Magazzino *BMC Environmental Science* (2024) 1:4
https://doi.org/10.1186/s44329-024-00003-5

BMC Environmental Science

COMMENT

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The impact of deep learning on environmental science

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Abstract

Deep Learning (DL), a subset of Machine Learning (ML), has emerged as a powerful tool in environmental science, reshaping the landscape of data analysis and interpretation. This study focuses on the remarkable impact of DL on various aspects of environmental science, including remote sensing, climate modelling, biodiversity assessment, pollution monitoring, and environmental health.

Keywords Deep learning, Environmental science, Artificial intelligence

Main text

Environmental Science (ES) confronts numerous challenges in comprehending the complexities of Earth's systems and responding to environmental changes. Deep Learning (DL), with its ability to discern intricate patterns from vast datasets, has positioned itself as a game-changer in this domain [1, 2]. This study delves into the multifaceted impact of DL on ES, shedding light on its applications and contributions across different disciplines.

One of the primary applications of DL in ES is in the analysis of remote sensing data. DL algorithms excel in image recognition and classification tasks, making them invaluable for interpreting satellite and aerial imagery. The most common DL architecture used in remote sensing is the Convolutional Neural Networks (CNNs). CNNs are designed to process images and learn spatial features from them. They consist of multiple convolutional layers, followed by pooling layers and fully connected layers. CNNs have proven effective in land cover classification, vegetation mapping, and deforestation monitoring. Additionally, DL models enhance the accuracy of detecting changes in land use and land cover, providing valuable information for ecosystem management and conservation efforts [3].

DL has demonstrated its efficacy in improving climate models by capturing intricate relationships within climate data. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are particularly useful for modelling temporal dependencies in climate datasets. DL models enhance the precision of climate predictions, facilitating better-informed decision-making in areas such as agriculture, water resource management, and extreme events [4].

Furthermore, the preservation of biodiversity is crucial for maintaining ecological balance. DL plays a pivotal role in biodiversity assessment through species identification, population monitoring, and habitat mapping. Object detection models, such as Faster R-CNNs, You Only Look Once (YOLO), and Single Shot Multibox Detector (SSD), enable efficient and accurate identification of wildlife in camera trap images. This technology aids conservation efforts by providing real-time information on species distribution and behaviour [5]. Faster R-CNNs are complex but slow, YOLO models are fast but less accurate, and SSD strikes a balance between speed and accuracy.

DL applications in ES extend to pollution monitoring, where the identification and quantification of

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pollutants are critical for environmental health. DL models applied to sensor data, satellite imagery, and air quality measurements enable the detection of pollutants such as particulate matter, greenhouse gases, and chemical spills. These models contribute to early warning systems and help devise strategies for pollution control and mitigation [6].

The impact of DL on the circular economy is profound, offering innovative solutions to enhance resource efficiency, waste reduction, and sustainable practices. DL applications contribute to the optimization of supply chain management, facilitating the tracking and recycling of materials within a circular framework. Intelligent systems, powered by DL algorithms, can analyze big datasets to identify opportunities for material recovery, minimize waste generation, and streamline recycling processes. Furthermore, DL enables predictive maintenance in circular economy systems, enhancing the lifespan of products and reducing the need for premature replacements. Advanced image recognition and sensor technologies, driven by DL, play a crucial role in automating sorting processes in recycling facilities, improving the accuracy of material separation. The integration of DL in circular economy models fosters a more resilient and sustainable approach to resource management, aligning with the principles of a circular economy. As the field continues to evolve, the synergy between DL and circular economy practices holds the potential to revolutionize the way we manage resources and minimize environmental impact [7].

The impact of DL on energy transition encompasses improvements in energy production, grid management, and energy consumption efficiency. DL algorithms boost the forecasting accuracy of renewable energy sources such as solar and wind, enabling better integration into the power grid. Smart grid systems, empowered by DL, optimize energy distribution, enhance reliability, and support the efficient utilization of renewable energy. Moreover, DL applications contribute to energy conservation through the development of intelligent systems that optimize building energy consumption, improve industrial processes, and enable predictive maintenance for energy infrastructure. The intersection of DL and energy transition is fostering a more resilient and sustainable energy ecosystem, paving the way for a cleaner and more efficient future. As the world continues to prioritize renewable energy, DL will play a pivotal role in shaping the landscape of energy production, distribution, and consumption [8].

The popularity of AI is on the rise, as a potential solution to environmental challenges through initiatives such as AI for Green proposals. Predictive DL techniques directly forecast a specified ecological factor or indirectly predict factors relevant to ecosystems, such as ecological factor prediction or risk assessment.

Despite the success of DL in ES, challenges persist. Issues such as data scarcity, model interpretability, and the need for domain-specific expertise hinder broader adoption [9, 10]. Future research should address these challenges, fostering collaboration between environmental scientists and machine learning experts. Continued research and collaboration will further unlock the potential of DL in advancing ES and promoting sustainable practices. The future directions of DL in ES are poised to revolutionize our understanding of the natural world and address pressing environmental challenges. Continued advancements in DL models should focus on improving interpretability and transparency, crucial for gaining the trust of researchers and policymakers. Interdisciplinary collaborations between environmental scientists, data scientists, and AI researchers can be essential to developing specialized DL models that cater to the unique characteristics of environmental datasets. The creation of standardized, diverse, and open-access environmental datasets may further propel DL applications, fostering innovation and enabling the comparison of models across different regions and ecosystems. Incorporating domain-specific knowledge into DL architectures enhances model performance, ensuring that AI-driven solutions align with the intricacies of environmental systems. Moreover, ethical considerations, such as fairness and bias mitigation, will be at the forefront of DL research, ensuring equitable access to benefits and minimizing unintended consequences. As DL continues to evolve, its potential to contribute to sustainable practices, conservation efforts, and climate change mitigation in ES remains immense.

Conclusions

DL has emerged as a revolutionary force in ES, providing innovative solutions to longstanding challenges. Its applications range from remote sensing to biodiversity assessment and pollution monitoring, contributing to a more profound understanding of ecological systems. Ongoing research and collaborative efforts are poised to unlock even greater potential for DL, further advancing ES and fostering sustainable practices.

Abbreviations

AI	Artificial Intelligence
CNNs	Convolutional Neural Networks
DL	Deep Learning
ES	Environmental Science
LSTM	Long Short-Term Memory
RNNs	Recurrent Neural Networks
YOLO	You Only Look Once
SSD	Single Shot Multibox Detector

Acknowledgements
Not applicable.

Author's contributions
C.M. wrote the entire article.

Funding
This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

Availability of data and materials
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Received: 31 January 2024 Accepted: 3 May 2024
Published online: 24 June 2024

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