sustainability

Review

Practical AI Cases for Solving ESG Challenges

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Abstract: Artificial intelligence (AI) is a rapidly advancing area of research that encompasses numerical methods to solve various prediction, optimization, and classification/clustering problems. Recently, AI tools were proposed to address the environmental, social, and governance (ESG) challenges associated with sustainable business development. While many publications discuss the potential of AI, few focus on practical cases in the three ESG domains altogether, and even fewer highlight the challenges that AI may pose in terms of ESG. The current paper fills this gap by reviewing practical AI applications with a main focus on IT and engineering implementations. The considered cases are based on almost one hundred publicly available research manuscripts and reports obtained via online search engines. This review involves the study of typical business and production problems associated with each ESG domain, gives background details on several selected cases (such as carbon neutrality, land management, and ESG scoring), and lists challenges that the smart algorithms can pose (such as fake news generation and increased electricity consumption). Overall, it is concluded that, while many practical cases already exist, AI in ESG is still very far away from reaching its full potential; however, one should always remember that AI itself can lead to some ESG risks.

Keywords: artificial intelligence; ESG; environment; social; governance; sustainability

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1. Introduction

1.1. ESG Overview

The term "environmental, social, and governance" encompasses a broad spectrum of topics related to the sustainable development of an organization [1]. Typically, it implies rigorously addressing the relevant issues in order to assess self-performance, set goals and priorities, evaluate risks and identify opportunities, design mitigation measures and transition strategies, direct resources, and perform other activities to achieve stable growth. The components of ESG have been gradually introduced since the 1960s in investment management with the idea of considering additional nonfinancial factors during the allocation of funds [2]. The term ESG was publicly introduced in 2015 in a joint report from financial institutions [3], and its ideas were further supported by the United Nations in its Sustainable Development Goals (SDGs) framework in 2015. The latter focused on overcoming climate change, social inequality, and poverty, as well as promoting peace and stable growth across the globe [4].

Overall, ESG can be viewed as the concept of responsibility toward the public and the environment, combined with the goal of generating profit [5]. According to [2], ESG is involved in the management of at least USD 17.5 trillion worth of assets (as of 2018), which is about a quarter of the USD 74.3 trillion global asset management industry. Recent research showed that organizations who consider ESG risks indeed perform better, in terms of having higher returns and less volatile portfolios [6,7]. This happens since the rapidly changing world requires fast-adjusting company strategies, which would be impossible to design without considering all relevant factors in advance. In addition to that, investors (especially equity funds) also become aware of reputation risks and, thus, incline not to fund "toxic" enterprises, for example, those who neglect the ecological impact of their activities or provide poor social security for their employees [8,9].

As the abbreviation implies, ESG issues fall into three major categories or domains, as illustrated in Figure 1. These are [10]:

- Environment—topics associated with the outside world and ecology;
- Social—issues tied to society and quality of life;
- Governance—problems involving the organization's efficient self-assessment and interaction with government agencies.

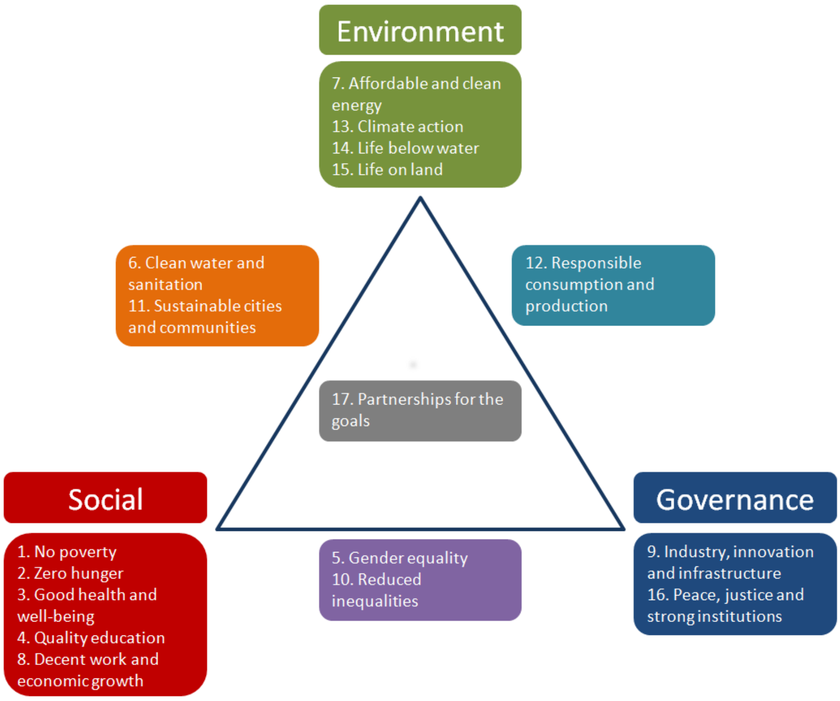


Figure 1. ESG topics and SDG targets.

1.2. AI Potential in ESG

As the quantity of available data keeps growing exponentially, it becomes more challenging for investors, companies, and state agencies to make balanced decisions in addressing ESG issues. For example, in the 1980s, stakeholders had to rely only on official statistics and some scarce public reports, while, in the 2020s, this information can be reinforced by news articles, social media reviews, data obtained from remote sensing (aerial and satellite), data from the Internet of things, and other sources [11]. Although for a given case, not all types of data will be pertinent (e.g., space images do not benefit the medical domain but are important for agriculture), it becomes quite labor-intensive to process all information in a tight timeframe, so stakeholders' decisions will still remain topical.

One of the best ways to accelerate data processing and enhance the understanding of the extracted information is to implement artificial intelligence algorithms [12]. AI is often described as incorporating practical tools and methods (the most notable ones being machine learning/ML and data analysis) suitable for solving various correlation, optimization, classification, and prediction problems [13]. While AI is a relatively new research area (e.g., when compared with Newton's classical physics), it has gained tremendous attention worldwide with dedicated R&D facilities founded by both governments and private enterprises. The latest successes of deep learning (DL) methods have pushed AI to the frontiers of research and development in practically every area.

Thus far, ML and DL methods have successfully demonstrated their performance in a multitude of areas, from logistics and lean manufacturing to image processing and text generation [14]. Consequently, it is not surprising that ML algorithms can easily be adjusted to address ESG challenges [15]. In fact, many issues were already studied, especially those related to ecology, such as CO_2 footprint calculations or soil degradation assessment [16]. According to [15], ML methods can be used to achieve 134 targets (79%) of the SDGs in the UN Agenda [17]: 93% for ecology, 82% for society, and 70% for economy.

1.3. Research Motivation

Currently, several systematic reviews of potential AI applications in ESG exist [18,19]. For instance, in [18], the authors discuss how AI helped to develop sustainable business models and illustrate this by giving examples of several multinational companies. However, there is only a brief mention of the smart algorithms' possible negative influence in terms of ESG. By contrast, Ref. [19] features a framework that helps to assess AI-related ESG impacts on various levels and then evaluate whether such impacts are negative or positive. The framework is tested on the sustainability reports of Microsoft Corporation (which is deemed to be one of the world leaders in the AI industry); however, a detailed description of the AI implementation cases is, rather, missing. Thus, to the best of our knowledge, there are no reviews that simultaneously provide a unified report, with details on the following features:

- Practical AI applications for each ESG domain;
- Challenges that AI can pose in terms of ESG.

We believe that such systemized information gathered in a single review will be quite valuable for readers considering ML technologies in the ESG domain. These readers include ESG program and portfolio managers (who require a good understanding of AI tool capabilities and limitations before investing in them), fellow data science researchers (who are looking for practical cases to test their findings), and the general audience (who want to broaden their knowledge on ESG and ML).

1.4. Research Scope

Before moving further, it is worth explaining what the phrase "practical AI application" means. In the current paper, this implies a computer algorithm that has the following features:

- It solves a production or business problem that is somehow tied to ESG;
- It is successfully tested on real data;
- It relies on ML methods (generally, AI is considered to be a broad term encompassing any method that mimics human intelligence, such as applying if–then–else rules or logical reasoning, but, here, we mostly focus on statistical approaches).

The scope of the ESG problems considered in the current paper is primarily linked to the different aspects of engineering and IT, which is attributed to the writing team's background in STEM (science, technology, engineering, and mathematics).

ML methods are considered in the context of a typical data science pipeline for solving production or business cases:

- Data analysis—obtaining useful insights from the statistical analysis of data;
- Predicting, classifying, or clustering something—evaluating the parameters' behavior or somehow grouping them;
- Optimization—using the outcome of one or both of the above steps to improve the desired results by finely tuning the problem input parameters.

Thus, if the discussed case matches at least one of the ML pipeline steps and also solves an existing ESG problem, then it is deemed to be a practical case. Because of this, the present research mostly refrains from pure fundamental AI studies.

1.5. Research Goals

The primal goal of the current paper is to provide details on the practical implementation of AI algorithms in solving existing ESG problems. Further discussion starts with laying out the research methodology. Then, various relevant AI cases are given for environmental, social, and governance applications. We also consider the challenges that ML poses to ESG.

2. Research Methodology

The analysis follows the PRISMA method [20], which was adjusted to the goals of the present research (Figure 2). The main sources of information were online materials found in scientific papers, public reports, industrial presentations, and knowledge bases. Detailed information on the search conditions is given below:

- Language: English (no translations considered);
- Year of publication: since 2012 (10-year time interval before the start of the current research);
- Timeframe of queries: December 2022–February 2023;
- Online sources (scientific reports): Google Scholar and Scopus;
- Online sources (public reports and industrial presentations): Google;
- Amount of analyzed search results from each query: 50;
- Basic keywords and phrases: "ESG", "environment", "social", "governance", "SDG", "sustainable development goals", "AI", "artificial intelligence", "ML", "machine learning", "algorithm", "challenge", "risk", "framework", "report", "overview", and "review".

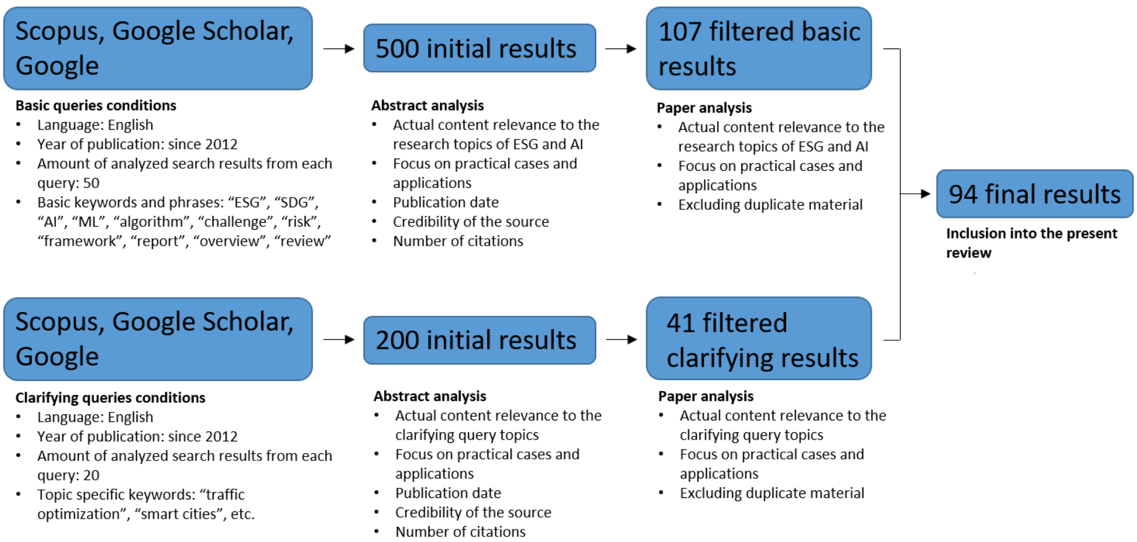


Figure 2. Research methodology pipeline.

These words were combined to form various queries, which could be divided into the following groups:

- ○ General information about ESG and SDG ("sustainable development goals review", "ESG framework report", etc.);
- ○ AI in each ESG domain ("machine learning environment", "AI algorithm governance framework", etc.);
- ○ AI as an ESG challenge ("ML social risks", "artificial intelligence challenge environment", etc.).

Each group featured up to ten various queries. All search phrases consisted of nouns without using prepositions and were given mostly in a singular form (except "goals"). If the query included abbreviations (i.e., "ML"), it did not simultaneously feature the same full phrase (i.e., "machine learning"). Similarly, queries included only a single synonym (i.e., either "report", "review", or "overview").

After excluding duplicate results, the outcome of the basic search was limited to 500 unique entities as a reasonable quantity of data for further studies. The abstracts of these entities were manually analyzed by the authors of the present paper and further filtered according to the following factors:

- Actual content relevance to the research topics of ESG and AI—for instance, ESG (extended similarity group) also refers to the sequence-based function prediction method for forecasting diverse functions of moonlighting proteins;
- Focus on practical cases and applications—as explained in Section 1.4;
- Publication date—preference was given to the most recent works (e.g., if two publications dated 2010 and 2018 both discussed smart cities, the latter was chosen as it included earlier data as of 2010 as well as more contemporary information as of 2018); the only exceptions were the original documents such as UN Sustainable Development Goals [4];
- The credibility of the source—peer-reviewed publications, as some material originated from Google Scholar;
- The number of citations—if several publications shared the same topic and were published during the same year, preference was given to a study with a larger number of citations (while this could be viewed as introducing bias, it is assumed that having more citations means a greater coverage of the results and hence a greater value to a broader community).

This analysis reduced the number of considered materials to 107 works, which were studied more closely and are outlined in the bulk of the present review.

It should be noted that additional clarifying queries focusing on particular applications or technologies were also considered during the studies (e.g., "AI traffic optimization"). These queries originated from the analysis of material provided through the search of basic keywords and phrases. Generally, such queries were generated when the initially found material only briefly outlined a particular topic, and more details were required to assess its relevance to the present research. Clarifying queries followed the same rules as basic search, with the exception of analyzing less material, i.e., 20 results per query and with only 2–3 variations in wording. This resulted in a total of 41 works for further detailed analysis.

Some information was also obtained through crosslinks and references found in general reviews on AI and ESG. However, most of such material can be independently found using search engines, with the exception of some specialized commercial and industrial reports.

The eventual decisions on material inclusion and the desired level of details were made jointly by the writing team with the main objective of being concise but at the same time highlighting the cases considered unconventional and interesting. As a result, the present study includes 94 references.

Since the main goal of the present paper is to list the practical AI applications, we did not assess the popularity of ML tools in various papers, nor do we present diagrams of publication statistics for each ESG topic. As such, only one or two typical examples are given to keep the discussion terse; however, in each ESG section, a selected ML application is studied in more detail to give the reader more background on the relevant case.

3. Results and Discussion

This section (and Sections 3.1–3.3) provides information on the current achievements of AI research in ESG. Firstly, general information on relevant SDG targets is provided. Secondly, practical examples of AI cases are presented, and some basic information on typical ML algorithms is given. Thirdly, a selected case is closely analyzed to illustrate the technology capabilities. Fourthly, a concise summary of the subsection is given.

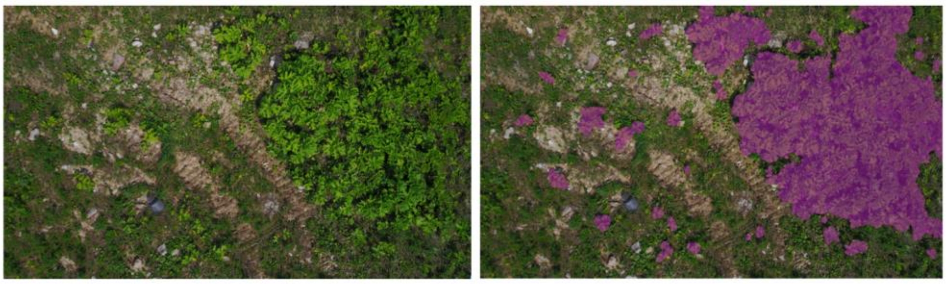
Section 3.4 differs from Sections 3.1–3.3 since it only gives a list of challenges posed by AI and our approaches to their resolution.

3.1. Environment

The most evident and straightforward area for ML implementation in ESG is ecology, which forms the first block of SDG targets in Figure 1. According to [15], AI methods may provide up to 93% of SDG targets for this domain. Examples include climate action [21], disaster monitoring [22], renewables [23], pollution reduction [24], forest restoration [25], and biodiversity preservation [26]. Many of these cases may be addressed by acquiring satellite or aerial images and subsequent procession using computer vision (CV) algorithms. Such images often include both optical and multispectral data and can be augmented with other remotely measured data [27]. Another major piece of information comes from tracking cameras (stationary or mounted on unmanned aerial vehicles (UAVs)) for wildlife observation of natural habitats [28]. Typically, CV algorithms rely on convolution neural networks, with the most classical architectures being the You Only Look Once (YOLO) family [29] and the Single-Shot MultiBox Detector (SSD) family [30].

A practical example of ML implementation in the environmental context is [31], in which the authors investigate the distribution of the plant *Heracleum Sosnowskyi*, which is considered an invasive species in northern and central Russia and some parts of Europe. Originally, the plant habitat was subalpine meadows and highland forests in the Caucasus region and northern parts of the Middle East, but in the 1970s, it was introduced in Europe as a silage plant and quickly spread in rural areas [32]. Apart from its aggressive competition with native plants, this hogweed contains phototoxic furanocoumarins [33], which greatly increases photosensitivity to ultraviolet light, and thus even a small amount of plant juice may cause severe sunburns when applied to human skin.

In [31], the authors proposed several prediction models based on publicly available environmental data to estimate whether hogweed will grow in certain areas by the year 2060. They implemented several climate models with the worst and best scenarios in terms of carbon emissions [34] and found that the most influential climatic parameters were the mean rainfall of the wettest months as well as the mean temperature of the wettest year quarter. The findings are alarming: There are significant chances of rapid plant propagation to the north of 60 latitude, where it does not currently grow (as of 2022) due to the cold climate [31]. Nevertheless, the spread of hogweed can be monitored and controlled by assessing the flora images obtained from UAVs. Such drones can automatically fly over large swaths of land, scan areas for the plant's presence, and inform local forestry companies about possible actions (Figure 3).



(**a**) (**b**)

Figure 3. Hogweed in a rural area: (**a**) original photo; (**b**) identified using CV.

Satellite images are most useful for simultaneously assessing huge portions of territory. Such images are captured with special sensors (mounted on Maxar, Landsat, Sentinel, WorldView, and similar spaceborne platforms) and can be obtained for almost any place on the planet with the required resolution. Additionally, the data can be captured for the same land repeatedly for a duration of several months or years, thus allowing for the observation of the area evolution both in the short term (wildfires, floods, etc.) and the long term (climate change, human activities, etc.). It is also beneficial that the basic satellite data (Landsat, Google Earth, etc.) is publicly available and thus can be readily used in achieving SDG targets.

For example, in forest management, ML algorithms are widely useful for the evaluation of the leaf area index, vegetation structure, moister level, and number of trees per acre [35–38]. These parameters provide a good health indication for a particular forest and may be used to evaluate the overall situation in the considered region [39]. Another closely related topic is the carbon neutrality target [40]. The background idea is that the emissions can be steadily compensated via vegetation CO_2 absorption. The overall area neutrality is evaluated in three steps. First, carbon dioxide spread is simulated using special biogeochemical models (Forest-DNDC) [41]. Second, plant taxation is performed for the area in question. Third, the capabilities of identified flora are compared with the presented levels of emissions (Figure 4). Therefore, one can easily assess whether more trees and bushes are required to compensate for the local CO_2 levels. When extrapolated on the scale of the whole country, the obtained data can be used for carbon reduction targets and provide the basis for domestic and international emission trading. A similar approach can also be used for other noncarbon sources of pollution [42].

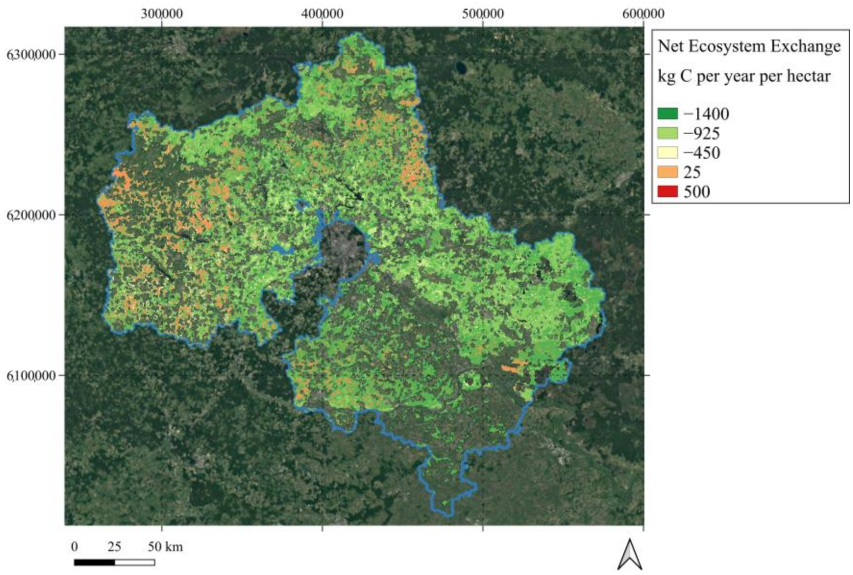


Figure 4. Calculated CO_2 absorption capabilities.

Overall, the environmental domain is a good source of practical cases, many of which can be solved by using CV methods. The obtained information can provide either a basic insight into the object of study or be utilized as input data for prediction or classification problems. Since environmental awareness has become crucial in most societies, in the coming years, there will likely be many new cases suitable for the implementation of AI tools.

3.2. *Society*

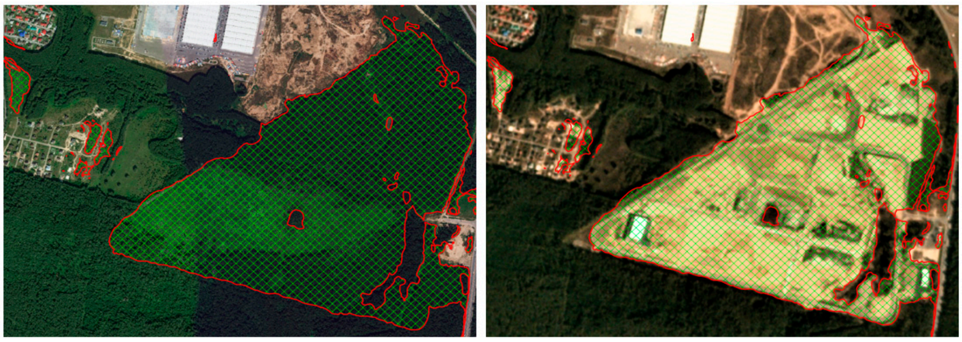
It is assumed that AI may be beneficial for 82% of social SDG targets (Figure 1), for example, SDG 1—eliminating poverty, SDG 4—quality education, and SDG 6—clean water and sanitation [15]. The recent SARS-CoV-2 pandemic also highlighted the necessity of disease spread modeling [43]. As can be seen from Figure 1, some society SDG targets are also tied to the environment sector, in particular, smart cities. Such cities are expected to be technologically advanced in gathering digital data and efficiently using them to govern urban infrastructure and assets [44]. Some relevant AI-supported cases are given below:

- Smart electric grids can be adjusted to customer demand and switch between various generation sources (wind farms, solar panels, thermal energy, etc.) [45,46]. A similar approach can be adopted to manage other resources like water or heating for intelligent buildings [47];
- Predictive maintenance of crucial infrastructure prevents accidents and disruptions [48];
- A human-centered environment leads to transparent residents–authorities interaction [49];

- Advanced healthcare helps in disease diagnostics and treatment planning [50,51];
- Optimized logistics and scheduling improves transportation sustainability [52];
- Traffic lights adjust to the road situation and prevent traffic jams [47].

The above cases are mainly solved by using various optimization and classifying /clustering algorithms (e.g., random forest [53], boosting [54], deep learning neural networks [55], and others [56]). CV methods are also extensively employed for smart city problems due to the wide use of cameras in modern urban environments [57].

Land management and cadaster revision also benefit from AI. First, satellites provide data images of the urban and rural areas in question. Next, various land objects like crop fields, townhouses, parks, or industrial plants are identified and classified in photos. Lastly, cadaster data are compared with the actual information on the object, and then the register is updated if necessary [58]. The advanced algorithms can extend even further and provide landowners with suggestions on different variants for subsequent area development, thus improving asset handling (Figure 5). For instance, when evaluating plans for building an apartment block, a developer can use ML tools to find and check similar edifices to verify the construction estimate and find the best construction team or building material vendor.



(**a**) (**b**)

Figure 5. Land development: (**a**) before construction; (**b**) after construction.

Another case is the use of AI for naval logistics in ice-covered seas. As global warming makes the Arctic region more suitable for shipping, this route becomes an attractive alternative for moving cargo between Europe and Asia. In particular, the distance between Murmansk (Russia) and Yokohama (Japan) is almost 7000 nautical miles shorter along the Northern Sea Route than the traditional path through the Suez Canal. Thus far, several works studied sea-ice behavior by combining classical ocean models and ML methods [59,60]. The main challenge here is to provide a computationally lightweight and reliable forecast with the scarcely available weather data so that the ship crew will be able to set the best course through the moving ice floes. For example, Ref. [61] reports such a cost-effective model based on U-Net architecture, which operates in two different regimes and is capable of predicting the ice thickness for the next 10 days. In [61], the model was successfully tested for the Barents Sea, the Labrador Sea, and the Laptev Sea regions, and its practical performance for ocean navigation was assessed.

On the whole, the most popular objects of study in the social domain are different aspects of smart cities' performance. Similar to environmental tasks, CV algorithms can be used here; however, the most practical cases are associated with optimization, prediction, and classification/clustering problems. As the urban population steadily grows, and IT technologies become more common, it should be expected that more practical AI cases will also arise with time.

3.3. Governance

The governance aspect of ESG can be either external or internal. The former involves company interactions with various stakeholders, most notably government agencies [15] and investors [2]. As of 2023, the appropriate universal AI legislature is somehow lacking, thus preventing any standardized approach to ML implementation [5,15]. The rapid advance of technology also makes it challenging to introduce a sound legal framework that will not become obsolete in the short term. Despite ongoing attention, this area still requires significant research, and drafting any new laws should include close communication with AI experts familiar with the topic. Otherwise, the proposed policies will likely be ineffective at best and even counterproductive at worst [15]. Nevertheless, some interesting applications of AI in governance already exist. For example, the results of [62] can be used to track tax evasion or greenwashing (marketing spin in which products or organizations are promoted as eco-friendly).

In the case of investors, the most practical application of AI is concerned with the automatic assessment of company performance based on its public press releases, financial reports, social review summaries, and news articles [63]. This approach implements natural language processing (NLP) algorithms, which can rapidly scan through the text to extract specific words (such as places, dates, and names) and generate summary reports [64]. In particular, in [63], the authors discussed a special model, esgNLP, which was initially created by using a pretrained Google BERT general English language model [65] and then further trained on ESG reports. As a result, the model was able to identify almost 1200 various ESG risk terms and evaluate their context in the sentence, thereby evaluating the overall company score based on its positive and negative references in the considered articles and reports.

In order to verify the obtained results, the authors determined Amundi Asset Management ESG scores [66] (which are routinely found by manually processing the company information) and compared them with the esgNLP calculations. While the results were different for the investigated companies, the study showed that the organizations with higher esgNLP scores on average had higher Amundi ESG scores as well [63].

A similar approach was applied in [2], where the authors focused on a comparison of AI-based scores from Truvalue Labs [67] and "traditional" assessment scores from MSCI ESG [68]. In contrast to the previous work, the results show a weak correlation between scores, which was attributed to a potentially more biased approach in a traditional assessment (larger companies can provide more data for reports used in assessment). The other possible reason was the information source. In the experiment, AI-based scores were mainly calculated from publicly available data, while the traditional assessment heavily relied on company disclosure [2]. It should be noted that, despite contradictions in scores, ML methods still have a strong potential in ESG assessment. Most likely, further development of NLP models will make them a valuable tool for investors and asset managers by providing supplementary data to make better decisions.

The internal aspect of governance, which is related to company self-assessment [69], focuses on the efficiency of its policy and bureaucracy. Once again, the most valuable tools here are based on NLP technology, which automates routine tasks such as checking document consistency [70], generating reports according to preset templates [71], implementing search engines [72], establishing knowledge bases [73], and supporting chatbots to assist employees [74]. However, NLP methods should be distinguished from standard robotic process automation (RPA) [75], which also simplifies everyday tasks. The main difference is that RPA simply remembers the order of user actions (such as keystrokes or mouse movement) and repeats them again and again. Thus, it is effective when one has to download attachments from 1000 emails but fails if it is required to sort these files according to some nontrivial rule.

The main AI technology for the governance domain is NLP, which focuses on text processing. While the external aspect of the governance domain still requires significant research, internal applications have already proven their efficiency. With the recent breakthroughs in heavyweight language models, a new era of practical AI cases is already starting to emerge.

3.4. Sustainable AI

So far, in the present paper, ML was merely considered as a tool for solving ESG problems. However, AI methods themselves can be the focus of the ESG analysis [5]. This can happen when an enterprise heavily relies on ML algorithms, allowing them to automatically relocate resources and adjust the manufacturing parameters without human participation. For example, when selecting an optimal operation regime of a thermal power station, if such an algorithm is not provided in advance with requirements for carbon footprint mitigation, it would never consider the ecological impact of its actions and would likely select an inexpensive but environmentally harmful fuel as long as it minimizes expenses but maximizes electric generation.

The other issue is ethics-based AI auditing, which needs to be addressed if ML algorithms are expected to make fair and safe decisions unbiased with unrepresentative datasets used for their training [15,76]. In [5], at least 173 AI auditing frameworks were mentioned, but the lack of universally adopted metrics and standards was highlighted. Overall, it is agreed that several criteria should be applied to AI systems such as nonmaleficence, transparency, responsibility, fairness, and privacy [77]. The designed algorithms should also be robust to cope with possible discrepancies in the input data, especially when operating on some highly important infrastructure [78]. The main challenge here is to transform the general framework criteria into practical measures with strict wording and quantitative description so that the stakeholders could apply them on a day-to-day basis. The most reasonable way would be to select one of the frameworks and adopt it as legislation with the help of an AI expert society.

There is also a large discussion on the social impact of AI as a disruptive technology [79]. Despite creating new IT jobs, ML typically leads to the automatization of certain business and technological processes. As a result, companies consider closing low-skill positions, and some of their employees suffer pay cuts or even lose their jobs, which became obsolete [15]. In addition to that, the companies failing to timely implement AI-enhanced production potentially become less competitive in the market and have fewer chances to obtain funding from investors. It should also be noted that private enterprises primarily focus only on the areas that provide clear economic effects (for example, production optimization in an assembly plant). At the same time, other problems with less evident impact on the business model become less attractive (e.g., a smart office for an oil rig), which leads to nonuniform progress toward some SDG targets [80]. This is also worsened by varying funding capabilities in that large enterprises have more opportunities to invest in AI than small businesses [15]. Likely, the best approaches here are improving public awareness of AI, promoting employees to develop professional skills in ML, and increasing funding of not-for-profit applications.

Many ML implementations such as tracking and person recognition can be seen as ethically questionable, especially when combined with calculating citizen scores and rankings [81]. Since different countries have varying cultural and political backgrounds, an application of public-related ML algorithms (e.g., recommendations on a social network) that worked fine in one environment may lead to dramatic consequences in other cases [15]. So, such tools should be used with great care and tested in advance with representatives of the new audiences.

Another interesting case is linked with fake news, which is defined as presenting misleading or false information that is claimed to be true. Such news appears on a routine basis in media often spreading around hot topics like celebrity scandals, rigged elections, or proposed tax cuts [82]. Once a rumor is out, it is very hard to deal with, as the public is prone to sensations and keeps circulating false data. The situation has become even worse with AI advancement since this technology provides quite powerful tools for fake news generation (especially with generative adversarial networks (GANs)) [83]. GANs are capable of efficiently mimicking training material to look almost authentic to the observer. GANs can easily adjust video and images by replacing faces and backgrounds (Deepfake), thus causing potentially huge reputation or economic harm [84]. Thus far, several practical methods have been proposed to detect and deal with fake graphic content [85,86], but some fundamental research is also required for better performance [87,88]. Similar fact-checking tools are available for text content as well [89,90].

The other question that requires a separate discussion is ChatGPT [91]. This AI-powered tool effectively mimics an interlocutor and is capable of keeping a meaningful discussion, writing lyrics, or generating a basic programming code. Undoubtedly, ChatGPT has tremendous potential; however, the surrounding hype and public expectations hinder an assessment of its practical value for the industry right now (as of the beginning of 2023). In order to work properly in the host company environment, ChatGPT should be trained and have constant access to the company's internal data and documentation. However, such access would be strongly opposed by the company's information security service (ISS), whose primal goal is to prevent the leakage of any sensitive information such as personal data, financial performance, or procedural knowledge ("knowing-how"). Thus, the first step here should be to adjust the expectations of both potential ChatGPT users and ISS. Based on that, the company's IT landscape should be redesigned so that ChatGPT would always only assess harmless general data but still provide great practical experience to users by, for example, helping to manage meetings and write memos.

Lastly, it should be noted that ML methods have become even more energy-demanding. For example, training a state-of-the-art GPT-3 NLP network requires almost 936 MWh—the same amount of power as 468,000 average electric kettles (2 kWh) or 12,480 lithium-ion Tesla car batteries (75 kWh). It is estimated that, by 2030, information and communications technologies (including AI) would need 20% of the world's electricity, which would lead to a great carbon footprint unless this issue is addressed in advance [92]. The computational difficulty of many ML-related problems also drives a demand for more graphical processing units, typically used in calculations. Their production involves the utilization of toxic materials and thus has a strong negative impact on the environment [93]. In particular, arsenic, phosphine, sulfidic and hydrofluoric acids are widely used in various steps of the semiconductor fabrication process. These materials pose a direct risk to human health and are also reported to increase the chances of cancer later in life. The above drawbacks can be partially solved by the implementation of the so-called "green AI", which uses specially designed neural networks with lower power consumption and, consequently, lesser ecological impact [94].

4. Conclusions

4.1. Research Summary

In recent years, ESG issues have garnered significant public and research attention. Climate change, social insecurity, and an uncertain economic future have become quite challenging problems; therefore, many novel proposals have been put forward in order to achieve the desired global sustainable development targets. AI algorithms have become one of the most promising tools to address ESG challenges by combing a vast volume of generated data and advanced processing methods to extract valuable knowledge and make optimal decisions in everyday life.

In the present paper, we considered practical examples of AI models for environmental, social, and governance domains. For example, we discussed the propagation of hogweed in northern Eurasia and described NLP tools to evaluate an organization's adherence to ESG principles. Several challenges posed by AI itself were also outlined, namely, the lack of universally adopted auditing frameworks, social impact as a disruptive technology, and ever-growing energy consumption demands.

It should be noted that the presented landscape of practical AI applications is deemed to be rather fragmented. We believe that this is primarily explained by varying business requirements (which significantly differ between industries) and uneven funding capabilities of large and small enterprises. Eventually, any technology requires significant investments prior to practical realization.

Nevertheless, each domain indeed has a high potential for growth, due to AI technology advancements (which also means the reduction in solution delivery costs) and the increasing decision-maker awareness of ESG issues. Unlocking this potential can be seen as the next logical step for all stakeholders, including private enterprises, state agencies, and fellow researchers. Thus, it should be expected that, in the near future, AI tools will be more engaged in dealing with ESG challenges.

4.2. Current Limitations and Further Research

The conducted research has some limitations, which are conditioned by the writing team's professional background (mostly, IT, oil and gas engineering, and agriculture). For example, the present paper hardly touches on such areas as medicine or finance. Without being an expert in these fields, it is difficult to highlight the actual practical problems and assess the efficiency of ML tools in dealing with them. This direction can be the next step for future research.

The other topic that definitely requires more studies is ChatGPT (and similar highly intelligent applications). Since the public release of the breakthrough version 3 coincided with the first submission of the current paper, we were not able to fully analyze the impact of this tool on the ESG domain. Such IT applications are truly disruptive and require a special investigation.

In terms of the study scope, the research methodology can also be extended by considering non-English sources. Many technical insights on successful AI implementations in industries can be obtained from national reports and white papers; however, these documents are rarely translated. Thus, an implementation of auto-translation tools can potentially provide a wider view of the topic.

Lastly, it could be interesting to assess the capabilities of cutting-edge ML technologies (such as neuromorphic computing and quantum machine learning) that have not been tested in practice yet but have strong potential in some areas.

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