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Review Article

Using artificial intelligence to predict aquatic pollution: A comprehensive review

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Abstract: Water contamination, or aquatic pollution, is a significant problem that endangers ecosystems, people's health, and the global economy. Laborious, expensive, and inadequate for real-time evaluations, traditional approaches to tracking and forecasting aquatic contamination include substantial manual sampling and laboratory testing. Pollutants and their origins are already complex, and the wide variety of chemical structures they contain further complicates matters. Because of these constraints, there is an ongoing, intense need for reliable predictions of pollution levels. The most promising method is artificial intelligence (AI), which can effectively interpret noisy data and handle nonlinear systems. When it comes to forecasting different types of water contamination, Artificial Neural Networks (ANNs) are among the most promising advanced AI models. To improve the forecasting accuracy of artificial neural networks (ANNs) for certain classes of pollutants, hybrid techniques, including radial basis function networks and small-world networks, have been developed. The field of water pollution research may also find success with Recurrent Neural Networks (RNNs) and Convolutional Neural Networks (CNNs). The purpose of this study is to shed light on research into how AI, and more specifically sophisticated models such as artificial neural networks (ANNs) and deep neural networks (DNNs), might improve the precision and effectiveness of pollution prediction.

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Introduction

New technology promises to guide us into the Fourth Industrial Revolution, significantly enhancing our quality of life in numerous ways. Innovations in data storage and analysis are the primary pillars upon which these forecasts rest (Javaid et al., 2022). Numerous potential uses have been identified in water science, and significant strides have been made in understanding the underlying mechanisms that give water its distinctive cosmic properties. This image is not without its flaws, though; many people will be left behind if ideas and practices related to manual labor become obsolete (Jan et al., 2021; Aziz et al., 2024). Despite numerous attempts to improve water quality, contaminants and their effects on aquatic life remain a significant environmental concern. This has led to the development of new research directions that employ various water-monitoring techniques (Mishra et al., 2023). Different technologies are used, including conventional chemical analysis and more recent systems that utilize remote sensors and advanced data processing techniques, such as artificial intelligence (AI) (Janga et al., 2023).

Prevention and forecasting are crucial components of environmental toxicology because contaminants have abrasive and damaging impacts on ecosystem health and, consequently, human health. Research on potential threats to aquatic ecosystems and biological organisms, or on contamination between these two sets of entities, is highly pertinent to this goal.

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Systematic and evolutionary development based on outcomes subject to pollutants makes it impossible for many dynamic biological agents of a given ecosystem, such as photosynthesis, respiration, and prandial experiments, to function freely. There are times when just a few species can do these activities due to extreme contamination or accidents. Furthermore, it is considered unprofessional to base one's first or fundamental warning models on the fact that traditional scientific instruments are often associated with the arts and pollution (Shetty et al., 2023). Traditional chemical treatment and filtration processes are usually costly and may generate secondary pollutants.

Recent studies have also explored the use of eco-friendly materials in wastewater treatment. For example, the valorization of diatomaceous earth as a sustainable natural coagulant has demonstrated high pollutant removal efficiency when its operating conditions are optimized using response surface methodology (Benouis et al., 2022). Despite improvements in treatment materials, accurate pollution prediction and early monitoring remain major challenges, which is where AI can provide significant advantages. AI has also demonstrated strong predictive capabilities in other environmental domains, such as short-term photovoltaic power forecasting, where machine learning models accurately estimate energy output under variable meteorological conditions, further highlighting AI's robustness in handling nonlinear environmental systems (Wang et al., 2019). One of the most promising applications of AI in the field of soft computing (SC) is the development of systems that can collect data, analyze it, and apply the results to the understanding of economic, social, and environmental issues, such as those arising from widespread pollution. However, researchers have not yet considered using fuzzy logic (FL) or artificial neural networks (ANNs) as decision-support systems to investigate the effects of aquatic contaminants. It is essential to note that there have been no scientifically mandated recommendations or assessments for utilizing FL and ANNs to predict aquatic ecosystems and pollutants. These high-tech parts have significant potential to help an approach succeed, according to much of the practical literature (George et al., 2023; Kamyab et al., 2023); therefore, this review aims to address these crucial gaps in the field.

Unlike previous reviews, this work provides a comparative evaluation of ANN-, RNN-, and CNN-based models, highlighting differences in prediction accuracy across pollutant types and identifying practical barriers to real-time deployment, including data scarcity, sensor failures, model interpretability, and scalability. The review concludes by outlining future research directions, particularly the integration of AI with IoT sensor networks and hybrid deep learning frameworks to improve aquatic pollution management. Regionally, machine-learning models have also been applied to predict pollution sources in the Euphrates and Tigris rivers in Iraq, offering a data-driven pathway for local water-quality governance (Rashid et al., 2024). However, despite substantial progress, existing reviews often evaluate AI models in isolation and do not systematically compare their suitability for different pollutant types and data structures. This review also addresses this gap by providing an integrated comparative analysis of ANN-, CNN-, and RNN-based approaches for predicting aquatic pollution.

Methodology

This review employed a structured literature screening approach to ensure that the included studies provide relevant and reliable insights into AI-based prediction of aquatic pollution. Scientific databases including Scopus, Web of Science, PubMed, IEEE Xplore, SpringerLink and ScienceDirect were searched using the keywords: “aquatic pollution,” “water quality prediction,” “artificial intelligence,” “machine learning,” “ANN,” “CNN,” “RNN,” “deep learning water monitoring,” and “IoT-based water sensors.”

The search covered publications from 2010 to 2024. Studies were included if they: (1) involved real or simulated aquatic ecosystems, (2) applied AI models for detection, prediction, or classification of pollutants, and (3) reported quantitative performance

Figure 1. Examples of aquatic pollution.

metrics (e.g., RMSE, accuracy, R^2). Studies that lacked methodological clarity, did not use AI, or were purely conceptual without data application were excluded. A total of 179 studies were initially identified, of which 96 met the inclusion criteria and were analyzed in this review.

Understanding aquatic pollution: Both point-source and non-point-source pollution are commonly used to describe the various causes of water contamination that originate in homes, businesses, and farms (Fig. 1). Point-source pollution occurs when a single, discrete source releases a large amount of pollutant into the water system. Currently, this form of pollution is regulated by national environmental management legislation. It is well known that non-point-source pollution originates from dispersed sources. Due to the lack of obvious points of entrance into the water system, it is challenging to control and manage. Authorities are concerned about this type of pollution, but there is no established regulatory framework in place to address it. Sediment sorption, desorption, volatilization, suspension, settling, and erosional transfer of contaminants into the aqueous phase are all governed by complicated abiotic processes. Additionally, biotransformation in certain species adds another layer of complexity, making it difficult to quantify and detect this pollution (Viman et al., 2010).

The ever-increasing volumes of industrial, agricultural, and household wastes being dumped into this vital resource are making it increasingly difficult to maintain clean, drinkable freshwater supplies (Ingrao et al., 2023). A growing number of toxicological studies are being conducted to identify compounds harmful to many aquatic organisms. One could wonder if there is not a more cost-effective way to foresee these negative consequences. As part of our ongoing effort to reduce pollution in aquatic environments, this study examines the ability of existing AI algorithms to quantify toxicological endpoints based on the biophysical properties of key chemicals in water contamination.

Sources and types of aquatic pollution: But how is contamination of aquatic ecosystems different from pollution of other kinds? Differentiating concentrations of hazardous substances in aquatic (freshwater and marine) ecosystems from solid waste and air pollution, among other types of pollution, is the dilution power of water, persistence, and potential transfer among the three main water media - soil, water, and air (Krithiga et al., 2022). One of the key benefits of water pollution in solving pollutants is its diluting capacity. The ability to rapidly dilute the water supply in a small basin is directly proportional to the retention period. In addition to chemical and physical measures to reduce contaminants in water, the aquatic system provides a unique long-term pathway for the substance's transmission. To start, many pesticides end up in the water because aquatic organisms can ingest them. Afolalu et al. (2022) found that powdered contaminants can bind to wave sediments, remaining there until fully released, thereby entering the aquatic food chain. An essential element that causes the environmental behavior of the complex and persistent aquatic pollutant is its connection with the air while in motion. This feature is in addition to phase shifts and internal organic and behavioral abnormalities. Therefore, the process of precipitating water droplets can play an important role in reducing air pollution. Both natural and human-made sources contribute to the exceptional attributes of aquatic pollution. Human-made sources encompass various activities, involving the use and release of water by industrial and municipal entities, the treatment and purification of water systems, the need for artificial moisture, and runoff and discharges into the atmosphere (Pecorari et al., 2020; Banoon et al., 2023).

Submerged habitats in the aquatic environment range from small wetlands to large rivers, lakes, reservoirs, estuaries, and oceans. They are fundamental to human existence, economic development, and prosperity in all of their physical forms. Aquatic ecosystems support consumption, recreation, economic activities, fisheries, navigation, and countless other human needs. A variety of human activities, both within and outside of the natural environment, can contaminate waterways. Due to the vast array of contaminants and the abundance of pollution sources, there is an infinite number of distinct types of pollution. The world's most prevalent sources of aquatic pollution are rising emissions of nutrients and pesticides, sediment load, untreated animal waste, oil and gasoline leaks from the industrial industry, mining waste, and waste from cleaning cars, ports, and ships (Tsoraeva et al., 2020; Kumar et al., 2021).

Impact on ecosystems and human health: Pollution substantially compromises the ecosystem; natural habitats and species could cross the border of extinction due to pollution, and greatly affects human health. The need to eliminate such newly discovered toxins has been rising in this context (Rathi et al., 2021; Shahid et al., 2021; Morin-Crini et al., 2022). Water quality has declined, and ecological balance has been disrupted due to the discharge of numerous organic pollutants into natural waters, a direct consequence of our increasingly urbanized and industrialized societies' overexploitation of natural resources, waste production, and toxic substance discharges. The major cities of these nations are major contributors to pollution and waste, as they are also the world's most important cultural, scientific, and economic hubs. Micropollutants are compounds that pollute water in minute amounts but can still cause serious problems if present in large enough quantities (Rojas and Horcajada, 2020; Bayabil et al., 2022; Mukhopadhyay et al., 2022).

Ecosystems are affected by the following: (a) Pollutants, including pesticides, heavy metals, and industrial chemicals, can be harmful to aquatic life and cause the decline or extinction of particularly vulnerable species. Pollutants can also damage or eliminate vital ecosystems for biodiversity, including mangroves, wetlands, and coral reefs; (b) Aquatic pollution, through bioaccumulation and biomagnification, also disrupts the food chain. When contaminants accumulate in the systems of living things, especially those at the top of the food chain, it is referred to as bioaccumulation. This can cause harmful side effects and infertility. When contaminants move up the food chain, they become more concentrated and have a greater impact on the health of predators, such as birds and other animals, described as biomagnification; (c) Dead zones, in which most aquatic life cannot survive, can be created when algae die and decompose, which absorbs oxygen and creates hypoxic (low-oxygen) conditions. Algal blooms can be caused by eutrophication, which results from excess nutrients, particularly nitrogen and phosphorus, from agricultural runoff; (d) Acid rain and industrial discharges can change the pH of water, and toxic compounds like polychlorinated biphenyls (PCBs) and polycyclic aromatic hydrocarbons (PAHs) can change this chemistry. These can linger in the environment and cause long-term damage to ecosystems.

Furthermore, human health is significantly endangered by aquatic pollution. Lead, arsenic, and mercury are pollutants that can contaminate water sources. These contaminants can cause cancer, neurological abnormalities, and developmental problems in children, among other chronic health issues. Agricultural runoff and sewage pose a significant threat to water quality, leading to waterborne diseases such as giardiasis, dysentery, and cholera. Food poisoning, brain damage, and chronic disorders are among the major health hazards that can be posed by consuming seafood that is contaminated with heavy metals, algal bloom toxins, or industrial pollutants. A decline in quality of life and an increase in mental health issues might result from water body degradation.

Artificial intelligence in environmental science: The original goal of AI was to create machines with the same level of intelligence and learning capacity as living things. The idea encompasses a wide range of applications, including traditional logic, reasoning, planning, inference systems, and problem solving. Two primary branches of artificial intelligence are known as "symbolic AI" and "connectionist AI." 'Symbolic AI,' also known as 'Good Old-Fashioned Artificial Intelligence' (GOFAI), aims to use formal manipulation rules to understand and represent knowledge, reasoning specifically about the semantics of concepts and computations, with declarative language playing a crucial role. Fuzzy set theory has recently been included in the symbolic toolbox for engineering and scientific problem solving (Maruyama, 2021; Hitzler et al., 2022; Zhang, 2022; Zanni-Merk and Jeannin-Girardon, 2022; Zhang et al., 2023) because of its conceptual power and, to a certain degree, its capacity to handle uncertainty with many interfaces to other mathematical theories, like probability, rough sets, and possibility theory.

Anaerobic digestion, wastewater treatment, and natural supplements are three areas where environmental chemists have recently focused on intelligent computational methods based on artificial intelligence approaches, especially support vector machines (SVMs) and ANNs. Modern ecologists rely heavily on this technique when investigating marine coatings that prevent fouling, the quality of sediment and groundwater, and similar subjects.

Factors contributing to AI's widespread appeal include its data-driven nature and its capacity to model extremely non-linear phenomena; the ease with which it can handle complex matrices without requiring extensive pre-treatment; and the chance to incorporate the representation of intricate conceptual structures—present in both natural and artificial systems—into models without imposing model structures based on physical or a priori understanding of the system (Ye et al., 2020; Hmoud Al-Adhaileh and Waselallah Alsaade, 2021; He et al., 2021; Masood and Ahmad, 2021; Konya and Nematzadeh, 2024).

Applications of AI in environmental monitoring: An important aspect of water quality management in future intelligent cities, this system can strengthen the current "gold" standard manual techniques for monitoring water crises in smart cities, reduce the number of false alarms and warnings, and achieve more accurate and dependable automatic control in water treatment facilities (Lowe et al., 2022; Waleed Mustafa, 2022). The water quality sector has leveraged artificial intelligence, utilizing cutting-edge methods, novel data types, and decision-support tools built on AI agents, fuzzy logic, and neural networks. To monitor various forms of water contamination in real-time, on-site, and for early identification. Recently, Li et al. (2023) proposed a machine-learning-based soft-sensor framework for innovative water-quality management in rural sewage treatment facilities. In their system, soft monitoring models infer difficult-to-measure parameters (e.g., COD, NH_4^+-N, NO_3^--N, PO_4^{3-}-P) from easily measured signals. They can detect unexpected changes in water quality in real time, providing a practical example of AI-enabled soft monitoring in wastewater systems (Li et al., 2023a). According to Dai and Wang (2022), Wang (2024), and Li et al. (2024a), it can also create and verify models for a wide range of environmental variables, nitrate, nitrite, ammonia, temperature, dissolved oxygen consumption, color, odors, biochemical oxygen demand, heavy metals, organic contaminants, and total sediment flux are all factors to consider. Several

AI systems exhibit numerous beneficial traits. The capacity to handle imperfect, imprecise, and uncertain data, together with fault tolerance and real-time performance, is among these. The aforementioned features enable real-time decision-making by combining previously unutilized essential information and significantly reducing the time to respond to unforeseen incidents (Denoeux et al., 2020; Abbas et al., 2024).

When ANNs and other AI predictive models were initially employed to evaluate the accuracy of air pollution data around the turn of the century, research into the application of AI algorithms to data quality in environmental informatics began. Applying AI principles and techniques to address the unique challenges of environmental monitoring is one way to explore its potential. Fast data processing, adaptable and nonlinear processes, and predictive models are crucial for AI-based environmental monitoring (Ye et al., 2020; Reddy et al., 2020; Hassan et al., 2023).

Traditional methods vs. AI in pollution prediction: Two approaches have been proposed in the literature to address issues with pollution prediction: traditional methods and AI-based methods. For specific systems and data vectors with respect to time, location, and stated time, conventional approaches might be seen as an adaptive bottleneck. Traditional approaches rely on a mathematical correlation between input and output data, but they also have a wealth of historical data and methodologies at their disposal. To construct this relationship and estimate an unknown or uncertain data point, two types of models are typically employed. Due to the non-linear and complex nature of water quality problems, previous methods have not been very effective because there is a limited mathematical representation of the relationships between input and output parameters. Complex and non-linear natural structures cannot be adequately represented using traditional approaches. Limited input and output parameter strategies based on these structures are used to anticipate and control water quality in complex, nonlinear engineering problems in the field of water resources science.

Both natural aquatic systems and the prediction of water contamination have made extensive use of important methodologies. We can now track changes in water quantity and quality using newly developed technology. Some of these technologies may be readily accessible at the measuring site. On the other hand, some can be moved to different parts of the aquatic ecosystem. Conventional approaches are used to monitor these systems, despite their technological, geographical, and temporal properties. To minimize the impacts of pollution on society, the economy, and ecosystems, it is crucial to know the quality of water at specific points in time, where the findings were obtained, and what types of pollution the water is likely to contain in the future. Using water-quality monitoring data, numerous algorithms have been developed to forecast pollutant concentrations at various points in aquatic systems.

AI is a powerful analytical tool with many potential applications, including the development of systems to evaluate environmental quality, identify and characterize pollution sources and pollutants, manage ecological and environmental concerns, preserve aquatic ecosystems, and implement intelligent early warning systems for pollutants. Research areas related to water pollution could greatly benefit from AI's self-learning and self-adaptive capabilities, which have the potential to address previously unsolved challenges. When there is insufficient evidence or mistakes occur randomly, it can still handle it. The building of an environmental quality assessment system, the establishment of a model for the analysis of sources and pollutants, the creation of a model for the optimization of ecological systems, a model for environmental economics, a model for the protection of water resources, a model for the carrying capacity of the environment, and other related and covered topics span a wide range of disciplines and fields of study. Many people refer to the AI technology that relies on this or applied research across disciplines as a scientific policy model or model-based reasoning. Whether there is a lack of solid proof or random errors, AI can handle them all and find solutions to challenges that have never been handled before. When it comes to reducing pollution in aquatic environments, it really

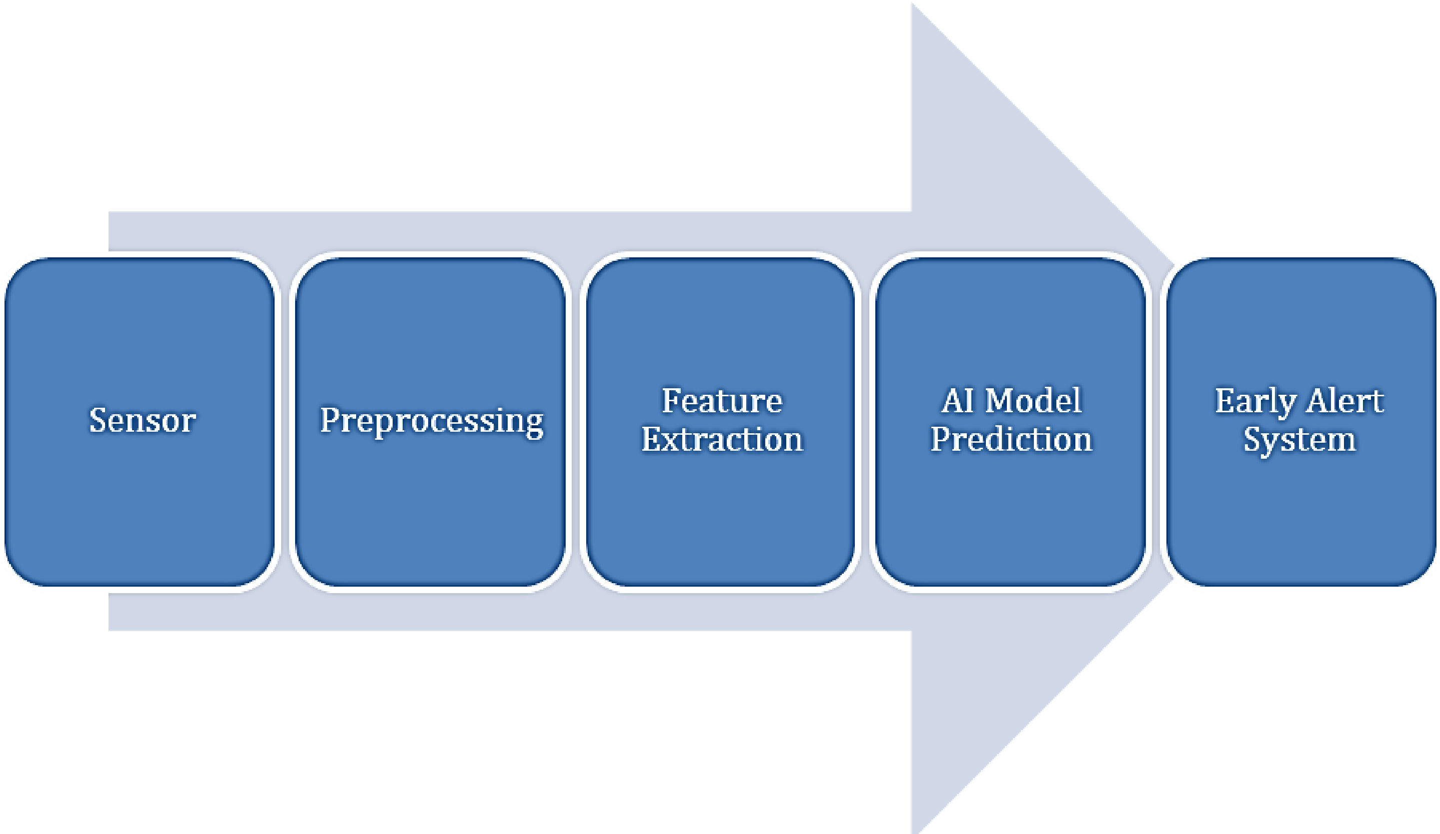

Figure 2. Workflow of AI-based aquatic pollution monitoring.

shines. The anticipated benefits of AI in toxicology and the construction of water body models are most apparent in these areas.

AI Techniques for predicting aquatic pollution: The two main concepts encompassed by the AI umbrella are deep learning and machine learning. Part of machine learning (ML) is optimization methods like genetic algorithms and simulated annealing, as well as supervised learning techniques like logistic regression, decision trees, and support vector machines, and unsupervised learning techniques like K-means clustering and hierarchical clustering. There are three main types of Deep Learning (DL): ANNs, CNNs, and RNNs. Beyond environmental applications, machine learning–based forecasting models have also demonstrated strong performance in other dynamic systems, such as short-term photovoltaic power prediction, where regression-based algorithms and hybrid ML frameworks significantly improve forecast accuracy (e.g., Machine Learning Approaches for Short-Term Photovoltaic Power Forecasting) (Radhi et al., 2024).

The general workflow of AI-based aquatic pollution monitoring involves several sequential stages, from data acquisition and preprocessing to model-based prediction and decision response systems (Fig. 2). Real-time aquatic data undergo signal correction and feature extraction, followed by AI-based predictive modeling (e.g., ANN, CNN, and RNN), and trigger environmental alert or response actions when pollution risk is detected. This workflow establishes the data-processing foundation needed before applying specific AI algorithms such as ANN, CNN, and RNN, which are discussed in the following subsections.

To better understand the functional capabilities of different AI models in predicting aquatic pollution, Table 1 provides a comparative summary of commonly used architectures, their typical data inputs, strengths, and limitations. As shown in Table 1, different AI models offer complementary benefits depending on the type of data and pollution

Table 1. AI models used in aquatic pollution prediction.

AI Model	Target Pollutant/Parameter	Data Source	Strengths	Limitations	Key References
ANN	Nutrients, algal bloom occurrence	Time-series WQ data	Learns nonlinear patterns	Weak temporal memory	Park et al., 2021
CNN	Oil spills, microplastics, turbidity mapping	Satellite/underwater images	Strong spatial detection	Requires large labeled datasets	Falqueto et al., 2019
RNN/LSTM	Heavy metals, DO, pH trends	Sensor time-series streams	Handles time-dependent patterns	Higher training cost	Pyo et al., 2023
Hybrid ANN-RBF	Pesticides, salinity variation	Spatial water sampling datasets	High spatial accuracy	Lower generalizability	Abbas et al., 2021

Table 2. Summarizes the complementary roles of ANN, CNN, and RNN models in aquatic pollution prediction, showing how each model aligns

Model Type	Primary Function	Data Type Used	Typical Applications	Strengths	Limitations
ANN (Artificial Neural Network)	Learns non-linear relationships among water quality variables	Numerical environmental measurements (e.g., pH, DO, nutrients, temperature)	Predicting pollution levels, water quality index estimation	Flexible, can model complex environmental systems	Does not handle time dependence well without extensions
CNN (Convolutional Neural Network)	Detects spatial patterns in images	Satellite images, drone images, underwater photographs	Oil spill detection, microplastic identification, algal bloom region mapping	Excellent at image pattern recognition	Requires large labeled image datasets
RNN / LSTM (Recurrent Neural Network)	Captures temporal patterns over time	Time-series datasets from IoT and in-situ sensors	Forecasting daily/seasonal changes in pollutants	Best for time-dependent prediction	Higher computational cost and more complex tuning

characteristics. While CNNs are best suited for spatial pattern detection in visual datasets, RNN-based models outperform other approaches for forecasting pollution trends over time. Hybrid ANN configurations further enhance spatial precision but may require model-specific calibration for each aquatic environment. As shown in Table 2, each model family performs optimally under different conditions: ANN models are effective for nonlinear parameter prediction, CNNs excel at spatial pollution identification from imagery, and RNN-based models outperform others for forecasting temporal dynamics.

Supervised learning models: To understand how aquatic organisms respond to various stimuli, researchers often employ logistic models. These models include driving fixed effect components and categorical variables. Genotoxicity testing against varying temperatures, chemical concentrations, and pH levels, as well as data on acute and chronic survival assessments, are a few examples. Multiple logistic regression models can be employed to forecast the presence or absence of a species based on environmental driver factors, natural capital abundance, Environmental Quality Standards—Biological Methods (EQS-T), and temperature, nitrates, phosphates, copper, chromium, and chemical oxygen demand, among others.

Logistic regression is a powerful machine learning model that can be used to predict the likelihood of relevant outcomes or components. Topics include instances of pollution, chemical species present or absent, and the sources of emissions or discharges to the receiving environment, which may consist of surface waters, ponds, lagoons, and seas. The longevity of wastewater treatment facilities is also monitored using multivariate logistic models. The model is useful for directing environmental compliance strategies by measuring the extent to which pollutants are removed from the effluent discharges of these treatment facilities. It can also identify the reasons for environmental nonconformities, such as contaminants with a higher priority for persistence or hazard.

Unsupervised learning models: When output data is unavailable, unsupervised learning is performed solely on the input data. Data labeling is not necessary. The following methods are part of unsupervised learning: clustering algorithms, dimension reduction, and anomaly detection. Hierarchical clustering and K-Means clustering are two examples of clustering algorithms. Using these approaches, we may create a hierarchical dendrogram of genes with similar expression levels and partition the variance decomposition into a directed k. Based on the closeness of features, K-means clustering divides data into k clusters. You can use it to find places where the pollution is about the same. By combining or dividing preexisting clusters, hierarchical clustering constructs a cluster tree that graphically represents data relationships. Anomaly detection and dimensionality reduction methods cluster data based on density, which helps identify pollution hotspots and anomalies.

One method for reducing the dimensionality of a dataset while preserving most of its variation is Principal Component Analysis (PCA). Using it, high-dimensional pollution data can be better shown and understood. By using this method, massive amounts of biological data can have their functional information compressed into components that can be ranked according to their explanatory power. Then, these parts can find clusters in the data that have a common function. When clustering high-dimensional data, such as water quality measures, dimensionality reduction techniques like t-Distributed Stochastic Neighbor Embedding (t-SNE) can be a lifesaver. One component of anomaly detection is the use of trainable neural networks, called autoencoders, which can reconstruct input data. Instances of exceptional contamination can be identified when the reconstruction error is large, a phenomenon known as anomalies.

Artificial neural network (ANN): ANNs are widely used to model non-linear relationships in water-quality datasets, including dissolved oxygen, pH, turbidity, and nutrient concentrations. They are particularly effective when pollution levels are influenced by multiple interacting environmental factors. However, traditional ANN models do not

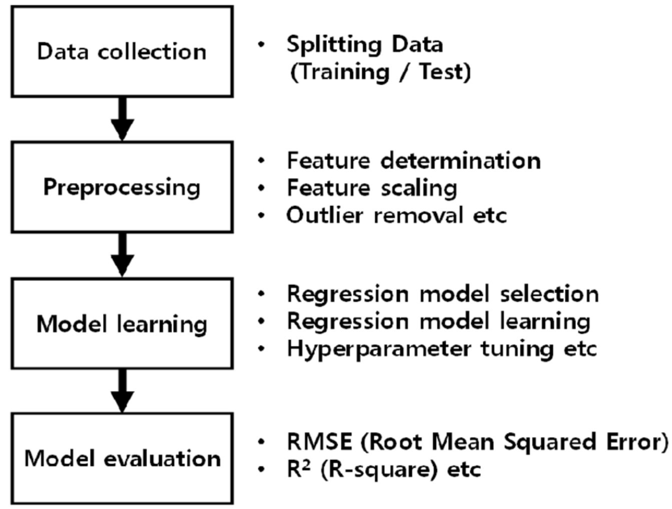

Figure 3. Machine learning regression analysis flow chart.

retain temporal memory, making them less suitable for predicting seasonal or daily pollutant variation unless combined with recurrent memory structures (Maier and Dandy, 2000; Park et al., 2021; Yu et al., 2021). Huo et al. (2014) provided one of the earliest demonstrations of ANN effectiveness by predicting lake eutrophication with high accuracy using nutrient, chlorophyll, and hydrological inputs.

Convolutional neural network: CNNs are particularly effective for detecting and characterizing spatial patterns in aquatic environments, especially when pollution is observed through imagery. As illustrated in Figure 3, the regression-based machine-learning workflow underlying CNN pollution-detection models follows a structured pipeline, beginning with feature extraction and flowing into deep-layer prediction stages. For example, early work by Fiscella et al. (2000) demonstrated that SAR-image-based CNN models can successfully identify marine oil spills using texture and scattering signatures. CNNs are commonly applied to satellite images, drone-based monitoring, sonar scans, and underwater photography to identify oil spills, algal bloom spread, turbidity zones, and microplastic accumulation. Additionally, Musić et al. (2020) demonstrated that deep neural networks can detect underwater litter with high precision, confirming the utility of CNNs for benthic pollution assessment. Recent developments also include deep CNN frameworks capable of hyperspectral HAB detection, such as the model proposed by Garza and Wessels (2023), which efficiently combines remote sensing data with DCNN classification. Their layered convolutional operations allow the model to automatically extract visual features, such as color gradients, texture changes, and surface patterns associated with pollution, without requiring manual parameter tuning. However, CNN performance typically depends on the availability of large, well-labeled image datasets, and model accuracy may decrease when water conditions vary significantly across regions or seasons (Falqueto et al., 2019; Xu et al., 2022; Li et al., 2024b). This challenge was addressed by Yang et al. (2022), who integrated CNNs with spatio-temporal data fusion to improve chlorophyll-a inversion accuracy in dynamic coastal systems.

Recurrent neural network: RNNs, including Long Short-Term Memory (LSTM) architectures, are designed to model temporal dependencies in time-series datasets, making them highly suitable for forecasting trends in water pollution indicators. These models process sequential sensor data, including dissolved oxygen, temperature, nutrient levels, and chlorophyll concentration, to predict short-term and seasonal changes in pollution levels. Jiang et al. (2021) further showed that LSTM–CNN data fusion models outperform single-source learning when predicting sewer-network water quality using multisensor and meteorological datasets. By retaining information from previous time steps, RNN and LSTM models outperform traditional ANN models when pollutant behavior varies over time or is influenced by climatic and hydrological cycles. However, these models require careful tuning and substantial computational resources, and their performance may decline when sensor data streams are noisy or incomplete (Pyo et al., 2023; Saha et al., 2024; Li et al., 2023b; Li et al., 2025).

Case studies and applications: Trace metals are released, transported through the environment, and accumulated in various microorganisms in a world shaped by construction activities. Their amazing properties make hydroponics one of the most effective ways to improve microorganism growth by eliminating extraneous elements that can impede metal bioavailability. Considered as strong markers of metal bioavailability to plants, the ecological system can be characterized as "the chemistry of metal speciation and the phenomenon of their interaction with living organisms". Estimating the toxicity and activity of metals across different environmental matrices is straightforward by quantifying photosynthetic pigments in microalgae cells exposed to metals.

Prediction of the chemical contaminants: First, the current modeling approach relies on chemical analysis to identify the most harmful pollutants. Second, it takes into account known toxic dose-effect relationships. Third, it models an individual or immediate prognosis based on the correlation between biological processes and toxicant concentrations. The interdependencies of harmful doses across body levels and varying degrees of environmental subsystem organization are explained by models of system-cascading prognosis. Whatever the specific model used, every method has limitations that artificial intelligence algorithms' automated learning features help address.

There is great development in mathematical models for estimating the environmental consequences of contaminants in aquatic environments. These models, to varying degrees, mirror the structure and operation of many important processes of living entities or sections of individual organisms, at different levels of exposure to harmful chemicals. The link between the concentration of harmful substances in the medium and the physiological properties of the living organism is primarily reflected in the mathematical relationship that governs these effects. Using these models, we may better assess the dangers posed by chemical pollutants and find ways to lessen their impact on living things, their functions, the structures and linkages in our planet's systems, and the pathogenic processes that affect them. Incorporating AI into environmental monitoring, evaluation, and forecasting has opened up a world of possibilities.

Monitoring microplastics: Recent advances in artificial intelligence have significantly improved automated monitoring and classification of microplastics in aquatic environments. Ugwu et al. (2021) demonstrated that deep convolutional neural networks trained on large image datasets can accurately classify different microplastic shapes and textures, achieving high detection performance with minimal manual intervention. Similarly, Lorenzo-Navarro et al. (2021) developed a deep-learning–based vision system trained on more than 20,000 microplastic images and showed that automated counting and classification can match the accuracy of traditional manual identification methods while drastically reducing processing time. Additional improvements have been reported by Ren et al. (2023), who integrated a CNN with micro-Raman spectroscopy for precise polymer-type identification, achieving classification accuracies above 95%. Although fully automated microplastic sensors are not yet available, AI-driven image analysis and spectral learning techniques now provide a robust foundation for rapid, reproducible, and scalable microplastic detection in environmental monitoring programs.

Early warning systems: Early warning (EW) is the practice of monitoring and issuing warnings to society before a notable change in air or water quality. The Aquatic Environment Protection Agency (AEPA, Environmental Protection Agency, Tunis Bay) claims that this is a useful instrument for reducing major accident hazards and preserving ecosystem balance. Early warning helps ensure the safety of drinking water services. According to research by the French organization F-POP and the European organization DRIEEAP, as well as the Future Oriented Monitoring of Water Health in Forests (FORMitile), reported by the European Union, it reduces environmental damage, authority, and societal impacts.

Machine learning, artificial intelligence, and inference enable one to store, clean, and handle data. Better environmental management and impact assessment follow from AI systems mimicking cognitive processes, including learning, reasoning, motor control, and adaptable vision to detect human speech and grasp natural language, as well as visual perception and decision-making, thereby enabling better environmental management and impact assessment. AI has been used to support early identification, diagnosis, and management of agricultural diseases. Furthermore, several models are combined to improve accuracy, as environmental heterogeneity and the uncertainty of the required judgments affect them.

Real-world examples of using AI in aquatic pollution prediction: There are numerous real-world examples of how artificial intelligence has been useful for predicting, monitoring, and managing aquatic pollution. Deep-learning–based automated biodiversity assessment systems have recently been deployed on the Tigris River, where CNN models accurately identify fish species and support ecological monitoring programs. This application demonstrates how AI can enhance large-scale assessment of aquatic ecosystems in rivers of significant ecological and economic importance (Salman et al., 2025). Here are a few noteworthy instances: (1) the Monterey Bay Aquarium Research Institute (MBARI) in California employs artificial intelligence models to foretell when harmful algal blooms (HABs) will occur in Monterey Bay. HABs can be predicted using machine learning algorithms that sift through vast amounts of data on factors such as water temperature, nutrient levels, and other contextual variables. Therefore, by using these AI tools, we can safeguard marine life and public health by providing early warnings, enabling timely action, and facilitating mitigation. (2) The European Space Agency's (ESA) Sentinel-1 satellite mission uses artificial intelligence to monitor and record oil spills in the Mediterranean Sea. To detect and monitor the spread of oil spills, Convolutional Neural Networks (CNNs) analyze satellite imagery. The ability to quickly detect and monitor events enables faster responses and cleanup, which in turn minimizes environmental harm. (3) Predicting water quality: The Public Utilities Board (PUB) of Singapore has introduced an intelligent water management system that makes use of AI to predict the quality of water in reservoirs and rivers. Water quality sensors collect time-series data, which Recurrent Neural Networks (RNNs) use to forecast future conditions. The proactive management of water resources, including the provision of safe drinking water and the mitigation of pollution, is enabled by accurate forecasts. (4) Ocean cleanup's plastic pollution tracking: Artificial intelligence is employed to monitor and foretell the whereabouts of oceanic plastic pollution. To track and forecast plastic waste migration, machine learning models analyze data from satellite imagery, ocean currents, and wind patterns. To remove plastic from the oceans more efficiently and effectively, cleanup activities are guided by predictions. (5) Academics at the University of Reading are using AI to track levels of heavy metals in the River Thames. Algorithms trained on data collected by water-quality sensors can identify and forecast concentrations of heavy metals, such as mercury and lead. Protecting aquatic life and public health requires continuous monitoring and early identification to take corrective actions. (6) AI for Lake eutrophication prediction: Scientists employ AI to foretell when Lake Erie will experience eutrophication due to an overabundance of nutrients in the water. To predict when eutrophication will occur, for their training, LSTM networks look at nutrient levels, weather trends, and land use records from the past. Predictions are useful for taking action to lessen nutrient runoff, which in turn lessens the likelihood of toxic algal blooms and dead zones. (7) Detection of water pollution in real time: The Ganges River is being monitored by devices powered by artificial intelligence in India. Sewage and industrial effluents are detected in real-time by Internet of Things (IoT) sensors and artificial intelligence algorithms. Water quality and health risks can be improved through rapid response and repair enabled by immediate detection. These practical examples highlight the substantial impact of AI on water pollution prediction, monitoring, and management. Protecting and sustaining aquatic ecosystems can be accomplished through AI use by researchers and policymakers, enabling better predictions, faster interventions, and more effective management of water resources.

Challenges and limitations of AI in aquatic pollution: The potential of AI technologies to monitor and manage aquatic pollution is enormous, but several obstacles must be overcome before they can be fully realized. If AI is to be useful in monitoring and managing aquatic pollution, these limitations and problems must be addressed. To overcome these challenges and ensure that AI helps marine ecosystems stay healthy, experts in AI and environmental science (ES), legislators, and business leaders must work together. To improve the efficacy and dependability of AI solutions in this vital domain, challenges pertaining to data quality, model interpretability, computational resources, system integration, environmental variability, ethical issues, skill shortages, sustainability, and so on must be addressed.

Data quality and availability: Numerous overlapping prediction variables are common in data investigations. Datasets including incomplete variables, such as shifts, encroachment on testing and training, and related incomplete variables and data timestamps, may be amenable to resolution using these data processing techniques. By implementing these data processing approaches, the quality of the structured dataset will improve, enabling the AI-P model to generate actionable predictions reliably. Data observation errors, sensors unable to measure a particular parameter, sensor mismatches or failures, and other data-related issues, such as data ingestion or additional parsing faults, are the main causes of missing data in the dataset. Applying data processing techniques like data cleaning, data imputation, and data correction—in conjunction with feature extraction transformation—to handle data queries and replace missing records—while also facilitating water data flow patterns—can help minimize the effects of these data errors. It is common practice to collect empirical data from multiple sources to conduct concurrent tests and validate the model before using it in water quality models. It is common for time series data to contain errors, missing values, or precautionary values. By creating the schema function of the WaterML2 extension, which provides metadata for standard descriptions of water data, these data concerns can be addressed or avoided.

The accuracy and completeness of the data used to train AI-P models are crucial to their success. Here are the standards that water-quality data used by AI-P models must meet. Data quality, including completeness and error-free information, directly impacts the precision of AI-P model-based predictive modeling.

Interpretability and explainability: The interpretability community has been seeing a surge in interest in recent years, elevating the topic to the forefront of AI discussions. The process of describing AI models is typically what people mean when they talk about interpretability, which is a relative term. Both explainability and interpretability are closely related concepts, yet there are many ambiguities between the two. Aspects of the model that are addressed by explainability include honesty, clear and succinct explanations, and impartial data processing. Having ideas supported by specific definitions is what we mean by interpretability. Many fields have begun to recognize the growing importance of explainable AI, prompting academics to seek out new ways to answer questions about AI models. Users are given an interpretability degree in the typical reports of the Aquatic Toxicity Database, which is a mathematical rule-based model that falls into the category of transparent AI methods. Many artificial intelligence models, particularly deep learning algorithms, are often called "black boxes" because of their opacity and complexity. Because of this opacity, stakeholders may find it hard to believe and comprehend the model's forecasts. To acquire insights and make informed judgments, it is essential to develop methods for analyzing and explaining AI model outputs. But it's not easy to have explainability without sacrificing model accuracy.

Future directions and research opportunities: With the completion of our thorough review, the following section offers researchers a selection of noteworthy, up-to-date predictive analyses across four main areas of study: managing pollution, reducing waste, predicting seawater quality, and dealing with wastewater and pollutants. Each section includes a summary of the following: questions, datasets, domain consideration, target pollutants, comments, and possible additional contents for future research. To broaden the scope of the study, we would really appreciate any future questions that point researchers in the right direction and identify research gaps within these four areas.

The use of AI and machine learning algorithms to environmental engineering challenges is becoming increasingly popular. From accurately defining and managing sewage systems to predicting the quality of surface water and the dispersion of pollutants in rivers and oceans, these issues span a broad spectrum. The latter, however, usually takes a back seat and deals with topics such as diving applications and AI definitions, inventing various constraints, the most common kinds of pollution, and possible difficulties and considerations, in that order. Applications related to the environment in the field have thus been scattered. With that in mind, the primary goals of this review are (1) to provide a thorough and up-to-date overview of the current state of research, data, and parameters concerning aquatic pollution and the potential outcomes of inaction, and (2) to pique the interest of researchers in the area, pinpoint knowledge gaps, and, most importantly, familiarize readers with cutting-edge modeling techniques to motivate the development and implementation of waste and pollution management strategies based on artificial intelligence.

Integration with IoT and sensor networks: More and more, AI is being linked to the Internet of Things (IoT) and sensor networks, enabling the easy application of AI's intellectual interface to generate predictive data across many fields. Because of the high complexity of the water domain, AI has developed analytical and expert methods for handling large-scale applications and a wide range of information. Nevertheless, when integrated with data producers on a massive scale, it continues to pose difficulties. This restriction on the expansion and integration capacity of higher water IoT technology interfaces is mostly due to restrictions in objective intelligence. Large data sets typically necessitate powerful computers and expertise with AI software. On the flip side, there can be no timing setbacks when accounting for the vast expanse of water, especially in non-conservative dynamic seas, and for fluctuations in both space and time. As a result, this data leakage limits foreign analytic tasks to the essential goals of reactive predictive structures and environments that are frequently used. Specifically, sensors and smart meters offer substantial reactive data that might be used to train the AI system.

Advancements in AI algorithms: Advances in AI algorithms are transforming the monitoring and management of aquatic pollution. These developments provide strong resources for the preservation of aquatic ecosystems by making predictions more accurate, processing data in real time, making models more interpretable and scalable, integrating with other technologies, creating adaptive, robust models, encouraging ethical AI practices, and fostering collaborative research. To properly leverage AI's capabilities to tackle the complex problems of water contamination, ongoing innovation and collaboration across disciplines are crucial.

The ensemble guessing frameworks are built utilizing a combination of different AI techniques to enhance the models' predictability and resilience. There has been a plethora of hybrid AI models developed that combine two or more AI algorithms to produce superior prediction results. We improved or integrated the BayesOpt process with the GA process to make it even better. According to Kushwaha et al. (2023), the GA-based microalgae intervention was enhanced to improve predictions using a fuzzy-augmented microalgae wastewater quality model.

Challenges and current limitations: Although AI-based models have shown strong potential in predicting aquatic pollution, several challenges continue to limit their effectiveness in real-world applications. One major limitation is the availability and quality of the data. Reliable AI prediction requires continuous, high-resolution datasets; however, many monitoring stations in freshwater and marine environments provide irregular, incomplete, or noisy measurements. Missing sensor values, seasonal disruptions, and variations in sampling methods can significantly reduce model accuracy. A second challenge involves model generalizability. Models trained in one aquatic ecosystem (e.g., lakes) often perform poorly when transferred to different systems (e.g., rivers or estuaries) due to differences in hydrodynamics, pollution sources, and climatic factors. This limits the development of universal prediction frameworks, requiring local calibration for each region.

Furthermore, deep learning models such as CNNs and RNN/LSTM networks often function as black-box systems, offering limited interpretability regarding which environmental variables influence predictions and why. This lack of transparency makes it difficult for environmental managers to trust and apply model outputs in decision-making processes, particularly when policy enforcement is involved. Finally, real-time deployment remains a challenge, especially in resource-limited settings. Integrating AI systems with IoT sensor networks requires stable connectivity, computational power, and maintenance capacity, which may not be consistently available in many developing regions. Addressing these limitations will be crucial to transitioning AI models from research settings into operational water-quality management systems.

Conclusions

This review highlights the growing role of artificial intelligence in modeling, detecting, and forecasting the dynamics of aquatic pollution. The comparative evaluation of ANN, CNN, and RNN/LSTM architectures demonstrates that each model family offers distinct advantages, depending on the type and structure of the environmental data. ANNs are effective at capturing complex, nonlinear relationships among water quality variables, while CNNs excel at identifying spatial pollution patterns from satellite and underwater imagery. RNN and LSTM architectures provide superior performance for forecasting temporal changes in pollutant levels due to their ability to preserve sequential information. Together, these models form a complementary toolkit for advancing data-driven water-quality assessment and early warning systems. Despite these advances, several research gaps remain. Current AI models often rely on limited or inconsistent monitoring data, reducing their generalizability across different aquatic environments. Model outputs also tend to function as black-box decisions, limiting interpretability and hindering adoption by environmental regulators. Furthermore, real-time integration with sensor networks remains technically and financially challenging in many regions, particularly in developing countries. Future research should focus on developing hybrid modeling frameworks that integrate the strengths of ANN, CNN, and RNN models to capture pollution's spatial and temporal dynamics simultaneously. Advancements in explainable AI (XAI) are also needed to improve transparency and increase trust among environmental decision-makers. Additionally, expanding IoT-enabled monitoring networks and establishing shared, open-access water-quality datasets would enhance model reliability and enable more robust cross-regional validation. Addressing these challenges will accelerate the transition of AI-based aquatic pollution prediction from experimental research toward widespread operational implementation, supporting more efficient water resource management and ecological protection.

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