An Intelligent Framework for Environmental Impact Assessment Using Artificial Intelligence

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ABSTRACT

The restoration of terrestrial ecosystems promotes sustainable land resource development and aids in the preservation of the natural world. For increasingly severe land degradation, contemporary and effective strategies for the preservation of ecological purposes must be developed The proposed framework integrates Natural Language Processing (NLP) and Machine Learning (ML) techniques to analyze environmental data obtained from Environmental Product Declarations (EPDs) and Life Cycle Assessment (LCA) reports. NLP is employed to extract and process relevant environmental information, while a Random Forest algorithm is utilized to develop predictive models for environmental impact assessment. The framework is trained using product-specific data and seven environmental impact categories and subsequently validated using an independent testing dataset. Our findings show that the model had an accuracy of 85%, 72%, 65%, and 71% in predicting the values of the following impact categories: global warming possibility, abiotic depleting potential for fossil fuels, acidity capacity, and the photochemical ozone generation potential. Our approach shows that by learning from the outcomes of the earlier LCA research, sustainability can be predicted with a defined variability. The quantity of data provided for training also affects the model's efficacy.

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1. INTRODUCTION

The methodical inspection, measurement, and assessment of the natural world and all of its constituent parts constitute the fundamental process of environmental surveillance. Its primary objective is to monitor the existing state of the environment and spot any changes that might be detrimental to the environment or public safety. Manual sampling, laboratory testing, and statistical evaluation are examples of conventional environmental surveillance methods [1]. Unfortunately, these methods have drawbacks such expensive expenses, drawn-out processes, and low precision.

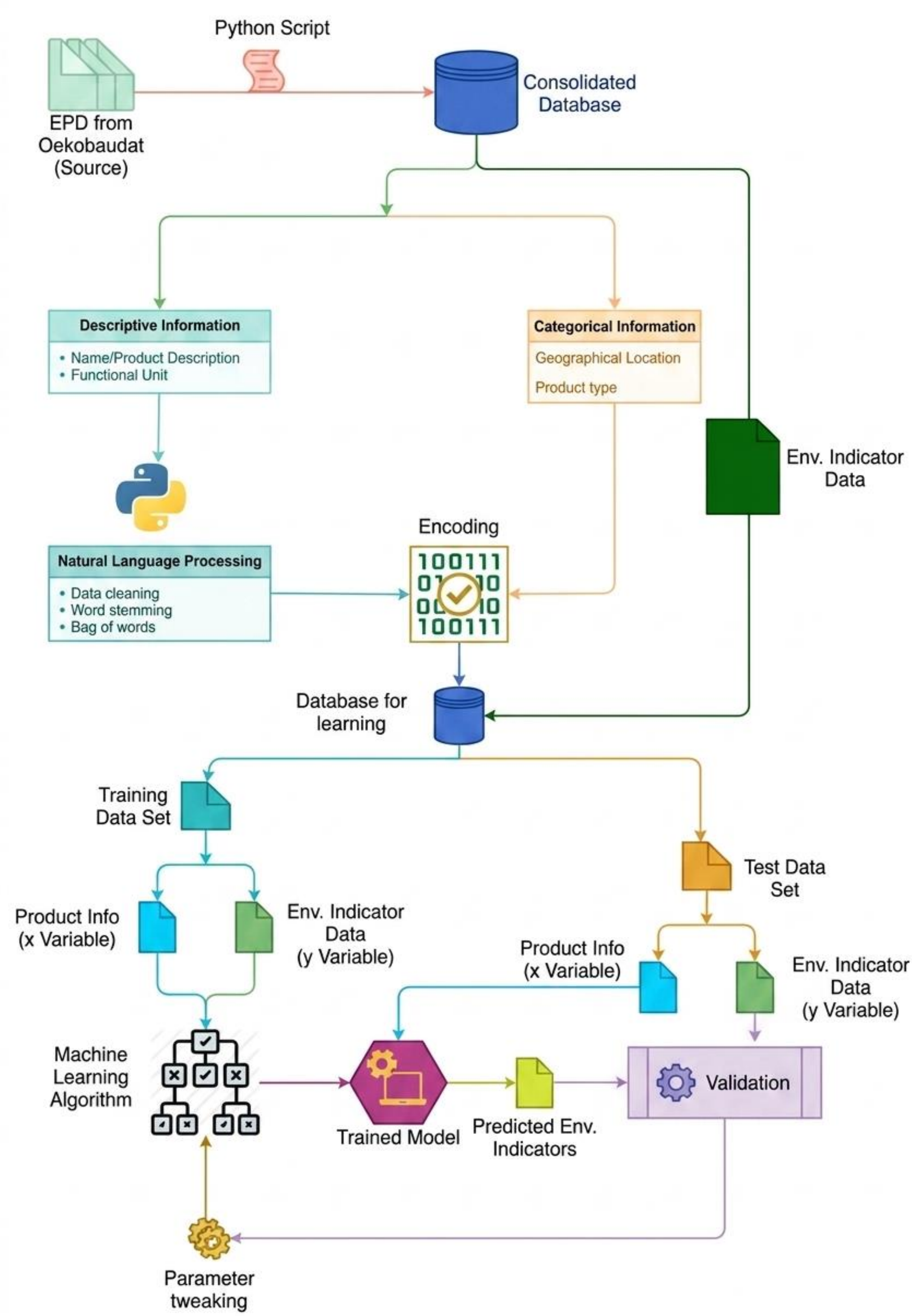


Figure 1. An Illustration of the Ensemble Technique's Flow

Along with the encoded data, the outcome of a green impact subcategory is also kept in the data base during the course of the life cycle impact evaluation. Figure 1 depicts the process. A number of problems limit the effectiveness of traditional environmental surveillance methods. One of the main challenges is the cost of using these techniques [2]. Manual sample and laboratory evaluation are expensive processes that require specialized personnel, tools, and chemicals. Because of this, environmental surveillance programs frequently have a limited scope, employ tiny sampling sizes, and fail to give an entire picture of the state of the ecosystem. Another major issue with old procedures is how time-consuming they are. Manual testing and laboratory testing might take weeks or even months to produce results, delaying decision-making and crisis management in the event of pollution emergencies or natural disasters. Furthermore [3], the accuracy of conventional environmental monitoring methods is limited by the subjectivity of human sight and the possibility of human mistake. Inconsistent data collection and processing may result from the human interpretation needed for sampling method and laboratory evaluation.

Accurate catastrophe forecasts [4], pollutant source identification, and thorough air and water quality surveillance are all made possible by the use of AI for ecological monitoring. An overview of the benefits of ecological surveillance, the difficulties with traditional approaches and possible AI-based solutions are given in this article. A number of noteworthy AI applications in ecological monitoring are emphasized, demonstrating their benefits to efficient environmental oversight. By making it possible to better comprehend, anticipate, and mitigate environmental dangers [5], AI technologies improve environmental tracking.

However, obstacles to achieving AI's full potential include issues with data availability, oversight, and security as well as a lack of trained AI specialists in the environmental sector. In areas where technology infrastructure is still emerging, these problems are more noticeable. In order to safeguard sensitive data, the study promotes proactive data governance initiatives by governments. Despite these obstacles [6], AI in environmental surveillance has a bright future. Developments in AI algorithms, data gathering methods, and processing capacity are anticipated to further increase the precision and effectiveness of polluted monitoring and management.

2. LITERATURE REVIEW

[7] Proposes an artificial intelligence-assisted intelligent planning framework for managing the terrestrial ecological system's ecological restoration. Balancing the supply and demand of ecosystem services and use AI to dynamically create Biological Retreat Configurations (BRCs) that aid in better understanding how urban expansion affects environmental processes. When combining commercial development with environmentally friendly conservation, these factors might serve as theoretical references. In order to effectively classify environmental resources using the Bayes network model, the BRC of the Changsha Zhuzhou Xiangtan (CZX) metro region was created. The ecological passage and ecological plan points were determined using the LCR model and the conventional circuit theory.

An overview of the benefits of ecological monitoring, the difficulties with traditional techniques and possible AI-based alternatives are given in this article [8]. A number of noteworthy AI applications in environmental surveillance are emphasized, demonstrating their benefits to efficient ecological management. By making it possible to better comprehend, anticipate, and mitigate environmental dangers, AI technologies improve environmental monitoring. However, obstacles to achieving AI's full potential include issues with data availability, oversight, and privacy as well as a lack of trained AI specialists in the environmental sector. In areas where technology infrastructure is still emerging, these problems are more noticeable. In order to safeguard sensitive data, the study promotes active data governance initiatives by authorities.

Although integrated assessment models (IAM) and AI agents have been used to partly automate LCAs in order to address these issues [9], the possibility for automating is not described in the literature studies that are now available. Despite the dependable outcomes given by the authors of multiple studies, we believe that AI tools and IAMs offer intriguing ways of automating all four stages of LCA with numerous opportunities for future research. However, uptake in the LCA industry beyond the proposed tool is modest. All four stages of LCA can benefit from automated LCA in terms of both resources and time effectiveness; however, there is not enough research to thoroughly evaluate the quality of automation LCA.

In order to assess the environmental advantages and ecological costs of AI technology, this study thoroughly examines current scientific literature and policy papers. The study evaluates the environmental effects of AI infrastructure, such as energy use, water use, waste electronic production, and critical mining operations [10], in addition to AI applications for ecological evaluation, predictive modeling, and operational improvement using a comparison analytical paradigm. The results show that by increasing forecasting accuracy, maximizing resource efficiency, and facilitating real-time ecosystem monitoring, AI greatly improves environmental choices. However, these benefits are offset by significant environmental costs brought on by resource-intensive equipment manufacturing, expanding e-waste waters, and energy-intensive data facilities. AI-driven environmental remedies may unintentionally increase ecological pressures, according to the study, which highlights a glaring sustainability contradiction.

The primary goal of this work is to provide a conceptual framework that will assist researchers in applying modern machine learning algorithms to optimizing under the sustainability standards of technical projects [11]. A Web of Science bibliographical search was conducted in order to create this theoretical framework. The writings have been examined and the conceptual structure has been implemented using the chosen documents and a hermeneutic process. The variables of the suggested theoretical structure and their connections are graphically represented by a pyramid form. ADAPTS is the abbreviation for the five dimensions that make up the conceptual structure. The following are included in the base: (1) the desired application; (2) the available information; (3) the methodology employed; and (4) the machinery training tool. (5) The essential Sensing is at the summit of the pyramid. To demonstrate its application, a research case is suggested.

3. METHODS AND MATERIALS

3.1 Source of Data: EPD

EPDs are frequently posted on websites that are subject to regulations established by stakeholders, including governments, trade associations, and non-governmental organizations. The public has access to EPD data derived from EN 15804: A1, which allows users to take into account the ecological impacts of buildings and construction materials. The EPDs are published in Germany by the Institut Bauen und Umwelt e.V. (IBU), a group of building material manufacturers. The Federal Ministry of the Environment Buildings and Community has given IBU permission to disseminate EPDs [12]. The ÖKOBAUDAT system is a standard database that provides online access to EPD data determined by EN 15804: A1. In a similar vein, European nations such as France have publicly accessible sector-specific database of EPDs known as INIES. The ÖKOBAUDAT database's building product EPD results were used in our study. Because they adhere to the EN 15804: A1 standard, all EPDs have harmonised information. Our study relies heavily on the usage of harmonized source data, and the EPDs in ÖKOBAUDAT can be downloaded as XML format.

3.2 AI's Impact on Biodiversity

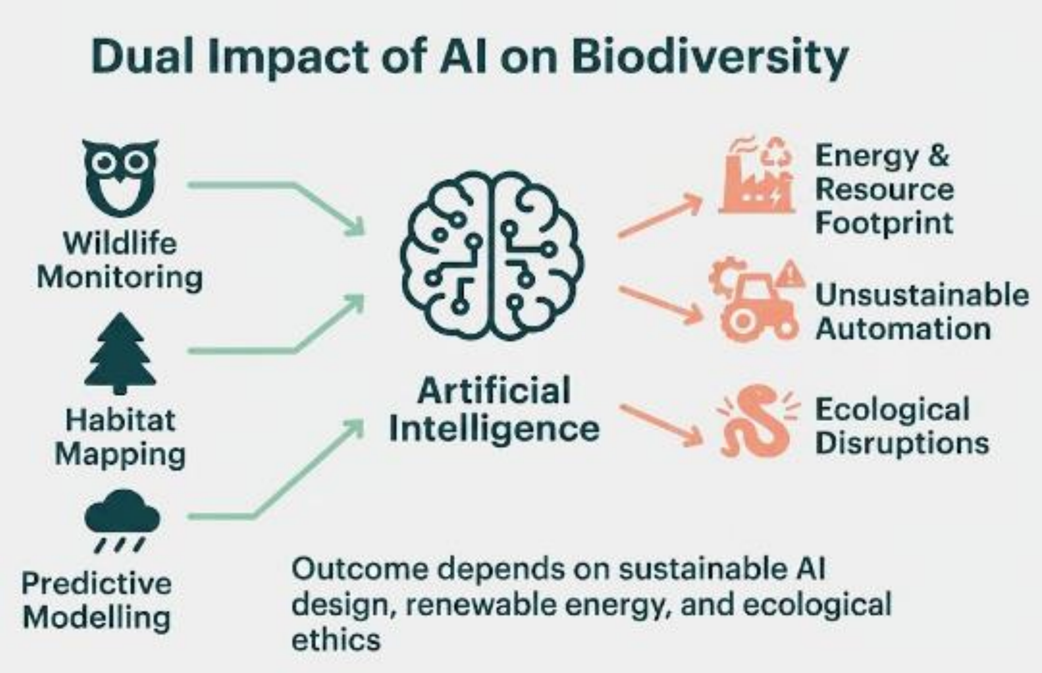


Figure 2. Architecture of the Proposed Artificial Intelligence Environmental Assessment System

By providing tools for monitoring and preservation, AI has the ability to greatly enhance biodiversity, but it also poses indirect hazards due to its effects on the surroundings [13]. Figure 2 shows how the Proposed Artificial Intelligence Environmental Assessment System.

3.3 Beneficial Effects

- Wildlife monitoring: AI-driven drones, video traps, and acoustic can track population patterns, automatically detect species, and flag illicit activities like cutting and hunting. This makes conservation efforts quicker and more precise.
- Ecosystem Monitoring and conservation: AI can analyze environment data and satellite images to detect important habitats, track forest loss, and identify habitat loss, assisting organizations and governments in putting specific conservation measures into place.
- Predictive modeling: AI systems can forecast how pollutants, climate change, and alterations in land use will affect environments, directing conservation efforts and reducing the extinction of animals.
- Sustainable Resources Control [14]: By lowering human pressure on natural environments and encouraging biodiversity-friendly activities, AI improves precision farming, fisheries administration, and ecological management.

3.4 Adverse Effects

- Environmental Impact of AI Facilities [15]: The energy-intensive operations at AI data centers and the mining of rare earth materials for hardware lead to pollution, greenhouse gases, and habitat destruction, all of which endanger species.

- ○ Promotion of Sustainable Practices: Robotics or AI-driven industrial efficiency may unintentionally lead to an escalation in resource abuse, such as intensive farming or excessive fishing, which can damage ecosystems.
- ○ Unintended Biological Effects: AI operations in ecosystems, such as computerized pest management or species migration, may have unforeseen consequences that upset current ecological equilibrium.
- ○ AI's impact on climate change is complicated and multifaceted. It contributes both personally and indirectly to carbon dioxide emissions, but it also presents substantial prospects for adaption and reduction.

Table 1. Greening AI Techniques

Challenge	AI-Based Solution	Expected Environmental Benefit
High computational energy demand	Use of energy-efficient model architectures (e.g., TinyML, pruning, quantization)	Reduced carbon footprint from model training and inference
Fossil fuel dependence of data centres	Transition to renewable-powered data centres	Reduction in indirect CO_2 emissions
Hardware-related emissions	Recycling, modular design, and green electronics manufacturing	Lower environmental degradation and waste
Unregulated expansion of AI	Establishment of AI sustainability policies and emission audits	Encourages responsible and transparent AI use
Lack of awareness	AI literacy programs emphasizing sustainability	Promotes eco-conscious innovation and usage

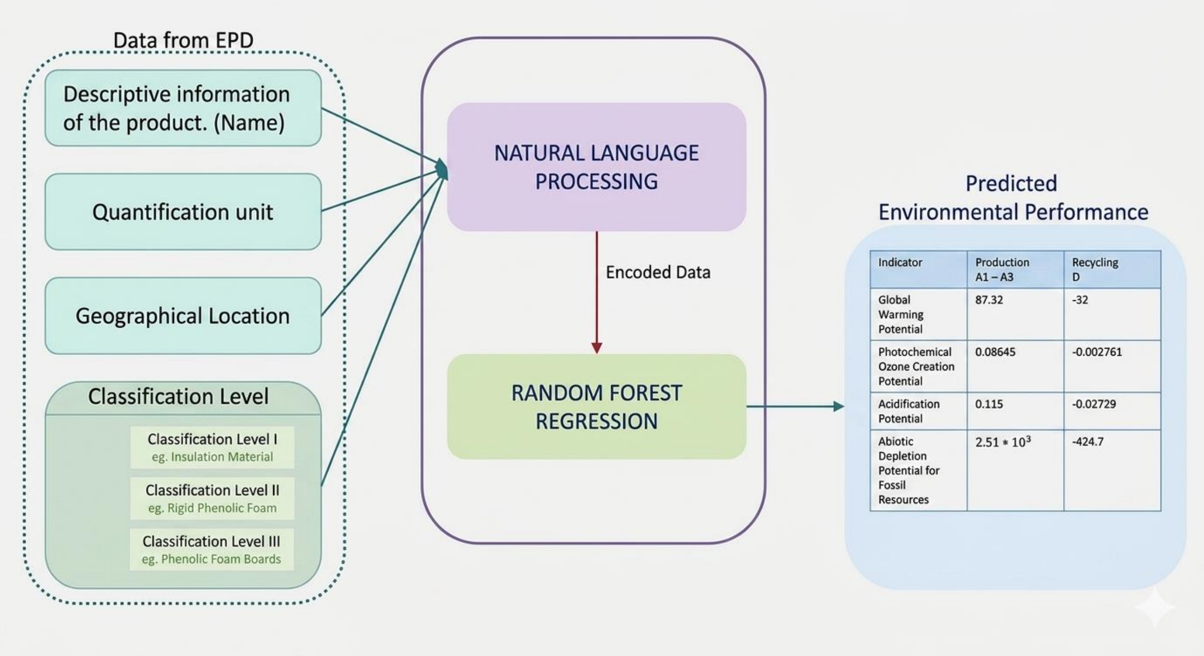
Table 1 illustrates a greening plan for AI [16], whereas Table 2 illustrates the dual role of AI in global warming.

Table 2. AI Intelligence's Dual Role in Climate Change

Aspect	Positive Impacts (Mitigation & Adaptation)	Negative Impacts (Contribution to Emissions)
Energy	AI optimizes energy use in buildings, industries, and transport through smart grids and automated systems.	Data centres and model training consume large amounts of energy, often from fossil fuels.
Climate Forecasting	AI enhances accuracy of weather prediction and climate modelling for better disaster preparedness.	High computational demand for complex simulations increases energy footprint.
Resource Management	Supports forest monitoring, precision agriculture, and biodiversity tracking.	Production and disposal of AI hardware contribute to e-waste and emissions.
Industry & Supply Chains	Improves efficiency, reduces material waste, and promotes decarbonisation.	Encourages consumption and automation that may increase material demand.
Human Behaviour	Promotes sustainable urban planning and energy-saving habits through AI-assisted apps.	Encourages high-tech lifestyles (e.g., autonomous transport, e-commerce) that indirectly raise emissions.

4. FINDINGS AND CONVERSATION

Here, AI approaches are employed as a case study to forecast the environmental implications of construction items because sufficient EPD data is available in the ÖKOBAUDAT system. The developed approach can, in theory, be applied to any item group for which agreedupon PCRs have been used to create EPDs. The database's integrity of EPDs produced after data processing is divided into two datasets as the initial step in the study. The outcomes of the chosen impact groups are then predicted using only the input factors. The algorithm's input data and its prediction are shown in Figure 3 [17].



Indicator	Production A1 – A3	Recycling D
Global Warming Potential	87.32	-32
Photochemical Ozone Creation Potential	0.08645	-0.002761
Acidification Potential	0.115	-0.02729
Abiotic Depletion Potential for Fossil Resources	$2.51 * 10^3$	-424.7

Figure 3. Machine learning model both inputs and outputs

Outcomes and Model Effectiveness

The model's performance is defined by R2. For instance, an R2 of 100% indicates that every projected outcome is within the range of its means in Figure 3. The model's performance for various impact categories is shown in Table 3. Additionally, the table shows the computed error in the genuine and expected values.

Table 3. Mean squared error (MSE), R-squared analysis (R^2), and the number of data points of the predicted impact categories

Impact Category	Number of Data Points	Mean Squared Error	R-Squared Results
Photochemical Ozone Creation Potential	196	0.07	70%
Abiotic Depletion Potential for Fossil Resources	196	0.01	77%
Global Warming Potential	196	0.28	81%
Acidification Potential	196	1.12	68%

The average squared distinction between the expected and actual values is measured using a statistical technique known as MSE. The model is usually evaluated using the root of MSE, sometimes called RMSE, since the unit of MSE increases than its actual error value. While R2, which is based on the relationship between the actual value and the predicted value, is less susceptible to outliers, a smaller MSE value implies a stronger model.

Outliers can affect regression models. Outliers are located underneath each effect classification, points that deviate from the grouping cloud of point values, as seen in Figure 3. Few outliers include important data, and not all of these are mistakes. But their presence has an impact on the predictive model as a whole. Data points from the lesser number of EPDs of particular categories were recognized as exceptions in our case research. For example, the initial categorization group for 53 EPDs was "metals." While "steel and iron" accounted for 33 EPDs, "aluminum" (3), "leads" (1), and other categories had fewer EPDs. The model's capacity to correctly anticipate data is limited by minimal data for learning.

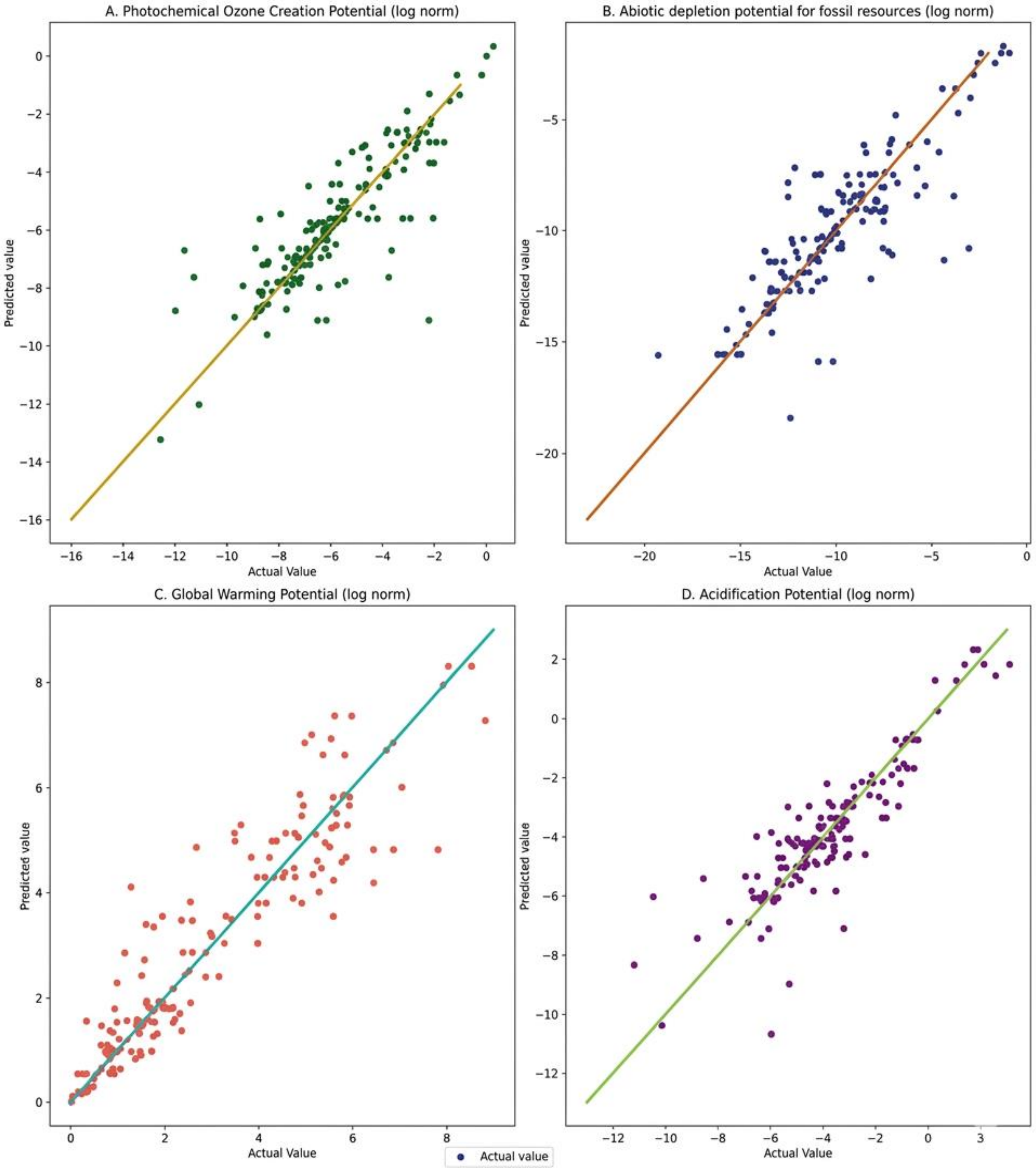


Figure 4. Prediction Plot Representation for the Complete Dataset across each Impact Category

The model performs better than 60%, according to the R2 results for the Global Warming Potential (GWP), Photochemical Ozone Creation Potential (POCP), AP, and Abiotic Depletion

Potential for Fossil Resources (ADPF). In relation to the instruction data size utilized, the GWP, ADPF, and POCP outcomes are deemed acceptable. With the exception of a few outliers, the regression findings visualization in Figure 4 demonstrates that the actual results are around the prediction line. A biased model may have a great R2 score [18], whereas a decent model may have a low R2 value, according to several researches. One method of cross-verifying the constraints of R equivalence analysis are to evaluate the residual diagram [19].

Table 4. The seven environmental metrics from the EPD "reinforcement steel wire" and their actual and predicted values

Environmental Impact Indicators	Original Values	Units	Predicted Values
Photochemical Ozone Creation Potential (POCP)	0.000266	kg Ethene eq.	0.00019152
Abiotic Depletion Potential for Fossil Resources (ADPF)	7.627	MJ	6.102
Global Warming Potential (GWP)	0.6834	kg CO_2 eq.	0.564
Acidification Potential (AP)	0.001282	kg SO_2 eq.	0.00071792

Furthermore, because the descriptive data is bagged and encoded, the amount of characteristics utilized is significantly greater than the standard database's size. In these situations, a larger database improves the model's accuracy in Table 4. Overall, the outcomes of our approach showed that regression analysis could be used with qualitative data from the first-implemented product.

5. CONCLUSION

An AI-based model can anticipate the environmental effects of goods and services with less time, information, and modeling requirements due to the growing demand for such information. However, in order to effectively anticipate a product's environmental implications, an AI-based model needs a lot of data. In order to publish LCA results in a standardized style, this research uses an existing database of EPDs to demonstrate a functional AI-based prediction engine. Our approach is not meant to replace a thorough life cycle assessment (LCA) study; rather, it is meant to serve as a check to quickly estimate the environmental implications of a product or company given the current phase of production and the limited quantity of EPDs offered.

Because there is a sufficient EPD database, construction goods are employed as a case study. Since ANN works best with large databases and RF is an ensembles tree-based method that works better with more features, we choose to utilize the RF method even though previous research suggested using ANN as the ML approach. NLP must be utilized to handle and describe a significant amount of descriptive data utilizing LCA study findings published in an EPD as our data source. The RF regression models are then fitted with the defined data. By using product data as input, the learned model will forecast the outcomes of the the ecological footprint domains.

Overall, this study demonstrates how AI policy may successfully encourage corporate green innovation and how it plays a part in both the long-term development of businesses' internal organizational and technological capacities as well as external policy benefits.

Therefore, future efforts to further integrate AI with green transformation should focus more on enhancing firms' AI application capabilities, facilitating the execution of smart manufacturing situations, and enhancing the ability of various types of firms to take in and translate the perks of AI policy into green innovation outcomes, rather than just expanding infrastructure and extending pilot zones.

REFERENCES

[1] Curmally, A., Sandwidi, B. W., & Jagtiani, A. (2022). Artificial intelligence solutions for environmental and social impact assessments. In *Handbook of environmental impact assessment* (pp. 163-177). Edward Elgar Publishing.

[2] Koyamparambath, A., Adibi, N., Szablewski, C., Adibi, S. A., & Sonnemann, G. (2022). Implementing artificial intelligence techniques to predict environmental impacts: case of construction products. *Sustainability*, *14*(6), 3699.

[3] Bagheri, M., Bazvand, A., & Ehteshami, M. (2017). Application of artificial intelligence for the management of landfill leachate penetration into groundwater, and assessment of its environmental impacts. *Journal of Cleaner Production*, *149*, 784-796.

[4] Ibn-Mohammed, T., Mustapha, K. B., Abdulkareem, M., Fuensanta, A. U., Pecunia, V., & Dancer, C. E. J. (2023). Toward artificial intelligence and machine learning-enabled frameworks for improved predictions of lifecycle environmental impacts of functional materials and devices. *MRS Communications*, *13*(5), 795-811.

[5] Luque, A., De Las Heras, A., Ávila-Gutiérrez, M. J., & Zamora-Polo, F. (2020). ADAPTS: An intelligent sustainable conceptual framework for engineering projects. *Sensors*, *20*(6), 1553.

[6] S. S. Karthik, Dr. V. Vijayalakshmi, & Dr. G. Zayaraz. (2024). A Short Survey on Energy Efficiency, Harvesting, and Management for Internet of Things. International Innovative Research Journal of Engineering and Technology (IIRJET), *10*(2). https://doi.org/10.32595/iirjet.org/v10i2.2024.199.

[7] Mohammadi Kashka, F., Tahmasebi Sarvestani, Z., Pirdashti, H., Motevali, A., Nadi, M., & Valipour, M. (2023). Sustainable systems engineering using life cycle assessment: application of artificial intelligence for predicting agro-environmental footprint. *Sustainability*, *15*(7), 6326.

[8] Kaab, A., Sharifi, M., Mobli, H., Nabavi-Pelesaraei, A., & Chau, K. W. (2019). Combined life cycle assessment and artificial intelligence for prediction of output energy and environmental impacts of sugarcane production. *Science of the Total Environment*, *664*, 1005-1019.

[9] Yin, X., Li, J., Kadry, S. N., & Sanz-Prieto, I. (2021). Artificial intelligence assisted intelligent planning framework for environmental restoration of terrestrial ecosystems. *Environmental Impact Assessment Review*, *86*, 106493.

[10] Wani, A. K., Rahayu, F., Ben Amor, I., Quadir, M., Murianingrum, M., Parnidi, P., ... & Latifah, E. (2024). Environmental resilience through artificial intelligence: innovations in monitoring and management. *Environmental Science and Pollution Research*, *31*(12), 18379-18395.

[11] Yu, K. H., Zhang, Y., Li, D., Montenegro-Marin, C. E., & Kumar, P. M. (2021). Environmental planning based on reduce, reuse, recycle and recover using artificial intelligence. *Environmental Impact Assessment Review*, *86*, 106492.

[12] Sanusi, A. N., Bayeroju, O. F., & Nwokediegwu, Z. Q. S. (2023). Framework for leveraging artificial intelligence in monitoring environmental impacts of green buildings. *International Journal of Advanced Multidisciplinary Research and Studies*, *3*(1), 1194-1203.

[13] Ligozat, A. L., Lefevre, J., Bugeau, A., & Combaz, J. (2022). Unraveling the hidden environmental impacts of AI solutions for environment life cycle assessment of AI solutions. *Sustainability*, *14*(9), 5172.

[14] Iyer, V. G. (2025). Strategic Social Environmental Assessment (Sea) Process For Sustainable Intelligent Systems To Achieve Artificial Intelligence (AI) Excellence. *Journal of Emerging Trends in Economics and Management Sciences*, *16*(2), 52-64.

[15] Liao, M., Lan, K., & Yao, Y. (2022). Sustainability implications of artificial intelligence in the chemical industry: A conceptual framework. *Journal of industrial ecology*, *26*(1), 164-182.

[16] Wang, Q., Li, Y., & Li, R. (2024). Ecological footprints, carbon emissions, and energy transitions: the impact of artificial intelligence (AI). *Humanities and Social Sciences Communications*, *11*(1), 1-18.

[17] Pagallo, U., Ciani Sciolla, J., & Durante, M. (2022). The environmental challenges of AI in EU law: lessons learned from the Artificial Intelligence Act (AIA) with its drawbacks. *Transforming Government: People, Process and Policy*, *16*(3), 359-376.

[18] Devineni, M., & Kaliappan, V. K. (2025). Enhancing Cloud Security: The Role of Artificial Intelligence in Real-time and Proactive Cyber Threat Detection. *Journal of Wireless Networks and Communication Systems*.

[19] Krishnan, S. R., Nallakaruppan, M. K., Chengoden, R., Koppu, S., Iyapparaja, M., Sadhasivam, J., & Sethuraman, S. (2022). Smart water resource management using Artificial Intelligence—A review. *Sustainability*, *14*(20), 13384.