The Role of Artificial Intelligence in ESG Ranking Evaluation

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Abstract

Environmental, Social, and Governance (ESG) criteria have become fundamental for evaluating the sustainability and ethical impact of companies. However, the assessment of company adherence to ESG guidelines varies significantly due to multiple influencing factors, making reliable and consistent evaluation a considerable challenge. This paper provides an overview of ESG criteria and rating frameworks, followed by an exploration of Machine Learning (ML) and Artificial Intelligence (AI) techniques applied to the objective evaluation of ESG ratings. Specifically, the study examines how ML and AI can enhance the quantitative assessment of ESG performance by optimizing key aspects such as data processing, ESG scoring, real-time monitoring, transparency, and accountability. The analysis highlights the potential of AI and ML in making ESG evaluations more objective, data-driven, and aligned with global sustainability goals.

Keywords

ESG assessment, Machine Learning, Sustainability

1. Introduction

Environmental, Social, and Governance (ESG) criteria have become essential for evaluating a company's sustainability and ethical impact. Investors, regulators, and stakeholders increasingly rely on ESG metrics to assess corporate responsibility and long-term financial performance. A strong ESG profile is associated with reduced financial risks, enhanced brand reputation, and improved compliance with global sustainability regulations. As a result, ESG considerations have gained prominence in corporate decision-making and investment strategies.

Despite its increasing importance, ESG assessment remains a complex and evolving challenge. Unlike traditional financial metrics, ESG factors are often qualitative, non-standardized, and difficult to quantify. Existing ESG rating frameworks exhibit significant inconsistencies due to variations in methodologies, data sources, and weighting schemes. These discrepancies hinder comparability across organizations and industries, underscoring the need for more objective, data-driven approaches to ESG evaluation.

In this context, Artificial Intelligence (AI) and Machine Learning (ML) offer promising solutions to enhance ESG measurement. AI-driven analytics can process vast amounts of structured and unstructured data, improving the extraction and standardization of ESG-related information from corporate reports, regulatory filings, and news articles. Sentiment analysis techniques can assess public perception of companies by analyzing media coverage and social network discussions, while predictive modeling enables risk assessment and scenario analysis, facilitating proactive decision-making. Furthermore, natural language processing (NLP) and deep learning (DL) techniques enable real-time monitoring of ESG compliance, ensuring that assessments remain dynamic and reflective of emerging risks and trends.

By leveraging these capabilities, ML models can mitigate the subjectivity inherent in ESG assessments by identifying patterns and relationships across diverse data sources. This enhances the accuracy, consistency, and reliability of ESG rankings, making them more transparent and actionable for investors and policymakers.

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This paper explores how AI and ML can optimize ESG ranking methodologies and address key challenges in traditional ESG scoring, section 2 provides an overview of ESG dimensions and the challenges associated with ESG measurement, section 3 examines the application of ML and AI to ESG assessment, highlighting key techniques and methodologies. section 4 discusses optimization strategies for ESG measurement using AI and ML, with related challenges discussed in section 5. Finally, in section 6 and section 7 we discuss some conclusions and future directions.

2. ESG overview

In this section, we provide an overview of ESG and its dimensions. Following that, we present the existing frameworks and metrics used in ESG evaluation, and then discuss the challenges associated with their standardization.

2.1. ESG dimensions and metrics

In 2005, the development of global guidelines and recommendations on how to integrate sustainability into finance gave rise to Environmental (E), Social (S) and Governance (G), (ESG) guidelines [1]. ESG is a standard or principle utilized as a guideline by investors that intend to evaluate a corporate behavior along with future financial performance [1].

The principle behind ESG is that there are a number of issues related to the use of various forms of resources, ranging from resource management, supply chain management, organizational health and safety policies to the environment [2], that can have a positive or negative impact on society [3]. Consequently, these issues can have a direct or indirect impact on the financial viability and transparency of industries and governments [4].

More specifically, the ESG principles represent a value-based investment philosophy, that pursues value growth by utilizing a long-term orientation. These principles led to the development of a range of evaluation frameworks and metrics that are employed both by organizations and investors to assess the achievement of ESG goals.

According to the Principles for Responsible Investment (PRI), responsible investment is the employment of ESG factors in investment decisions and active ownership as part of a broader strategy and practice [5].

This principle is founded on three fundamental factors that assess the sustainability and social impact of business activities. Consequently, they serve as essential considerations in investment analysis and decision-making processes.

The ESG consists of individual elements, which need to be deeply detailed [6]:

- The **environmental** criteria (E) evaluates the energy consumption of a company, the waste it generates, the resources it utilizes, and the overall impact on living organisms. It also encompasses carbon emissions and climate change. Since every company relies on energy and resources, it inevitably influences and is influenced by the environment.
- The **social** criteria (S), focuses on the relationships of a company, and reputation within the communities where it operates. It includes aspects such as labor relations, diversity, and inclusion. As every company functions within a broader and diverse societal framework, maintaining positive stakeholder relationships is crucial.
- The **governance** criteria (G) pertains to the internal structures, policies, and processes that a company implements to govern itself. It ensures compliance with regulations, facilitates effective decision-making, and addresses the expectations of external stakeholders. Given that companies are legal entities, strong governance is essential for their sustainability and ethical operations.

The aforementioned ESG dimensions include both qualitative and quantitative aspects to evaluate. Therefore, these dimensions impact directly on the realization of ESG frameworks.

2.2. Challenges in ESG Measurement

As stated in the previous section, the assessment of ESG ranking is characterized by significant variability. This can be attributed to both the multitude of criteria involved in its evaluation and to the variety of the dimensions involved in its measurement, which are both qualitative and quantitative. These difficulties have led to the emergence of multiple ESG assessment frameworks. In fact, the absolute index for ESG has not yet been established [7], and evaluation criteria differ within the agencies [8, 9]. Nevertheless, to gather and standardize social and governance data remains a challenge due to many qualitative factors.

In fact, the standards utilized as guidelines both for ESG reporting and evaluation are several. The most widely utilized include [10]:

- Global Reporting Initiative (GRI)
- Sustainability Accounting Standards Board (SASB)
- Task Force on Climate-related Financial Disclosures (TCFD)

Several reporting standards, such as the GRI, the SASB, and the Task Force on Climate-related Financial Disclosures (TCFD), adopt distinct perspectives and methodologies for collecting, analyzing, and presenting ESG data. These differences can lead to variations in how companies disclose their sustainability performance, making it challenging to establish uniform benchmarks for comparison across organizations and industries. One of the primary aspects is **framework variability**.

This lack of unified standards (GRI vs SASB vs MSCI, etc.) represents a first challenge in the evaluation of ESG.

Another critical factor pertains to the industries under analysis. The importance of ESG metrics varies significantly across different sectors [11], revealing the **sector-specific** differences in ESG evaluations. For instance, carbon emission reduction is a priority for companies in the energy sector, where greenhouse gas emissions are a major concern. Conversely, financial institutions may focus more on governance-related factors, such as risk management and ethical investment practices. Similarly, water consumption is a crucial sustainability factor for industries like manufacturing and agriculture, but it is less relevant for technology firms. These sector-specific variations underscore the need for tailored ESG assessment models that address the unique challenges and priorities of each industry.

Lastly, varying **priorities** among different stakeholders further contribute to the variability in ESG evaluations. Investors, corporations, and regulators may assign differing levels of importance to environmental, social, and governance factors based on their strategic objectives and regulatory obligations [12]. For instance, some investors may prioritize environmental sustainability and carbon neutrality, while others may place greater emphasis on social responsibility, such as diversity, equity, and inclusion (DEI) initiatives. Regulators, in turn, may focus more on ensuring compliance with legal frameworks and corporate governance standards. These divergent perspectives can lead to discrepancies in ESG evaluations, influencing decision-making processes and ultimately shaping the integration of sustainability into corporate strategies and investment decisions.

3. Machine Learning and AI for ESG Calculation

In this section, we review the existing research on the application of machine learning (ML) and artificial intelligence (AI) techniques for the objective prediction of Environmental, Social, and Governance (ESG) scores. Previous studies have explored different ML-based approaches to improve ESG assessment, leveraging financial and non-financial data.

Early research efforts primarily focused on applying traditional ML algorithms to ESG prediction. In [13], the authors examined six different ML classifiers on ESG data spanning from 2005 to 2019. Their findings indicate that the Random Forest classifier outperforms other models across multiple metrics, achieving an accuracy of 78.50%. Similarly, in [14], the authors conducted five experiments addressing different challenges in ESG scoring. One of these experiments demonstrated that ESG scores could be inferred from financial variables by applying six distinct ML algorithms.

Building on these approaches, subsequent studies have incorporated more sophisticated AI methodologies. The work in [15] explores a broader range of ML models, including Random Forest, Decision Tree, Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), Naïve Bayes, Support Vector Machines (SVM) with linear and radial basis function (RBF) kernels, and polynomial regression. Their study highlights the potential of these algorithms to predict ESG scores based on Firm Financial Performance (FFP) metrics.

More recently, advancements in natural language processing (NLP) and reinforcement learning have been integrated into ESG prediction frameworks. In [16], the authors employ Named Entity Recognition (NER) to extract ESG-related information from corporate reports and apply Reinforcement Learning techniques to refine ESG scoring methodologies.

These studies collectively illustrate the evolution of ML and AI techniques in ESG prediction, from early classification models based on structured financial data to more advanced approaches incorporating textual analysis and reinforcement learning.

4. Addressing ESG measurement with AI and ML

As previously stated in subsection 2.2, traditional ESG assessment methods face several limitations, which can be translated into technical aspects where AI and ML can play a significant role.

In fact, as differences arise from several frameworks, sector-specific necessities, and different priorities, also arises the need to integrate diverse and often incompatible data sources. Therefore, one of the main technical challenges is the **heterogeneity of ESG data sources**. This heterogeneity makes it difficult to establish consistent and comparable ESG indicators across different entities and frameworks. In addition, currently methods are only based on historical data, which makes it difficult to monitor the activities of the involved company in real-time. Therefore, AI and ML can offer support by working on both **real-time and historical data**. Finally, the application of AI on real-time data, can help in identifying **anomalies and detect risks**.

Therefore, the integration of AI and ML techniques holds strong potential for enabling a more objective, scalable, and data-driven ESG evaluation.

4.1. Integration of Heterogeneous Data

The integration of heterogeneous data sources required for ESG measurement involves combining data of various types and from diverse environments, including:

- **Financial reports and corporate disclosures**, which provide structured information on company performance and ESG-related initiatives [17];
- **News articles, social media, and public sentiment**, which offer unstructured yet valuable insights into a company's social and environmental impact perception [18];
- **Environmental sensor data and satellite imagery**, enabling real-time monitoring of environmental indicators such as emissions or land use [19];
- **Regulatory filings and compliance reports**, which contain mandatory disclosures and help assess adherence to ESG-related regulations [20]

AI-powered NLP techniques, such as NER and sentiment analysis, can extract relevant ESG insights from unstructured textual data [21, 22]. Additionally, ML models can integrate structured and unstructured data sources, generating comprehensive ESG profiles that facilitate objective assessments and reduce discrepancies across reporting frameworks. For instance, the claim of reduced emissions and the annual report of a company, can be cross-validated with satellite imagery and public sentiment extracted from news sources.

4.2. Supervised and Unsupervised Learning for ESG Scoring

ML techniques can enhance ESG scoring by leveraging both historical data and real-time inputs:

- **Supervised Learning**: Regression models (e.g., Random Forest, XGBoost) and deep neural networks can estimate ESG scores based on historical performance, financial indicators, and external ESG factors [23, 24].
- **Unsupervised Learning**: Clustering methods (e.g., K-Means, DBSCAN) can identify patterns and group companies with similar ESG performance, reducing inconsistencies in manual classifications [14, 25].

By applying these models, ESG ratings can become more consistent, data-driven, and less dependent on subjective expert assessments. For example, supervised models can predict a ESG score using historical data, while clustering can group firms with similar sustainability profiles despite differing reporting styles.

4.3. Real-time ESG Monitoring and Anomaly Detection

AI-driven ESG monitoring systems can continuously track real-time data sources to detect sustainability-related risks and anomalies:

- **Anomaly detection techniques** (e.g., autoencoders) can identify discrepancies in ESG reporting, flagging inconsistencies or manipulations in corporate disclosures [14].
- **Time series forecasting models** can predict ESG trends, enabling proactive risk mitigation and corporate governance adjustments [26].

Unlike traditional ESG assessments, which often rely on periodic disclosures, AI-based monitoring ensures that ESG ratings reflect real-time market conditions and emerging risks [27]. For instance, an AI system can flag sudden drops in emission transparency using anomaly detection, while forecasting models anticipate future ESG risks from ongoing trends.

5. Challenges of AI in ESG: Transparency and Accountability

While AI and ML models provide significant advantages, they also introduce challenges related to interpretability and potential bias. Ensuring transparency in AI-driven ESG models is crucial for regulatory compliance and stakeholder trust. Key approaches to address these concerns include:

- **Explainability techniques**: SHAP (Shapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations) provide interpretable justifications for ESG scores, improving trust in AI-based evaluations [28].
- **Bias mitigation**: Ethical AI frameworks and fairness-aware ML techniques help ensure ESG scores are free from systemic biases related to industry, geography, or corporate size [29].

Integrating these mechanisms into ESG evaluation frameworks ensures that AI-generated scores remain interpretable, fair, and aligned with regulatory requirements.

6. Discussion

While AI and ML significantly improve ESG evaluation methodologies, several challenges remain:

- **Data Availability and Standardization**: ESG data remains inconsistent across industries and regulatory environments, requiring efforts to establish unified reporting standards.
- **Regulatory Compliance**: AI-driven ESG models must adapt to evolving global regulations, ensuring compliance with disclosure frameworks such as the GRI [30] and SASB [31].
- **Computational Efficiency**: Balancing model complexity and computational cost is critical for scalable, real-time ESG ratings.

Future research should focus on refining AI-driven ESG methodologies by integrating domain-specific knowledge, improving model interpretability, and developing standardized AI-based ESG frameworks.

7. Conclusions

In recent years, assessing ESG performance has become increasingly relevant for companies, investors, and regulatory bodies. The growing emphasis on sustainability has led organizations to integrate ESG criteria into decision-making processes. However, measuring these factors remains methodologically and operationally challenging. ESG evaluations often suffer from a lack of standardization, as different rating agencies apply distinct methodologies, leading to inconsistencies in reported scores. Additionally, the mix of quantitative and qualitative metrics introduces subjectivity, making it difficult to ensure transparency and comparability across assessments.

The application of AI and ML has emerged as a promising solution to enhance ESG evaluations by reducing subjectivity, improving data processing efficiency, and enabling predictive modeling. AI-based approaches have been explored for tasks such as extracting sustainability-related information from unstructured text data and predicting ESG scores using financial performance indicators. However, despite these advancements, AI applications in ESG analysis are still at an early stage and lack a unified framework. Existing studies focus on different aspects of ESG evaluation, often addressing specific challenges rather than providing a comprehensive approach.

To fully realize the potential of AI-driven ESG assessments, several key challenges must be addressed. Ensuring the interpretability and transparency of AI models is essential to maintain trust in ESG ratings. Moreover, bias in historical data must be carefully managed to prevent AI models from reinforcing existing inconsistencies. Additionally, AI-based assessments should align with evolving regulatory requirements to ensure their credibility in investment and corporate governance contexts.

Future research should prioritize the development of more standardized ESG evaluation frameworks, the improvement of data quality and accessibility, and the integration of hybrid approaches that combine AI capabilities with expert knowledge. Only through a comprehensive and interdisciplinary perspective can AI-driven ESG ratings become reliable, transparent, and widely adopted tools, supporting more informed decision-making processes and sustainable business practices.

Declaration on Generative AI

The authors have not employed any Generative AI tools.

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