG score prediction. Creating a broad collection of trees improves model complementarity and ensemble prediction performance. RF increases tree variety by randomising training and input data sets. RF creates fresh preparing informational collections by arbitrarily examining the first set with substitution. A perceptions might be copied because of testing with substitution in the crisp preparation informational indexes. Overall, 63.2% of the first preparation information as copies. RF randomizes variable sets once new preparation informational indexes are made to increment tree assortment.

Variable set randomization arbitrarily chooses factors for each new preparation dataset. At each parting point, every RF tree creates via scanning the arbitrary variable set for the ideal split. Since preparing informational indexes and variable sets are haphazardly created, RF trees ought to grow freely and in an unexpected way. When all trees are developed, RF coordinates them by averaging their singular projections, which makes RF stable. This coordinated forecast methodology brings down huge mistakes and makes RF more precise than its part trees. RF estimates the impact of every variable on the model's general forecast presentation utilizing information stage. Variable importance is assessed by ascertaining the misfortune in forecast precision from permuting variable qualities. At the point when forecast exactness drops, a variable turns out to be more fundamental, as well as the

other way around. The connection between a variable and its result might be upset by haphazardly permuting its qualities, thusly supplanting the first factor with the permuted one diminishes expectation precision. Permuting the result variable's worth would diminish RF's prediction accuracy. If the variable is not associated to the output, permuting its values won't affect prediction accuracy since all tree splitting decisions are unaffected. Comparing variable importance exposes their output relationship.

RF evaluates the variable relevance of each variable together, including multivariate interactions. Redundant variables that are substantially associated with output are punished and given less weight. Variable significance may be used to choose the most relevant variables in an RF, helping users focus key aspects and comprehend input-output correlations. This is especially beneficial for high-dimensional data, when identifying key variables is crucial. Since the data has no internal structure, kernels or convolutional layers are not needed. Dropout, L1 and L2 regularisation, and batch normalisation are used. Optional embedding layers improve model performance and training time for categorical input. The embedding layers are taught end-to-end with the network and reduce the number of variable dimensions, decreasing model parameters and computing cost. They also have a regularising impact. Each categorical feature f_i has its own embedding layer emb_i which solely receives f_i . After passing through the activation function, the emb_i outputs are concatenated with each other and unaltered numerical model inputs and delivered to hidden network layers. Softmax layer predicts ESG.

3.4 Evaluation parameters

In this work, prediction performance is tested using three commonly-used indices: the coefficient of determination (R2), the Root Mean Square Error (RMSE), and the Mean Average Error (MAE). To compare the prediction performance of different models, a composite performance index (PI) including R2, RMSE, and MAPE was established. Standard deviation (SD) and mean error (ME) are presented as metrics to analyze the proposed prediction model's performance. Eqs. (3)–(6) depicts RMSE, MAE, SD, and ME.

$$RMSE = \sqrt{\frac{\sum_{k=1}^n (y_k - \hat{y}_k)^2}{N}} \quad (3)$$

$$MAE = \frac{\sum_{k=1}^n (y_k - \hat{y}_k)^2}{N} \quad (4)$$

$$SD = \sqrt{\frac{1}{N} \sum_{k=1}^n (y_k - \mu)^2} \quad (5)$$

$$ME = \frac{1}{N} \sum_{k=1}^n (y_k - \hat{y}_k)^2 \quad (6)$$

where n implies number of sample data, μ implies the observed data arithmetic mean value, y_k represents \hat{y}_k denotes observation and prediction's value.

4. Results and Analysis

The results of the research are summarised in this section. Figure 5 shows the R2 scores for the three pillar scores (E, S, and G) and the combined ESG scores, while Table 5 includes the corresponding MAEs for the prediction models. We can see that CatBoost has outperformed the other individual models, with XGBoost and NNs in third and fourth place, respectively. CatBoost's success is attributed to its novel approach to categorical variables. We can see from the ensemble performance that the Naive NN ensemble has actually increased the performance of the individual NN model, but this was not enough to catch up to gradient boosted tree models. While this heterogeneous ensemble

surpassed all of its constituents on the test set, it was still the greatest overall performer. Success is due to the fact that it brings together the best features of each model family to uncover new connections between the input and the target data. Predicting the environmental rating was simplest, followed by ESG and social scores. Thought to be the most difficult to model, governance score was the most difficult. This is due to the fact that organized financial and foundational data contains very little information about governance structure. in the first table, the ESG score and the criteria employed are listed.

Table 1. Prediction score of Proposed random forest algorithm in comparison with ANN, DNN and SVM.

	Proposed Random Forest	ANN	DNN	SVM
ESG Score	9.5	16.2	17.2	22.5
E score	10.7	19.3	18.2	27.6
S score	8.9	16	19.5	24.3
G score	12.7	15.1	17.2	21.6
Resource Use	11.4	18.4	15.8	22.4
Emissions	7.4	13.5	16.8	20.4
Env. Innovation	8.5	17.6	19.5	21
Workforce	13.4	15.6	18.2	22.3
Human Rights	16.4	14.2	15.6	19.3
Community	12.0	17.3	20.1	29.2
Product Resp.	10.4	13.9	15.7	20.6
Management	11.7	16.2	17.3	22.5
Shareholders	9.2	15.4	18.3	21.7
CSR Strategy	6.9	16.3	16.9	20.6

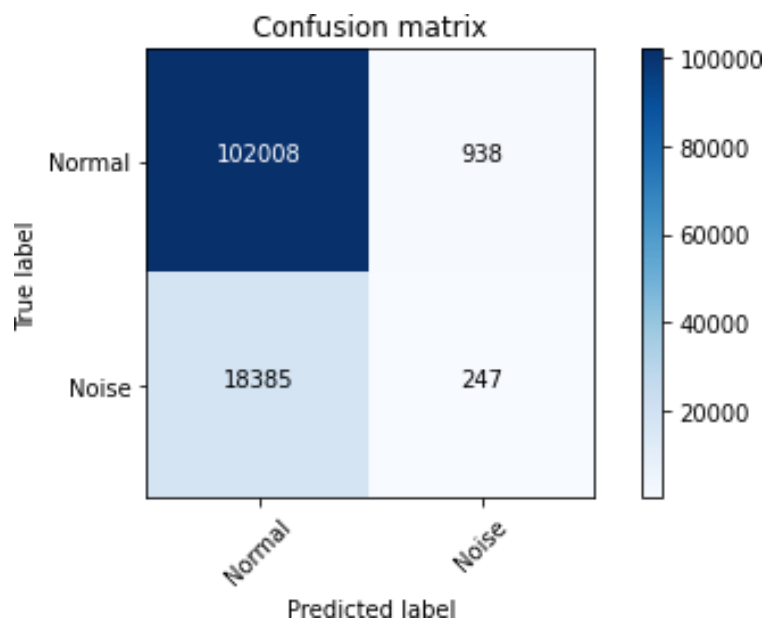


Figure 4. Confusion matrix of the proposed random forest ESG prediction system

Table 2. Accuracy, RMSE, MAE, SD, ME of Proposed random forest algorithm in comparison with ANN, DNN and SVM.

	Accuracy	RMSE	MAE	SD	ME
ANN	87.8	1.17	1.32	2.1	3.95
DNN	92.3	0.86	0.92	1.4	3.44
SVM	79.6	3.45	3.39	3.7	5.78
Proposed RF	99.9	0.33	0.360.6	0.6	1.79

Machine learning methods are used to predict ESG results. Smaller companies may accurately forecast their ESG scores since only financial data are used as input variables. For comparison, a variety of machine learning methods are used. We found the proposed random forest method to be the most accurate, with low RMSE and MAE values.

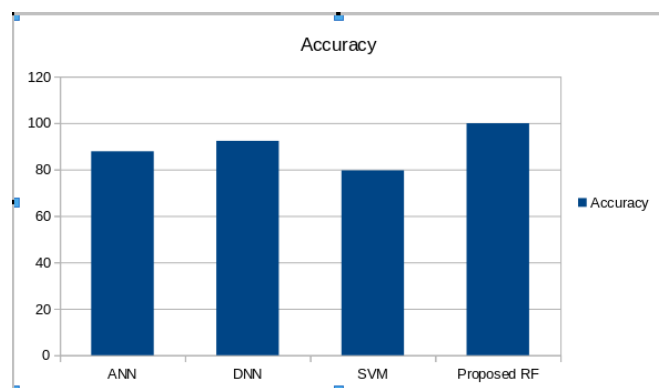


Figure 5. Accuracy of the proposed random forest ESG prediction system

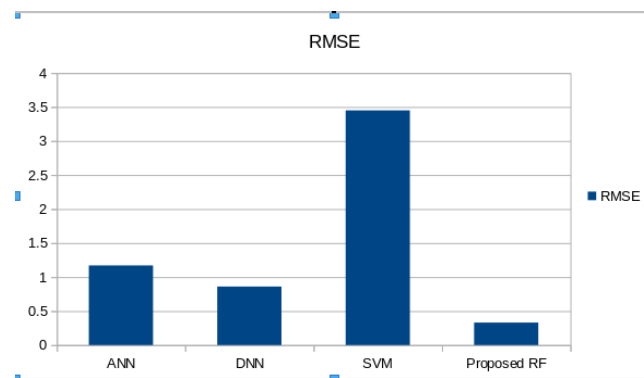


Figure 6. Root Mean Square Error of the proposed random forest ESG prediction system

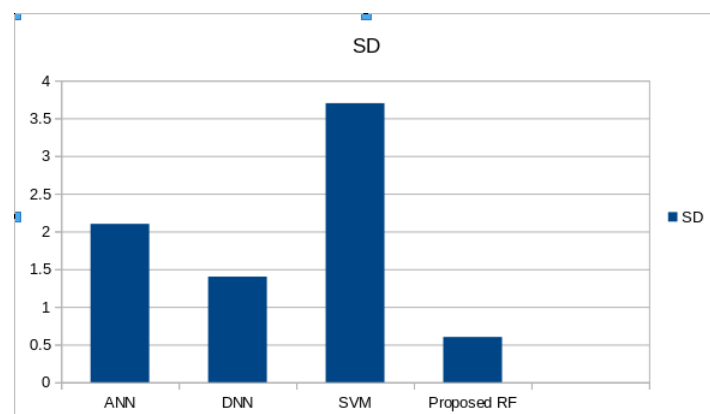


Figure 7. Standard Deviation of the proposed random forest ESG prediction system

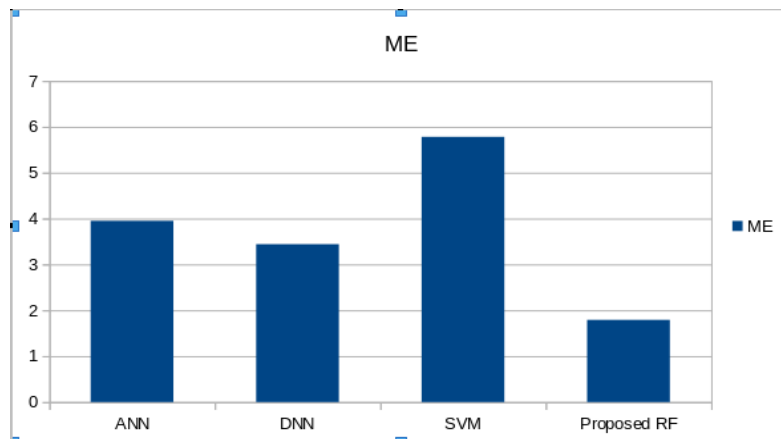


Figure 8. Mean error of the proposed random forest ESG prediction system

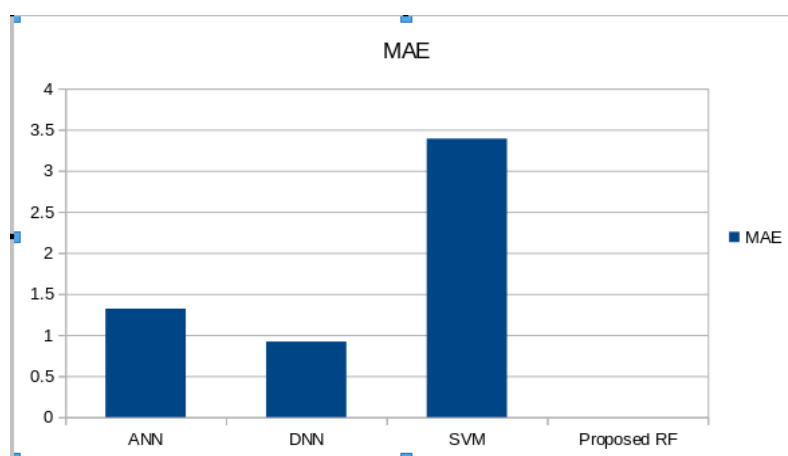


Figure 9. Mean Absolute Error of the proposed random forest ESG prediction system

It may be inferred from this experiment that financial-related factors can be used to predict ESG ratings. Businesses of all sizes might benefit from this information. As ESG's relevance grows, even small organisations should be aware of their ESG-related metrics. When comparing ESG scores from this experiment, organisations should be aware that the estimated scores are relative values, not absolute values. Hyper-parameter tunings are not used; all algorithms are run with their default parameters.

5. Conclusion

Sustainability reports and subjective evaluations are used to calculate ESG scores, which are based on a company's freely supplied information. Ratings provided by various suppliers might vary significantly, and owing to proprietary methods, reconciliation is almost always impossible. The process of generating ratings takes a long time due to the labor-intensive nature of the system. In addition, it is fairly uncommon for smaller businesses to fail to provide sustainability reports. As a result, the pool of potential investment candidates is narrowed. Using publicly accessible data instead of sustainability reporting, this study provided a solution to the problems outlined above. Training heterogeneous ensemble models utilising neural networks and random forests was used to do this. The input comprised of core data, such as information on the industry, location, and financial performance of the organisation. Using a Random Forest model, we were able to explain 54% of the total ESG score variation, with a mean absolute error of 0.36 percentage points. The pillar scores (E, S, and G) and particular measures like Human Rights have a high explainability level. Compared to the baselines and earlier work we discovered for the issue, our outcomes were superior.

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