Implications of Artificial Intelligence in Environmental Engineering

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Abstract

As environmental destruction progresses at an alarming rate, the threat of ecological catastrophes and the potential damages that communities around the world face demand that solutions be implemented immediately. Environmental engineers are at the forefront of grappling with the rippling effects of climate change, and to keep up with these challenges, a novel method of solving environmental crises must come to play: artificial intelligence. Artificial intelligence (AI) models can make educated predictions, identify significant patterns, and analyze large amounts of data, to help optimize and improve current environmental engineering processes for the future. This paper surveys different applications of AI that have been used by environmental engineers to enhance current technologies and practices in disciplines ranging from the petroleum industry to carbon capture. Additionally, we consider the ethical implications and unintended consequences that can result from an increased use of AI. Discussing the utilization of artificial intelligence in environmental engineering can ultimately help develop more effective methods for combating current environmental challenges, and further examination on the ethical implications of this usage can help ensure environmental justice for all.

Introduction

Artificial intelligence (AI) is growing in popularity and increasingly being used across several different disciplines. From using ChatGPT for homework answers to complex facial recognition software, artificial intelligence is taking the world by storm. Still, many grapple with the complexities of artificial intelligence and what the term actually means. The Oxford English Dictionary defines artificial intelligence as “the capacity of computers or other machines to exhibit or simulate intelligent behavior” (Oxford English Dictionary, n.d.). More specifically, artificial intelligence is a leading technology that uses and trains empirical data to improve the efficiency of current processes and enable progress for future (Manyika, 2022). AI can be considered a broader term than encompasses fields such as machine learning, neural networks, data mining, etc., (Salih et al., 2020). In the context of environmental engineering, artificial intelligence is used as a tool to process data and analyze the behavior and patterns of different physical systems, so data from the past can be accurately interpreted for future applications (Krzywanski, 2022). Even for those that understand what it means, how it works is not understood to the same degree. Using artificial intelligence can be divided into three steps: identification, prediction, and execution; identification includes algorithms gathering past data collections, prediction entails an analysis of the data with the purpose of identifying patterns and constraints, and execution includes presenting and applying the data interpretations found (Salih et al., 2020). AI is used as an alternative to current methodologies and regulation systems.

Applying AI to current methods can lead to an optimized performance with the goal of achieving a better product than one which was made through human interaction.

The usage of artificial intelligence is becoming increasingly popular in environmental engineering creating both benefits as well as unintended consequences. AI enhances engineering systems by accomplishing goals with higher accuracy, less computing time, and greater cost-efficiency than current practices. AI also has the potential, if broadly implemented, to fight some of the emerging climate disasters globally. However, with increased usage, artificial intelligence could have consequences, that potentially outweigh any advantages of using the technology. Loopholes, faulty data, data manipulation, etc., are all potential issues that could arise. As such, the ethics of implementing artificial intelligence is widely contested, as models have the potential for exacerbating existing systemic bias. Thus, analysis of the use of artificial intelligence in environmental engineering is needed to discuss whether the benefits outweigh the ethical concerns that come with increased use and development of these technologies.

General Uses

Artificial intelligence's potential is developing in the field of environmental engineering. In many different fields of study, AI's capabilities are being harnessed to fight environmental degradation around the world. Either by solving current inconsistencies and gaps of knowledge or supplementing already successful processes, the benefits of artificial intelligence are the gateway to the future for solving climate catastrophes. While there are several environmental engineering applications, we will highlight just a few recent ways that AI is being employed.

Hydraulic Fracturing

Hydraulic fracturing, one of the fastest-growing industries of today, is one of the many beneficiaries of artificial intelligence advancements. Hydraulic fracturing, or fracking, is a widely used technique in which oil and gas is collected through drilling and pumping fluids and high pressures into reservoirs (Jackson et al., 2014). However, even as fracking is growing in popularity for being environmentally friendly compared to other processes, such as coal mining, there are still many obstacles that come with the current practice. One such problem is non-uniform production from different production sites in horizontal wells. This problem arises from different stages of fracking producing different rates and amounts of gas, making big operations inefficient and prone to uncertainty (Huang et al., 2020). Due to different clusters underperforming, pumping schedules were optimized through the implementation of modeling algorithms and machine learning from different fracking simulators (Morozov et al., 2020). Other similar issues arise, such as problems with activating different natural fracture networks (Keshavarzi & Jahanbakhshi, 2013). Using artificial intelligence can help current fracking process reach its target design. Several machine learning algorithms have been developed to examine different fracturing zones through parameters such as size, number, location, angles of perforations, rock strength, permeability, etc., which help generate different predictive models that help characterize different reservoirs and make fracking production more efficient (Morozov et al., 2020). Empirical examples of success when using machine learning include model prediction of the Bakken formation oil production, neural networks used to predict water production in wells drilled in Denton, Texas, and shale gas simulation models for resource yields (Awoleke & Lane, 2011). This has further implications on the success of the fracking industry as a whole. In addition to increasing the accuracy and efficiency of fracking operations, machine learning has aided in digitizing and structuring oil companies. By optimizing fracking productivity, artificial intelligence is paving the way for the industry has become more economically viable and environmentally friendly.

Carbon Capture

Artificial Intelligence is also at the forefront of updating current carbon capture technology. Carbon capture is the process of storing harmful greenhouse gases, such as carbon dioxide, in underground geological formations so these gases can never reach the atmosphere. Machine learning models are being used to simulate storage centers and the long-term effects of storing carbon at different locations(Wen et al., 2022). Current obstacles in finding potential capture locations are making sure there is not a pressure buildup from redirecting large amounts of carbon dioxide into the ground. These pressure buildups can lead to fracturing in underground formations, causing leakage of carbon into the atmosphere and surrounding groundwater resources (Lemieux, 2011). A recent advancement in artificial intelligence can assist in solving this issue. U-FNO, a neural operator, can simulate pressure levels to find the best injection rates, creating a faster and more accurate carbon capture process. The model is used to select correct injection sites, control pressure buildup, maximize storage efficiency, and predict the spread of carbon dioxide up to 30 years after the initial injection (Wen et al., 2022). Location simulations help ensure that the risk of carbon leakage is mitigated and also allows scientists to pick locations that are the most successful long-term. Carbon capture is essential to creating negative emissions, so ensuring that the process is accurate, fast, and cost-efficient means one step to a better chance of mitigating climate change as a whole.

Flood Forecasting

Weather forecasting and natural hazard risk management can also benefit from utilizing artificial intelligence algorithms. Natural disasters have the ability to impact anyone from anywhere. According to the World Health Organization, natural disasters impact over 150 million people each year (World Health Organization, n.d.). Among other hazards, floods stand out as the most frequent and devastating disaster, causing irreparable environmental, social, and economic damage. Additionally, floods are particularly prone to increases in frequency and intensity due to climate change, so the potential for damage is only increasing. Currently, systems do not provide sufficient information for accurate forecasting which can lead to dangerous evacuation situations. For instance, current hydrology models can estimate river flows through meteorological forecasts, but still are not fully effective for other water applications and for floods with short-lead times (Sene, 2010). However, utilizing artificial intelligence to forecast floods through analyzing huge data sets can create accurate predictions to prevent the worst impacts. This can be achieved by using data gathered from past rainfall and flood simulations, which can then be processed through machine learning systems to provide predictive analysis on patterns that are present in these past datasets (Nile, 2018). This process reveals key insights such as the time, location, and severity of different flood paths, as well as emergency planning and recovery responses (Wagenaar et al., 2020). Two such models are being used now: the hydrological model that can make water level predictions in different bodies of water, and the invasion model which can predict what area will be most likely affected by future floods (Sirisena et al., 2020). By using real and high-quality data sets, AI can create accurate forecasting in just milliseconds, including predicting floods that present uncommon behavior.

Predicting Tornado Formations

In addition to successful flood forecasts, artificial intelligence is also being utilized for tornado predictions. Tornadoes are an emergent threat, as their strength, quantity, and damage can be highly destructive to human population centers and the surrounding environment (Zeng et al., 2022). Climate change only exacerbates the possible damage done by tornadoes, and challenges remain in preventing further destruction. Current algorithms suffer from inaccuracies that lead to high false-alarm rates and underperforming detection and classification abilities (Zeng et al., 2022). Machine learning is optimizing pre-existing algorithms so accurate and rapid forecasting of tornado formations can be ensured (Basalyga et al., 2021). Forecasting algorithms can produce better tornado warning decisions by predicting a storm's longevity, wind, hail, and tornado conditions; AI models are also more beneficial than regular human-developed models because they can interpret large swaths of data and can assess the variability of a storm's tornado potential (Steinkruger et al., n.d.). Furthermore, models should be varied towards each user's preference, so every model can be contextualized to which location it is being used for. Specified parameters allow for a more optimized forecasting system that is necessary to fight against these escalating destructive natural disasters.

Monitoring Biodiversity

The severe and widespread implications of biodiversity loss and the newest technologies are needed to combat intensifying challenges. Biodiversity loss is closely coupled with climate change, and biodiversity is key to combating numerous threats including deforestation, carbon emissions, water pollution, and other environmental crises (Torres, 2016). Recently, the University of Fribourg developed an artificial intelligence model to identify regions in need of biodiversity protection and conservation, a crucial first step of utilizing emerging technologies to improving the sustainability of several ecosystems. This model, named CAPTAIN (conservation area prioritization through artificial intelligence), allows for the integration of several parameters such as biodiversity data, conservation budgets, climate vulnerabilities, and human uses of the land to make educated decisions about future efforts of conservation at certain locations (Silvestro et al., 2022). Protecting regions with higher ecological diversity is more valuable than protecting a higher number of regions, which is why AI is such a beneficial tool to use (Li, 2020). Regions with higher diversity of animals and plants or regions that house key species are more useful to protect than focusing on just a higher number of regions that might not be as important to the earth's ecosystem. Choosing which regions to conserve can include quantifying trade-offs between the costs and benefits of biodiversity protection, i.e., are the costs of conservation worth the resources gained from combatting biodiversity loss in that specific area. CAPTAIN helped improved prevented species loss by 26% compared to current protection policy, which is an impressive start to other technologies being developed for this purpose (Silvestro et al., 2022). Policymakers should make use of advancing technology like artificial intelligence in order to mitigate ecosystem loss.

Limitations

There are still multiple limitations to implementing artificial intelligence in environmental engineering. There are many broad vulnerabilities to using AI that risk the accuracy and effectiveness of systems that use the technology. Implementing AI into pre-existing systems requires the machine learning's algorithms to be accurate and updated, and it also requires distributing the technology in an efficient and equitable way. These broad parameters often limit the effectiveness and success of using artificial intelligence.

Modeling Restrictions

Artificial intelligence is at the forefront of averting climate disasters due to its capacity to use past data to generate accurate predictions about the future. However, despite the potential for good, there are a few limitations to its capabilities. Firstly, the efficacy of AI depends on when and how training models were built. There are multiple questions that need to be answered on whether a model is appropriate to use in certain contexts, including the following: What community's data was the model based off of and can it be applied broadly? When was the model created? Have there been any trends that have changed since the initial creation of the model? How can the model stay updated and unbiased? These questions and concerns have significant implications for the utility of artificial intelligence and will effectively limit its efficiency. For environmental engineering in particular, access to the most updated knowledge and discoveries related to the environment is necessary to create the most functional and successful solutions.

As the ecosystem and geographical areas evolve because of climate change, there are many limitations to using AI modeling (Galaz et al., 2021). Machine learning models rely on the past data collection to make predictions about the future, but as important factors that models are based upon continuously evolve, there may not be a stable stasis point for models to use that can ensure full accuracy. Ecological conditions can shift, reverse, and result in surprising conditions that are unpredictable. For instance, using AI to optimize fracking can only be efficient if oil and gas extraction sites remain consistent over time, which is difficult to claim as true. As mentioned above, a potential use of AI in the fracking industry is to create models that characterize reservoirs to make fracking production more resourceful; however, as reservoir and geological landscapes change, models that might have worked in the past, are no longer accurate now. Another notable example of this limitation is AI's role in carbon capture. Past models were successful because they could select the best sites to store carbon and could predict any future consequences that arose if that site was used. Still, these predictions are only valuable if the data they rely on is still relevant, which, as previously stated is not always the case. To avoid this obstacle, either new models need to be periodically updated or old models need to be continuously updated. Both of these potential solutions take additional resources, time, and manpower to maintain which decreases the initial benefits of using artificial intelligence in the first place. This also leads to an economic disparity between AI users, as smaller companies or users that do not have consistent funding can not necessarily harness the same benefits in an accessible way.

Resources/Distribution

If AI were to become common and widely applied to many industries and locations, doubts arise about if (1) there are the necessary resources to implement AI widely and (2) if the eventual implementation is equitable. "Equal access to AI-technologies does not guarantee equal or fair outcomes (Galaz et al., 2021)." AI's potential impact on existing socioeconomic conditions, implicates a new digital divide. The existing digital divide describes the inequity between groups that can access developing technology and those who cannot (Riggins & Dewan, 2005). Artificial intelligence has the potential to only exacerbate and grow the digital divide, as more advanced and/or wealthy groups can capitalize on this easy access, while those that do not have access to the technology only get more disadvantaged (Carter et al., 2020). This could impact society on the local, business, and country level. Local businesses who do not have the technical knowledge or resources to implement AI to aid them leaves them a step behind big businesses who can access and update their technology. In the context of using artificial intelligence to aid in making more efficient environmental regulations, a possible reality could be only wealthier groups accessing the benefits of the technology. If businesses or people with better resources can gather data more efficiently than poorer communities, AI models are only being trained with data exclusive to those with superior access to resources.

Summary Table:

Field:	How AI is being utilized:	Environmental Benefits:	Limitations:
Hydraulic Fracturing	Used to optimize pumping schedules and analyze various fracking sites to determine the most productive areas.	Fracking offers environmental benefits compared to alternative natural gas production methods.	Shifting reservoir conditions means models must remain updated.
Carbon Capture	Used to simulate storage centers to predict the success and long-term effects of using that area.	Capture is essential to storing carbon, an environmentally destructive gas, and prevents air and water pollution.	Continuous data on potential storage sites is needed to make accurate predictions.
Floods	Used to forecast the severity and location of future floods.	Floods heavily impact the environment and over 150 million people per year and are only intensified by climate change.	Floods patterns and characteristics are constantly changing, preventing the usefulness of past data. Difficult to implement forecasting models in areas that have limited resources.
Tornados	Used to make accurate and rapid forecasts on future tornado formations.	Tornadoes are extremely destructive to human population centers and hurt surrounding environment like wildlife, forests, habitat, etc.	It takes a lot of resources to personalize models for areas with varying tornado patterns.

Biodiversity	Used to identify regions in need of biodiversity protection so ecological diversity and to prevent species loss.	Ensuring biodiversity is key to combating deforestation, carbon emissions, water pollution, and improving the sustainability of several ecosystems.	Limited resources can be used for conservation efforts, and data needs to be constantly analyzed to keep models updated.

Ethics

The use of using AI in environmental engineering presents many ethical concerns. Algorithms can inherit "coded bias," propagate social justice concerns, and make harmful and inaccurate predictions due to misapplied or manipulated data. Strong and accurate environmental regulations are key to check against companies or operations that violate rules pertaining to climate protection efforts. Current enforcers, such as the Environmental Protection Agency (EPA) are battling internal obstacles such as limited resources, limited regulatory effectiveness, and lack of agency cohesion (Demortain, 2020). To solve this problem, machine learning is being used to supplement and enhance current regulatory practices. Still, several downsides can arise from using AI in environmental regulating.

The data being used in AI algorithms could be vulnerable to a phenomenon known as "coded bias," which results when models are trained using racist datasets, making algorithms inherently discriminatory. This phenomenon was observed when AI was implemented in other industries. When used in the criminal justice system, machine learning models have been known to incorporate racial bias into judicial, profiling, and sentencing algorithms to harmfully discriminate against certain races (McGovern et al., 2022). If AI models in environmental engineering were to be trained off of biased data, many serious and negative outcomes could occur. For instance, algorithms could direct oversight away from facilities located in minority or low-income communities based off of misrepresented data, which results in AI systemically worsening existing discrimination (Hino et al., 2018).

Even unbiased models still have the potential to exacerbate current environmental injustice and unfair environmental practices. Currently, there have been several instances of social justice concerns with environmental regulations. Minority and low-income populations were disproportionally affected by the lead water crises in Flint, Michigan, and the EPA purposefully dismissed the locations in which poor communities and people of color were located (Mohai, 2018). Artificial intelligence may only perpetuate these acts of environmental injustice. Weather radar systems serve as example of potential injustice. Weather radar systems rely on reflecting energy into the atmosphere to gather information about storms; many majority Black communities in the Southeast have limited radar coverage due to their distance from radar sites , making it difficult for machine learning models to gather information about storms that could impact those areas (McGovern et al., 2022). This results in less data being collected about storm patterns in those areas, causing some communities to be less prepared for natural hazards compared to others. By not ensuring equal access to benefits from machine learning, AI reproduces unequal opportunities and treatment between different communities.

Lastly, there are many concerns associated with the quality and accuracy of data that is being fed to artificial intelligence algorithms. Successful implementations depend on the quality and accuracy of the data being used. This data is sometimes self-reported or and can be subject to misuse or manipulation by those who are using it, leading to harmful and inaccurate data models (Hino et al., 2018). As an example, relying solely on self- reported data for detecting hailstorms would likely result in the data being skewed towards population dense regions like major cities and urban areas. This could cause AI to over-predict storms in urban areas and under-predict storms in rural areas, creating inaccurate predictions. (McGovern et al., 2022). Furthermore, if the data being trained is not fully representative of its target community, the models will not be successful nor accurate (McGovern et al., 2022). Developers of AI tools must directly engage with the various populations of areas that they are going to implement the technology in; otherwise, they risk overlooking relevant community knowledge. This can be remedied by seeking to consult with local providers that are more aligned and knowledge about each community itself. Another example that demonstrates the potential inaccuracies that could result from AI is if a diverse geographic area were to be analyzed. Machine learning models will ignore small portions of the data set and instead look for patterns on the more common areas, causing errors for small sites that were deemed inconsequential. Thus, data can easily be misapplied for the wrong uses and the quality of the data being used can heavily impact the success of a model.

Artificial intelligence is not magic, and engineers should seek to understand the unintended consequences of increasing the implementation of artificial intelligence in environmental science. Even though industries may benefit and become profitable through use of artificial intelligence, it should not come at the expense of the safety and well-being of others. As the potential for inequity and discrimination increases against vulnerable communities, these ethical consequences demand that we address the question of who really stands to benefit from implementation of artificial intelligence.

Discussion

Environmental engineering is becoming increasingly significant to our everyday lives, and as the field develops new technologies, the potential benefits and drawbacks of applying artificial intelligence, as well as the ethical implications associated with the process, are still being discussed. To access the benefits of optimizing practices that might be the key to solving deadly environmental disasters, one must still analyze the relevant and known risks associated with new applications of AI. These risks extend beyond the users of AI and includes externalities. Even the physical infrastructure simply needed for AI implementation can be environmentally destructive itself, requiring rare earth mining and substantial material and energy consumption, which could "further imperil the delicate ecological balance of our era" (Crawford & Joler, 2018).

Additionally, if inequality and systemic bias against communities that are already facing injustice becomes more pronounced, using artificial intelligence could be considered a net-negative solution. Whether it's through purposeful discrimination or exclusion by way of ignorance as previously mentioned , the AI's application to engineering might become the next form of continued structural violence against vulnerable communities. Conversely, it's worth considering if structural violence is inevitable due to other factors, and whether AI can instead serve as a solution to offset the disproportionally dangerous effects of climate change that disadvantaged communities face. These considerations should guide how future decisions are being made by companies, industries, and policymakers. Focusing on an impact that could affect a greater number of people, means a trade-off with prioritizing structural violence that vulnerable communities have repeatedly endured. Further research should consider detailing, projecting, or cataloguing the effectiveness and results of wide-spread application of the technology, as AI risks becoming the next pathway of ignorance and neglect by big industries and governments.

Other research agendas could involve developing tools to address emerging issues such as racially coded bias, how to make AI more environmentally sustainable, increasing development on how models could become more adaptable or updatable, and creating ways to make data more applicable and accessible to all areas. Having technology that can institute checks and balances on other AI applications would be crucial for safe and ethical implementation. Additionally, AI can be applied to other parts of environmental engineering, such as monitoring water and air quality, analyzing better locations for landfills, or detecting/preserving endangered wildlife. Comprehensive research and consideration of the applications of artificial intelligence in environmental engineering will aid in creating more efficient solutions to solve environmental catastrophes, while also minimizing the likelihood of furthering structural violence and environmental injustice.

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