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Assessing the Environmental Impact of Artificial Intelligence in Achieving Sustainable Development Goals

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Abstract
This study examines the impact of Artificial Intelligence (AI) on Sustainable Development Goals (SDGs) 13, 14, and 15, with emphasis on environmental sustainability. Each Sustainable Development Goal (SDG) was analysed separately to investigate the potential applications of Artificial Intelligence (AI). The subtopics were created to thoroughly address different aspects of sustainable development within these goals. The data collection process entailed the acquisition of pertinent case studies, instances of artificial intelligence (AI) implementations, and empirical evidence for every Sustainable Development Goal (SDG). This study enhances comprehension of how artificial intelligence (AI) can either promote or impede the advancement of environmental sustainability in relation to Sustainable Development Goals (SDGs) 13, 14, and 15. It provides valuable insights for policymakers, researchers, and practitioners who are seeking effective solutions to accomplish sustainable development objectives. Through our investigation, we have determined that AI has the potential to have a beneficial impact on 25 specific objectives within this group, whereas 8 objectives have shown a discouraging effect.

Keywords: Artificial Intelligence, Sustainable Development Goals, SDG, SDG13, SDG14, SDG15

Introduction

Artificial Intelligence (AI) is a cutting-edge field of research that tries to build intelligent computers that can carry out activities that generally need human cognitive abilities, such learning, problem-solving, reasoning, and decision-making.Computer science, mathematics, neurology, and cognitive psychology are among the many fields that have come together to create AI. Fundamentally, AI aims to create approaches and algorithms that let computers evaluate massive volumes of data, recognize patterns, and adjust to different circumstances to mimic human intelligence.

At the heart of AI is a set of key technologiesthat give machines intelligence and autonomy. Machine Learning is an essential aspect of AI in which methods allow machines to gain insight from data without explicit programming. Supervised learning entails training models on labelled data so that they can make predictions on fresh, previously unseen data. Unsupervised learning, on the other hand, works with unlabelled data to uncover patterns and structures. Reinforcement learning is a reward-based strategy in which machines learn by receiving positive feedback for good acts and negative feedback for bad ones.

Natural Language Processing (NLP) aims to bridge the gap between human and machine language. NLP algorithms allow machines to understand, interpret, and generate human language, allowing humans to engage with machines via speech or text. NLP applications range from chatbots to sentiment analysis in social media, machine translation, and speech recognition[1].

Computer Vision is a critical technology that enables robots to analyse and comprehend visual input in the same way that humans do. Computer vision uses image and video analysis to perform tasks such as object detection, image segmentation, facial recognition, and autonomous vehicle navigation.

AI applications are numerous and multidisciplinary, affecting practically every facet of modern life. AI aids in the diagnosis of diseases, the analysis of medical imaging, and the personalization of treatment regimens for patients in healthcare[2]. AI-driven algorithms in finance aid in fraud detection, risk assessment, and algorithmic trading, hence optimising financial decision-making. AI is also revolutionising education, with adaptive learning platforms that personalise instructional content to the needs of individual students.

Sustainable Development Goals (SDGs)

The Sustainable Development Goals (SDGs) concept evolved as a successor to the Millennium Development Goals (MDGs) and symbolises a paradigm change towards an integrated and holistic approach to global development. The United Nations (UN) established the SDGs in September 2015 as a transformative agenda aimed at solving critical issues such as poverty, hunger, climate change, inequality, and environmental degradation.

The SDGs have evolved since the Rio Earth Summit in 1992, when the notion of sustainable development acquired international prominence. The adoption of the 2030 Agenda for Sustainable Development was a watershed moment, encompassing 17 SDGs and 169 goals aimed at guiding countries towards a more sustainable future[3]. The SDG’s basic concepts are universality, indivisibility, and leaving no one behind. These principles emphasise that all countries are equally accountable for accomplishing the goals, regardless of wealth level, and that the goals are interconnected, necessitating a comprehensive and integrated strategy.

Each of the 17 SDGs focuses on a different facet of sustainable development while acknowledging their interdependence. The SDGs cover a wide range of social, economic, and environmental factors, from eradicating poverty (SDG 1) to achieving zero hunger (SDG 2) to promoting gender equality (SDG 5) and tackling climate change (SDG 13). The effective implementation of the SDGs necessitates a collaborative and coordinated effort on the part of numerous stakeholders.Governments have a critical role in developing policies, mobilising resources, and setting regulatory frameworks that promote long-term growth. International organisations promote international cooperation and information sharing, whereas academia contributes through research, innovation, and capacity building. In addition to campaigning for sustainable practises and promoting responsible business strategies, civil society and the commercial sector play essential responsibilities.

Sustainable Development Goals (SDGs) are a visionary roadmap for driving global development towards sustainability and inclusion. Academia, politicians, and other stakeholders may make a significant contribution to the realisation of a more sustainable and equitable society by fostering increased understanding and involvement with the SDGs.

AI Technologies and their Potential Contributions to SDGs

The association of Artificial Intelligence (AI) and the Sustainable Development Goals (SDGs) is a revolutionary nexus in which AI capabilities are leveraged to meet the numerous challenges outlined in the 2030 Agenda for Sustainable Development. This symbiotic relationship between AI and the SDGs presents itself in a variety of ways, including societal progress, environmental conservation, and economic growth. The complex interplay between AI and the SDGs highlights the promise of AI technologies in achieving sustainable and inclusive development, propelling progress towards a more equal and resilient world.

AI for Environmental Conservation

Artificial Intelligence (AI) is becoming increasingly significant in environmental conservation by disrupting traditional methods and enhancing human skills.The Sustainable Development Goals (SDGs) encompass 17 global objectives designed to address various challenges facing humanity. Within these goals, SDGs 13, 14, and 15 specifically focus on environmental sustainability as depicted in Figure 1. SDG 13 aims to combat climate change and its impacts, while SDG 14 targets the conservation and sustainable use of oceans, seas, and marine resources. SDG 15 seeks to protect, restore, and promote the sustainable use of terrestrial ecosystems, forests, and biodiversity. Together, these goals highlight the critical importance of environmental stewardship in achieving sustainable development worldwide.

Figure1: SDG's corresponding towards environmental outcomes

AI helps researchers and conservationists to monitor ecosystems, track wildlife populations, and detect environmental changes in real time by utilising the power of big data, machine learning, and predictive analyticsshown in Figure2. AI-powered technologies, such as remote sensing and image recognition, make habitat monitoring and biodiversity assessment more efficient[4].

SDG	Significance of AI in Environment
	AI possesses the capability to conduct thorough analysis of climate data, formulate climate change scenarios and provide support for environmental policies.
	AI has the capability to aid in the observation of marine ecosystems and safeguarding the welfare of marine organisms.
	The utilization of AI is a beneficial approach towards promoting and conserving wildlife as well as achieving sustainable land usage.

Figure. 2: Impact of AI on SDG's related to environment

AI algorithms improve resource management and aid in the development of sustainable policies, the mitigation of climate change consequences, and the support of precision conservation initiatives. The combination of AI with environmental conservation not only improves knowledge of complex ecological phenomena, but also allows for more effective conservation policies to protect our planet's vulnerable ecosystems for future generations.

Literature Survey

According to our analysis of relevant evidence, AI could act as a facilitator on 134 targets (79%) across the SDGs, generally through technology advancements that may allow to overcome certain current restrictions. However, the development of AI may have a negative influence on 59 targets (35% across all SDGs).

In this study, our emphasis is on the environmental dimension. Table 1 provides a comprehensive breakdown of each target associated with the environmental aspects of every SDG.

Table1:Detailed assessment of each SDG target with respect to AI as a facilitator or deterrent

SDG	Target	Facilitator	Determent	Reasoning
13	13.1	Yes		There are indications that AI breakthroughs will aid in the understanding of climate change and the modeling of its potential consequences. As a result, enhancing adaptation capacity to climate change [5]. AI can also aid in the prediction and forecasting of extreme weather occurrences, as well as early agricultural production predictions, all of which improve climate change adaptation planning.
	13.2	Yes	Yes	Same as 13.1, 7.2 and 7.3
	13.3	Yes		There is evidence that AI will support the flow of knowledge, capacity building, and educational results, notably in the climate spheres, and that AI can operate as a facilitator for education more broadly [6].
	13.a			No published data on the effects of AI on this goal could be found.
	13.b	Yes		Same as 13.3
14	14.1	Yes		The automatic detection of potential oil spills and the provision of necessary information for decision-making. Furthermore, AI may be used to anticipate marine litter in order to estimate litter categories, which is essential for successful management [7].
	14.2	Yes	Yes	For autonomous underwater vehicles, mobile autonomous process sampling can be utilized to recognize characteristics in order to determine probabilistic states for adaptive control of survey navigation and activation of targeted water samplers[9]. Furthermore, spatial numerical optimization tools based on Integer Linear Programming allow for the delineation of numerous management and protection zones, as well as maritime zoning that balances biodiversity conservation and fishing sector objectives Artificial intelligence (AI) tools can also provide a cost-effective approach to monitor beach safety across wide areas without compromising marine species through deployed nets. In this sense, AI-based real-time remote sensing of fish swarms might contribute to focused fishing for trawlers, boosting efficiency, but can also have a negative impact on resilience if not managed[5].
	14.3	Yes		According to the literary works, autonomous underwater vehicles (AUVs) can increase observability, such as algal bloom zones, ocean acidification, and ocean circulation, which aids in achieving this goal. The integrated coral observation network (ICON) employs real-time integration of satellite, in-situ, and radar data sources to forecast biological phenomena such as coral bleaching, coral spawning, upwelling, and other marine behavioral or physical oceanographic events [7].
	14.4	Yes		Employing machine learning to identify and recognize global trawler fishing activity based on data from a satellite-based automatic information system (AIS), AI as autonomous underwater vehicles (AUV) equipped with sensors, communication devices, and navigational intelligence can perform effective and broad-range monitoring missions of cage-based aquaculture system surroundings [10], thereby maximizing productivity and potentially indirectly contributing to reducing overfishing.
	14.5	Yes	Yes	Simulated annealing, subsequently followed by next-generation Integer Linear Programming solvers, might help prioritize marine

				and coastal units for prospective inclusion in, or transformation into, conservation networks that eventually span a specific amount (e.g., 10%) of the overall area of the ecosystems [11]. However, we believe that further research is needed to investigate the long-term impact of AI on equity and fairnessfor, in this example, conservation area priority.
	14.6			No published data on the effects of AI on this goal could be found.
	14.7	Yes	Yes	Marxan or Integer Linear Programming (ILP) algorithms in systematic conservation planning software can create management plans that balance habitat protection and small-scale fisheries around small central Pacific Ocean islands [12]. The true value of conservation planning at the local level is in the process of recognizing and conceptualizing the management issue, collaborating with communities to collect data using participatory methodologies, and including communities in management decision-making [13]. However, if the use of AI is not supervised in terms of the justice and fairness of AI-based judgments, these technologies may have a negative impact on this goal [14].
	14.a	Yes		Machine-learning tools may be used to detect and monitor biodiversity, integer linear programming (ILP) can be used to plan protected areas, AI-based remote-sensing tools can detect oil spills, autonomous underwater vehicles (AUVs) can detect acidification and litter, and overall ocean health can be promoted [14]. Furthermore, participatory planning with Bayesian Believe Networks (BBNs) can be used to understand the interrelationships of factors influencing coastal communities' fishing activities and the implementation of customary marine tenure, as done in the Kei Islands (Indonesia).
	14.b	Yes		Bayesian Belief Networks (BBNs) can be used to examine the potential reallocation of artisanal fishing effort to other sites as a result of the establishment of a new, non-take region, such as an offshore aquaculture site along the Basque continental shelf [15].
	14.c	Yes		Convolutional neutral networks (CNNs) can assist in the processing of automated information system (AIS) data to identify vessel characteristics and detect AIS positions indicative of fishing activity in order to produce a worldwide dynamic footprint of fishing effort [15]. Furthermore, AI in the form of machine learning and image recognition algorithms can be used to review video observations in order to determine the amount of fish caught and the type of fish [16].
15	15.1	Yes		Gonzalez et al. [17]demonstrates how unmanned aerial vehicles (UAV) outfitted with tiny thermal imaging sensors and AI can be used to autonomously count, monitor, and classify species over relatively broad areas. Such data can be extremely useful in more correctly estimating populations and, as a result, planning conservation efforts. AI technology aids in decreasing traditional monitoring schemes' time and resource limits, which now hinder conservation and restoration activities. Furthermore, AI technology has the potential to make biodiversity monitoring non-invasive.
	15.2	Yes	Yes	AI may be used to analyze, anticipate, and map forest structure elements that serve as indicators of forest status via remote sensing[18]. When employed for better conservation, effective

				restoration, or restoration planning, detailed understanding of forest structures might serve as an enabler for this aim. However, it should be noted that such comprehensive maps could also be used to more effectively and efficiently use or exploit forest ecosystems, therefore additional research is required to assess the long-term implications.
	15.3	Yes		Neural networks and goal-oriented techniques can be used to better classify vegetation cover types based on satellite photos while also processing a huge number of images in a very short period of time[19]. As a result, these AI techniques aid in identifying desertification trends over large areas or, more broadly, in identifying and monitoring threats to the planet's natural resources such as offshore drilling and oil spills, urban sprawl, fracking, mountaintop removal mining, and ocean overfishing [20]; also relevant for targets 14.1 and 14.2. Such data can be utilized for planning, decision making, and management to prevent additional desertification or even reverse trends by identifying the key drivers.
	15.4	Yes	Yes	The work published in [21] modelled and mapped hot and cold spots of various ecosystem services such as aesthetic, biodiversity, and life-sustaining values of a mountain area (i.e. the Southern Rocky Mountains) as observed by people and biophysically modeled. The biophysical models were created using the AI for Ecosystem Services (ARIES) modeling framework. As mentioned in [21], such knowledge can be used to assist mountain ecosystem protection. Pattern-recognition approaches are used in [22] to model niches and estimate the distribution of 106 mountain plant species. However, such explicit information on the geographical distribution of ecosystem services could be utilized to more efficiently and inefficiently extract ecosystem services in mountain areas, with negative consequences.
	15.5	Yes	Yes	The literature reveals a favorable impact of AI on this aim through the use of pattern recognition and other AI approaches to create massive databases of target biodiversity, which aids in finding significant conservation sites. [23], for example, describes how animal diversity can be accessed via unsupervised multiresolution analysis and its auditory footprint. [24] describes how deep learning algorithms can be utilized as a very efficient approach to automatically identify animals from camera trap images with the same 96.6% accuracy as human volunteers. However, as we have already stated for other aims, such better biodiversity knowledge could be exploited for poaching or resource exploitation.
	15.6	Yes		The African Orphan Crops Consortium's mission is to use AI technology to sequence, assemble, and annotate the genomes of 101 traditional African food crops. The term "orphan crops" refers to traditional African food crops that have long been overlooked in favor of western foods. Based on an appraisal of the parties engaged, project outputs are likely to be shared fairly and equitably [25].
	15.7	Yes		AI could either aid or hinder this goal by enabling the creation of more vast and comprehensive biodiversity databases. Several studies on biodiversity monitoring tools are discussed in references [26][23].

	15.8	Yes		The Cacophony project utilizes machine learning to classify pests such as rats, stoats, and possums from thermal video feeds. One of their future goals is to directly remove the pest species after identification by shooting it with a paintball gun loaded with toxic paint pellets (the paint is afterwards licked off by the pest animal, thus the plan) in order to rid New Zealand of predators [27].
	15.9	Yes		As described in goal 15.1, the use of AI-driven planning tools in environmental decision making that can balance and trade-off biodiversity protection and ecosystem service delivery. Social fairness can be considered in a variety of ways in planning. [28] describes how country-level purchasing power parity (a proxy for a country's wealth) and each country's percent cover of the total basin area can be integrated as equity factors in a Danube River basin catchment management plan aimed at conserving fish biodiversity and conserving and delivering ecosystem services.
	15.a	Yes		The literature gives evidence that AI is indirectly supporting this goal: Marxan or Marxan with Zones systematic conservation planning studies address cost-effectiveness to optimize biodiversity conservation [29]. As a result, conservation measures planned with this program are more likely to enhance financial resources for biodiversity conservation than traditional approaches that identify conservation areas only based on species richness. The divide between research and conservation experts is discussed in [30]. There is a definite need to better identify issues of justice and transparency in cost-effective conservation planning, as well as to account professional knowledge gaps.
	15.b	Yes		There could be an indirect positive link between AI and this goal: The use of unmanned aerial vehicles (UAVs), hyperspectral image sensors, and machine learning algorithms to process, map, and analyze data on forest types, deforestation activities, and conservation areas may aid in the mobilization of resources for sustainable forest management, forest conservation, and reforestation [17].
	15.c	Yes		If approaches to systematic conservation planning (SCP) are augmented with social context. To generate biodiversity conservation plans that accommodate both landscape level species protection and local, social demands, SCP that incorporates social processes, such as livelihood adaptation or agricultural intensification, is suggested [31]. In this vein, [32] proposes a method for integrating data on social well-being (economic well-being, health, political empowerment, education, and culture) into SCP in order to support similar aims as in [31], as well as to facilitate adaptive management.

Methodology

The methodology utilized in this paper involves a thorough and systematic approach to gathering pertinent data, analysing current literature, and presenting a convincing framework for understanding the application of AI in accomplishing the SDGs. The following steps were undertaken:

a) Literature Review: A thorough review of academic journals, conference papers, reports, and associated publications revealed key ideas, theories, and empirical studies linked to AI and its potential for promoting the SDGs. Search engines and databases such as PubMed, IEEE Xplore, and Google Scholar were utilized to find scholarly resources and papers.

b) Selection of SDGs: Following a review of the 3 SDGs, it was decided to focus on each one independently to investigate the potential applications of AI. Subtopics within each goal were developed to provide comprehensive coverage of the multiple dimensions of sustainable development.This paper analyses the impact of AI, depicted in Figure 3, where green blocks indicate AI acts as a facilitator for achieving the target, while orange blocks signify its deterrent effect.
c) Data Collection and Analysis: Relevant data, case studies, and examples of AI-powered solutions were gathered and reviewed for each SDG. This entails examining the outcomes, challenges, and opportunities presented by applying AI to certain SDG objectives.
d) Integration and Synthesis: The information gathered was processed and used to create a coherent narrative for each SDG. The links between the goals and cross-cutting topics were also discovered to highlight potential synergies and collaboration across fields.

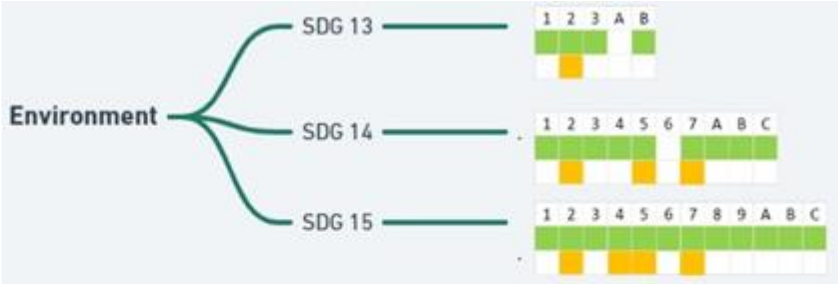

Figure 3: Detailed assessment of the impact of AI on the SDGs

Discussion and Conclusion

The three SDG groups related to environmental outcomes are SDG 13, 14 and 15. In this group we identified that 25 targets could have a positive impact of AI. With reference to SDG 13, Climate Action, AI can improve climate modelling and forecasting, allowing us to better comprehend climate change and its consequences. AI-powered systems have the potential to optimise energy consumption, resulting in lower greenhouse gas emissions and better energy efficiency. AI can help in the analysis of massive amounts of climate data, assisting in the creation of effective climate change mitigation and adaption measures. However, if not handled correctly, the carbon footprint of AI training and data centres can contribute to environmental degradation. Artificial intelligence applications may not be able to completely replace the requirement for human engagement and decision-making in climate-related policy, potentially diminishing responsibility. For life below water, AI can help in marine species identification and monitoring, as well as conservation and the protection of endangered species. Underwater robots and sensors powered by AI can help assess marine ecosystems and detect pollution, contributing in the preservation of healthy marine environments. At the same time, we need to keep a check on Noise pollution caused by AI-powered marine monitoring devices as they has the potential to upset marine life and disrupt natural behaviours. Finally, for SDG 15, Life on Land, AI can aid in wildlife conservation by tracking animal movements, identifying poaching, and analysing ecosystem health. Drones and satellites driven by artificial intelligence can monitor deforestation and land use changes, thereby promoting sustainable land management practises. Furthermore, despite many examples of positive impact the adoption of AI-driven agricultural practises may result in monoculture and biodiversity loss.

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