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REVIEW ARTICLE

Artificial Intelligence (AI) for Environmental Sustainability: A Concise Review of Technology Innovations in Energy, Transportation, Biodiversity, and Water Management

Asif Raihan[1*], Arindrajit Paul[2], Md. Shoaibur Rahman[3], Samanta Islam[4], Pramila Paul[5], Sourav Karmakar[6]

[1]Institute of Climate Change, National University of Malaysia, Bangi 43600, Selangor, Malaysia
[2]Department of Computer Science, University of Colorado Boulder, Boulder, CO 80309, United States
[3]Department of Agroforestry and Environment, Hajee Mohammad Danesh Science and Technology University, Dinajpur 5200, Bangladesh
[4]Department of Environmental Science and Engineering, Jatiya Kabi Kazi Nazrul Islam University, Mymensingh 2220, Bangladesh
[5]University of Graz, Graz 8010, Austria
[6]University of Tartu, Tartu 50090, Estonia

Corresponding Author: Asif Raihan. Email: asifraihan666@gmail.com
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Abstract
Artificial Intelligence plays a crucial role in addressing various environmental sustainability challenges through technological innovations in the fields of energy, transportation, biodiversity, and water management. Thus, the present study aims to present a concise review of Artificial Intelligence (AI) toward achieving environmental sustainability. The main areas of concentration in innovations in the field of energy encompass neural networks, expert systems, pattern recognition, and fuzzy logic models. Artificial Intelligence enables the creation of advanced prediction models for renewable energy production, enhancing the allocation of resources and management of the power grid. Moreover, computer vision and decision assistance have been used in the field of transportation. Additionally, the use of Artificial Intelligence and machine learning is growing to predict and enhance water resource conservation. Besides, machine learning and natural language processing techniques are being used in biodiversity research to predict ecological services. However, regular monitoring of initiatives is necessary to enhance environmental sustainability.

Keywords: Artificial Intelligence; Technology innovations; Energy; Environment; Sustainability

Introduction

The pressing global environmental difficulties of the 21st century have highlighted the significance of Artificial Intelligence (AI) as a crucial field of study for addressing many sustainability issues (Frank, 2021).

Artificial Intelligence (AI), initially introduced by John McCarthy in 1956, refers to the field of study and development of intelligent machines. Computer science encompasses the field of Artificial Intelligence (AI), which relies on previous learning experiences to improve its ability to solve complex environmental issues (Jha et al., 2019). According to Poole et al. (1998), AI refers to the intelligence exhibited by advanced machines, which is distinct from the natural intelligence displayed by humans and animals. Wang and Srinivasan (2017) define AI as the scientific and engineering field that aims to create machines with intelligence comparable to that of humans. Nishant et al. (2020) and Duan et al. (2019) observed that AI robots acquire knowledge through experience while carrying out activities begun by humans, in order to adapt to new inputs and overcome environmental obstacles.

Therefore, in our present era of the digital world, the limitations of human thinking have been tackled by AI, leading to the emergence of intelligent machines equipped with artificial brains that can interact with human brains (Jha et al., 2019; Frank, 2021). Addressing environmental sustainability challenges is a complex task (Raihan & Tuspekova, 2022a; 2022b; 2022c; 2022d; 2022e). However, the arrival of AI has made it easier to tackle common environmental problems by actively prioritizing the well-being of individuals (Nishant et al., 2020). The environment, economy, and society are interconnected aspects of sustainability (Olawumi & Chan, 2018; Raihan & Bari, 2024). According to the UN document known as the "Brundtland Report," sustainability is defined as sustainable development, which means ensuring that the current generation's needs are met without jeopardizing the ability of future generations to meet their own needs (WCED, 1987). According to Morelli (2011) and Nishant et al. (2020), environmental sustainability refers to the ability to meet the resource and service requirements of both current and future generations, without compromising the health of the ecosystem for humans.

Regrettably, the world is presently in a precarious condition with regard to the impacts of global warming and climate change (Leahy, 2019; Raihan et al., 2023). Consequently, it is imperative that we take immediate action by adopting ecologically friendly and sustainable products (Frank, 2021; Raihan, 2023a). Furthermore, the degradation of the environment, combined with climate catastrophe, is one of the complex environmental concerns (Raihan et al., 2022a; 2022b) that necessitate advanced and novel Artificial Intelligence (AI) solutions (Nishant et al., 2020). AI and environmental sustainability can be categorized into four main areas: sustainable agriculture, preservation of environmental resources, waste and pollution management, and pollution monitoring and treatment (Nishant et al., 2020). According to Jha et al. (2019), the development and utilization of Artificial Intelligence are necessary for achieving environmental sustainability due to its durability throughout the previous 50 years. Nishant et al. (2020) state that the research on AI for environmental sustainability spans multiple academic fields. Significantly, Artificial Intelligence is utilized in various domains such as energy, transportation, water, and biodiversity to effectively tackle the prevailing global and regional environmental challenges. It is worth noting that these sectors have made significant advancements and continue to evolve. AI has been applied practically in transportation and biodiversity in several developed nations (Nishant et al., 2020).

These applications include but are not limited to, using advanced routing plans to collect e-waste, protecting the ocean from pollution, utilizing AI-powered autonomous garbage collection trucks, and enhancing wildlife conservation for biodiversity. However, it is necessary to consolidate the current body of literature on the utilization of Artificial Intelligence (AI) in the fields of transportation and biodiversity. It is important to highlight the limited use of AI for promoting environmental sustainability in sectors such as energy, transportation, water, and biodiversity (Nishant et al., 2020). This research identifies a significant gap in understanding how AI may be used to promote environmental sustainability. Specifically, it explores how AI can tackle environmental concerns related to energy, transportation, water, and biodiversity in order to accomplish the Sustainable Development Goals (SDGs), as depicted in Figure 1.

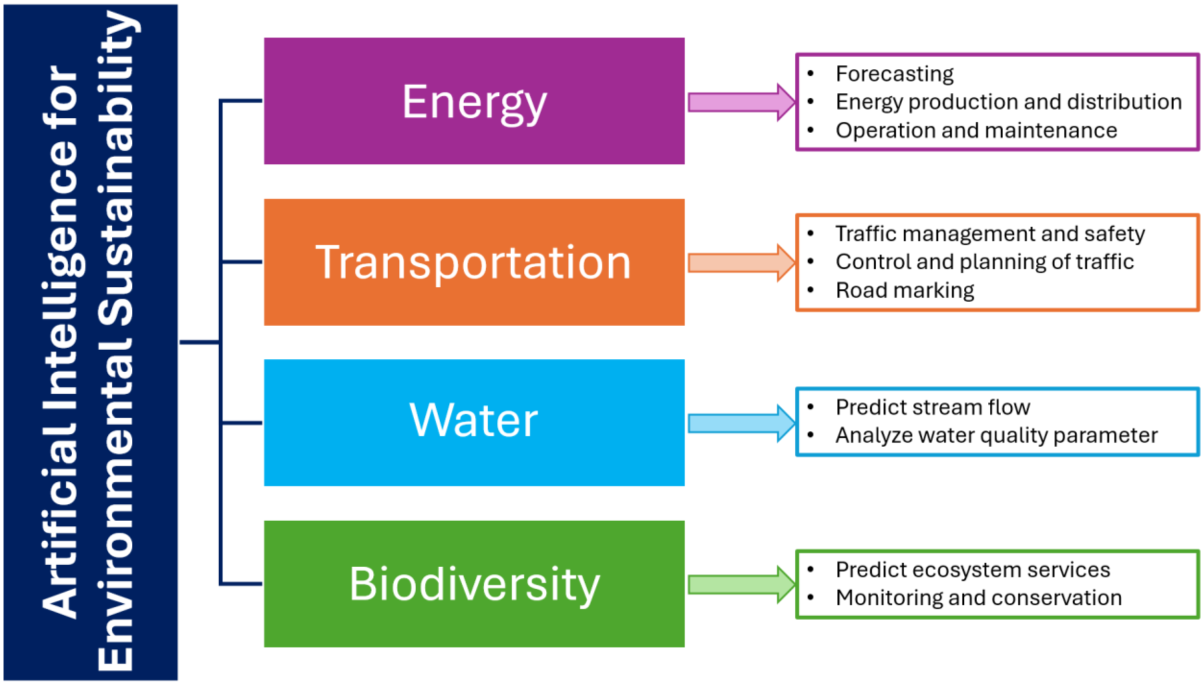

Figure 1. Artificial Intelligence (AI) for promoting and maintaining environmental sustainability.

Artificial Intelligence levels and domains

Artificial Intelligence has been categorized into three distinct tiers (Strelkova & Pasichnyk, 2017). The three degrees of intelligence are Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). According to Strelkova and Pasichnyk (2017), Artificial Narrow Intelligence (ANI) refers to robots that are specifically taught for a certain activity and are capable of making judgments solely inside that specific domain. Artificial Narrow Intelligence (ANI), commonly referred to as Weak AI, is exemplified by Google search. The term Artificial General Intelligence (AGI), also referred to as Strong AI, is defined by Wang and Goertzel (2007) as the ultimate form of synthetic intelligence. Artificial General Intelligence represents the point in the development of Artificial Intelligence when computers acquire the cognitive capacity to make decisions similar to humans. A prime illustration of this is autonomous autos. Cully et al. (2015) described Artificial Super Intelligence (ASI) as the stage of Artificial Intelligence where its cognitive abilities surpass those of the best human brain in various domains, including scientific ingenuity, general wisdom, and social skills. AI enables organizations to address environmental difficulties and improve sustainability performance by using autonomous interactions, such as robots, to solve problems like garbage removal (Frank, 2021).

Artificial Intelligence encompasses six fields, namely logic and methodologies, which are dedicated to addressing difficulties related to environmental sustainability (Jha et al., 2019). According to Jha et al. (2019), the implementation of any AI requires the involvement of machine learning (ML), which refers to the numerous learning processes of machines. The objective of ML is to provide computers with prior facts, experiences, and statistical information. This data is helpful in optimizing the execution of given activities aimed at resolving specific issues, particularly those related to the environment. Machine learning employs many mathematical methods to create highly intelligent machines that contribute to the development of new technologies through the use of applications for analysis (Jha et al., 2019). To analyze water quality data, Machine Learning (ML) is utilized to predict stream flow (Demirci et al., 2019; Nishant et al., 2020). Artificial Neural Networks (ANN), as described

by Jha et al. (2019), are a specialized method or logic that is designed for certain tasks. Unlike traditional computational tasks that are coded, ANN operates based on inherent tasks. Therefore, in contrast to comprehensive programming, learned neural networks possess numerous advantages over conventional systems due to their trainable nature. For instance, in the context of parallel reasoning, it has the ability to anticipate and project water resource factors (Maier & Dandy, 2000). In the sphere of agriculture, crop nutrition levels may be predicted (Song & He, 2005) and weeds can be distinguished from crops (Gliever & Slaughter, 2001).
Thirdly, robotics involves integrating several domains by leveraging the cognitive abilities of people, encompassing emotions and cognitive processes. According to Nishant et al. (2020), AI robots are able to carry out tasks by imitating human movements and other actions. The use of robots is prevalent in various aspects of farming, such as seeding, planting, fertilizing, weeding, spraying, irrigating, harvesting, and shepherding (Jha et al., 2019). The utilization of robots simplifies tasks, and it is important to acknowledge that the same tasks that may be performed by a robot would often require a greater number of human workers to accomplish (Jha et al., 2019). The utilization of Natural Language Processing (NLP) is a dynamic concept that primarily involves AI's ability to mimic human cognition (Kurdi, 2017; Nishant et al., 2020) by comprehending and interpreting material in order to generate human-like language (Szeliski, 2014; Nishant et al., 2020). According to Poria et al. (2017) and Nishant et al. (2020), combining Computer Vision (CV) and NLP enables machines to learn from voice and visual data, leading to the field of affective computing. Zadeh (1975) defines Fuzzy Logic (FL) as a method of human reasoning that permits the consideration of values beyond the typical binary Boolean logic. Fuzzy Logic decision support systems have been utilized to tackle routing-related issues, such as mobility-on-demand and fraud prevention (2019). Expert Systems (ES), as defined by Nishant et al. (2020), involve the utilization of knowledge bases and databases, along with inference engines, to address intricate problems. Recent research has demonstrated the utilization of Expert Systems, which combine Machine Learning models and Fuzzy logic, to enhance decision-making (Kumar, 2019; Nishant et al., 2020).

Methodology

This research utilized a methodical desk review to investigate the utilization of Artificial Intelligence in addressing environmental sustainability in many domains such as energy, transportation, water, and biodiversity. The published Systematic Review (SR) on Artificial Intelligence and environmental sustainability utilized the same processes as other models or principles that are commonly employed in Systematic Reviews. When constructing the Systematic Review (SR), this study adhered to internationally recognized standards that have been established by other scholars (Raihan, 2023b). These standards have been chosen for their potential to demonstrate validity compared to other analytical frameworks. The systematic review is the optimal framework as it allows for the acquisition of unbiased secondary information. Significantly, while discussing Artificial Intelligence and environmental sustainability, the methodology adhered to the well-recognized Preferred Reporting Items for Systematic Review (Tawfik et al., 2019).

Research question

Tawfik et al. (2019) noted that the issues asked in the Systematic Review are pertinent. The investigation commenced with a preliminary examination of each article, guided by a thorough survey of current literature, in order to address the specific question: how is Artificial Intelligence utilized to tackle environmental sustainability?

Initial investigation and concept confirmation

Preliminary research was conducted to ensure the viability of the proposed concept. This was primarily done to avoid any repetition of the question being addressed while ensuring that an adequate number of papers were made accessible for the review. In addition, the search keywords were specifically targeted towards Artificial Intelligence and environmental sustainability, which were deemed reliable based on the chosen methodology. To enhance the retrieval of comprehensive findings and gain a more profound comprehension, searches were conducted on Google Scholar utilizing the terms "Artificial Intelligence" AND "Environmental Sustainability" to address the asked inquiries.

Inclusion/exclusion criterion

In order to gather 50 papers for this study, specific inclusion criteria were established. The sources were obtained for two main topics: Artificial Intelligence and environmental sustainability. There were no restrictions on the nation of origin, but the publication date had to be within the past ten (10) years. After retrieving 50 articles, all duplicates were eliminated, resulting in a reduction in the number of articles to 38. The papers were assessed for inclusion in the final review by reviewing their title and/or abstract and conducting an initial reading of the whole article. After reviewing the titles and/or abstracts, a total of 13 publications were deemed irrelevant and hence excluded. As a result, 25 publications were evaluated for potential inclusion following a comprehensive evaluation.

Results and discussion

AI in the energy sector

According to Nishant et al. (2020), Artificial Intelligence (AI) has been claimed to contribute to the conservation of natural resources and the reduction of energy consumption in human activities. The primary areas of attention in energy research include neural networks, expert systems, pattern recognition, and fuzzy logic models (Demirci et al., 2019; Tyralis et al., 2019). These domains encompass energy production and distribution, operations, and maintenance, which have been of significant interest in the field of energy (Wang & Srinivasan, 2017; Ordiano et al., 2018; Merizalde et al., 2019; Nishant et al., 2020). Machine learning algorithms are utilized for predicting future outcomes (Olowu et al., 2018), whereas NC algorithms are employed to address multi-objective issues (Li et al., 2018). The majority of these methods, as utilized by researchers, are included in fuzzy logic (FL) systems to provide decision support for forecasting (Liu et al., 2018). It is important to note that using numerous models leads to more precise outcomes, especially when combining various techniques such as area neural networks (Wang & Srinivasan, 2017). Artificial Intelligence enables the creation of advanced prediction models for renewable energy production, enhancing the allocation of resources and management of the power grid (Ahmad et al., 2021; Raihan, 2023c).

AI in transportation

There is considerable research available on the applications of Artificial Intelligence (AI) in sustainable transportation. The majority of published articles are on machine learning (ML) (Abduljabbar et al., 2019). Furthermore, the utilization of computer vision to assist in decision-making was observed in the domains of traffic management and safety, as well as in public transit and urban mobility (Liyanage et al., 2019). The application of

AI in transportation involves the use of machine learning, statistical models, and time series models to control and plan traffic (Liyanage et al., 2019). Computer vision techniques have primarily been utilized for road marking (Nishant et al., 2020).

AI in water sector

Since 2015, there has been considerable research interest in the optimization of water resource conservation through the use of Artificial Intelligence (AI) technologies in the field of water resources. Artificial neural networks, specifically the adaptive neuro-fuzzy inference system, support vector machine (SVM), decision trees (particularly random forest), multiple regression, autoregressive moving average model (ARMA), the adaptive neuro-fuzzy inference system, and spline regression are commonly used machine learning models in this field (Salcedo-Sanz et al., 2016; Ochoa & Urbina-Cardona, 2017; Nishant et al., 2020). The most widely used technique is the Genetic algorithm. In addition, widely used machine learning models integrate artificial neural networks (ANN), such as ANFIS, with genetic algorithms (Rodriguez-Soto et al., 2017; Nishant et al., 2020). One example is the utilization of machine learning (ML) models to forecast stream flow and examine water quality characteristics (Demirci et al., 2019).

AI for biodiversity

When it comes to modeling ecosystem services, rule-based systems such as ARIES are widely used and well-regarded. As highlighted by Death (2015), this software incorporates multiple machine learning (ML) models that assist researchers in comprehending different relationships through data analysis tools (Death, 2015). Moreover, there are numerous instances of Artificial Intelligence (AI) being utilized to enhance biodiversity monitoring and conservation, as evidenced by various examples (Kwok, 2019). Emphasizing the need to avoid excessive use of resources that lead to environmental problems, as well as providing information on the ecosystem and its diverse range of species, where access to AI-related information could be beneficial. Nishant et al. (2020) found that biodiversity research has developed effective techniques for estimating or valuing land-related service offerings. Moreover, Artificial Intelligence (AI) can utilize machine learning (ML) or natural language processing (NLP) techniques to accurately forecast environmental services in biodiversity research (Toivonen et al., 2019; Nishant et al., 2020). Artificial Intelligence (AI) offers a novel approach to effectively tackle biodiversity issues across different temporal and spatial scales. Research on AI for sustainability primarily explores the application of genetic algorithms (GA) in Artificial Intelligence (AI). GA is commonly used in machine learning (ML) models for biodiversity, along with other popular techniques such as artificial neural networks (ANN) and Bayesian networks (BN) (Nishant et al., 2020).

Challenges of using AI for environmental sustainability

Artificial Intelligence has been proven to effectively tackle environmental concerns in a sustainable manner. However, it faces a significant obstacle in its reliance on historical data for machine learning. The reason for this is the inherent unpredictability and dynamic nature of Artificial Intelligence, as it is challenging to integrate a wide range of human behaviors into machine learning models. Consequently, historical data predating significant human activity accurately depict past ages and climate cycles, making it challenging to estimate potential climate change. Furthermore, it is crucial for machine learning practitioners to carefully address the issue of minimizing variation when incorporating prior data into models. The inclusion of new data in these models might lead to generalizations, which in turn can result in erroneous predictions of future events. This phenomenon is referred to as variance-bias tradeoffs (Nishant et al., 2020).

Moreover, the heightened susceptibility to cyber threats poses a significant obstacle when implementing AI for the purpose of promoting environmental sustainability. Effective management of cybersecurity risks is crucial when integrating data for Artificial Intelligence (AI) applications. Nevertheless, the increasing prevalence of cybersecurity threats due to hacking poses a significant obstacle to tackling environmental sustainability concerns. This is because unauthorized individuals are able to obtain access to crucial data, and isolated measures are less successful in mitigating the danger of cybersecurity breaches. Insufficient performance measures and unpredictable human responses to different AI-supported initiatives pose additional hurdles in utilizing AI for environmental sustainability (Nishant et al., 2020). The assessment and surveillance of actions are crucial in promoting environmental sustainability. Integrating technical and analytical performance into a comprehensive metric is crucial for the success of AI in achieving environmental sustainability, despite the complexity and frequent lack of success in measurement. AI applications possess comparable decision-making capabilities to humans, yet their emphasis differs significantly in terms of human reactions to judgments. It is important to comprehend the behavioral reactions while avoiding the prevalent issue linked to technological progress caused by the trap of rebound effects (Nishant et al., 2020).

Conclusion

This study provided a comprehensive analysis of how Artificial Intelligence might contribute considerably to the advancement of environmental sustainability in various areas, including biodiversity, energy, transportation, and water. Monitoring plays a crucial role in harnessing the power of Artificial Intelligence and promoting environmental sustainability. Nevertheless, a range of actions is necessary to assess the positive and negative effects of Artificial Intelligence on environmental sustainability. While there are some promising solutions available to address environmental sustainability concerns, the failure to address the majority of these challenges renders the deployment of these technologies unsustainable. In order to achieve environmental sustainability and fully harness the potential benefits of AI for current and future generations, it is imperative that future research prioritizes the exploration of the individual issues associated with each AI technology, as well as their effective implementation. Consequently, sustainable solutions in domains such as biodiversity, energy, transportation, and water might be more prominent. Effective metrics extend beyond solely technical aspects as the genuine worth of AI lies in its ability to enable and promote environmental governance. Policies should address the pressing need to overcome the issues associated with AI applications in order to achieve a sustainable future for both current and future generations. AI offers advantages such as enhancing environmental governance, optimizing industrial environmental performance, mitigating environmental risks, and ensuring safety. In order to make meaningful progress toward environmental sustainability, it is necessary to have timely, precise, and accurate measuring and monitoring of interventions.

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Authors contribution: Asif Raihan contributed to the study's conception and design. Material preparation, methodology development, reviewing literature, extracting information, synthesize, and manuscript writing were performed by Asif Raihan, Arindrajit Paul, Samanta Islam, Pramila Paul, and Sourav Karmakar. The first draft of the manuscript was written by Asif Raihan and Md. Shoaibur Rahman commented on previous versions of the manuscript. All authors read and approved the final manuscript.

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