AI driven Investment Insights Using ESG Prediction Models

Mrs. Sujata Khedkar#1,Ketaki Dhananjay Nalawade#2, Tasmiya Sarfaraz Khan#3,

Purtee Santosh Mahajan#4, Srushti Satish Sambare#5

#Computer Engineering Department,Vivekanand Education Society's Institute of Technology, Chembur, Mumbai - 400071, India

[1]sujata.khedkar@ves.ac.in

[2]2021.ketaki.nalawade@ves.ac.in

[3]2021.tasmiya.khan@ves.ac.in

[4]2021.purtee.mahajan@ves.ac.in

[5]2021.srushti.sambare@ves.ac.in

***Abstract*— In order to develop a tried-and-true investment strategy that takes advantage of the correlation between environmental, social, and governance (ESG) factors and financial success, this study looks at the statistical influence of ESG concerns on economic investment. As mandated reporting requirements are implemented and investors take sustainability into account when making investment choices, there is an increasing demand for transparent and reliable ESG ratings. The goal of this paper is to examine several approaches that may be applied to forecast the ESG ratings of businesses.**

Keywords— ESG factors , financial performance , ESG ratings.

I . Introduction

Environmental, social, and governance, or ESG, compliance is a relatively new field of study that has grown in prominence recently due to the importance of these issues in the worldwide discourse[3]Businesses, investors, governments, and society at large all care about ESG and related topics, and they are increasingly prioritizing ESG compliance when entering into agreements[1].Consequently, as national policies and investor interest in ESG investments take corporate ESG factors into account, the size of the investments is also growing quickly, and each company's expectations and interest in ESG management are rising sharply. However, there is a dearth of data-driven analysis and discussion of ESG trends[5].

II . Motivation

Predicting ESG ratings entirely automatically using natural language processing (NLP) algorithms, without the need for human judgement, could save costs for businesses and, most importantly, be accessible to small and medium-sized businesses. Additionally, automatic methods ought to guarantee that the ratings are clear and perhaps reconstructable by any stakeholder[1].ESG standards are used by most socially conscious investors to evaluate investments.Investors frequently use the term "environmental, social, and governance" (ESG) to evaluate corporate policies and forecast future financial performance[4].

III. Literature review

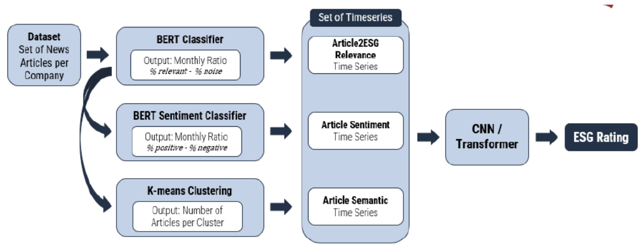
[1] **Model inputs:**

Text Classification: News articles were categorized as either ESG-relevant or irrelevant using BERT-based algorithms. A weak-supervision strategy was utilized to classify a portion of data using semantic similarity between articles and ESG category definitions.

Sentiment Analysis: SieBERT was used to forecast the sentiment of ESG-related publications, resulting in a sentiment time series for each firm. The sentiment ratios for good and negative news were calculated monthly.

Semantic analysis involved grouping the articles by content using DistilBERT embeddings and a k-means clustering technique. Six clusters were found, with each depicted as a time series that tracked dominating subjects for each organization.

Figure 1: Overview ESG Prediction Model



ESG Rating Prediction Models : Several deep learning models were used to forecast ESG scores based on the generated time series. Four models were assessed: basic CNN (convolutional neural network) , Deep CNN , CNN with single or many Transformer layers.

The models saw the task as either a classification or regression issue, with the input being a 9x12 matrix comprising nine categories of monthly time series data for each organization. The appendix included model hyperparameters, optimisers, and settings, as well as early termination conditions to prevent overfitting.

[2] Four testable hypotheses or notions are formulated to address the research question: (1) HPS1: Firms with lower ESG risk ratings tend to have lower returns on investment;

(2) HPS2: The risk associated with stocks tends to increase in tandem with ESG risk level; (3) HPS3: Firms with lower ESG Risk achieve higher returns than those with higher ESG Risk; and (4) HPS4: Invest stocks with low ESG risk and short stocks with high ESG risk to achieve extraordinary returns.

The following are the steps to test Hypotheses HPS1 and HPS2:
✓ Load two .csv datasets (S&P500, ESG data).
✓ Calculate the Expected Returns E[r] and the total risk for all stocks.
✓ Merge the data frame with the E[r], total risk, and ESG data. The merged data frame is shown in Table 2.
✓ Graph the Expected Returns and ESG Risk.
✓ Graph Expected Returns and Total Risk.
✓ Graph Total Risk and ESG Risk.
✓ Investigate correlations across all variables.
✓ Remove all rows with missing ESG Risk observations.
✓ Find the Correlation between E[r] and ESG Risk using: “np.corrcoef(df_master[‘Expected Return’], df_master[‘ESG Risk Score’])”

The process of estimating the returns of an ESG portfolio involves the following steps:
✓ Import pandas and load the ESG.csv file.
✓ Handling of missing observations.
✓ Sort the ESG Firms into quintile buckets (‘Q1,’ ‘Q2,’ ‘Q3,’ ‘Q4,’ ‘Q5’) using the qcut method available in the Pandas library.
“df_esg[‘Quintile ESG Rank’] = df_esg[‘ESG Risk Score’].transform(lambda x: pd.qcut(x, 5, labels = quintile_rank_labels))”
✓ Merge S&P 500 Returns and ESG risk data frames.
“df_returns_esg = df_returns.merge(df_esg, left_on =‘Ticker’, right_on =‘Symbol’)”
✓ We find the average return for every stock belonging to a particular portfolio based on its ESG rank. Estimate the return on equally weighted ESG portfolios by calculating the average return, grouped by date and ESG Rank “quintile_returns = df_returns_esg.groupby([‘Date’, ‘Quintile ESG Rank’])[‘Returns’].mean()”.
✓ We drop the missing observations in the quintile_ returns data frame. The daily quintile-returns data frame displays the average returns of ESG-risk firms, which are sorted into buckets by quintile
Calculate the average E[r] across quintile ESG Portfolios using “quintile_returns.mean()”.

[3] **Data Collection:** The study makes use of the Sustainalytics ESG Risk Rating emphasis Database, which contains ESG ratings for 5,012 organizations across 11 sectors, with an emphasis on financial institutions. **Textual and Empirical Analysis:**Topic Modelling (LDA) is a machine learning approach used to extract latent themes from analysts' textual comments on ESG ratings. The model found 13 key topics related to ESG performance across industries. **Sentiment Analysis:** Natural Language Processing (NLP) was used to identify positive or negative attitudes in analyst remarks and relate them to particular ESG problems.**Sector Focus:** The research looked at sector-specific ESG matters, with a particular emphasis on governance difficulties for financial institutions and environmental concerns for sectors such as energy and utilities. **Comparison of Best and Worst Performers:** Financial firms were classified as "Best" or "Worst" based on ESG ratings, and their relevant themes and attitudes were examined.

[4] **Data Collection :** ESG ratings for India's top 500 firms were gathered from the MSCI (Morgan Stanley Capital International) and Refinitiv platforms. Financial measures such as ROA (Return on Assets) and ROE (Return on Equity) were also acquired using the Trendlyne platform. **Machine learning models include:** Several machine learning approaches, including Regression, were used to investigate the link between ESG disclosure and company performance. Random Forest, Support Vector Regression, K-Nearest Neighbour, and Neural Networks were the models utilized in the study.**Measuring performance :**

The study focused on two financial measures (ROA and ROE) to assess business performance and how ESG ratings affected these ratios. **Analysis:**The study employed statistical approaches to investigate how ESG disclosures affected financial results and sustainable investments, with the goal of determining the impact of ESG transparency on decision-making and corporate performance.

[5] **Data collection:** Between May 2006 and December 2021, 16 media outlets provided ESG-related news stories. Following filtering, 7,049 articles were examined.
Period Division: The data was separated into three periods. ESG was first introduced between 2006 and 2018.
2019-2020: ESG disclosure regulations become more widespread and are adopted by large institutions.
2021: Increased ESG implementation following COVID-19.
Topic Modeling: The Latent Dirichlet Allocation (LDA) technique was used to determine major ESG topics and trends for each era.

[6] **Data collection:** It makes use of the 850,000 ESG-related stories in the Dow Jones News dataset.**Text parsing:** Stanford CoreNLP is used to process the text in order to extract entities (such as individuals or organizations) and the connections between them.Creating a **Knowledge Graph:**Relationship and Entity Extraction:

Verbs and nouns are recognised to create triples (subject-predicate-object).Refinement involves the use of semantic tools such as WordNet and sentence transformers to integrate related items and relationships.**Evaluation:** The method's accuracy in identifying legitimate relationships in news items was 85%.**ESG Analysis:** The knowledge graph that resulted (7.2 million statements, 4 million entities) showed patterns in the discourse surrounding ESG, including increasing attention to corporate governance, gender identity, and climate change over time.

[11] **Framework:** ESGReveal comprises three components. The ESG Metadata Module establishes ESG standards, criteria, and indications for data extraction. The Report Preprocessing Module structures ESG reports by removing text and table data and prepares them for analysis. The LLM Agent Module retrieves and extracts particular ESG data based on metadata and structured reports.ESG reports are analyzed to form a knowledge base. LLMs then retrieve and extract pertinent data using prompts generated by the ESG metadata. **Application:** ESGReveal was tested on ESG reports from 166 Hong Kong Stock Exchange businesses, and several LLMs (including GPT-4) were evaluated for data extraction accuracy. **Results:** GPT-4 was the most accurate, with 76.9% for data extraction and 83.7% for disclosure analysis. The study also discovered inconsistencies in company ESG disclosures, notably in environmental and social reports.

[12] Data gathered from 348 Indonesian non-financial enterprises (2021-2022).The variables include idiosyncratic risk, financial report quality (earnings management), ESG disclosure (GRI standards), risk disclosure (COSO ERM), and audit quality.**Analysis:** Structural Equation Modeling (SEM) was used to analyze correlations and the moderating influence of audit quality. **Findings:** ESG disclosure and audit quality decreased idiosyncratic risk, although financial report quality and risk disclosure had no significant effect. The influence of the other factors on risk was not enhanced by audit quality.

[13] Data collection makes use of Refinitiv's ESG ratings and basic data. The Heterogeneous Ensemble Model enhances prediction accuracy by combining machine learning methods such as XGBoost, CatBoost, and feedforward neural networks. Feature Selection extracts pertinent financial indicators from the core information. The model is trained using past data and tested using data that hasn't been seen before.By offering a more unbiased, data-driven method, it seeks to address the shortcomings of conventional ESG ratings.Model performance is evaluated using a variety of metrics.

[15] **Data collection:** phrases classified as irrelevant, quasi-related, or pertinent to ESG subjects are gathered from Corporate Sustainability Reports (CSRs).**Model training:** Using this dataset, a Transformer-based model (such as BERT) is refined to categorize phrases according to their applicability to ESG considerations.**Transfer Learning:** To illustrate the model's capacity for generalization, the trained model is applied to earnings call transcripts in order to identify ESG conversations without the need for additional training.**Evaluation:** BERT obtained the highest score (78.3%) when the model's performance was assessed using F1-scores.

[16] **Data Collection:** Three thousand headlines from The New York Times, Reuters, and The Independent were collected.**Annotation:** Participants categorized headlines and determined the importance of ESG factors; inter-annotator agreement was evaluated for consistency.**Sentiment Analysis:** A variety of ML and DL techniques were used to categorize headlines as neither positive nor negative.**Training the Model:** Random Under-Sampling was employed to correct class imbalance in an annotated dataset.
Based on weighted sentiment ratings, the ESG-Miner tool computed scores for the three ESG domains.**Evaluation:** The accuracy of the tool was assessed by contrasting its performance with manual annotations.**Validity Considerations:** Subjective annotations, sample size, and other possible threats to validity were examined.

IV. References

[1] Tanja Aue, Adam Jatowt, Michael Färber Predicting Companies' ESG Ratings from News Articles Using Multivariate Time Series Analysis arXiv:2212.11765 [q-fin.GN] https://doi.org/10.48550/arXiv.2212.11765

[2] K. R. Teja and C. -M. Liu, "ESG Investing: A Statistically Valid Approach to Data-Driven Decision Making and the Impact of ESG Factors on Stock Returns and Risk," in IEEE Access, vol. 12, pp. 69434-69444, 2024, doi: 10.1109/ACCESS.2024.3401873.

[3] Marco Mandas, Oumaima Lahmar, Luca Piras, Riccardo De Lisa,ESG in the financial industry: What matters for rating analysts?,Research in International Business and Finance, Volume 66,2023,102045,ISSN 0275-5319, https://doi.org/10.1016/j.ribaf.2023.102045.

[4] E. Twinamatsiko and D. Kumar, "Incorporating ESG in Decision Making for Responsible and Sustainable Investments using Machine Learning," 2022 International Conference on Electronics and Renewable Systems (ICEARS), Tuticorin, India, 2022, pp. 1328-1334, doi: 10.1109/ICEARS53579.2022.9752343.

[5] H. Seo, D. H. Jo and Z. Pan, "Big Data Analysis of 'ESG' News Using Topic Modeling," 2022 IEEE/ACIS 7th International Conference on Big Data, Cloud Computing, and Data Science (BCD), Danang, Vietnam, 2022, pp. 183-187, doi: 10.1109/BCD54882.2022.9900604.

[6] S. Angioni, S. Consoli, D. Dessì, F. Osborne, D. Reforgiato Recupero and A. Salatino, "Exploring Environmental, Social, and Governance (ESG) Discourse in News: An AI-Powered Investigation Through Knowledge Graph Analysis," in IEEE Access, vol. 12, pp. 77269-77283, 2024, doi: 10.1109/ACCESS.2024.3407188.

[7] Jaeyoung Lee, Misuk Kim, ESG information extraction with cross-sectoral and multi-source adaptation based on domain-tuned language models, Expert Systems with Applications, Volume 221,2023,119726,ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2023.119726.

[8] Shen, H. Assessment of financial risk pre-alarm mechanism based on financial ecosystem using BPNN and genetic algorithm. Soft Comput 27, 19265–19279 (2023). https://doi.org/10.1007/s00500-023-09317-z

[9] T. R. Teor, I. A. Ilyina and V. V. Kulibanova, "The Influence of ESG-concept on the Reputation of High-technology Enterprises," 2022 Communication Strategies in Digital Society Seminar (ComSDS), Saint Petersburg, Russian Federation, 2022, pp. 184-189, doi: 10.1109/ComSDS55328.2022.9769074.

[10] Gunnar Friede, Timo Busch & Alexander Bassen (2015) ESG and financial performance: aggregated evidence from more than 2000 empirical studies, Journal of Sustainable Finance & Investment, 5:4, 210-233, DOI: 10.1080/20430795.2015.1118917

[11] Yi Zou, Mengying Shi, Zhongjie Chen, Zhu Deng, ZongXiong Lei, Zihan Zeng, Shiming Yang, HongXiang Tong, Lei Xiao, Wenwen Zhou ESGReveal: An LLM-based approach for extracting structured data from ESG reports https://arxiv.org/abs/2312.17264 [cs.CL]

[12] Arfiansyah, Z., Murwaningsari, E., & Mayangsari, S. (2024). Financial Report Quality, ESG Disclosure, Risk Disclosure, Audit Quality, and Idiosyncratic Risk: Evidence from Indonesian Companies. Journal of Risk and Auditing, 6(1), 4839-4858.

[13] Krappel, M., Bogun, M., & Borth, D. (2021). Predicting ESG Ratings Using a Heterogeneous Ensemble Model. In KDD-MLF ’21, August 14–18, 2021, Singapore.

[14] Sokolov, Alik & Mostovoy, Jonathan & Ding, Jack & Seco, Luis. (2021). Building Machine Learning Systems for Automated ESG Scoring. The Journal of Impact and ESG Investing. 1. 39-50. 10.3905/jesg.2021.1.010.

[15] Raman, Natraj & Bang, Grace & Nourbakhsh, Armineh. (2020). Mapping ESG Trends by Distant Supervision of Neural Language Models. Machine Learning and Knowledge Extraction. 2. 453-468. 10.3390/make2040025.

[16] Jannik Fischbach, Max Adam, Victor Dzhagatspanyan, Daniel Mendez, Julian Frattini, Oleksandr Kosenkov, Parisa Elahidoost Automatic (2024).ESG Assessment of Companies by Mining and Evaluating Media Coverage Data: NLP Approach and Tool https://arxiv.org/abs/2212.06540 [cs.IR]