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Deep Learning and Artificial Intelligence in Sustainability: A Review of SDGs, Renewable Energy, and Environmental Health

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Abstract: Artificial intelligence (AI) and deep learning (DL) have shown tremendous potential in driving sustainability across various sectors. This paper reviews recent advancements in AI and DL and explores their applications in achieving sustainable development goals (SDGs), renewable energy, environmental health, and smart building energy management. AI has the potential to contribute to 134 of the 169 targets across all SDGs, but the rapid development of these technologies necessitates comprehensive regulatory oversight to ensure transparency, safety, and ethical standards. In the renewable energy sector, AI and DL have been effectively utilized in optimizing energy management, fault detection, and power grid stability. They have also demonstrated promise in enhancing waste management and predictive analysis in photovoltaic power plants. In the field of environmental health, the integration of AI and DL has facilitated the analysis of complex spatial data, improving exposure modeling and disease prediction. However, challenges such as the explainability and transparency of AI and DL models, the scalability and high dimensionality of data, the integration with next-generation wireless networks, and ethics and privacy concerns need to be addressed. Future research should focus on enhancing the explainability and transparency of AI and DL models, developing scalable algorithms for processing large datasets, exploring the integration of AI with next-generation wireless networks, and addressing ethical and privacy considerations. Additionally, improving the energy efficiency of AI and DL models is crucial to ensure the sustainable use of these technologies. By addressing these challenges and fostering responsible and innovative use, AI and DL can significantly contribute to a more sustainable future.

Keywords: artificial intelligence (AI); deep learning (DL); sustainability; renewable energy; environmental health; regulatory oversight

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1. Introduction

The emergence of artificial intelligence (AI) and deep learning (DL) technologies has marked a transformative period in various sectors, particularly in sustainability. These innovative tools have demonstrated remarkable potential in promoting sustainable practices, especially within the realms of renewable energy and environmental health.

The role of AI and DL in mitigating energy consumption and environmental degradation is increasingly recognized. Strubell et al. (2020) underscored the financial and environmental implications of training and tuning neural network models, thereby emphasizing the necessity for sustainable practices in AI research [1].

In the renewable energy sector, smart building energy management has greatly benefited from the application of these technologies. A comprehensive review by Yu et al. (2020) highlighted the potential of deep reinforcement learning (DRL) in tackling energy optimization challenges [2]. Furthermore, recent studies have illuminated the potential of AI in enhancing green construction, where automatic control systems address issues related to cost reduction, resource management, and safety enhancement [3].

AI and DL have also proven effective in fault detection within renewable energy systems. For instance, a deep learning-based system proposed by Pierdicca et al. (2020) for anomaly detection in photovoltaic images demonstrated the efficacy of AI in maintaining the health of renewable energy systems [4]. In addition, the generation of synthetic datasets for solar cell defect analysis using deep convolutional generative adversarial networks (DCGANs) represents a significant advancement in the field [5].

In the recycling industry, AI and DL have been leveraged to improve waste management. Noh (2021) proposed a recycled clothing classification system using AI and IoTs, demonstrating the potential of these technologies [6]. Moreover, AI and machine learning algorithms have been employed to optimize the production of sustainable biofuels derived from renewable resources [7].

AI and DL have also been utilized in predicting the potential of photovoltaic power plants under climate change. A study by Othman et al. (2020) used deep learning to estimate the future production of a photovoltaic power plant in Tunisia [8].

In waste management, Mookkaiah et al. (2022) developed a smart IoTs-based solid waste management system using computer vision, showcasing another application of AI and DL [9].

Furthermore, these technologies have been used to forecast photovoltaic production. Cordeiro-Costas et al. (2022) applied machine learning and deep learning models to photovoltaic production forecasting [10].

Despite these promising developments, the rapid advancement of AI and DL necessitates comprehensive regulatory oversight to ensure transparency, safety, and ethical standards. This review paper aims to provide an in-depth understanding of the current state of AI and DL in sustainability and discuss future directions, particularly the potential of these technologies in addressing environmental issues for a more sustainable future.

2. Ai, DL, And Sustainable Development Goals (SDGs)

Artificial intelligence (AI) and deep learning (DL) are transformative technologies with significant potential to support the achievement of the sustainable development goals (SDGs). These technologies have been rapidly growing and have made substantial impacts in various decision-making domains, including healthcare, industry, agriculture, education, and finance [11,12].

A comprehensive analysis of the impact of AI on each of the 17 goals and 169 targets of the 2030 Agenda for Sustainable Development found that AI could support the achievement of 128 targets across all SDGs. However, it might also inhibit 58 targets, indicating the need for careful and ethical application of these technologies [13].

In the context of Industry 4.0, AI has revolutionized sectors such as agriculture, education, and finance, contributing to poverty reduction and economic growth, particularly in emerging economies [12]. In the realm of education, AI and deep learning have shown significant promise in enhancing students' learning experiences and outcomes. For instance, the advent of AI tools, like ChatGPT, has necessitated a re-evaluation of traditional student performance evaluation approaches in higher education [14]. Furthermore, the application of deep learning strategies has been observed to boost mathematics achievement and practical intelligence among high school students [15]. Notably, in the domain of language learning, the significance of active listening, an often-underestimated skill, has been underscored. Active listening has been found to profoundly impact various facets of the language learning process, including phonology, morphology, and pragmatics [16]. Additionally, the integration of deep learning technology in physical education has enabled the real-time monitoring and analysis of students' exercise steps and heart rates, offering valuable insights into the effectiveness of teaching methodologies [17]. These advancements highlight the transformative potential of AI and deep learning in reshaping educational paradigms and fostering enhanced learning outcomes. In the medical field, AI has been instrumental in combating the COVID-19 pandemic and improving healthcare delivery [11]. Guidelines for reporting medical AI research to clinicians have been developed, proposing a clinical artificial intelligence research (CAIR) checklist and specific performance metrics guidelines to present and evaluate research using AI components [18].

The importance of interpretable deep-learning models in the context of developing ethical AI systems and data-driven solutions compliant with the SDGs has been emphasized. Transparency and interpretability in AI models are crucial to ensure their ethical and responsible use [19].

Beyond healthcare, AI and DL have also shown promise in the field of plant biology, with discussions on the potential of exascale computing and explainable AI in achieving the United Nations Sustainable Development Goals. Accurate phenotyping and daily-resolution climatype associations for refining ideotype production to specific environments at various levels of granularity are needed [20].

In the realm of sustainable infrastructure, the role of 3D concrete printing (3DCP) and AI-supported Digital Twin(DT) applications in achieving the relevant sustainable development goals (SDGs) set out by the United Nations has been explored. A standardized conceptual framework for leveraging AI-supported DT federations has been identified as future work [21,22].

The impacts of AI on SDGs have been analyzed, drawing a few fundamental inductions for ESG (climate, social, governance) amidst fast innovative and social change. The viewpoints of ecological, social, and public strategy to dissect the effects of AI on sustainable development with a particular spotlight on the progression of the SDGs (sustainable development goals) have been consolidated [23].

However, the unregulated roll-out of AI technologies poses risks to the achievement of the SDGs. The unscrupulous history of Big Tech means it cannot be trusted to operate without regulatory oversight. Effective pre-emptive regulatory options have been proposed to minimize scenarios of AI damaging the SDGs [24].

Recent advancements have highlighted the role of the Internet of Things (IoTs) and machine learning in achieving the SDGs, with use cases in health, energy, and cities [25]. Furthermore, the application of Deep Graph Learning (DGL) has been proposed to address societal challenges and improve people's daily lives [26]. A knowledge graph-based deep learning framework has also been developed for efficient content similarity search of SDG data [27].

The rapid advancements in AI and DL have been evident in various sectors, but a comparative analysis reveals some disparities. For instance, the machine-building sector in Ukraine, a key industry for the country's economic development, has been grappling with the challenges and opportunities of digitalization, especially in the formation of intellectual capital [28]. This indicates a gap between the potential of AI and its actual implementation in certain industries.

In the agricultural sector, while there's a surge in poultry production, challenges related to pollution, land erosion, and competition for resources persist. The integration of big data, coupled with AI, presents an opportunity to address these challenges and optimize poultry production [29].

Furthermore, the marine sciences sector has been leveraging AI for fish behavior recognition, which can significantly impact fishing gear selectivity. However, the data required to interpret fish interactions with fishing gear, especially for temperate fishes, is still lacking. This underscores the need for more comprehensive datasets to train deep learning models effectively [30].

In conclusion, while AI and DL have the potential to significantly contribute to the achievement of the SDGs (Table 1), comprehensive regulatory oversight is necessary to ensure that these technologies are used ethically and responsibly. The future of sustainable development will undoubtedly be shaped by the responsible and innovative use of AI and DL.

Table 1. Popular applications of AI in sustainable development goals (SDGs)

SDG Goal	Application
No Poverty	Predicting poverty regions [31,32], optimizing social security payments [33], improving microfinance services [34,35]
Zero Hunger	Crop yield prediction [36], Crop disease detection [37], precision agriculture [38]
Good Health and Well-being	Disease outbreak prediction [39,40], telemedicine services [41], AI-assisted diagnosis [42,43]
Quality Education	Personalized education [44], AI-assisted grading [45]
Gender Equality	Analysis of gender bias data [46]
Clean Water and Sanitation	Water quality monitoring [47,48], water scarcity prediction [49,50], optimizing water distribution systems [51,52]
Decent Work and Economic Growth	Enhancing productivity, job creation, forecasting economic trends [53]
Industry, Innovation, and Infrastructure	Optimizing operations, reducing maintenance costs [54], predictive maintenance [55]
Reduced Inequalities	Identifying and predicting social inequality, AI in policy-making [56], targeted interventions for inequality reduction
Climate Action	Creation and improvement of climate models, climate change prediction, carbon footprint tracking [57]

3. Ai And DL In Renewable Energy

The renewable energy sector is experiencing a profound transformation, largely attributable to the advancements in artificial intelligence (AI) and deep learning (DL). These technologies have ushered in a new era of efficiency and sustainability, sparking widespread interest among researchers and industry practitioners alike. The advancements and applications of AI and DL in the renewable energy sector can be broadly categorized into several primary domains. As illustrated in Figure 1, these domains encompass a wide range of functionalities, from energy forecasting and anomaly detection in power systems to more intricate applications such as renewable energy system design and grid stability. The interplay of AI and DL across these domains underscores their pivotal role in shaping the current and future landscape of renewable energy. The graph provides a structured overview of the multifaceted impact of AI and DL in this sector, streamlining their role in energy forecasting, system health assessment, and various other crucial aspects that were detailed in the preceding sections. An insightful study by Strubell et al. (2020) underscored the importance of energy-efficient AI and DL models, emphasizing their critical role in renewable energy research [1].

The efficacy of AI and DL is particularly apparent in electrical power systems where these technologies have been successfully deployed for the prediction of optimal power flows. Notably, Fioretto et al. (2019) combined deep learning and Lagrangian dual methods to predict AC optimal power flows, thereby elevating the accuracy of the widely adopted OPF linear DC approximation by at least two orders of magnitude [58]. Leveraging this pioneering work, Zhou et al. developed a deep reinforcement learning-based, data-driven method for rapid optimal AC power flow solutions, thereby equipping power grid operators with the tools to make swift, effective decisions [59].

In the domain of solar power generation, DL has proved invaluable for forecasting solar irradiance. Moncada et al. (2018) applied DL to provide meaningful insights for solar power optimization [60]. Building upon this, Zhou et al. (2021) proposed a novel hybrid deep learning method that amalgamates clustering techniques, convolutional neural network (CNN), long short-term memory (LSTM), and attention mechanism with the wireless sensor network. This method adeptly overcomes the prevalent challenges associated with the PV energy generation forecasting problem [61].

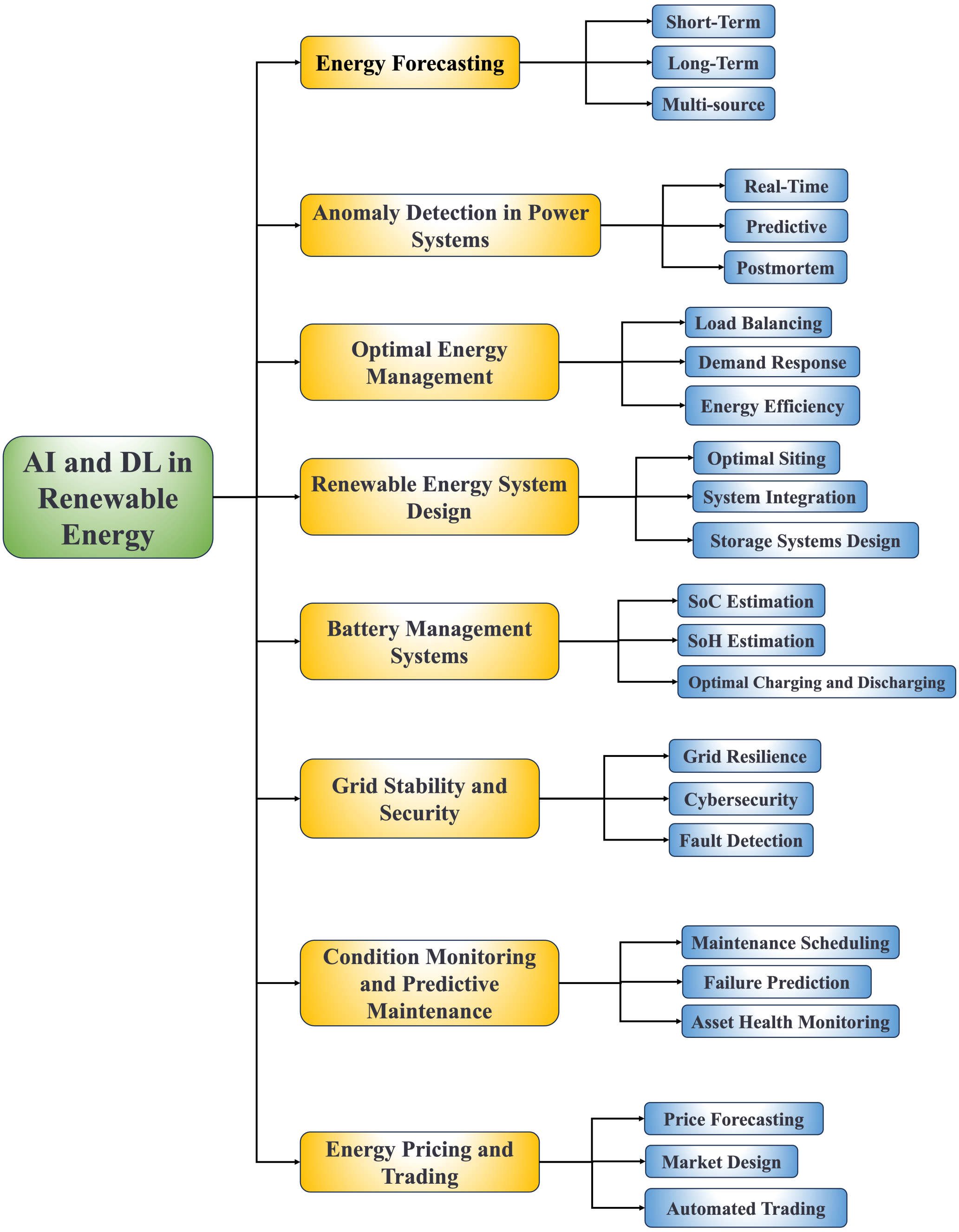

Figure 1. The application of AI and DL in the field of renewable energy; orange represents the different application scenarios; blue represents subscenarios within those scenarios.

AI and DL have not only entered but also transformed various fields, and renewable energy is no exception. Particularly in the context of photovoltaic (PV) power plants, they have shown impressive strides in system health and fault detection. A striking illustration of this is the solAIr system, an innovative integration of AI into renewable energy infrastructure [4]. By harnessing the power of deep learning, solAIr provides an automated fault detection mechanism for PV power plants. The system relies on thermal images captured by unmanned aerial vehicles (UAVs) equipped with thermal infrared sensors. These images, once processed through the AI algorithm, reveal crucial insights about the health status of the solar panels. Notably, it can identify and localize anomalies in the photovoltaic cells, thereby informing the necessary maintenance actions. This blend of AI, DL, and UAVs elucidates a promising trend in renewable energy management, where technology is used to optimize energy production, reduce costs, and increase the lifespan and reliability of PV power plants. The real-world application and impact of AI and DL in such a context demonstrate their undeniable potential in driving the future of renewable energy.

The rapid evolution of AI and DL in the renewable energy sector has led to a plethora of research studies, each offering unique insights and methodologies. A comparative analysis of the recent literature reveals distinct trends and gaps that need to be addressed.

Mahmoud and Slama [62] introduced an AI-powered community energy management system that emphasizes peer-to-peer energy trading. Their approach focuses on maximizing consumer advantages and renewable energy utilization through reinforcement learning techniques. This contrasts with the work of Mirjalili et al. [63], who conducted a comparative study of various machine learning and deep learning methods, such as KNN, SVR, AdaBoost, and DNN, for predicting energy balance in hybrid building-renewable energy systems. Their research highlighted the superior accuracy of the DNN and KNN algorithms in forecasting energy balance.

Benabed [64] analyzed the relevance of AI for energy optimization and business internationalization. The study underscores the importance of digitalization in connecting business operations and relationships, emphasizing the role of AI in optimizing energy consumption in various sectors, including renewable energy.

Peppas et al. [65] conducted a multimodel assessment for secondary smelting decarbonization, emphasizing the role of hydrogen in the clean energy transition. Their study offers a comprehensive overview to aid decision-makers in comparing the environmental impacts caused by different energy sources, highlighting the potential of the hydrogen produced by renewables as the most environmentally beneficial option.

From the above studies, it is evident that while there is a consensus on the potential of AI and DL in optimizing renewable energy systems, the methodologies and areas of focus differ. Some studies emphasize the importance of peer-to-peer energy trading, whereas others delve into the comparative performance of various algorithms. There is also a growing interest in integrating AI with business operations and exploring the environmental impacts of different energy sources.

Despite the advancements, there remains a gap between academic research and industry demands. While academic studies offer innovative methodologies and insights, the practical implementation and scalability of these solutions in real-world scenarios need further exploration. Additionally, there is a need for more comprehensive studies that consider the socio-economic and environmental implications of integrating AI and DL into the renewable energy sector.

In their comprehensive review, Gu and Li (2022) delve into the potential of deep learning for managing and optimizing wind and wave energy, systematically reviewing a variety of models and methods, such as convolution neural networks (CNNs), recurrent neural networks, long short-term memory (LSTM), deep brief networks, deep neural networks (DNNs), gated recurrent networks (GRUs), and deep hybrid models. They highlight the effectiveness of these methods in addressing the inherent instability and complex data linked with these renewable energy sources and emphasize that the unique challenges of wave and wind energy make them ideal for the application of deep learning methods. Through various performance parameters, they explore the strengths and weaknesses of each model and underscore the fact that despite the longer training times, deep learning structures are adept at handling large datasets and can be efficiently trained with modern GPUs. They predict that with advancements in deep learning techniques and cost management, there is immense potential for the growth and maturation of renewable energy applications based on deep learning. They advocate for the continual reorganization of existing research to provide valuable insights, avoid redundancies, and potentially reveal novel applications, thus underscoring the promising future of renewable energy management and optimization through advanced machine learning techniques [66].

In the broader power systems context, Sarajcev et al. (2022) conducted a detailed review of the application of AI in power system transient stability assessment. They scrutinized a range of techniques, including machine, deep, and reinforcement learning [67]. Meanwhile, Damjanovic et al. (2022) presented an innovative reinforcement learning (RL)-based approach for securing the operation of power systems through autonomous topology changes, with due consideration of various constraints [68].

Furthermore, the integration of AI in the hydrogen energy sector, particularly in fuel cell technologies, has been a focal point of recent research. AI has been instrumental in optimizing energy management strategies for hydrogen fuel cell vehicles. For instance, Wang et al. (2023) proposed a GM-based energy management strategy for hydrogen fuel cell buses, enhancing output efficiency and fuel economy [69]. Moreover, Fayyazi et al. (2023) highlighted the role of AI and machine learning in the energy management, control, and optimization of hydrogen fuel cell vehicles, emphasizing the potential for advancements in prediction, control, and vehicle-to-everything (V2X) applications [70]. Additionally, AI has facilitated the development of predictive models for energy and hydrogen production from solar thermochemical plants, as demonstrated by El Jery et al. (2023), who utilized artificial neural networks to forecast energy efficiency and hydrogen production rates under various scenarios [71]. Zhang et al. (2023) also applied a half-power prediction strategy to effectively manage hydrogen consumption in fuel cell city buses, showcasing a promising avenue for reducing hydrogen consumption and enhancing fuel economy [72]. These studies underscore the burgeoning role of AI in fostering innovations in the hydrogen energy sector, particularly in enhancing the efficiency and sustainability of fuel cell technologies.

In conclusion, the impactful integration of AI and DL into the renewable energy sector has demonstrated significant advancements in power flow optimization, solar irradiance prediction, system health assessment, and fault detection. Their ability to manage large datasets and adapt to inherent instabilities associated with renewable energy sources underscores their potential to reshape the future of this sector. Real-world impacts such as more effective decision-making for power grid operators and identifying photovoltaic cell anomalies have been notable. However, considering the substantial energy and computational requirements of these models, future research must focus on the development of energy-efficient methodologies. Alongside, reevaluation of existing research is needed to avoid redundancies and foster continuous innovation. The integration of AI and DL in renewable energy management offers a promising yet challenging future, requiring balanced efforts in energy efficiency and technological advancement.

4. AI And DL in Environmental Health

The rise of AI and DL in environmental health is fueled by their ability to process and learn from vast amounts of data, providing deeper insights and facilitating timely interventions, as illustrated in Figure 2. The transformative potential of AI in healthcare is evident in various domains. For instance, in the context of epilepsy, a prevalent neurological disorder, DL techniques have significantly advanced the diagnostic procedures. Shoeibi et al. (2020) expounded on these advances, explaining how DL automates the once laborious and error-prone process of feature extraction from EEG and MRI data, thus enhancing the efficiency and accuracy of epileptic seizure detection [73]. This automation, combined with the integration of cloud computing and specialized hardware for biomedical tasks, has not only increased the accessibility of computational resources but also fostered a collaborative research environment.

Shifting focus to the environmental health, the emergence of geoAI represents a leap forward in handling complex spatial data. By effectively combining advancements in spatial science, AI, and DL, geoAI extracts insightful knowledge from large-scale spatial data. As outlined by VoPham et al. (2018), this powerful approach has vast implications for environmental epidemiology [74]. GeoAI's strength lies in its capacity to process large volumes of spatial and temporal data, ensuring efficient computation and offering the flexibility to adjust algorithms and workflows based on the unique characteristics of spatial processes. Moreover, geoAI's scalability allows for the effective modeling of various environmental exposures across different geographic regions. Its potential extends to measuring previously elusive exposures, thereby contributing to an improved understanding of the relationships between environmental exposures and disease. Consequently, geoAI is set to revolutionize environmental health, redefining how we predict, detect, and manage environmental health concerns.

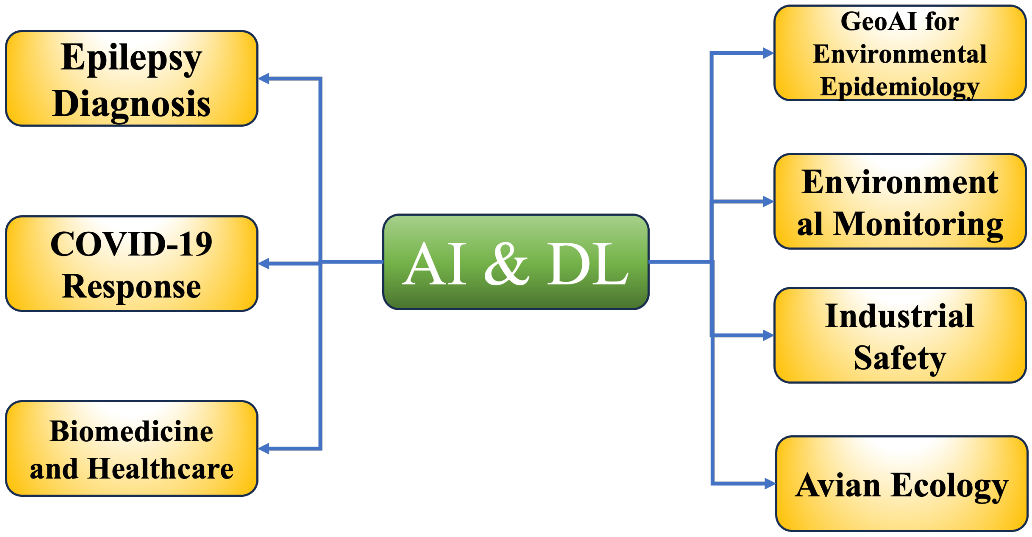

Figure 2. Applications of AI and DL in environmental health.

The COVID-19 pandemic dramatically highlighted the significant role of AI, machine learning (ML), and deep learning (DL) technologies in responding to global health crises. Through the study of Alafif et al. (2020), we gain invaluable insights into how AI-based ML and DL methodologies have been applied in diagnosing and treating COVID-19. These methodologies span a vast spectrum, encompassing non-invasive detection measures, severity score assessments, disease transmission modeling, and even aspects of drug production and vaccination development. In addition, these AI technologies have been effectively employed in large-scale data analysis, such as COVID-19 case data and social media data, providing a critical understanding of outbreak patterns, transmission paths, and impacts. Furthermore, ML and DL have been instrumental in epidemic protection and public monitoring efforts, including airport security checks, patient tracking, and epidemic detection. These advancements not only enhance our ability to manage the current pandemic but also pave the way for leveraging AI in the containment and control of future health crises [75].

In the realm of environmental monitoring, AI and DL have been leveraged to improve the prediction of harmful algal blooms. For instance, Lee and Lee (2018) demonstrated the effectiveness of DL models in predicting harmful algal blooms in South Korea's major rivers, outperforming traditional regression analysis [76].

AI and DL have also been applied in the field of biomedicine and healthcare. Cirillo et al. (2020) examined the current sex and gender gaps in a subset of biomedical technologies used in relation to Precision Medicine, providing recommendations to optimize their utilization to improve the global health and disease landscape and decrease inequalities [77].

In the context of industrial safety, Campero-Jurado et al. (2020) presented a smart helmet prototype that monitors the conditions in the workers' environment and performs a near real-time evaluation of risks using AI [78].

AI has also been used in avian ecology to derive information on bird population movement trends. Akcay et al. (2020) employed several state-of-the-art generic object-detection algorithms to learn to detect birds in natural scenes, demonstrating the potential of computer-aided counting in real-world bird monitoring applications [79].

The integration of AI and DL in environmental health has witnessed a surge in research endeavors, each contributing unique methodologies and insights. A comparative analysis of the recent literature sheds light on the diverse applications and the existing gaps in this domain.

In order to further understand the diverse applications and the existing gaps in this domain, a comparative analysis of the recent literature is presented.

Franzo et al. [29] delved into the challenges and opportunities presented by the increasing demand for poultry meat and eggs. They highlighted the potential of "big data" in conjunction with advanced statistical techniques to maximize farm profitability, reduce environmental impacts, and enhance animal and human health. This approach contrasts with the work of Wang and Ye [80], who focused on the high-quality development of tourism in the Taihu Lake Basin, China. Their perspective offers a glimpse into the future of healthcare, where AI-driven solutions can redefine precision global health.

Saber et al. [81] conducted a time-series investigation by comparing the global supply-chain-linked economic and environmental impacts of manufacturing industries in China and the US. Their study underscores the significance of AI in analyzing the environmental sustainability impacts of these two major economies, which collectively account for a significant portion of global manufacturing output.

Krittanawong and Kaplin [82] discussed the transformative potential of AI in global health, especially in the context of the COVID-19 pandemic. They highlighted the capabilities of advanced DL models, such as GPT-3, in assisting physicians with repetitive tasks and basic telehealth services. Their perspective offers a glimpse into the future of healthcare, where AI-driven solutions can redefine precision global health.

In conclusion, AI and DL are playing a crucial role in the field of environmental health, contributing to the improved prediction, detection, and management of various environmental health issues. However, the complexity and diversity of environmental health data necessitate further research into advanced AI and DL models and methods.

5. AI And DL in Smart Building Energy Management

The integration of artificial intelligence (AI) and deep learning (DL) in smart building energy management has steadily gained traction, resulting in considerable enhancements to the prediction, optimization, and automation of diverse energy management tasks, as illustrated in Figure 3. One impactful review by Woschank et al. (2020) [83] elaborates on the use of AI, machine learning, and DL in Smart Logistics, offering a conceptual framework that carries significant implications for future investigations.

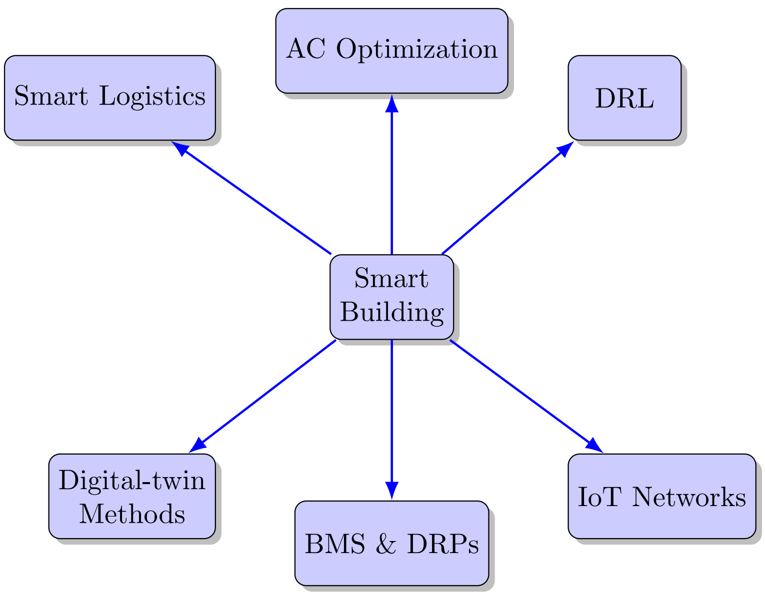

Figure 3. Revolution of AI and DL in smart building energy management.

Exemplifying the potential of AI and DL in energy management, Elsisi et al. (2021) [84] developed an innovative method that synergizes deep learning with the IoTs to manage air conditioner operations, consequently reducing energy consumption. By deploying the YOLOv3 algorithm, their system can effectively identify the number of individuals in a specific zone, thus enabling optimal air conditioner usage in smart buildings.

The emerging realm of deep reinforcement learning (DRL), a branch of AI, demonstrates considerable potential for addressing smart building energy management challenges. A thorough review by Yu et al. (2021) [2] of DRL applications in this context sheds light on the existing hurdles and paves the way for prospective research directions.

Digital-twin-based methods, as Agostinelli et al. (2021) [85] illustrate, can be instrumental in devising intelligent optimization and automation systems for residential district energy management. Their research underscores the efficacy of systems combining three-dimensional data models with the IoTs, AI, and machine learning to enhance renewable energy production.

A comprehensive exploration of AI applications in smart buildings is presented by Farzaneh et al. (2021) [86]. This study delves into research across key AI domains, such as energy, comfort, design, and maintenance, analyzed through the prism of a building management system (BMS) and demand response programs (DRPs).

Efficiency in managing energy within IoTs networks can be achieved through robust deep-learning frameworks, as demonstrated by Han et al. (2021) [87]. Their approach employs a range of preprocessing techniques to contend with the heterogeneity of electricity data, alongside an efficient decision-making algorithm for short-term forecasting over resource-constrained devices.

The interconnectedness between IoTs-based real-time production logistics and cyber-physical process monitoring systems is crucial for managing the complexity and flexibility of smart factories. A study by Andronie et al. (2021) [88] elucidates this point through a quantitative literature review that covers AI applications in smart buildings.

Recent advancements in machine learning and deep learning for building energy are critically examined by Ardabili et al. (2022) [89]. Their systematic review introduces promising models and evaluates the performance of these techniques in various forecasting tasks related to energy.

The integration of AI and DL in smart building energy management has been a focal point of numerous research endeavors. A comparative analysis of recent studies reveals both the depth of advancements and the existing gaps in this domain.

Bouktif et al. [90] emphasized the importance of short-term electric load forecasting for efficient power grid management. They introduced a deep learning approach, specifically long short-term memory (LSTM) models, for energy load forecasting. Their approach stands out due to its ability to learn long-term dependencies in electric data, resulting in accurate predictions. This contrasts with the work of Solyali [91], who conducted a comparative analysis of various machine learning strategies, including artificial neural networks (ANNs), multiple linear regression (MLR), and support vector machines (SVMs), for electricity demand estimation in Cyprus. Their findings underscored the superiority of SVM and ANN in providing reliable and precise outcomes.

Zhang et al. [92] introduced a fine-grained deep-learning approach for thermal comfort modeling in smart buildings. Their research highlighted the linear relationship between comfort and air conditioning setpoints, aiding in the optimal control of controllable setpoints. This approach complements the work of Elsisi et al. [84], who utilized deep learning and the IoTs for managing air conditioner operations, focusing on energy consumption reduction.

Despite the significant advancements in AI and DL for smart building energy management, a gap remains between academic research and industry demands. While academic studies often focus on specific use cases or scenarios, the industry requires holistic, scalable, and adaptable solutions that can cater to diverse building types, environments, and energy management challenges. Furthermore, the integration of real-time data, user preferences, and external factors, like weather conditions, into AI-driven energy management systems remains a challenge that needs addressing.

In conclusion, while AI and DL have brought about transformative changes in smart building energy management, there is a pressing need to bridge the gap between research innovations and practical industry requirements. Future studies should focus on developing comprehensive, adaptable, and user-centric solutions that can seamlessly integrate into the dynamic landscape of smart building energy management.

In summary, AI and DL have revolutionized smart building energy management by augmenting prediction, optimization, and automation capabilities. These technologies underpin innovative approaches to energy management, drive advancements in DRL for addressing complex challenges, and facilitate the exploration of digital-twin-based methods. They have also contributed to enhancing various domains, from energy and comfort to design and maintenance, and have become vital in managing the complexity and flexibility of smart factories. Although significant progress has been made, the complexity and diversity of building energy data necessitate the further exploration and development of more sophisticated AI and DL models and techniques. Future research is expected to further push the boundaries of efficiency and effectiveness in this rapidly evolving field.

6. Challenges and Future Directions

The application of AI and DL in various sectors, such as achieving the sustainable development goals (SDGs), renewable energy, environmental health, and smart building energy management, has shown great promise. However, several challenges need to be addressed to fully harness the potential of these technologies. In this section, we discuss some of these challenges and propose the potential future directions for research. A visual representation of these challenges and directions is provided in Figure 4.

6.1. Explainability and Transparency of AI and DL Models

The lack of transparency and explainability in AI and DL models is a significant barrier to their widespread adoption. As these models become intricate and sophisticated, their decision-making processes become increasingly opaque. This opacity, often referred to as the "black box" problem, can lead to mistrust and reluctance to adopt AI technologies, particularly in critical sectors such as renewable energy and environmental health, where the stakes are high [93,94].

The future of AI research should, therefore, prioritize the development of methods and techniques that enhance the explainability and transparency of these models. This could involve incorporating interpretability techniques into the model design. For instance, rule-based explanations can provide a clear and understandable logic for the model's decisions, making it more transparent. Similarly, visualizing the internals of a model can offer valuable insights into its decision-making process, thereby improving its explainability [94].

Moreover, the development of hybrid models that combine the predictive power of deep learning with the transparency of simpler models could be another promising avenue for research. Such models could provide the best of both worlds: high performance and interpretability. Advanced posthoc model agnostic explainability techniques, such as LIME and SHAP, have been applied to machine learning-based credit scoring models, highlighting the potential of these techniques in enhancing the explainability of AI models [95].

6.2. Scalability and High Dimensionality of Data

In the era of big data, the ability to handle and process vast amounts of data has become a critical challenge. This challenge is particularly pronounced in sectors such as environmental health and smart building energy management, where large volumes of spatial and temporal data are generated [96]. These data, characterized by their high dimensionality and volume, require sophisticated processing and analysis techniques that can handle their scale and complexity [97].

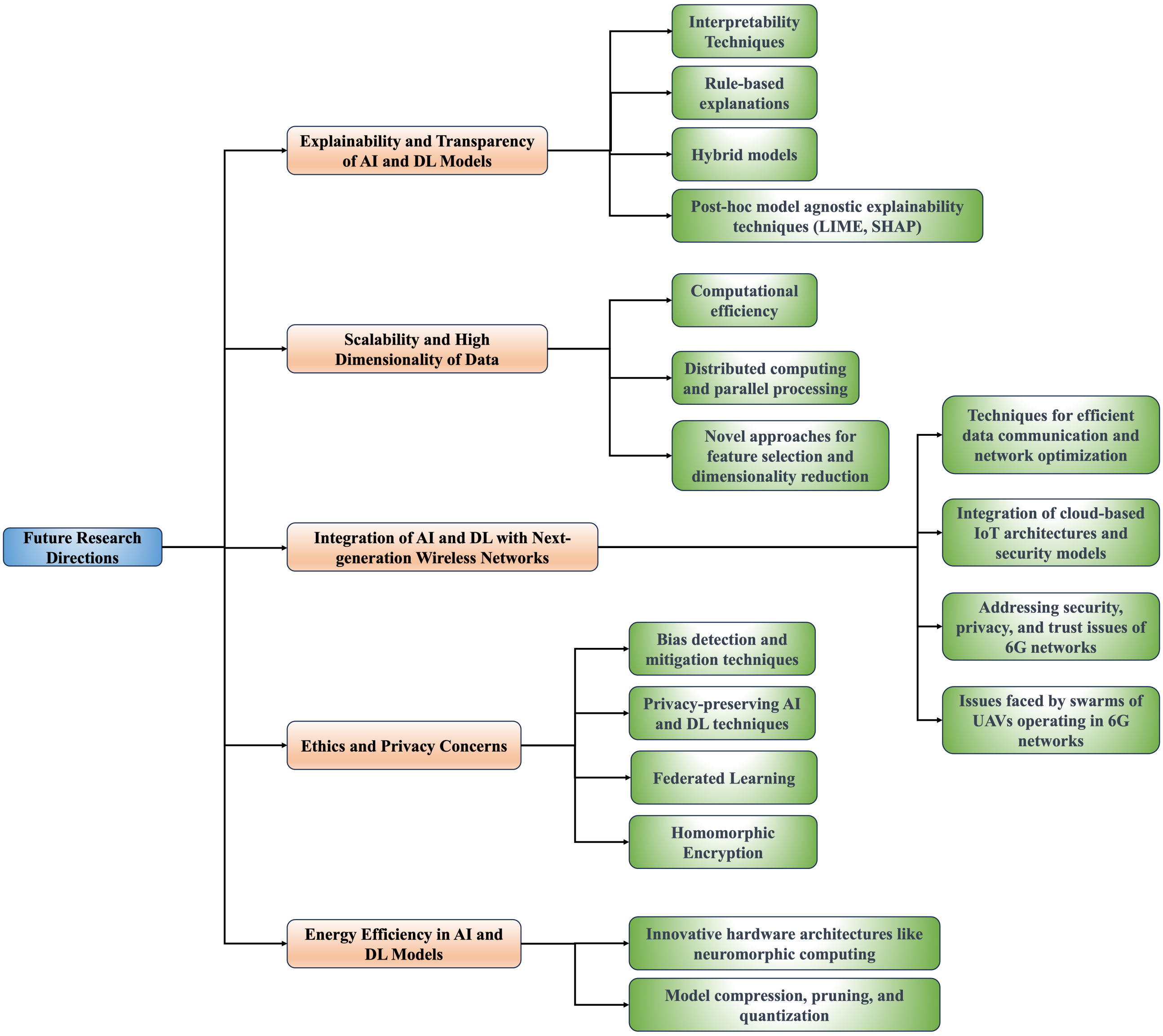

Figure 4. Future research directions. The different colors represent the level of abstraction of potential research methods.

Future research should, therefore, focus on developing scalable AI and DL algorithms that can efficiently process and analyze these large datasets. This involves not only improving the computational efficiency of these algorithms but also their ability to extract meaningful insights from high-dimensional data. Techniques such as distributed computing and parallel processing can be leveraged to handle the computational demands of large-scale data processing [98]. These techniques can distribute the computational load across multiple processors or machines, thereby significantly reducing the time required for data processing.

In addition to computational efficiency, data compression techniques can be employed to manage the high volume of data. By reducing the size of the data without significant loss of information, these techniques can make the data more manageable and easier to process.

Moreover, the high dimensionality of the data poses its own set of challenges. High-dimensional data can lead to overfitting and increased computational complexity in AI and DL models. Therefore, novel approaches for feature selection and dimensionality reduction should be investigated. These approaches can help in identifying the most relevant features and reducing the dimensionality of the data, thereby improving the efficiency and effectiveness of AI and DL models [99].

6.3. Integration of AI and DL with Next-Generation Wireless Networks

The rapid advancement of wireless networks and internet of things (IoTs) technologies poses challenges to the integration of AI and DL in renewable energy and smart building energy management. While fifth-generation (5G) networks can support various Internet of Everything (IoE) services, they might not be able to completely fulfill the requirements of novel applications. Sixth-generation (6G) wireless systems are envisioned to overcome these limitations, with AI playing a crucial role in managing networks and improving energy efficiency [100]. Future research should focus on exploring recent advances made toward enabling 6G systems and devising practical guidelines to cope with the challenges posed by these next-generation wireless networks. This includes investigating techniques for efficient data communication, network optimization, and security in AI and DL-enabled IoTs environments. In particular, the integration of cloud-based IoTs architecture, services, configurations, and security models needs to be examined, along with the latest advancements in cloud-based IoTs attacks [101]. Furthermore, the security, privacy, and trust issues of 6G networks, as well as the improvements over the 5G architecture, should be addressed [102]. The security and privacy, intelligence, and energy-efficiency issues faced by swarms of UAVs operating in 6G mobile networks also warrant attention, especially with the integration of blockchain and AI/ML with UAV networks utilizing the 6G ecosystem [103].

6.4. Ethics and Privacy Concerns

As artificial intelligence (AI) and deep learning (DL) technologies continue to permeate various sectors, it becomes increasingly crucial to address the ethical considerations and privacy concerns associated with their use [104,105]. AI models, trained on extensive datasets, inherently risk encoding and perpetuating the biases present in the data, potentially leading to unfair practices [106,107]. This risk is not merely theoretical; recent studies have shown that biases in AI models can have significant real-world impacts, such as reinforcing existing social inequalities [108,109].

In order to combat this, the development of robust bias detection and mitigation techniques is essential. These techniques aim to ensure the creation of fair and unbiased AI models, thereby promoting justice and fairness in AI applications [104]. Furthermore, the exploration of privacy-preserving AI and DL techniques is crucial to safeguard sensitive data and ensure compliance with stringent data protection regulations [110,111].

One promising avenue in this regard is the use of federated learning, a technique that allows for decentralized learning across multiple devices [112,113]. By keeping data localized, federated learning can significantly reduce the risk of data breaches and unauthorized access. However, it's worth noting that even in a federated learning system, sensitive information can sometimes be inferred from shared model parameters, necessitating further security measures [114].

Another promising technique is homomorphic encryption, which enables computations on encrypted data [115]. By using homomorphic encryption, it is possible to perform machine learning on data while it remains encrypted, thereby providing strong privacy guarantees.

These advancements not only protect individual privacy but also foster the more ethical use of AI and DL technologies. However, it is important to note that these techniques are not a panacea; ongoing research and vigilance are needed to ensure that AI and DL technologies are used ethically and responsibly [105].

6.5. Energy Efficiency in AI and DL Models

The escalating energy consumption and computational demands of artificial intelligence (AI) and deep learning (DL) models present significant obstacles to their broad implementation, particularly in environments with limited resources [116]. It is imperative that future research concentrates on the creation of energy-efficient AI and DL models. This could involve exploring techniques such as model compression, pruning, and quantization, which have the potential to decrease the computational and memory requirements of these models [117]. Furthermore, the investigation of innovative hardware architectures, such as neuromorphic computing, could offer promising avenues for enhancing the energy efficiency of AI and DL models [118,119].

However, it is crucial to address the environmental implications of AI and DL models. Training these models requires significant computational power, which often translates to high energy consumption. This energy is predominantly generated using fossil fuels, leading to an increase in greenhouse gas emissions [120,121]. For instance, countries like China and India, which are major hubs for AI research and application, have witnessed an upsurge in carbon emissions due to increased energy consumption from nonrenewable sources [122]. Moreover, rapid economic growth, often driven by technological advancements, including AI, can exacerbate environmental degradation [123].

While AI and DL offer substantial potential for sustainable development, they also present a series of challenges that need to be addressed. These include enhancing the explainability and transparency of AI models, managing the scalability and high dimensionality of data, integrating AI and DL with next-generation wireless networks, and addressing ethical and privacy concerns. Moreover, the energy efficiency of AI models remains a critical area for improvement. Future research should focus on these challenges, aiming to ensure the responsible and effective use of AI and DL technologies for a more sustainable future [124,125].

6.6. Environmental Impact of AI Systems

In recent years, the integration of AI systems in various sectors has shown both positive and negative impacts on the environment. For instance, Mikhailova and Sharova [126] highlighted the potential of AI systems to reduce human impact on the environment, especially in the healthcare sector. However, they also emphasized the importance of considering the environmental impact of AI systems when formulating ethical standards, especially during their development, testing, and application phases.

Furthermore, the integration of IoTs-enabled technologies and AI has paved the way for the development of smart cities, enhancing the quality of life for urban dwellers while promoting sustainability and productivity [127]. This integration not only offers solutions to urban challenges but also presents opportunities for designing and managing futuristic urban environments.

Moreover, the application of AI-based algorithms in environmental monitoring, such as the detection of harmful bloom-forming algae, has shown promising results. Gaur et al. [128] conducted a comparative assessment of various AI-based algorithms and found that the ResNeXt-50 model could identify algae with high accuracy, emphasizing the potential of AI in eco-environmental approaches towards sustainability.

7. Conclusions

In conclusion, this paper has reviewed the recent advancements and applications of artificial intelligence (AI) and deep learning (DL) in driving sustainability across various sectors, including achieving the sustainable development goals (SDGs), renewable energy, environmental health, and smart building energy management.

AI has the potential to contribute to 134 out of the 169 targets across all SDGs, making it a powerful tool for promoting sustainable practices. However, the rapid development of AI and DL technologies highlights the need for comprehensive regulatory oversight to ensure transparency, safety, and ethical standards.

In the renewable energy sector, AI and DL have demonstrated significant potential to optimize energy management, fault detection, and power grid stability. These technologies have also shown promise in waste management and predictive analysis in photovoltaic power plants, contributing to the efficiency and sustainability of renewable energy systems.

In the field of environmental health, the integration of AI and DL has facilitated the analysis of complex spatial data, improving exposure modeling and disease prediction.

These technologies have also enhanced the accuracy and efficiency of diagnostic procedures and environmental monitoring.

However, several challenges need to be addressed to fully harness the potential of AI and DL in driving sustainability. These challenges include the lack of explainability and transparency in AI and DL models, the scalability and high dimensionality of data, the integration of AI and DL with next-generation wireless networks, and the ethical considerations and privacy concerns associated with these technologies.

Future research directions should focus on developing techniques that enhance the explainability and transparency of AI and DL models, create scalable algorithms for processing large datasets, explore the integration of AI with next-generation wireless networks, and address ethical and privacy considerations. Additionally, improving the energy efficiency of AI and DL models is crucial for ensuring their sustainable use.

By addressing these challenges and fostering responsible and innovative use, AI and DL can significantly contribute to a more sustainable future. The integration of these technologies in various sectors has the potential to optimize processes, improve decision-making, and drive us towards achieving global sustainability goals.

In conclusion, AI and DL are powerful tools that can shape a more sustainable future by addressing societal challenges and promoting responsible and ethical practices. Continued research and development in these fields will be key to unlocking the full potential of AI and DL in driving sustainability across various sectors.

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