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The Role of Machine Learning Algorithms in Driving Sustainable Development Goals: A Comprehensive Survey

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Abstract

The United Nations (UN) sustainable development goals (SDGs) are our common goal to end poverty, protect the planet, and ensure peace and prosperity by 2030. Technology adoption by the masses, more so Machine learning (ML), can enable these SDGs. This survey examines the various ways in which ML algorithms are working towards SDGs for various sectors such as health, education, energy and the environment. ML can deal with complex data sets. It can predict behavior and optimize decision-making. Thus, it can play an important role in solving global issues. In health care ML helps to improve the disease diagnosis, epidemic prediction and personalized medicine for better health care. Adaptive learning software and predictive analytics powered by ML will enhance the learning experience while minimizing dropouts. In the energy sector, ML can help manage the grid smartly, predict renewable energies, and optimize resources. Thus, it can make energy cheaper and cleaner. ML applications in the environment include climate modeling and deforestation monitoring to aid climate action. ML has a lot of potential but is still being held back by data scarcity and algorithmic bias. Moreover, developing countries face resource constraint issues. It is important to ensure responsible implementation by setting effective measures to address ethical concerns. This study shows that we need interdisciplinary collaboration, scalable solutions, policy integration, etc., if ML is to have maximal impact on the SDGs. ML can help create a sustainable and equitable future by overcoming these challenges and boosting innovations in key sectors. ML has the potential of helping us achieve great things. However, the same ML can cause a lot of damage if not used responsibly.

Keywords: Sustainable Development Goals; Machine Learning; Artificial Intelligence; Health; Education; Energy and The Environment.

1 | Introduction

SDGs were approved by all UN member countries in 2015 as a universal framework that addresses some of the most pressing issues facing humanity and the planet [1]. They're meant to eradicate poverty and reduce inequalities, improve health and education, economic growth, and provide protection to ecosystems among many other targets [2]. However, state that human pressures such as heavy groundwater abstraction, deforestation, urbanization, and agricultural expansion now constitute significant barriers to the attainment of these goals, because all these slowly create stress on regional water supplies. Climate change, as temperatures rise, induces accelerated evaporation, changes patterns of precipitation, becomes a global scale aggravator on increasing frequency and severity of extreme weather events such as droughts and floods [3]. Figure 1 shows the SDGs as defined by the UN.

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Figure 1. Summary of UN SDGs (1).

In an analysis of the status of the SDGs, the economic ones such as SDG 8 (decent work and economic growth), SDG 9 (industry, innovation, and infrastructure), and SDG 12 (responsible consumption and production) also show progress in some areas achieving closer to the target. Still, it bears standstill performances in other areas such as SDG 4 (quality education), and SDG 11 (sustainable cities and communities), as well as SDG 13 (climate action) where the going continues to be significantly slow with even many areas not reaching their targets. It is usually easier for developed nations to meet several goals, especially in terms of infrastructure and economic development. In contrast, the very most South Asia and Sub-Saharan Africa face sometimes great challenges, particularly when it comes to issues like inequality and poverty, hunger, and education [4].

One of the other global issues that must be tackled with urgency across all regions is about climate change action (SDG 13) and sustainable urbanization (SDG 11) so that the 2030 ambitions will be realized [5]. Figure 2 shows SDGs integrated framework.

Figure 2. SDGs integrated framework.

This research highlights how innovative mechanisms and/or technologies will help advance the SDGs. Artificial Intelligence (AI) is a transformational technology that can help achieve SDGs. ML can be an effective tool when used for optimal resource utilization, energy efficiency, and environmental monitoring, given its emerging capabilities in data processing, pattern recognition, and predictive modeling [6]. The applications range from urban sustainability [7] to water saving [8, 9], clean energy [10-12] and waste management [13, 14].

ML's contribution to sustainability has not been without problems. The dilemma that needs to be resolved is the cost of the environment in the development and deployment of ML models, particularly energy consumption, and carbon emissions [15]. Moreover, the concerns with regard to algorithmic bias, explainability, and fairness raise multiple ethical considerations [16]. Therefore, a balanced approach is needed to find the sweet spot at which one enjoys the advantages of ML while managing the risks associated with the responsible adoption of ML into the sustainability projects. This paper seeks to present an exhaustive appraisal of the current contribution of ML to sustainability. It, therefore, examines contemporary ML methods, their applications in different sustainability areas, and the extent of their influence on meeting SDGs. Originality has been in the thorough discussion of how ML may spur innovation while exposing the ethical questions and structural challenges when placing ML within sustainability frameworks. This review will provide significant input to the growing discourse on sustainable development in the coming era of AI by way of systematic summary of ML usages, challenges, and future directions.

The rest of this paper is organized as follows. Section 2 provides the background for this survey. Moreover, section 3 provides an overview of previous research and its contribution to achieving the objectives. Section 4 explains the contribution and recommendations. Finally, section 5 presents the conclusions.

2 | Background

2.1 | SDG

The goals for sustainable development are the agendas of the United Nations towards the end of 2030. A comprehensive plan forecasted for and taught to tackle the variety of global challenges, from well-being, through economic prosperity, to environmental protection. Each SDG would have positive correlations or fair synergies or synergies in trade-offs with the other SDGs [2]. The application of the circular economy would help achieve some SDG targets; however, other trade-offs require more consideration [17]. The SDGs most related to everyone describe resource efficiency, green economy jobs, and quality of life improvement along with sustainable consumption and production patterns.

2.2 | Machine Learning

ML is a subfield that deals with soft computing and is usually categorized under computer science; it studies the algorithms that learn from the data and subsequently predict in an e-learning activity. It builds models from training sets and makes predictions based on data [18]. ML techniques can be dimension reduction and ensemble learning, meta-learning, reinforcement learning, supervised learning, unsupervised learning and deep learning.

Deep learning, one of the methods of ML, learns multiple feature levels of data along with its representations to provide state-of-the-art predictions. Deep reinforcement learning is the combination of reinforcement learning and deep learning for solving very complicated decision-making tasks in multiple types of environments [19]. Quantum ML uses quantum systems to outperform classical systems in the resolution of specific ML problems. Their practical applications include sentiment analysis, health sciences, robotics, smart grids, stocks, and much more. That is the new promising frontier in applying ML to various real-life situations [20]. Figure 3 below shows a comprehensive overview of machine learning.

Figure 3. Overview of machine learning.

3 | Review of the Related Literature: The 17 Sustainable Development Goals

The substantial amount of research evaluating ML's applications and contextual efficacy has led to significant attention to the integration of ML into a variety of industries. Considering the scope of coverage as well as possible areas that could need more research, this section examines how ML is being used in several sustainability sectors. A thorough analysis of the 17 SDG and how ML affects them is provided in this section of the paper.

3.1| SDG 1: No Poverty

It is worth mentioning that the first Sustainable Development Goal (SDG 1) is aimed towards universal eradication of extreme deprivation by the year 2030; such deprivation is currently described as living on less than $1.90 a day [21], and it entered into all its dimensions as defined nationally, made social protection systems effective and ensured that equal access to economic resources is provided, as well as built resilience against socio-economic shocks. Thus, this goal brings people and families a dignity in which they can have opportunities for growth and self and collective betterment [22].

The challenges of the attainment of SDG1: Inequality in economic opportunities, where poverty is worsened by unequal access to jobs, education, and basic services, especially in rural and marginalized areas. Scanty data where governments and organizations usually lack timely and accurate localized data to understand distribution and trends in poverty properly Economic vulnerability, where many remain exposed to threat by forces of nature, diseases, and variations in market activities, which only serve to relegate them to the poor [23]. Complex poverty dimensions, since poverty is multidimensional, and exists beyond incomes like education, health care, and living standards. Financial exclusion barriers, limited access to banking and credit facilities in poor areas participates in economic participation (24).

ML provides innovative tools to overcome such challenges-these include predictive modeling, automated data analysis, and optimization strategies. In helping governments, NGOs, and policymakers better target resources, ML also improves the design of evidence-based interventions. Below is Table 1, the table includes some research papers that discuss and provide some solutions to meet the previous challenges and present the role of ML in this regard.

Table 1. Summary of some published papers that illustrate the role of ML in achieving the SDG 1.

Reference	Year	Method	Summary
[25]	2024	VGG16 + F	- The study analyzes and predicts poverty in South Africa using satellite imagery.
[26]	2022	CNN	- The study utilized ML methods to analyze satellite imagery and construct detailed poverty maps, which were then used to improve the distribution of social assistance.
[27]	2021	XGBoost	- ML was employed to estimate the integrated poverty index (IPI) by analyzing various spatial variables, enhancing the accuracy of poverty mapping.
[28]	2021	Automated ML (AutoML)	- Identifies debt-risk factors in impoverished households using AI to propose targeted financial interventions.
[29]	2024	ML Algorithms	- The authors used ML to enhance poverty classification and resource allocation systems in developing nations.
[30]	2023	AI, Bibliometric Analysis	- AI's potential role was reviewed in alleviating poverty, highlighting key research themes and challenges.
[31]	2021	Decision Trees, Random Forests	- The ML approaches were used to assess and monitor poverty status in Jordanian households for better policymaking.
[32]	2022	XGBoost, Mobile Data	- The researchers combined mobile phone data and ML to identify ultra-poor households for effective poverty intervention.
[33]	2024	Boosting Algorithms, Decision Trees	- The boosting algorithms were applied to predict poverty levels and classify household wealth in the Philippines.
[34]	2024	Neutrosophic logic, ML	- The study leverages the strengths of these methods to assess poverty more comprehensively, incorporating uncertainty and imprecision in socio-economic data. - The integration of NS logic and ML enhances the accuracy and interpretability of poverty measurement indicators.

3.2| SDG 2: Zero Hunger

SDG 2 is to achieve Zero Hunger, namely, to eradicate hunger, attain food security, improve nutrition, and promote sustainable agriculture. The goal underlines the inter-linkages between food security, nutrition, rural transformation, and sustainable agriculture [35]. Globally, despite efforts, about 690 million people are hungry, and under-nutrition is continuing to rise due to various stresses in food systems, including climate shocks, locust crises, and the COVID-19 pandemic [36]. The world is nowhere on track to meet the goal of Zero Hunger by 2030; rather, signs show an increase in hunger and food insecurity. Therefore, we must increase our commitment to integrating inland fishery services into the SDGs promoted by policies and development schemes to further enhance those SDGs [37]. For example, inland fishery services are critical to Zero Hunger and other such goals as No Poverty; Clean Water and Sanitation; Responsible Consumption and Production; Life on Land; among others. It is essential to deal with such trade restrictions and distortions to agricultural markets if indeed a global affordable food approach is to be realized in zero hunger [38].

One of the many challenges impeding the way towards the attainment of SDG 2 is Food Insecurity, which now permanently adheres to more than 720 million people over the world who suffer from extreme hunger [39]. This situation manifests itself as an unequal distribution of food and poverty. Effects of Climate Changes, Extreme Weather Conditions like draughts or floods and unusual rainfall patterns result in disrupted agricultural productivity. Pest and Disease Management; Pest and disease reduce yield production from crops, especially in places where people have no effective solutions for them. Supply chain inefficiencies, post-harvest losses, and waste because of storage and transportation exacerbate the problems of food scarcity. Lack of agricultural innovations, Most smallholder farmers in many developing nations cannot access modern agricultural technologies [40].

AI and ML models are frequently employed to accomplish several SDG 2 goals and offer practical management strategies to combat hunger at the local level. Using soil, weather, yield, and geographic information systems, as well as satellite, irrigation, livestock, and economic data, AI and ML models are used for descriptive, predictive, and prescriptive methods to analyze economic, social, and environmental indicators of the Agriculture Supply Chain (ASC) [41, 42].

Big data, sensors, IoT infrastructure, robots and data analytics are all crucial parts of the infrastructure for smart agriculture, which includes the new fields of precision agriculture, digital agriculture, smart irrigation, and smart agriculture. These solutions provide quicker and more reliable supply chain management, increase transparency, save costs, and boost farmers' profitability. Agricultural activities are powered by AI and ML models used to predict future outcomes and make operational decisions in real time , and developing novel business models [43, 44]. Table 2 includes some papers that discuss challenges and present the role of ML in this regard.

Table 2. Summary of some published papers that illustrate the role of ML in achieving the SDG 2.

Reference	Year	Method	Summary
[45]	2024	Clustering	- The study assessed SDG 2 progress using clustering to evaluate performance in European countries.
[46]	2020	Custom ML Model	- The authors developed Persephone to streamline interdisciplinary evidence synthesis for SDG 2.
[47]	2024	ANN Model	- ML was applied to enhance crop yield prediction and resource management for food security.
[48]	2025	ML methods, DNN models	- The automated crop disease identification is used to improve agricultural productivity.
[49]	2025	Deep learning models	- The integrated satellite data with ML are combined for predicting agricultural productivity.

3.2| SDG 3: Good Health and Well-Being

It is about reducing the mortality rates, promoting mental health, preventing substance abuse, and universal health coverage. Aside from that, unintended effects may occur due to sustainable building practices in Australia; mold and condensation might manifest in newly constructed houses [50]. In India, groundwater gets polluted, and the impurities emerging out of it led to several health hazards, mainly from fluoride and nitrate ingestion. Forest conservation happens to be one of the prime activities, which contributes towards the good health and sustainable well-being by protecting traditional medicine and controlling the incidence of infectious diseases [51]. Healthcare managers consider it essential; however, they are most specifically dependent on SDG 3 in crafting public policies that have better health outcomes [52]. The COVID years have added importance and urgency to the emphasis on building health systems by governments to achieve universal health coverage. Overall, SDG 3 aims at wholesome lives and well-being for everyone; it also discusses many health-related problems and provides access to worldwide healthcare services.

ML plays a role in achieving SDG 3. The ADAM application, for instance, aids employees in reducing anxiety through a rule-based model of ML with productivity improvements as a result [53]. Furthermore, big data analytics would help refine predictive models of disease progression and personalize treatment strategies, as it is called by SDG 3 [54]. Applying ML and multiple data sources would also effectively identify risk factors, optimize resources, and improve health outcomes [55]. It could also address how drinking water sources vary spatially-with the demonstration from one study in Ghana-and lead to well-targeted policy action directed towards improving access to safe drinking water [56], thus contributing to SDG 3 on population health and well-being. Thus, indeed, ML and data analytics become the centerpiece of future healthcare, collective mental health, and dedicated access to essential resources for good health and well-being as codified in SDG 3. Table 3 includes some papers that talk about the role of ML in Achieving SDG 3.

Table 3. Summary of some published papers that illustrate the role of ML in achieving the SDG 3.

Reference	Year	Method	Summary
[57]	2021	Supervised, unsupervised and reinforcement Learning	- The study reviewed ML applications in radiology, genetics, EHRs, and neuroimaging.
[58]	2018	ML models	- The study transformed patient risk stratification for infectious diseases.
[59]	2022	ML models	- The authors discussed the innovations and challenges in deploying ML in healthcare.
[60]	2024	ML models	- The researchers studied the applications and challenges of integrating ML and AI in life-course epidemiology.
[61]	2023	CNN, AI tools	- This article provided an in-depth analysis of AI's potential in clinical practice, including its applications in disease diagnosis, treatment recommendations, and patient engagement, while also discussing ethical and legal challenges.
[62]	2021	ML models	- The study exploree the potential benefits and challenges of ML in a comprehensive health perspective, integrating cultural, social, and environmental factors into public health research.

3.4| SDG 4: Quality Education

Education is transformed into universal and equitable quality education for all humans to access the opportunities of lifelong learning. This includes all types of education, from free primary schooling and access

to secondary education at its elementary level, to affordable vocational and higher education. These are just a few of the targets of SDG 4 [63]. Education is the means, the most reliable means to sustainable development, nation-building, and peace. According to findings from a research study in Austria, universities perform substantially well in their research outputs having concrete positive effects on SDG 4 in conjunction with SDG 3 [64]. The scope of SDG 4 is typically expected to prepare children and young people with the requisite skills and knowledge not just for today but also for tomorrow.

ML methods could also help accomplish SDG 4, in creating quality education. The ANN-based LA systems can help education stakeholders access learner data, using regression analysis, pattern recognition, and predictive analytics, to make sound decisions from information gleaned [65]. Such systems may also include making learning outcome enhancement better employability and entrepreneurial skills through adaptive learning. ML algorithms can also predict student performance in courses early on, enabling intervention to provide timely support. ML can also predict the suitability of mobile applications for children, thus aligning with the tenet of SDG 4 that handles inclusivity and equitable quality education [66]. Improved learning experience, lifelong learning opportunities, and the end of universal literacy and numeracy will, therefore, contribute further to the direction of achieving SDG 4 by developing interventions through ML techniques in education. Below in Table 4, some papers are recorded to illustrate the role of ML in achieving SDG 4.

Table 4. Summary of some published papers that illustrate the role of ML in achieving the SDG 4.

Reference	Year	Method	Summary
[67]	2020	AI, ML methods	- The study discussed AI's impact on various SDGs, emphasizing its role in improving education and inclusivity.
[68]	2024	AI, ML methods	- This paper reviewed AI's role in supporting educational continuity during the COVID-19 pandemic.
[69]	2023	Reinforcement learning	- The research applied reinforcement learning algorithms to personalize learning experiences and improve engagement.
[70]	2022	ANN model	- This paper presented an approach of statistical analysis to identify the most common factors that affect the students' ANNs to predict students' performance within the blended learning environment of Saudi Electronic University (SEU).

3.5| SDG 5: Gender Equality

Striving for gender equality is within the essence of the SDGs that aim to eradicate discrimination, violence, and harmful practices. It also forms the basis for pursuing gender equality as one of the ends of sustainable development considering the rise in violence against women during the COVID-19 pandemic [71]. SDG 5 envisages evidence-based policy making through public-private partnerships and corporate strategies empowering women and girls, and grant access to equitable resources and technologies [72].

Promoting gender bias-correcting measures can involve the use of ML technologies. Research has revealed that overly masculine-dominated design processes generate a great deal of gender bias in technology development [73]. The alteration of the incorporation of gender theory and diversity into ML approaches prevents the generation of biased algorithms, which tend to disadvantage women. Gender equality is the whole of SDGs since it mandates that the needs of women will receive the same attention as that of men [74]. ML and tensorization of bias will lead to the acceleration of SDG 5 and other related objectives in developing a fairer and more sustainable future. Table 5 includes some papers that talk about the role of ML in Achieving SDG 5.

Table 5. Summary of some published papers that illustrate the role of ML in achieving the SDG 5.

Reference	Year	Method	Summary
[75]	2022	Analysis of 120 papers on gender biases in ML/AI system	- The study analyzed academic publications to map current research on gender-specific biases in ML and AI systems.
[76]	2024	ML models for forecasting SDG scores	- The study aimed to forecast global SDG scores by 2030 using ML models to identify priority areas.
[77]	2020	Data segmentation using ML	- The authors presented an approach to expounding triggers of SDG indicators through data segmentation.
[78]	2022	Recommendations for ensuring sex and gender equity in ML/AI tools	- The researchers presented recommendations for ensuring sex and gender equity in ML/AI tools in dermatology.

3.6| SDG 6: Clean Water and Sanitation

The aim is to bring about universal availability, and sustainable management of water and sanitation for all. The target includes outcome targets such as drinking safe and affordable water, ending open defecation, improving water quality, and increasing water use efficiency. Means of implementation targets include extending water and sanitation support to developing countries and supporting local engagement in water and sanitation management [79].

ML can be one of the enablers to realize (SDG 6). A National Blueprint Framework (NBF) has 24 indicators concerning water and SDG 6, which include the need to provide complementary indicator targets and policy quantitative goals to improve monitoring progress [80]. The information is hereby supported by Earth Observation (EO) and cloud computing for SDG 6 countries in the Nile basin concerning water stress and urbanization indicators [81]. In addition, it proposes a physics-informed deep learning model for hydraulics state's estimation in water distribution systems to develop efficiently simulate and plan for access to clean water [82]. SDG 6 is very important for health improvement, school attendance, and poverty alleviation. Further, the UN is pushing for increased donor commitments to the water sector, which should unlock SDG 6. Table 6 illustrated some papers that discuss role of ML in Achieving SDG 6.

Table 6. Summary of some published papers that illustrate the role of ML in achieving the SDG 6.

Reference	Year	Method	Summary
[83]	2021	ML Models, including CNNs	- SustainBench introduces benchmarks to evaluate ML models for SDG-related tasks, including water management.
[84]	2024	Deep learning models	- The research applies models to predict water quality indices, ensuring better water resource management.
[85]	2023	Bayesian Networks, ML Regression Models	- Bayesian models predict flooding events, aiding water resource planning and disaster management.
[86]	2021	Gradient Boosting Machines (GBM), Ensemble Learning	- Ensemble models analyze river pollution data, identifying critical pollution trends for mitigation.

3.7| SDG 7: Affordable and Clean Energy

SDG 7 is to provide everyone with access to affordable, reliable, sustainable and modern energy. This objective comprises targets for universal access to modern energy; increasing the proportion of renewable energy in the global energy mix; as well as increasing two-fold the improvements made towards energy efficiency [87]. It is also intended to enhance access to research, technology, and investments in clean energy as well as enabling improved access to energy services by the developing world. However, making progress toward each of these targets is most critical for economic development and poverty reduction and general well-being [88].

AI, through ML, has been employed to prioritize the SDGs and assess their associations with wealth acquisition. SDG 7 is positively associated with wealth. ML algorithm predicts battery RUL with improved accuracy and robustness which enhances its contribution to SDG 7: Clean and Affordable Energy and SDG 13: Climate Action [89]. Below is Table 7, the table includes some research papers that discuss and provide some solutions to meet the previous challenges and present the role of ML in this regard.

Table 7. Summary of some published papers that illustrate the role of ML in achieving the SDG 7.

Reference	Year	Method	Summary
[90]	2023	LSTM	- This research employed LSTM networks to predict short-term energy demand, ensuring grid stability and efficient renewable energy integration.
[83]	2021	Benchmarks for ML applications	- The authors introduced SustainBench, benchmarks designed to monitor SDGs, including tasks relevant to sustainable energy and other critical global challenges.
[91]	2023	Rule-Based Data Extraction	- The researchers presented an approach combining qualitative coding and rule-based extraction for identifying relevant datasets for SDG research.
[92]	2020	Decision Trees and RF	- This research studied energy efficiency enhancement through the application of ML models in residential and industrial settings.
[93]	2024	Gradient Boosting Models	- The study demonstrated how gradient boosting enhances energy management in systems integrating multiple renewable sources.

3.8| SDG 8: Decent Work and Economic Growth

SDG 8 aspires to inclusive economic growth, full employment, and decent work for all; policies for job creation, resource efficiency improvement, equal pay, youth employment, ending modern slavery and child labor, protecting labor rights, and promoting safe working environments are covered under it (87). Other indicators are sustainable tourism, universal access to financial services, trade-support aid, and global employment strategy for the youth.

The relationship between SDG8 with SDG2 was assessed using ML techniques among poor urban households in Southern Africa (94). The study also found that household income and education levels are the most significant predictors of food security. With the Labour Inspection Checklists Dataset, LICD has been introduced to facilitate more effective labor inspections. A study of the Indian subsidiaries of MNCs indicated the importance of SDG 8 practices like workforce diversity and equal opportunity for achieving SDG 8 and hence creating a decent work environment (95). Below is Table 8, the table includes some papers that talk about the role of ML in Achieving SDG 8.

Table 8. Summary of some published papers that illustrate the role of ML in achieving the SDG 8.

Reference	Year	Method	Summary
[45]	2024	Clustering Algorithms	- The study introduced clustering algorithms to evaluate Italy's alignment with SDGs related to climate change and the agrifood market.
[96]	2022	ML for Artefact Detection	- The UN SDGs is expanded by leveraging the interrelationship between science and technology through ML applications.
[77]	2020	Data segmentation techniques	- The authors presented a consilient approach to expounding triggers of SDG indicators through data segmentation, unifying understanding.

3.9| SDG 9: Industry, Innovation, and Infrastructure

SDG 9 concerns itself about resilient infrastructure, sustainable industrialization, and innovative improvement. This includes the development of sustainable infrastructures, inclusive industrialization, and research and enhancement of industrial technologies (97). SDG 9 further concerns itself with connection, efficient transportation, and any innovation that may support economic, social, and environmental hurdles (38). It also includes universal access to information and financial markets, technology development, and industrial diversification.

In line with SDG 9, that is Industry, Innovation, and Infrastructure, ML can play a crucial role. An example study has been improving localization accuracy in magneto-inductive underwater wireless sensor networks (MI-UWSNs) for applications in industrial IoT, for monitoring gas and oil pipelines. By employing ML techniques for predicting localization estimation accuracy, the study's outcome revealed accuracies level ranging from 95% up to 97% (98). A new technique is also presented to assemble an MI-TD coil to increase localization accuracy.

Another research underlined wind energy partaking to SDG 9 through the London Array wind farm (99). Wind energy establishes an enabling environment of energy security while also promoting economic growth and development of infrastructure. In this way, since countries can develop infrastructure using clean energy by employing wind energy, the greenhouse gas emission toll can be reduced and many SDGs achieved by these countries (100). This is a clear show of how ML and sustainable energy sources can innovate and develop infrastructures within SDG 9. Below is Table 9, the table includes some research that talks about the role of ML in Achieving SDG 9.

Table 9. Summary of some published papers that illustrate the role of ML in achieving the SDG 9.

Reference	Year	Method	Summary
[90]	2023	Deep learning	- Energy demand prediction is explored for smart grids to improve renewable energy integration.
[67]	2020	Data Segmentation Models	- The study discussed ML approaches to analyze SDG data and identify key development indicators.
[101]	2021	Gradient Boosting	- ML applications were investigated for optimizing industrial processes and waste reduction.
[102]	2021	Ensemble Models	- ML models are integrated for fostering innovation in sustainable urban development.

3.10| SDG 10: Reduced Inequalities

It aims to empower inequalities among countries and within nations through representation, recognition, and distributive justice. Despite such recognition, distributive justice applies to situations in which forest-dependent populations need support [103]. It has been denoted that Building Volume per Capita would be related to economic and housing inequalities, which would be in line with SDG 11 sustainable cities and communities (104). SDG 10 addresses income inequalities in terms of inclusion and ending discrimination through equality policies.

ML could provide a strong basis for reducing inequalities, especially in the field of healthcare. In their analysis, Gao et al. [105] discussed how AI models need to be unbiased such that they do equally well with respect to all ethnicities to minimize health disparities. Transfer learning has been shown to improve model performance for data-disadvantaged ethnic groups thereby decreasing disparities related to healthcare caused by data inequality. Also, according to Chancel et al. (106), the SDGs addressing inequalities on-going and contemporary can concretely help countries toward achieving SDG 10. Achieving buy-in from the key actors makes an important difference in leveraging SDGs efficiently. Overall, ML that is ethical and inclusive will go a long way toward helping to reduce gaps within and between countries, as it will meet SDG 10. Below is Table 10, the table includes some papers that talk about the role of ML in Achieving SDG 10.

Table 10. Summary of some published papers that illustrate the role of ML in achieving the SDG 10.

Reference	Year	Method	Summary
[107]	2024	Clustering algorithms	- Clustering models assessed Italy's alignment with SDG targets for better policymaking.
[55]	2021	Decision trees, regression models	- Synergy analysis was demonstrated among SDGs for prioritization using ML techniques.
[108]	2023	AI algorithms, ML	- AI and ML were used to identify and address gender gaps in education and employment data globally.
[109]	2024	ANN model	- Urban disparities are performed using spatial data and ML methods, aiding city planning.

3.11| SDG 11: Sustainable Cities and Communities

The issues of sustainable development concerning the urban areas and communities are noted by the SDG, which will help in addressing the global challenges on sustainability. The urban areas focus on poverty reduction, education, gender equality, good water supply and energy, as well as the promotion of economic growth and climate action [110]. The implementation of an Electric Vehicle Strategy in Dundee enhances energy affordability and sustainable community principles. The programs looking to older adults have synergy to SDG 11 and beyond [111].

ML can help monitor progress towards SDG 11 in Sustainable Cities and Communities. Yeh et al. [83] introduced SustainBench, a set of benchmarks for measuring SDGs using ML. Peng et al. [112] used ML to identify densely populated-informal settlements in Chinese cities. This initiative aims to lower barriers for ML and provide standard benchmarks for evaluating models across various SDGs. Below is Table 11, The table includes some papers that talk about the role of ML in Achieving SDG 11.

Table 11. Summary of some published papers that illustrate the role of ML in achieving the SDG 11.

Reference	Year	Method	Summary
[113]	2022	Neural Networks, LSTM	- Models improve public transport routes, reduce congestion, and enhance urban mobility efficiency.
[114]	2024	Image Recognition Algorithms	- Satellite imagery and ML assess urban heat islands, supporting climate-adaptive urban planning.
[115]	2024	Optimization Algorithms	- ML supports integration of renewables in urban grids, ensuring sustainable energy management.
[116]	2024	Anomaly Detection Algorithms	- Real-time anomaly detection improves safety and reliability of public transportation systems.

3.12| SDG 12: Responsible Consumption and Production

Sustainable development is achieved through an SDG 12-dimension, responsible consumption and production. Trade-offs usually underline the balancing challenges between competing economic growth and environmental protection [17]. Achieving SDG 12 targets can directly include circular economy practices by SDGs 6, 7, 8, and 15. Sustainable circular economy models based on Industry 4.0, including smart waste management systems, contribute to the advancement of SDG 12 in countries like Indonesia [117]. Responsible production and consumption, according to SDG 13, are called for to contend with climate change. The overlap between SDG 12 and SDG 13 characterizes the necessity of sustainably addressing as they increase production and consumption levels to lessen climate impacts [87]. Achieving SDG 12 may require synergy among the goals and negotiating trade-offs to address the obstacles presented in the SDG agenda.

ML features as a significant contributor to realizing the dream of SDG 12. This is especially true in predicting the remaining useful life of mining shovels, optimizing maintenance schedules, and reducing costs: thus, working towards responsible production [45]. It can also help open analyses of the possible correlation between the progress made in SDG and changes in well-being to shine a light on how these responsible consumption and production exercise wealth. Organizations using ML techniques will thus find themselves being sustainable and lessening their environmental impact and mostly encouraging responsible consumption and production [118]. Below is Table 12, the table includes some papers that talk about the role of ML in Achieving SDG 12.

Table 12. Summary of some published papers that illustrate the role of ML in achieving the SDG 12.

Reference	Year	Method	Summary
[47]	2024	AI Techniques, ML	- Review highlights AI applications promoting sustainable practices, emphasizing AI's role in achieving SDG 12.
[76]	2024	Predictive ML Models	- ML predicts global SDG trends, guiding policymakers for achieving responsible production and consumption goals.
[119]	2024	Time Series Analysis	- Implements time-series ML to predict food loss and waste, promoting sustainable consumption practices under SDG 12.
[120]	2023	Unsupervised Learning Models	- Explores ML's role in transforming waste recovery processes into sustainable resource optimization systems.

3.13| SDG 13: Climate Action

Prior to discussing SDG 13, which strives for sustainable development by fighting climate change through building resilience, integrated measures, and knowledge and capacity development, it should be noted that the UNFCCC plays key roles in an area of concern with global climate change, affecting economies, lives, and livelihoods [35]. I would say that this SDG directly touches upon, unlike the other set of goals, a corollary one, namely, SDG 7, on clean energy, clean water, responsible consumption, and, ultimately, life on land. Urgent actions to be taken must be taken to limit and adapt to the effects of climate change [72].

ML can play an important role in implementing SDG13 For example, ML algorithms have the potential for predicting the remaining useful life of batteries and hence, contribute to meeting the carbon gas budget and furthering climate action [121]. Furthermore, ML also has its applications in investigating the adsorption mechanism relating to carbon dioxide in porous carbons, thus contributing towards climate changes mitigation [122]. In addition, the intersection between ML with Earth observation and remote sensing would also help understand the phenomena of modern slavery and exploitative labor practices that take place in the context of degradation and pollution affecting climate change. Ultimately, through ML techniques such as those employed in battery RUL prediction and carbon capture, all stakeholders will better improve the efficacy and precision of initiatives undertaken in the name of climate action which, much in the long run, would amount to a more sustainable and resilient society [123]. Below is Table 13, The table includes some research papers that discuss and provide some solutions to meet the previous challenges and present the role of ML in this regard.

Table 13. Summary of some published papers that illustrate the role of ML in achieving the SDG 13.

Reference	Year	Method	Summary
[90]	2023	Deep Learning (LSTM)	- Proposes a deep learning model to predict energy demand, enhancing renewable energy integration and grid stability, supporting climate action initiatives.
[124]	2023	Deep Learning and AI Techniques	- Reviews AI and deep learning applications in achieving SDGs, focusing on renewable energy and environmental health.
[125]	2022	Various ML Techniques	- Discusses how ML can reduce greenhouse gas emissions and help society adapt to climate change.
[83]	2021	ML Benchmarks	- Introduces benchmark tasks utilizing ML models to monitor SDGs, including climate action, providing a framework for future research.

3.14| SDG 14: Life Below Water

SDG 14 works on the conservation of oceans, seas, and other marine resources, with emphasis on mangrove ecosystems. SDG 13 Addressing Climate Action reduces emissions for health, water, consumption, and biodiversity. The UNFCCC state parties adopted mechanism of resilience, capacity building, and policy integration into adaptation and mitigation climate change framework [126]. The implication is well beyond the economies of nations but extends into the lives and livelihoods of people in the world emphasizing the collaborative efforts in achieving the society [127]. Realizing SDG 14 is very crucial for conserving marine ecosystems and for the well-being of coastal people.

ML is profoundly apt to realize SDG 14. Predicting pollution, monitoring the health of rivers, and building real-time forecasts on water quality are some of the functions performed by ML technology. Previous studies have incorporated ML for enhancing the node localization accuracy in MI-UWSNs, besides proposing a Smart Platform-ML-GSM [128] based water quality monitoring system for rivers, which aims to reduce pollution

from oil palm plantations [98]. The above-mentioned goals are aligned with SDG 14 under which underwater life is protected, and clean water is assured. Below is Table 14, the table includes some papers that talk about the role of ML in Achieving SDG 14.

Table 14. Summary of some published papers that illustrate the role of ML in achieving the SDG 14.

Reference	Year	Method	Summary
[129]	2024	Metaverse & ML Algorithms	- Focuses on integrating ML and metaverse technologies to handle ocean pollution and sustain marine ecosystems.
[130]	2024	CNN for Satellite Data	- Analyzes coral reef health using satellite imagery processed through convolutional networks.
[131]	2024	Reinforcement Learning for Navigation	- Develops AI-driven marine vehicles for underwater exploration and environmental monitoring.
[132]	2024	UAV-Integrated ML Models	- Identifies and maps marine litter from aerial UAV data using robust ML techniques.

3.15| SDG 15: Life on Land

It enshrines the goal for sustainable development - SDG 15: Life on Land. It should Protect, restore, and promote the sustainable use of terrestrial ecosystems. This goal is also closely related to SDGs on Climate Action, Good Health, Clean Water, Sanitation, and Responsible Consumption and Production [35]. As such changes in climate speak to altering physical environmental conditions, these changes influence land ecosystem configurations and water resources [133]. Therefore, reaching SDG 15 urgently needs action on climate change measures, policy integration, and disaster resilience.

ML is the most important proof for SDG 15. It predicts how deep the erosion will be in the watershed, aids in conservation planning, and provides standard benchmarks for models' evaluation [83]. Combining ML with statistical models would act as the icing on the cake of urban planning and management. And of course, wind energy for different SDGs the London Array wind farm extracts this and reduces carbon emissions [99]. In that sense, ML can contribute significantly to monitoring and achieving SDG 15. Below is Table 15, the table includes some research papers that discuss and provide some solutions to meet the previous challenges and present the role of ML in this regard.

Table 15. Summary of some published papers that illustrate the role of ML in achieving the SDG 15.

Reference	Year	Method	Summary
[134]	2022	Deep learning models	- The study reviewed deep learning applications in Earth observation for monitoring SDGs, emphasizing biodiversity preservation.
[135]	2023	AI Tools and Predictive Analytics	- The study explored AI's potential in achieving SDGs related to societal aspects, including education and gender equality.
[136]	2023	Big Data Analytics and ML	- Big data and ML were discussed to monitor terrestrial ecosystems, aiding SDG 15 progress tracking.

3.16| SDG 16: Peace, Justice, and Strong Institutions

SDG 16 considers a SDG with its agenda for peaceful society, access to justice, and accountability institutions. It aims to unleash violence against children, rule of law, organized crime, corruption, and transparency [137]. In addition, achieving SDG 16 needs a cooperative approach involving parliaments and environmental governance frameworks. Cooperatives in the Philippines and Southeast Asia contributed to economic

development and social well-being; polycentric environmental governance addressed those environmental challenges in Southeast Asia and Eastern Africa [138].

ML undoubtedly contributes significantly to reaching SDG 16 toward peace, justice, and strong institutions [139]. Among Nordic higher education institutions, MOOCs related to SDG 16 include those that use ML to analyze and improve E-Learning courses as an alternative approach to filling the gaps in Education for Sustainable Development [140]. In effect, this innovation will be an added push toward SDG 16: peace, justice, and strong institutions. Table 16 shows some papers that talk about the role of ML in Achieving SDG 16.

Table 16. Summary of some published papers that illustrate the role of ML in achieving the SDG 16.

Reference	Year	Method	Summary
[141]	2019	NLP, Transfer Learning	- This research explored AI's role in tracking SDG 16 progress, utilizing NLP and transfer learning to measure peace, justice, and strong institutions.
[142]	2021	Naive Bayes, RF, Neural Networks	- ML techniques were examined like Naive Bayes and Random Forest for improving justice and peaceful institutions under SDG 16.
[134]	2022	CNN	- CNNs are applied in automating SDG 16 monitoring tasks, streamlining data collection and analysis.
[143]	2024	Deep Learning, Synthetic Data Generation	- The study proposed deep learning and synthetic data generation to enhance classifiers for SDG 16-related tasks, improving data availability and classification.

3.17| SDG 17: Partnerships for the Goals

SDG 17 defines and states that there should be cooperation to achieve sustainable development. It is meant to mobilize resources and domestic revenue generation, as well as international trade for long-term investments in energy, infrastructure, transportation systems, and IT infrastructure [144]. However, overall development assistance has increased, but the financial requirements remain. To mobilize science and technology, capacity development and the trade issues around systemic ones, SDG 17 has 17 targets and 25 indicators [145].

Previously, we mentioned some studies that illustrate the role of ML in achieving each of the SDG. These studies will help demonstrate how potentially ML tools fit into effects in higher education quality, healthy work environments, and predicting attainment toward health and education goals while contributing to greater SDGs which is the practical implementation of the concept of SDG 17.

4| Contribution and Recommendations

Research contributes significantly to our understanding and use of ML in achieving various SDGs. In many studies, ML has exhibited transformative ability in global challenges like poverty, education, climate change, health, and global partnership. For instance, with advanced data analytics and predictive modeling in place, the policymakers can track how progress is being made toward achieving SDGs even in the less represented areas. Such models, with the processing of big data, yield results insightful for guiding intervention areas so that they are targeted and fair.

One of the central contributions is expected to result from binarization in methods through manipulation of different ML models-deep learning, neural networks, supervised and unsupervised learning, and resource optimization algorithms techniques. These have proven significant in resource allocation, trend analysis, and partnership-building activities-those themes deemed critical for the success of SDG. For

instance, analyzing educational data through neural network modeling has enhanced accessibility/inclusivity as far as sources for quality education (SDG 4) are concerned. Moreover, using machine learning to drive climate models is instrumental toward sustainable cities and communities (SDG 11) in terms of energy optimization and reduction of environmental exposure risks. These works denote the significance of bringing together several disciplines; thus, drawing from them would be the expertise of computer science, environmental studies, public health, and social sciences. And this has proved crucial-innovative solutions to very difficult adversities, such as tackling climate change (SDG 13) and enhancing global partnerships (SDG 17)-would not have been possible without it.

While impressive breakthroughs have been achieved, considerable gaps persist in previous studies in directing ML toward achieving SDGs. An important one is focused on the narrow-localized solutions. Most of them are developed using datasets across the globe thus, they miss the unique social-economic, cultural, geographical, and environmental setting of a particular region. This limits their effectiveness or relevance for the target audience.

Another gap is that interdisciplinary approaches are lacking. Much research in ML on the other hand focuses mainly on scientific and/or technological issues. That is often divorced from sociology, economics, and public policy, which has significant connotations to address multidimensional issues that concern SDGs. Fieldwork, also lacks longitudinal studies that trace the impact of ML applications on the progress of SDGs in the long run. Most of the research evidence is merely proof of concept studies or short-lived implementations, leaving questions around scalability, sustainability, and unintentional side effects unanswered.

Furthermore, ethical frameworks and modalities for ML applications related to SDG are still in their infancy. There is a requirement for research to determine the design of such ML models-construction with transparency, equity, and accountability around issues of biases, inclusiveness, and data security.

Previous studies representation is also severely lacking for the low-resource setting-that is, the area where it could be argued that ML would have its maximum impacts. While most studies are focused on high-tech states, they forget the very many specific great challenges and opportunities in poorly resourced settings.

5| Discussion and Conclusions

ML algorithms have become an important part of achieving the SDGs, since they provide innovative solutions for even the most complicated global issues-such as poverty, education, and health. They also automate processes that improve efficiency and effectiveness toward achieving SDGs in the face of such global challenges as the changing climate. By using big data and predictive analytics, ML can bring evidence-based decisions, optimize resources, and personalize interventions, moving society toward sustainable growth. Yet ML has such great potential to drive SDGs only if those challenges of privacy, algorithmic bias, and accessibility are addressed ethically and with inclusive policies and infrastructure. That means interdisciplinary collaboration and research will be essential as we move forward to ensure that ML continues to be an agent of positive societal change-with equity and environmental sustainability in mind.

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Data Availability

The datasets generated during and/or analyzed during the current study are not publicly available due to the privacy-preserving nature of the data but are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that there is no conflict of interest in the research.

Ethical Approval

This article does not contain any studies with human participants or animals performed by any of the authors

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