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AI-powered Approaches to Environmental Challenges: Trends, Benefits, and Limitations

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Abstract

Dynamic and unpredictable characteristics of environmental processes create challenges in their management and regulation. Artificial intelligence (AI) offers a powerful solution for addressing these complexities. AI tools have become more and more popular across a range of fields and research domains due to their efficient development and rapid growth. We analyze key trends in AI applications, including predictive analytics for climate modeling, automated monitoring of biodiversity, and smart resource management. The benefits of these technologies, such as enhanced efficiency, real-time data analysis, and improved decision making, are discussed in detail. However, the study also identifies significant limitations, including data quality issues, algorithmic bias, and the need for interdisciplinary collaboration. By providing a comprehensive overview of the current landscape, this article aims to highlight both the potential and the challenges of leveraging AI to create sustainable solutions for a healthier planet. Over the past few years, there has been an exponential increase in interest in using AI in the environmental discipline. This paper aims to review the most recent uses of AI techniques in the environmental field, the prospects they offer, and their benefits and drawbacks.

Keywords: Environment, artificial intelligence, subject classification codes

INTRODUCTION

Systems with artificial intelligence (AI) can reason, make decisions, and learn from data. It can convert data from the real world into knowledge that can be used and understood by machines. It can also use planned optimization and solution-searching paths to make decisions (European Commission, 2020) [1]. Machines are capable of problem-solving, information extraction, behavior prediction, change adaptation, and learning from data. Numerous aspects with multi-source, multi-layer, multi-stage, and multi-objective characteristics are connected to most environmental engineering challenges. Currently, many private sector companies and public sector decision-makers underline how crucial it is for these intricacies to be effectively reflected. In the past, a variety of modelling tools have been created to simulate the operations of solid waste incinerators, air pollution control facilities, and water or wastewater treatment plants. Nevertheless, achieving the intended system performance is frequently challenging due to the unpredictable, interacting, and dynamic nature of these processes. Potential improvement requires integrated evaluation, which considers several uncertain and dynamic components in the studied systems within a broad framework, as opposed to analyzing them separately. The accurate forecasts, ongoing surveillance, risk assessments, and other beneficial outcomes of the advancements in AI will be a great advantage for analyzing environmental data [2]. Deep learning algorithms that comprehend data

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gathered by various sensors are being developed by researchers. Significant progress in environmental research, encompassing climate modelling, energy conservation, decision-making, and other areas, is being facilitated by these algorithms. In the past few years, the application of AI in waste management, sustainability, water management, and earth observation has become widely recognized [3].

ARTIFICIAL INTELLIGENCE APPLICATION IN THE FIELD OF ENVIRONMENTAL STUDIES

The past two decades have seen an increasing use of AI applications in environmental studies and analysis. In the early 2000s, environmental experts started using AI tools in their jobs. Knowledge-based systems, a class of computer programs created for problem-solving, were utilized for environmental assessment and decision-making before the development of machine learning [4]. The early users of AI faced many difficulties in setting up several performance criteria and selecting appropriate value ranges that could be realistically evaluated for every impact.

Over time, with development of machine learning, expert systems, deep learning, the field of AI has seen a significant change. They have completely changed how humans use computers to solve complicated issues. In the late 2000s, the application of machine learning (ML) in the field of environmental science developed, and in 2010 there was a surge in interest due to the development of deep learning (DL) algorithms [2]. As a result, machine learning now forms the basis of many software services and applications related to the environment [5].

Pioneering Artificial Intelligence Applications in Environmental Studies

The integration of AI techniques into environmental engineering practices has garnered significant attention in the past decade (2000–2010), offering novel approaches to address complex environmental challenges. When AI first entered the field of environmental engineering, scientists mainly looked into how rule-based and expert systems might be used to solve environmental problems [6]. Expert systems have been used in a variety of environmental sectors, including air pollution control, water quality management, and ecological risk assessment. These systems encode knowledge into a set of rules, mimicking human competence. For the purpose of creating rules, these early AI systems frequently used specialized programming languages like LISP or Prolog [7], which required in-depth subject knowledge. These systems were constrained by their static character and incapacity to adjust to shifting environmental conditions, even if they showed encouraging potential for decision assistance and problem solving. Notwithstanding these drawbacks, the early application of AI in environmental engineering served as a precursor to more sophisticated methods like ML and neural networks. The majority of studies focused on many techniques, such as fuzzy logic (FL), random forest (RF), support vector regression (SVR), and artificial neural networks (ANNs) [8].

Artificial Intelligence Applications in Contemporary Environmental Studies

Over the years, AI models which could overcome the past drawbacks were developed. Neural networks, DL, and ML advancements have increased their dependability and efficiency for usage in a variety of fields. Figure 1 shows the evolution of various AI models over the years.

AI techniques have become essential in several environmental fields in the past decade. They are often used in emission control, monitoring and prediction in air quality management, distribution system optimization, hydrological modeling, and water quality evaluation in the management of water resources. AI's skills in impact analysis, weather forecasting, and climate modeling are useful for studies on climate change [9, 10]. AI is used in ecological monitoring for species distribution modeling, habitat evaluation, and biodiversity tracking. Artificial Intelligence is used in land use change study for detection, categorization, and geographical analysis. AI-driven early warning systems, risk assessment, and reaction planning are beneficial to natural disaster management. AI is used in renewable energy optimization to improve the dependability and efficiency of solar and wind power plants. AI-driven waste management optimizes both recycling and trash management. Although it is by no means exhaustive, the list below illustrates how broadly applicable these techniques are [2].

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Weather Forecasting

From the literatures, it is evident that the most examined meteorological fields are wind, precipitation, temperature, pressure, radiation, and also attempts to predict extreme weather conditions like tornados, hails and storms. Figure 2 shows the process flow in using AI for weather forecasting. DL, RF, ANNs, support vector machine (SVM), and XGBoost are some of the several techniques utilized in the prediction process. In recent years, ML has advanced significantly in the field of weather prediction [11, 12].

The exponential growth of high-resolution radar observation, satellite data, numerical model output, and other meteorological data provides the data foundation for ML, especially deep learning, and greatly promotes the development of pure data-driven weather and climate prediction. Recent research has shown that AI and ML are highly adept in enhancing predictions of severe weather and the dangers that come with it [13, 14].

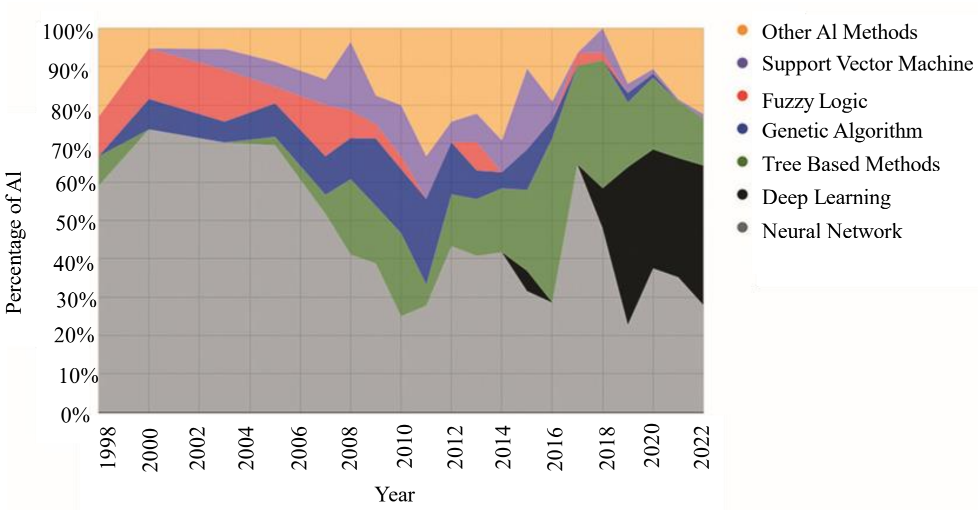

Figure 1. Evolution of artificial intelligence (AI) models over the years.

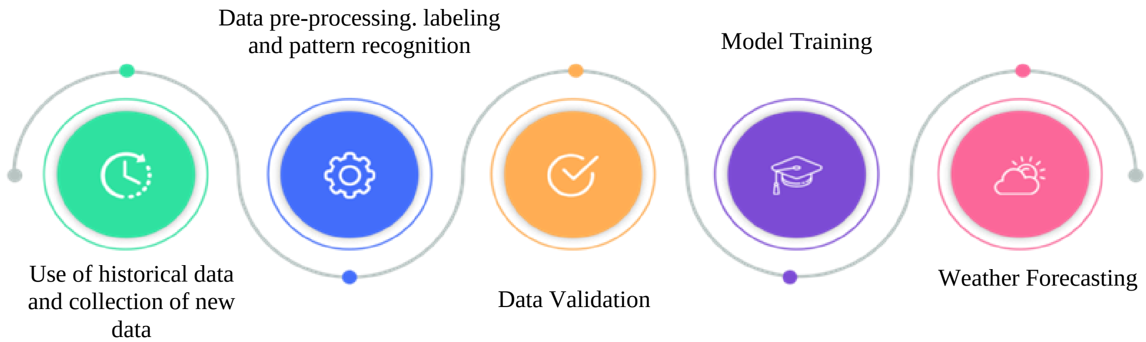

Figure 2. Weather forecasting using artificial intelligence (AI).

Having said that, the major limitation in this filed is the fact that the ecosystem and geographical regions alter due to climate change [15]. ML models employ historical data to predict future events, but since the key variables they are based on are always changing, there might not be a permanent stasis point that can guarantee perfect accuracy. Use of physics-AI hybrid modeling is a very recent innovation for a better accuracy of weather forecasting [16].

Renewable Energy Generation

Power grid stability is one of the new challenges that many countries around the world are facing as they transition away from fossil fuel power plants and towards the use of cleaner technologies, like

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harvesting energy from solar or wind radiation. Electricity from conventional power plants is more reliable and can be easily adjusted to meet changing consumer demand. In contrast renewable energy generation is heavily reliant on weather. As a result, precise forecasting is needed for both the meteorological and energy production domains. Research works are attempting to construct models utilizing techniques like RF, XGBoost, ANN, and DL in light of the evident accuracy limits of numerical weather prediction models [17]. The goal is to improve the accuracy of extremely short-range forecasts, which are typically reviewed for a few hours, as well as predating up to several days in advance.

Hydrological Prediction

Predictions of inflows are essential for water managers and policymakers because they affect reservoir operations, water distribution, flood control measures, and drought mitigation plans. The relationship between precipitation and streamflow is complicated because the water from precipitation is either trapped as snow or ice or is influenced by the plant and soil types in the watershed before it ultimately feeds into the streamflow. Therefore, physical models that attempt to simulate the workings of the hydrological processes' physical mechanisms are not particularly good at predicting streamflow based on precipitation data. On the other hand, precise forecasts facilitate optimal use of water resources by offering information on availability and allocation. AI models, coupled with the extensive hydrological datasets currently accessible, offer optimal conditions for developing tools focused on water resource management, flood and drought prediction, water quality monitoring, irrigation scheme optimization, dam management, carbonate saturation assessment, sedimentation process evaluation, and contaminant transport modeling, among other applications [18].

To predict the river inflow, several popular machine learning algorithms are available, including CatBoost, ElasticNet, K-nearest neighbors (KNN), Lasso, Light Gradient Boosting Machine Regressor (LGBM), linear regression (LR), multilayer perceptron (MLP), RF, Ridge, Stochastic Gradient Descent (SGD), and the Extreme Gradient Boosting Regression Model (XGBoost). According to a study by [19], CatBoost functioned at its best, proving its capacity to generate precise predictions on brand-new, untested data.

But as with the weather data here also there is the limitation that the even though we cannot consider evolving patterns in river inflow. And also, each river being different, it is difficult to generalize such a prediction.

Air Quality Prediction

Nowadays, air pollution is regarded as one of the most serious problems. There are many works done starting from late 2000s using AI in air quality predictions. lately. Research on AI and air pollution is ongoing.

Meteorological data, including wind direction, wind speed, humidity, and temperature, as well as predictors like PM2.5, PM10 (PM = particulate matter), SO_2, O_3, CO, and NO_2, are needed to forecast air quality, particularly in terms of the air quality index (AQI). AI may be used to analyse vast volumes of data to spot trends and patterns in air quality and emissions. This can support decision making and the creation of more efficient emission-reduction and air quality-improving measures by policymakers.

SVR, MLP regressor, RF, KNN, adaptive boosting (ADA Boost), and long short-term memory (LSTM) are some of the ML and DL algorithms that can be used to forecast air quality.

In a study done by [20], LSTM performed the best in predicting air pollution. [21] show that though all AI methods are better than the traditional statistical methods, it is more accurate to use a hybrid model.

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It should be noted that depending on the pollutants and the region, different techniques should be used to forecast air pollution. No predictor is suitable for every aspect of modelling and that no specific intelligent technique is appropriate for every unique scenario. So, we cannot say any of the above-mentioned methods in Figure 3 as the most effective method.

Water Quality Management

It is difficult to forecast and understand the quality of water. These difficulties stem partly from the complex processes that regulate water quality, as well as the laborious and costly data collection efforts that contribute to data scarcity. In these conditions the traditional methods for forecasting water quality like, conventional process-based and statistical models frequently fall short. AI has been used in water quality studies from the early 2000s. But most of those studies were just modeling the input-output relationship. Over the years, there is a huge advancement in this area, which span over various aspects of water quality including, monitoring wastewater treatment plants, optimizing their operating conditions, minimizing costs of wastewater treatment systems, predict water quality characteristics, assessing groundwater pollution and many more. It can be seen that AI and ML are very effective not only in categorization, prediction, and optimization of water parameters, but also in anomaly detection, control, pattern recognition, and feature extraction [22]. LSTM and ANNs were the most commonly used AI models for water quality monitoring and evaluation in the past decade, with LSTM showing a slightly higher accuracy [23].

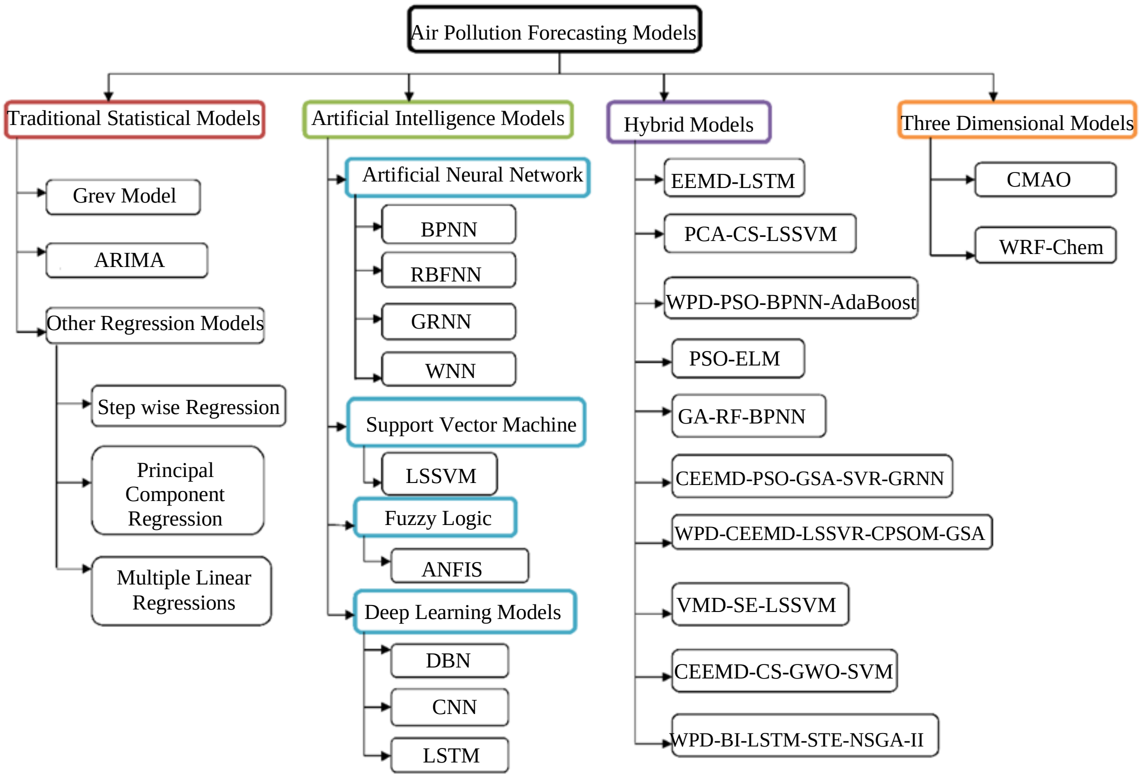

Figure 3. Different methods of air pollution forecasting [21].

There are tools available for environmental monitoring which can analyze water quality data and other environmental factors. These tools utilize ML algorithms to identify data patterns and predict future trends [3].

Use of internet of things (IoT) is another advancement. Remarkably, the IoT has enabled effective monitoring of water quality by enabling real-time data collecting from various sources. With the use of ML techniques, precise water quality forecasts may be made by analyzing the collected data [24].

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LIMITATIONS AND CHALLENGES OF USING ARTIFICIAL INTELLIGENCE IN ENVIRONMENTAL ANALYSIS

While ML models and AI tools have shown themselves to be cutting edge technologies in a number of scientific fields, they have encountered obstacles and challenges in the environmental field. Time series modelling and forecasting can be enhanced by ML approaches, but first the data has to be denoised and filtered. Also, scientists must have a solid knowledge of the underlying physics in order to apply AI to learn more about it. Policymakers, environmental scientists, and AI specialists must work together [25]. ML, due to its "black box" character, makes it difficult for consumers to comprehend the logic behind its predictions. Addressing ethical and social concerns, such as data privacy and algorithmic bias, is another important challenge [26]. Attempts to completely replace physical based numerical model with AI in various fields is resisted because of these reasons. AI methods still mostly rely on human experience, though it can employ transfer learning or unsupervised machine learning, which uses datasets to learn.

FUTURE OF ARTIFICIAL INTELLIGENCE IN ENVIRONMENTAL STUDIES

Combining AI with IoT and big data analytics will revolutionize environmental monitoring and management. The integration of AI into environmental studies is poised to transform the field by offering sophisticated tools for monitoring, predicting, and managing environmental resources. The future prospects of AI in this domain are highly promising, driven by the demand for more accurate, efficient, and scalable solutions to tackle complex environmental challenges. With the advancement in the field of artificial intelligence we can ensure that improved algorithms and comprehensive datasets will increase model accuracy in environmental predictions. AI will become an inevitable part of data-driven policy making, enhancing regulatory frameworks and compliance monitoring in the very near future. This data-driven approach will enhance the effectiveness and efficiency of environmental policies, ensuring better protection and management of natural resources. A personalized environmental solution for individuals and communities that will empower individuals and communities to contribute to environmental sustainability more effectively can be expected.

CONCLUSION

AI technology can increase precision, efficacy, and efficiency in environmental data processing, evaluation, and decision making. By utilizing AI's capabilities, environmental data and resources may be more effectively used to protect the health of our planet and its people. Applying AI technologies in the environmental field should be done so with caution nevertheless, since there can be restrictions and unexpected repercussions. To make sure that their data evaluations and judgements are accurate, ecologically sustainable, and efficient, environmental professionals should weigh the benefits and drawbacks of using AI techniques. Since AI and its tools are still in their early stages of development and are always developing, it is unfair to judge them only based on their current limits. The entire potential and benefits of AI in environmental management are yet to be fully harvested.

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