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Use of Artificial Intelligence to Access and Ensure Safe Drinking Water Supply: A Review

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Abstract

Ensuring access to safe drinking water is a critical public health challenge. Traditional water quality assessment methods are often labor-intensive and time-consuming. Artificial intelligence offers a promising alternative, providing rapid, accurate, and scalable solutions for monitoring and predicting water quality. This systematic review examines the application of AI. The review highlights various AI models, including artificial neural networks, support vector machines, decision trees, and ensemble methods, in predicting water quality parameters and detecting contamination events. The integration of artificial intelligence with Internet of Things devices for real-time monitoring is also discussed. Our findings suggest that artificial intelligence-based approaches significantly enhance water quality management, offering robust and efficient solutions for ensuring safe drinking water. The advancement in explainable artificial intelligence, has considerably elevated the trust in using AI in drinking water management.

Keywords: Artificial intelligence, safe drinking water, water quality prediction, environmental monitoring, machine learning, IoT, explainable artificial intelligence, XAI

INTRODUCTION

Access to safe drinking water is fundamental to public health and well-being. But not every nation has access to the same amount of water, particularly emerging countries where the water crisis is much more severe than developed nations. According to the World Health Organization, over 2 billion people worldwide do not have access to safely managed drinking water services. UNICEF projects that by 2025, half of the global population could live in areas with limited water access. Moreover, severe water scarcity may force 700 million people to relocate by 2030. By 2040, approximately one in four children worldwide is expected to reside in regions with extremely high-water stress levels. Notably, in many underdeveloped countries, tap water is often unsafe for drinking, unlike in developed nations. This shortage of clean water is intensified by factors such as pollution, climate change, and population growth. Drinking water, often known as potable water, is defined as water that is safe to drink and does not pose a risk to human health. A safe drinking water system is essential for public health and urban development. These systems have evolved dramatically, revolutionizing city operations and guaranteeing residents' access to clean, reliable drinking water. But one of the main aspects for the success of these systems is continuous monitoring and maintenance. Water quality necessitates a thorough evaluation of a number of factors, such as pH levels, turbidity, chemical composition, and microbiological pollutants. Maintaining the health of urban

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populations depends on this careful management because low water quality can cause a variety of waterborne diseases. As per World Health Organization, over 800 children die from diarrhea due to the use of contaminated water, poor water sanitation, and poor hygiene every day. Additionally, the sustainability and resilience of drinking water systems are critical to guaranteeing a high standard of living for all inhabitants as metropolitan areas continue to grow, emphasizing the necessity of perpetual care and investment. Traditional methods for water quality assessment, such as physical, chemical, and biological analysis, while effective, are often slow, labor-intensive, and resource-intensive.

METHODS

Chemical Testing

Analyzing the chemical composition of water to identify contaminants like heavy metals, nitrates, and pesticides.

Biological Testing

Using bio-indicators like algae and bacteria to assess the biological health of water bodies.

Physical Testing

Traditional methods for measuring physical parameters such as temperature, turbidity, and pH have limitations regarding scalability, speed, and real-time data provision. The advent of artificial intelligence (AI) has brought significant improvements to these methodologies. AI techniques can process large volumes of data quickly and accurately, allowing for real-time monitoring and prediction of water quality. Applications of AI and machine learning (ML) have been successfully implemented in monitoring water availability, quality, pollution, flooding, drought, ground water potential [1–7]. Simple modeling studies were the first uses of AI and ML in water environments, projecting correlations between inputs and outputs [8–10]. However, with the advancement in the field of AI in the past decade, there are more innovative applications and models. It can be said that to handle more complex issues in water, a range of AI and ML techniques are used.

This review aims to evaluate the current state of AI applications in water quality prediction and contamination detection, identifying the strengths, limitations, and potential future directions of these technologies.

AI TECHNIQUES IN DRINKING WATER QUALITY PREDICTION

Artificial Neural Networks and Deep Learning

Artificial neural networks (ANNs) have emerged as powerful tools in the domain of drinking water safety assessment. ANNs are computational models designed to replicate the neural structure of the human brain. They excel at learning intricate patterns from data and making precise predictions. Their ability to handle nonlinear relationships and adapt to diverse datasets makes ANNs particularly suitable for modeling the intricate interactions between different water quality parameters and their impact on human health, thereby contributing significantly to ensuring the safety of drinking water supply. By using their varied subgroups to simulate the intricate relationships present in water systems.

ANNs significantly contribute to the advancement of water quality assessment. ANNs, including feedforward neural networks (FFNNs), recurrent neural networks (RNNs), convolutional neural networks (CNNs), deep neural networks (DNNs), and adaptive neuro-fuzzy inference systems (ANFIS), offer solutions for different aspects of water quality management. FNNs, known for their simplicity and interpretability, are employed in tasks requiring pattern recognition and straightforward data interpretation. RNN process data sequentially and retain past knowledge. So RNNs account for time dependence, which is relevant for water quality assessments that works with a time-series dataset [4]. CNNs, with their ability to extract meaningful features from spatial data, are effective in image-based water quality analysis, such as identifying pollutants in satellite imagery or water samples. DNNs, capable of handling both linear and nonlinear relationships, are utilized for comprehensive modeling of water quality dynamics across large datasets, despite their computational demands. Each subgroup of ANNs contributes uniquely to enhancing our understanding and management of water quality, addressing challenges from pollution monitoring to resource planning with advanced computational methodologies [8–10].

Research has demonstrated that ANNs can accurately predict water quality parameters such as pH, turbidity, and contaminant levels. In 2021, Ismael et al. evaluated the drinking water suitability in Sudan using the Water Quality Index (WQI) method, employing ANNs for their analysis. specifically feed-forward backpropagation (BP ANN), to predict WQI, achieving high accuracy with R^2 values exceeding 0.95. Physiochemical and microbial assessments revealed widespread contamination, particularly with heavy metals like cadmium, leading to recommendations for urgent interventions such as chemical treatments or filtration to safeguard water resources. The ANFIS is a hybrid computational model that combines the adaptive capabilities of neural networks with the reasoning and inference capabilities of fuzzy logic. It aims to create a system that can learn from data (neural network aspect) and interpret linguistic rules (fuzzy logic aspect) to perform tasks such as classification, regression, and system control [11–14].

The ANFIS and ANN have been the predominant neural network technologies used for water quality monitoring and assessment over the past decade. It was found to be very effective for surface water quality prediction. a data set from India, showed that the FFNN algorithm achieved the highest accuracy (100%) for water quality classification (WQC), and the ANFIS model predicted WQI with accuracy very close to observational values. Deep learning (DL) models are ANNs with a large number of hidden layers, often called deep neural networks (DNNs). It includes deep versions of the networks (Deep FFNNs, RNNs, and CNNs) along with advanced architectures like generative adversarial networks, transformer networks, graph neural networks, and autoencoders [15–18].

DL models have the ability to overcome the limitations of traditional neural networks by capturing the implicit temporal and spatial correlations within data. Alfwzan et al., in 2024, highlighted this advantage in their research. approach to water quality forecasting, using DL—more specifically, Bi-directional Long Short-Term Memory networks is combined with computational fluid dynamics simulations to model the movement and diffusion of contaminants in water bodies [2]. The recommended method achieves the lowest error margins and the maximum prediction dependability and is said to be accurate in forecast several elements of water quality in advance, which can help with quality control and monitoring.

Luo et al., in 2024, introduced a novel hybrid DL model known as ED-CLA, which is based on the encoder-decoder architecture incorporating CNN, LSTM, and attention mechanisms [17]. This approach was designed to enhance the performance of individual models. It is suggested that this approach can be integrated with early warning systems for municipal water resource management, allowing for the accurate prediction of water quality degradation well in advance to get more time for remedial actions [19].

Support Vector Machines

Support vector machines (SVMs) are ML algorithms commonly used for classification and regression tasks. SVMs prove effective in situations where data points are not easily separable by simple linear boundaries, employing techniques to transform data into higher dimensions. This transformation helps SVMs effectively classify data that might be complex or overlapping in lower-dimensional spaces. Research supports the effectiveness of SVMs in water quality prediction and classification tasks, contributing to proactive decision-making for ensuring safe drinking water. Leong et al., (2019) demonstrated in their study on WQI in Malaysia, that SVM and LS-SVM models can accurately predict WQI using direct measurements of physical data, employing a polynomial kernel function for input parameter analysis [20–25].

Ensemble Methods and Decision Trees

Ensemble learning is a ML technique that combines multiple models to enhance prediction performance and accuracy. By aggregating the predictions of several models, ensembles can provide more robust and accurate results compared to any single model. This approach helps to offset the weaknesses of individual models while leveraging their strengths, leading to improved generalization and performance. Decision trees (DTs) are frequently used as base models in ensemble methods to create more reliable and accurate predictive models. The frequently employed one is random forest (RF) and gradient-boosted decision tree.

Ortiz-Lopez et al., in 2024, used ensemble methods to predict and thus avoid the time lag on treatment processes in the drinking water treatment plants when the water quality deterioration happens at the source [24]. Ensemble learning is a machine learning technique that combines multiple models to enhance prediction performance and accuracy. By aggregating the predictions of several models, ensembles can provide more robust and accurate results compared with any single model. This approach helps offset the weaknesses of individual models while leveraging their strengths, leading to improved generalization and performance. DTs are frequently used as base models in ensemble methods to create more reliable and accurate predictive models. Aldrees et al., in 2022, illustrated that ensemble learning markedly improves model effectiveness by reducing statistical errors when combined with standalone methods such as DTs, SVMs with support vector regression (SVM with SVR), and multi-layer perceptron neural networks [1]. The application of bagging and boosting ensemble techniques further mitigated these errors by transforming weaker learners into robust models, highlighting enhanced efficiency and accuracy in water quality prediction models. Alves Ribeiro et al., in 2020, emphasize the critical role of automatic anomaly detection in monitoring drinking water quality and the need to quickly recognize problems or anomalies in the water network to increase overall safety [3]. Their study done for a German water supplier, introduced a novel dynamic multi-criteria ensemble selection mechanism, non-dominated local class-specific accuracy, and found it is very effective in the development of stronger anomaly detection systems for drinking water quality monitoring. Poursaeid et al., in 2024, conducted research on water resources issue parameter management, focusing on ensuring safe drinking water. They utilized advanced machine learning models like ensemble bagged machine (EBM) and stochastic weighted ensemble bagged machine (SWEBM), which were optimized using Bayesian optimization. These models effectively simulated key parameters including DO, electrical conductivity (EC), pH, and river flow rate (Debi). SWEBM exhibited superior performance across various metrics, underscoring its potential to significantly improve precision in managing water quality. Mohseni et al., in 2024, conducted their study in India, focusing on the urban WQI to study the quality of groundwater in the urban and rural areas which is being used for drinking. They utilized the XGBoost ensemble model along with ANN, SVM, RFs, and multiple linear regression to predict the Weighted Arithmetic Water Quality Index (WA-WQI).

Their findings demonstrated that XGBoost effectively predicted WA-WQI, showcasing their potential for enhancing water quality management strategies in urban areas. There are a lot of other studies in the application of ensemble learning in water quality prediction like; dissolved oxygen prediction using the knowledge-guided Catboost (KGCatboost) model, predicting the detectability of pesticides in surface water as drinking water sources using LightGBM (Light Gradient Boosting Machine) model, chloride concentration ensembling multi-layer perceptron and stepwise cluster analysis models, the distribution of nitrate in ground water used for drinking supply using extreme gradient boosting (XGB) model, Chl-a (chlorophyll-a) concentration as indicator of algal concentration to maintaining the safety of the drinking water supply system using XGB [26–30].

Deep cascade forest (DCF) is an ensemble learning method that extends traditional DT-based models into a DL framework. Chen et al., in 2021, introduced two innovative models that utilize DCF as their foundational learning model. These models are the cost-sensitive DCF (CS DCF) and a version that integrates unsupervised learning models with greedy methods, termed USM-DCF G. The effectiveness of both CS-DCF and USM-DCF-G was demonstrated on an imbalanced drinking water quality dataset, where they outperformed the standalone DCF in prediction accuracy [31–33].

Integration with IoT for Real-Time Monitoring

The assessment of water quality has undergone a transformation with the introduction of data driven technologies such as sensors, the Internet of Things (IoT), AI, and geographic information systems. A few advantages of information-driven approaches over traditional methods include high-resolution data, predictive modeling, temporal and spatial analysis of water quality, and real-time monitoring. The water quality parameters can exhibit short-term fluctuations. However, it is said that global drinking water monitoring programs often fail to account for these short-term variations, potentially overlooking their health impacts [34–36].

Integrating AI with IoT devices for real-time water quality monitoring can help ensure the provision of clean and safe water for future generations. IoT sensors collect continuous data on various parameters, which are then analyzed by AI models to predict potential contamination events and provide timely alerts. Several studies are happening in this field as it gives better control over the water quality.

Momparler et al., in 2020, recommend using IoT technology for cost-effective smart water quality monitoring. This involves using sensors to detect variations in pH, turbidity, water level in the tank, temperature, and surrounding humidity. Singh et al., in 2022, emphasize that recent advancements in smart sensor technology, particularly in fully integrated wireless networks, with features like low power consumption, ease of cloud integration, robustness, and simple deployment of sensor nodes, will be contributing significantly to continuous in-line monitoring of water quality. A real-time water quality monitoring system was implemented in the River Ganga, India, due to the ecological importance and vulnerability of the Gangetic ecosystem. This system demonstrated highly reliable results. Jha, in 2020, used a cloud-based system using a microcontroller to investigate the water quality in several locations. Sensors in overhead tanks measure the water's quality; the collected data is saved in a CSV file and is then used to classify the water as drinkable or not using a DT-based classifier. Display systems and mobile devices were connected to obtain a real-time alert.

Bagheri et al., in 2023, have proposed a little more advancement in the use of IoT in water environments, by introducing TinyML. Deploying machine learning models on severely resource-constrained devices like microcontrollers, that have minimal memory, processing power, and energy is known as "TinyML," or "tiny machine learning." The real-time and low power inference is made possible by the ability to execute machine learning algorithms directly on these tiny devices without the requirement for constant cloud access and thus perform on device sensor data analytics [5]. The study reveals that microcontrollers equipped with TinyML models enable real-time environmental monitoring in water environments, eliminating the need for cloud data transfer or operator involvement. Also, this is said to be a cheaper tool to autonomously detect pollutants than traditional monitoring tools.

Use of Explainable Artificial Intelligence (XAI)

Water quality testing using traditional methods can be time-consuming and labor-intensive. It is very evident that a more accurate and efficient methodology will be to incorporate AI into the monitoring of water quality. However, the opacity and complexity of AI models can be a major deterrent to their widespread use in vital fields like drinking water quality monitoring, as it is directly related to the consumer's health and life. AI technologies created to make machine learning models' decision-making transparent and intelligible to humans are referred to as explainable artificial intelligence (XAI) systems. XAI intends to show how and why particular predictions or judgments are produced, in contrast to typical AI models which commonly operate as "black boxes" with opaque decision-making processes. According to Gohel et al., in 2021, XAI is an emerging field in AI that tries to answer the "wh" questions. XAI can address questions such as "Why was a specific output attained?", "How was a specific output attained?", and "When might a specific AI-based system fail?" In 2024, Nallakaruppan et al. researched the automation of water quality estimation using AI, leveraging XAI to identify the most critical parameters affecting water potability and to estimate impurities. Their study evaluated various machine learning models to classify water as drinkable or not, based on nine parameters: pH, hardness, sulphate, chloramines, trihalomethanes, conductivity, organic carbon, and turbidity. The RF model was chosen for the implementation of the XAI model using SHAP (SHapley Additive exPlanations), because of its higher accuracy. "SHAP" (SHapley Additive exPlanations) is a method used within the XAI model to explain the contributions of different parameters toward the classification of water potability based on their importance and unique properties and found a parameter as the most influential in determining water potability. A study done in Saudi Arabia by Mallick et al., 2024, showed an urgency to take action to improve water quality with over 35% of the studied samples being categorized as "Unsuitable."

The RF and deep neural network models were identified as the most effective for determining critical water quality parameters among various machine learning models. A three-pronged XAI approach was employed to interpret these models. This approach included model diagnosis through residual analysis, model parts using permutation-based feature importance, and model profiling via partial dependence plots, accumulated local effects plots, and individual conditional expectation plots. The XAI model profile showed that the main factors influencing WQI prediction were nitrate, pH, and total hardness. In turn, this comprehension will facilitate the development and implementation of remedial actions easier. In a study done in Bangladesh by Mia et al.

In 2023, XAI techniques were utilized to understand the relative importance and impact of various parameters on the Entropy Water Quality Index.

BENEFITS, CHALLENGES, LIMITATIONS, AND FUTURE DIRECTIONS

AI models offer significant advantages over traditional methods used in drinking water quality analysis, including faster data processing, higher accuracy, and the ability to handle large datasets. AI models are especially valuable in situations that demand real-time monitoring and swift responses. However, they also encounter challenges, including the necessity for large, high-quality datasets, the risk of overfitting, and the difficulty of interpreting complex models. There is also a need for robust infrastructure to support the integration of AI with IoT devices. Though the use of XAI has made AI applications more trustworthy, more studies in this direction are required as a community's health and life will be in the hands of AI when a drinking water plant is adopting an AI system. Future research should focus on improving the interpretability of AI models, enhancing data collection methods, and developing hybrid models that combine multiple AI techniques for better performance. Additionally, there is a need for more field studies to validate the effectiveness of AI models in real-world settings.

CONCLUSION

The application of AI in ensuring a safe drinking water supply represents a significant advancement in environmental monitoring. AI models offer superior accuracy and efficiency compared with traditional methods, providing scalable solutions for real-time water quality assessment. The integration of AI with IoT further enhances the potential for continuous and automated water quality monitoring.

The use of explainable AI (XAI) has enhanced the transparency of AI decision-making processes. However, additional research is required to improve the reliability of AI applications in ensuring safe drinking water. Ongoing research and development will be crucial in overcoming challenges and fully leveraging AI's capabilities in water quality management.

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