Artificial Intelligence Applications in Water Treatment Systems: A Mini Review

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Abstract: *Growing demands from rising populations, changes in climate, and new types of pollutants have revealed that traditional water treatment systems have limitations. AI has emerged as a valuable option, providing businesses with real-time ways to predict, monitor, and improve their operations. This review focuses on new developments in AI technology for treating water, including the purification of drinking water, handling wastewater, and desalination. This review details how machine learning, deep learning, and fuzzy logic work, how well they perform, their application problems, and their potential for integration. The analysis also examines the performance of various AI models in several fields, looks at their strengths when used, and points out where research is still needed. This paper combines research from various sources to show how AI is transforming water treatment today. The evidence highlights that AI can help make processes faster, consume fewer resources, and guide decision-making from data in water management.*

Keywords: *Artificial intelligence; water treatment; machine learning; process optimization; predictive modelling*

1．INTRODUCTION

Safe drinking water, care for nature, and global development depend on water treatment. However, more people are moving to cities, and growing industrialization and climate change have made water pollution a bigger problem worldwide. Using coagulation, sedimentation, filtration, and disinfection as methods, water treatment encounters difficulties such as inefficient operation, incomplete removal of modern pollutants, and significant energy use [1], [2], [42], [43] [44], [45]... Such problems require new treatment methods that are smarter, more flexible, and more efficient for tackling water pollution in urban and rural areas, especially places facing shortages and water pollution.

In the past decade, AI has become a significant game-changer for water treatment processes. Using machine learning, deep learning, and fuzzy logic helps make better decisions from data, enhance the way processes work, and track systems in real-time [3]. Using machine learning algorithms, big data can be used to forecast pollutant levels, manage chemical doses, and detect flaws, all of which make the system work more efficiently and at less cost [4]. Since AI handles unpredictable and fast-changing data well, it helps optimize numerous processes in water treatment and supports maintenance activities that ensure equipment wears less in a shorter time span [5]. This literature review looks at the most recent improvements in applying AI to manage drinking water, process wastewater safely, and desalinate seawater. The aim is to illustrate how AI is practical, point out present-day challenges it faces, and offer suggestions for future functional studies. Currently, the use of AI supports the creation of water treatment processes that are sustainable on a global scale and respond to changes in rules and nature [6].

2．OVERVIEW OF ARTIFICIAL INTELLIGENCE TECHNIQUES

Artificial intelligence (AI) refers to several techniques for programming machines that resemble human thinking to address different problems and make decisions. AI has become important in water treatment since it helps handle complicated data and improves how the systems operate. Machine learning (ML) is a key AI technique and is mainly divided into supervised, unsupervised, and reinforcement learning. In supervised learning, data is used as a starting point to instruct models for prediction or classification, and unsupervised learning looks for meaningful patterns in data that have not been put into labels yet. Agents in reinforcement learning figure out the best actions to get more rewards in the future and adjust to changes in the environment by making trial-and-error decisions [7], [8].

Deep learning (DL) depends on complex neural networks to understand the relationships between different types of data. CNNs perform well with spatial data that appear in image-based water quality monitoring, whereas RNNs handle different types of data that come as time-series readings [9].

The attributes of these architectures make it possible for deep learning models to do better than traditional ML approaches in complicated water treatment situations by automatically finding noticeable features in raw data.

In addition, expert systems imitate how people make decisions by using rules that support fault diagnosis and treatment planning in plant operations [10], [46], [47]. With unclear and uncertain information, fuzzy logic handles this by working with truth values, not just yes or no choices; this allows water treatment plants to keep control of turbulent conditions [11],[12] [48], [49]. Like evolution in nature, genetic algorithms solve challenging issues like adjusting system settings or scheduling by often picking and merging the best options [13].

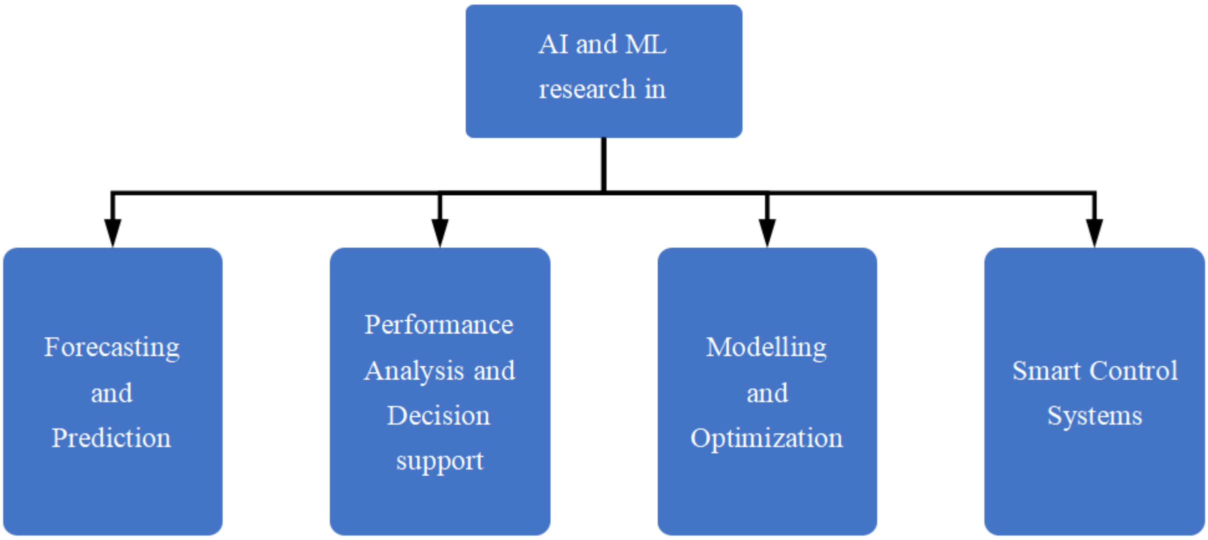

Figure 1: Areas of AI and ML research

Many AI frameworks and programs, including TensorFlow, PyTorch, and Scikit-learn, make it easier to use these techniques. They allow engineers and researchers to build ML and DL models using a range of user-friendly platforms. Adopting these technologies in water treatment research has sped up improvements in preventive upkeep, perfecting procedures, spotting problems, and real-time water management systems, helping make water treatment more effective and environmentally friendly.

3 . AI APPLICATIONS IN WATER TREATMENT PROCESSES

Artificial intelligence has been increasingly integrated into various domains of water treatment, offering significant improvements in efficiency, accuracy, and sustainability. In this section, important AI applications are discussed in the areas of water quality monitoring, improved wastewater treatment, desalination and membranes, drinking water processes, and managing resources.

3.1 Water Quality Monitoring and Prediction

To maintain clean water and safe ecosystems, monitoring water quality is very important. The combination of sensors, AI, and machine learning technology allows for immediate monitoring and finding unusual events in both treatment plants and natural water bodies. Continuous data for pH, turbidity, dissolved oxygen, and contaminant concentrations are collected by the sensors. Support vector machines and random forests, part of machine learning, study the data to identify any signs of pollution or problems with the system [14]. Many case studies show that AI models perform well in forecasting future water quality trends from historical and current readings from sensors. In one case, a neural network analyzing river water quality determined there would be a rise in contamination, so steps for early treatment were taken [15]. The features used and the predictive accuracy of different models from recent studies can be found in Table 1.

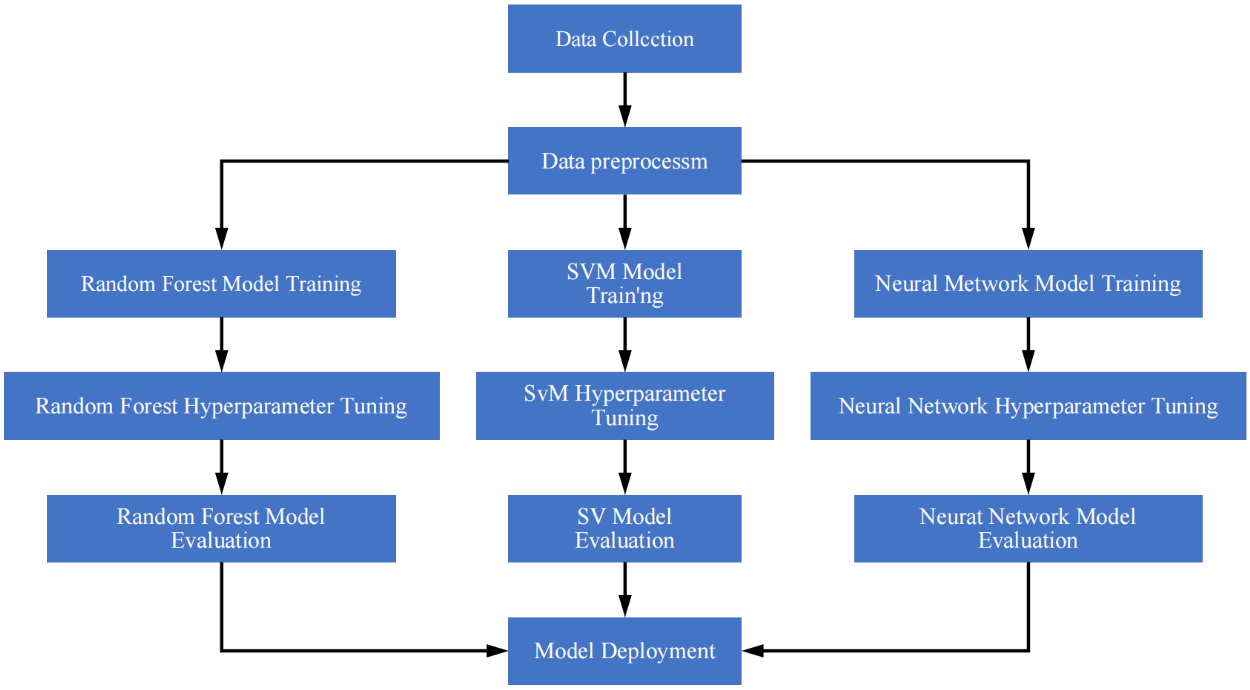

Figure 2: AI-Enabled Real-Time Water Quality Monitoring System Training.

Table 1: Summary of AI models for water quality monitoring

Model Type	Inputs	Output	Accuracy (%)
Random Forest	pH, turbidity, temperature	Anomaly detection	92
Neural Networks	Historical pollutant levels	Pollutant forecasting	89
Support Vector Machine	Dissolved oxygen, conductivity	Water quality classification	90

3.2 Wastewater Treatment Optimization

Improving aeration, adding chemicals, and handling sludge well can significantly lower the amount of energy and money needed for wastewater treatment. AI is commonly used for precise process management and to predict potential failures in advance. With reinforcement learning, aeration is managed so that oxygen is supplied in line with the sensors' feedback and with no decrease in treatment efficiency [16].

Through gradient boosting and deep learning models, faults such as those caused by pump failure or clogs are spotted before they affect plant operating conditions. This way of working reduces both the risk of downtime and the cost of maintenance. Fuzzy logic is integrated into an expert system to improve chemical dosage in wastewater based on uncertainties in the makeup of incoming wastewater and responses seen [17].

3.3 Desalination and Membrane Systems

Both desalination and membrane filtration are important in supplying freshwater, though difficulties such as membrane fouling lower the process's efficiency. The algorithms are capable of estimating how the membrane will function and how easily it might be fouled, using data such as pressure, flow rate, and water characteristics [18]. Research has pointed out that convolutional neural networks can spot fouling in membrane images even when it is very early and is almost impossible to see with human eyes [19].

Such models analyze the rate at which membranes become fouled, allowing cleaning to take place only when necessary and ensuring that less chemical is used and your membranes live longer. Table 2 presents a comparison of AI tools used to spot fouling and predict outcomes in several desalination systems.

Table 2: AI techniques for membrane fouling and performance prediction

AI Method	Data Used	Application	Benefits
CNN	Membrane surface images	Fouling detection	Early fault identification
Gradient Boosting	Pressure, flow, water quality	Performance prediction	Optimized cleaning cycles
Support Vector Machine	Operational parameters	Fouling classification	Accurate fouling status

3.4 Drinking Water Treatment

Predicting the level of contaminants and designing filtration for safety are the main ways AI is applied to drinking water treatment. Using historical information on contaminants, supervised models can predict when pathogens or chemicals may be found in water [20]. With these predictions, operators can apply adequate changes to filtration or disinfection right away.

Also, AI models imitate how filtration happens by exploring the interactions within the water and the materials used, supporting improvements to filter design and usage. Using fuzzy logic, controllers ensure the right amount of chlorine is used in disinfection by adapting to water quality changes, keeping safety in check, and wasting as little chemicals as possible.

3.5 Resource Management and Decision Support Systems

Decision support systems (DSS) driven by AI have given new possibilities to both water distribution networks and policy planning. By using AI, smart water grids can find leaks, set schedules for pumps, and forecast how much water will be needed, reducing waste [21]. Real-time adaptation of pump operations by reinforcement learning saves energy by responding to fluctuations in demand.

On a larger scale, these tools assist policymakers by replicating water resource situations, assessing pros and cons for the environment and the economy, and proposing sustainable solutions. Machine learning and multi-criteria decision analysis are included in these tools to guide solid and evidence-based decisions in water governance [22].

4 . COMPARATIVE ANALYSIS OF AI APPROACHES

How well artificial intelligence techniques work, how much they need for resources, how well we can understand them, and how much they can handle depend on several factors. Deciding on the right model to treat water depends on several factors such as the accuracy level, expenses, the data needed, and how easily data can be interpreted.

When dealing with contaminant prediction or process optimization, accuracy is generally considered the most important. Generally, the performance of a model is analyzed using figures like Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and R^2 (coefficient of determination). These relationships are shown mathematically as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}\,,$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Figure 3: Root Mean Square Error (RMSE), Mean Absolute Error (MAE) Formulas

According to studies, deep learning models such as CNNs and LSTMs achieve better predictive accuracy than simpler algorithms when it comes to complex systems with nonlinear patterns [23]. Still, these benefits are reached at the expense of more costly computer hardware and greater energy usage, which limits their use in small or rural areas [24].

The suitability of a model can be affected by what data is available. Support vector machines (SVM) and random forests handle modest amounts of data very well, which is why they are best for average-sized applications. Unlike other machine learning approaches, deep learning uses extensive collections of data that are often hard or costly to supply in the water sector [25].

It is important that safety-critical systems can be easily understood. The decision logic in decision trees and fuzzy systems is simple and helps build operator trust. At the same time, deep models are called "black boxes," and tools such as SHAP or LIME are used to explain them [26]. Often, stakeholders decide to choose interpretable models over those with the highest accuracy.

Costs must also be calculated for the computation needed and the level of implementation difficulty. Cost-effective solutions using rules work well for static tasks, but data-driven tasks often require moving toward more advanced automated approaches [27].

Table 3: Comparison of AI approaches in water treatment

AI Technique	Accuracy	Data Requirement	Interpretability	Cost
Decision Trees	Moderate	Low	High	Low
Support Vector Machine	High	Medium	Moderate	Medium
Artificial Neural Networks	High	High	Low	High
Fuzzy Logic Systems	Moderate	Low	High	Low
Deep Learning (CNN/RNN)	Very High	Very High	Very Low	Very High

While no single approach excels across all dimensions, hybrid models—such as combining fuzzy logic with neural networks—can balance accuracy and interpretability [28]. These integrations are emerging as promising strategies in next-generation water treatment systems.

5 . CHALLENGES AND LIMITATIONS

Although AI is expected to improve water treatment, there are still several problems preventing its broad use. Challenges in the field consist of issues related to not having sufficient data, issues with how models perform in other areas, and implementing the technology in reality.

There are still significant problems with not having enough reliable data. Many water treatment plants, mainly in poor areas, have not developed extensive and regularly maintained data sets. Often, there is only a small amount of historical operational data, and any that exists may suffer from errors, random missing parts, or incorrect calibrations [29]. Furthermore, data labeling, a key part of supervised learning, needs much effort and is difficult to obtain for important faults or unusual material issues [30]. Such troubles can cause the model to fail in its intended tasks.

It is also essential to consider if models can be generalized. Such AI models tend to perform poorly when used in other locations or treatment plants. Since the environment, treatment technology, and regulations change, trained models are challenging to apply to new locations. The problem of overfitting—models work well with known data but fail outside that data—is still common [31]. While cross-domain adaptation, continual learning, and ensemble methods look promising, they are not yet usual in water treatment systems [32].

However, getting the technology to function in the real world can be even more difficult. Many existing water treatment systems use old methods of collecting data that prevent them from working with today's AI tools [33]. Limited budgets, few people with the right skills, and unwillingness to adapt are made worse by the mysterious aspects of most AI models. A transparency shortage can reduce operator trust and regulators' support [34]. Therefore, more attention is focused on Explainable AI (XAI) frameworks because they can help with these issues [35].

To address these restrictions, engineers, data scientists, and policy leaders must partner to guarantee that AI-powered water treatment is scalable, reliable, and usable in actual practice.

6 . FUTURE RESEARCH DIRECTIONS

As the use of artificial intelligence (AI) in water treatment grows, future research needs to cover both new technologies and the practical challenges involved in application. There are various new paths that could considerably increase a model's performance, durability, ability to adapt, and responsible use.

6.1 Emerging Machine Learning Techniques

Both federated learning and transfer learning are exciting developments in AI for water treatment. Utilities involved in federated learning can train models together by exchanging only gradient updates, which keep their data private and adhere to related rules [36]. Training models in one place or system and using them in others, with limited new data, can be done more cost-effectively and quickly [37]. With advanced methods, AI becomes easier to integrate into any market, handling variability and a lack of data in different locations. If they were more widely used, stronger and broader AI-based tools could help in various water treatment processes.

6.2 Integration with IoT, Digital Twins, and Edge Computing

Water treatment management is being disrupted by combining AI with IoT devices, digital twins, and edge computing. Thanks to IoT sensors, it is possible to view precise data in real-time and see any unusual changes. Through digital twins, plants can be replicated virtually to optimize the way they operate before anything is done in reality [38]. By running data analysis close to where it is generated, edge computing cuts latency and relies on cloud services much less, which benefits any facility with limited or distant connectivity [39]. When used together, the technologies increase responsiveness, reduce the cost of treatment, and improve how water treatment systems are operated.

6.3 Ethical Considerations and Regulatory Frameworks

Responsible water treatment with AI depends on considering ethical topics and new rules. For there to be trust in AI, it must operate transparently, fairly, and honestly [40]. High-level regulations should ensure personal data protection, secure AI applications, and make it clear that every setup is safe to meet the regulations and uphold security [41]. Allowing policymakers, engineers, and ethicists to share ideas will allow standards to be made that balance new technologies with safety and the needs of society and the environment.

7 . CONCLUSION

AI is expected to bring about efficiency, reliability, and sustainability in the field of water treatment. The discussion in this review shows that many AI methods are efficiently applied in water quality monitoring, wastewater processing, desalination, and resource management. With proper computerized tools, it is possible to run the process more accurately, repair equipment in advance, and detect irregularities immediately, both helping operations run smoothly and making them more sustainable.

However, there are still issues preventing the mass adoption of these technologies. Limited data, poor data quality, and boundaries in modeling make this field quite challenging. At the same time, AI cannot easily be merged into existing infrastructure unless the challenges of system complexity and stakeholder acceptance are correctly handled. Since ethics and strict regulations are necessary, it is all the more important to ensure AI is used responsibly.

Moving forward, advances like federated and transfer learning may allow researchers to work with less data and improve how models respond to changes. By using AI together with IoT, digital twins, and edge computing, it will become simpler and faster to monitor the utilization of resources in remote or constrained areas. Yet, these new technologies will only be successful if society addresses ethical matters and creates thorough regulations to ensure things are clear, just, and responsible.

To sum up, AI can change water treatment by improving systems so they are smarter, operate more efficiently, and are more sustainable. It is important for science, engineering, and policy experts, alongside local communities, to keep collaborating to prevent AI problems and use its benefits fully. This will play an important role in ensuring both safe water and its continued availability as world challenges increase.

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