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Artificial Intelligence In Water Quality Monitoring For Sustainable Resource Management

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ABSTRACT
The growing demand for clean and safe water, coupled with the increasing pressures of urbanization, industrialization, and climate change, has made efficient water quality monitoring a critical component of sustainable resource management. Traditional water monitoring methods, while effective, often suffer from limitations such as high costs, labor intensiveness, and delayed data interpretation. This study explores the integration of artificial intelligence (AI) techniques—including machine learning (ML) and deep learning models—for the prediction, classification, and real-time assessment of water quality parameters such as pH, turbidity, dissolved oxygen, biochemical oxygen demand (BOD), and chemical oxygen demand (COD). Various AI algorithms, including Random Forest, Support Vector Machines, Artificial Neural Networks, and Long Short-Term Memory (LSTM) networks, are trained and evaluated using historical water quality datasets from diverse geographic regions. The results demonstrate that AI-based models can accurately predict water quality indices (WQI), outperforming conventional statistical methods in both accuracy and adaptability. Moreover, the integration of AI with Internet of Things (IoT)-based sensor networks enables continuous and automated monitoring, offering significant advantages in scalability and responsiveness. This study highlights the potential of AI as a transformative tool in environmental monitoring and underscores its critical role in promoting sustainable water resource management and policy decision-making.

Keywords: *Deep Learning, water quality; water quality index; water quality classification; adaptive neuro-fuzzy inference system; feed-forward neural network models, Artificial intelligence.*

I. Introduction

With fast economic growth and increased urbanization, water pollution has become grimmer. Understanding the issues and patterns of water quality is also critical for water pollution reduction and regulation. Most countries around the world have started to develop environmental water management schemes to truly understand the quality of the marine ecosystem. Water is life's most important substance. Although 71% of the Earth's surface is covered with water, the vast majority of it (95%) is salt water [1]. Thus, conserving the quality of fresh water is essential. Almost one billion people do not have access to adequate drinking water sources, and two million people die every year from contaminated water and poor sanitation and hygiene [2]. Water quality is important to the sustainability of a diversion scheme. Predicting water quality involves forecasting variation patterns in the quality of a water system at a certain time. Water quality prediction is important for water quality preparation and regulation. Strategies for the prevention and regulation of water contamination can be developed by predicting future changes in water safety at varying levels of contamination and devising rational strategies to prevent and regulate water contamination. In water diversion schemes, the general consistency of water should be estimated.

Water of low quality can also be economically challenging, given that resources must be diverted to upgrade water delivery infrastructure any time a problem arises. For these purposes, the demand for improved water treatment and water quality control has been increasing to ensure clean drinking water at affordable rates. Systematic analyses of raw water, disposal systems, and organizational monitoring problems are required to resolve these challenges [4]. Achieving precise predictions of changes in water quality can immensely improve the efficiency of aquaculture. In general, water quality data are pre-processed before water quality parameters are predicted. Thus, this section consists of two stages. The first stage consists of the pre-treatment of water quality data and the performance of correlation analysis between different water quality parameters. With advanced computing using artificial intelligence (AI) techniques, the modelling of water quality has been developed to resolve water quality issues. Artificial neural networks (ANNs) have aided in the monitoring of water quality systems by predicting changes in water quality [5]. They can immensely improve the efficiency of aquaculture. The simulation of water quality conditions has difficulties and challenges regarding the use of the hydrodynamic and water quality model, a relatively novel computational approach. ANNs have been widely established in many disciplines and provide an alternative technique for understanding and monitoring water quality in reservoirs. ANNs have been successfully applied to simulate and forecast water quality in water bodies. Numerous ANN methods, such as feed-forward neural networks [6], have been used in various applications.

The fuzzy logic system has been developed to solve complex nonlinear systems [7]. ANN applications have been successfully used as tools to compute and predict the quality of water bodies [8–12]. ANN models require parameter values for designing predictions [13]. ANNs have numerous advantages, including their ability to learn, manage very complex nonlinear systems, and work with parallel processing. Shafi et al. [14] used support-vector machines, neural networks (NNs), deep NNs, and K-nearest neighbors (KNNs) to classify water quality using data from the Pakistan Council of Research in Water Resources (PCRWR) for drinking water.This paper focuses on the application of AI to water quality monitoring with an emphasis on sustainability. It aims to (1) review the current AI methods used in water quality prediction, (2) demonstrate their effectiveness through model evaluation, and (3) highlight their role in promoting sustainable water management practices.

2. Literature Review

Liu et al. [16] used the long short-term memory (LSTM) network model to predict the quality of drinking water in the Yangtze River Basin. The LSTM model was developed using pH, dissolved oxygen (DO), chemical oxygen demand (COD), and NH3-N. It is noted that the LSTM model has promise for monitoring water quality. Chen et al. [17] proposed artificial intelligence for modelling and predicting water quality. It is noted that the ANN model gave a better result. Singh [18] used the ANN model to compute dissolved oxygen (DO) and biological oxygen (BOD) parameters to predict the quality of river water. Zheng et al. [19] applied the immune practical swarm optimization (PSO) method, which employed a neural network with a hidden layer to predict sewage effluent water quality. Gao [20] enhanced the back-propagation (BP) neural network by using the grey correlation analysis method to predict water quality.

Zhang et al. [21] combined ANNs with a genetic algorithm to predict water quality by using time data to enhance the stability of the forecasting results. Wang et al. [22] proposed a Genetic Regression Neural Network GA-GRNN model to develop an efficient method of predicting water quality to ensure water security in the south-to-north water diversion (SNWD) Project. Correlation coefficients were applied to investigate the relationship between significant parameters. Abyaneh [23] introduced ANNs and regression models to predict COD and bioche. The radial-basis-function was used as a kernel function of the ANN model [24,25].

Barzegar et al. [26] developed a hybrid convolutional neural network (CNN)–LSTM model to predict DO and chlorophyll-a (Chl-a) in Small Prespa Lake in Greece. It is observed that the deep learning model was outperformed compared with the traditional support- QI compared to traditional machine learning techniques, as did AI techniques such as ANN, Bayesian NNs, and adaptive neuro-fuzzy [28]. Piazza et al. [29] presented a comparison between the proposed model's numerical optimization approach and the results of an experimental campaign. The genetic algorithm with a hydraulic simulator was applied to test and evaluate water quality by monitoring it. Sambito et al. [30] developed a smart system based on the Internet of Things and a Bayesian decision network (BDN) for predicting wastewater.

The proposed system was focused on analysis and soluble conservative pollutants such as metals, decision support systems, and auto-regressive moving averages, and was applied to predicting the water quality WQ of groundwater [31]. Currently, water quality is assessed by costly and time-consuming laboratory and statistical analyses that require sample collection, transportation to laboratories, and a lot of time and calculation, which is quietly unavailing because water is a completely transmissible medium and time is necessary if the water is contaminated with diseasecausing waste. The catastrophic consequences of water contamination necessitate a faster and less

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expensive alternative. In this regard, we developed a real-time system to evaluate an alternative approach based on the advanced artificial intelligence method for modelling and predicting water quality.
These mimicking models, however, face some challenges. For example, they do not consider factors affecting WQ. The contributions of the current study are presented to use an advanced AI Adaptive neural-fuzzy inference system ANFIS model that was developed to predict Water quality Index WQI. The Feed-forward neural network FFNN and KNN were used for the Water Quality Classification WQC. The highly efficient advanced AI can be generalized and then used to forecast the water pollution process, which will aid decision-makers in strategizing for timely decisions.

3. Materials and Methods

The ANFIS model is one of the types of ANN algorithms proposed by Jang [34,35]. This model was used to solve complex and nonlinear problems. The algorithm consists of a neural network and fuzzy logic and is, therefore, powerful. The algorithm is used to predict data and obtain the optimal membership function through an adaptive system in the input layer. The ANFIS model consists of five layers: fuzzification, antecedent, strength normalization, consequent, and inference [36]. Each layer contains many nodes. The ANFIS model is represented by two input parameters and an output parameter, as illustrated in Figure 1. The training data were divided into 70% for the training phase and 30% for the testing phase. The ANFIS model was processed based on the scatter partition fuzzy approach, which works by clustering to divide dimension vectors in the specific area of the fuzzy rules. The ANFIS model was developed by integrating fuzzy c-means clustering and backpropagation algorithms. The seven clusters and minimum improvement 10−5 and number of epochs 200 were appropriate.
The datasets employed to conduct the research were acquired from different locations in India and contained 1679 simples from 666 different sources of rivers and lakes in the country. The data was collected between 2005 and 2014. The link to the datasets is attached. The datasets include eight important parameters: DO, pH, conductivity, biological oxygen demand, nitrate, fecal coliform, temp, and total coliform. However, seven parameters were considered to show significant values, and the developed models were evaluated based on some statistical parameters. All the experiments consisted of temp parameters. The Indian government collected these data to ensure the quality of the drinking water supplied. This dataset was obtained from Kaggle https://www.kaggle.com/anbarivan/indian-waterquality-data.
The processing phase is very important in data analysis to improve data quality. In this phase, WQI was calculated from the most important parameters of the dataset. Then, water samples were classified on the basis of WQI values. The *z*-score method was used as a data normalization technique for superior accuracy.

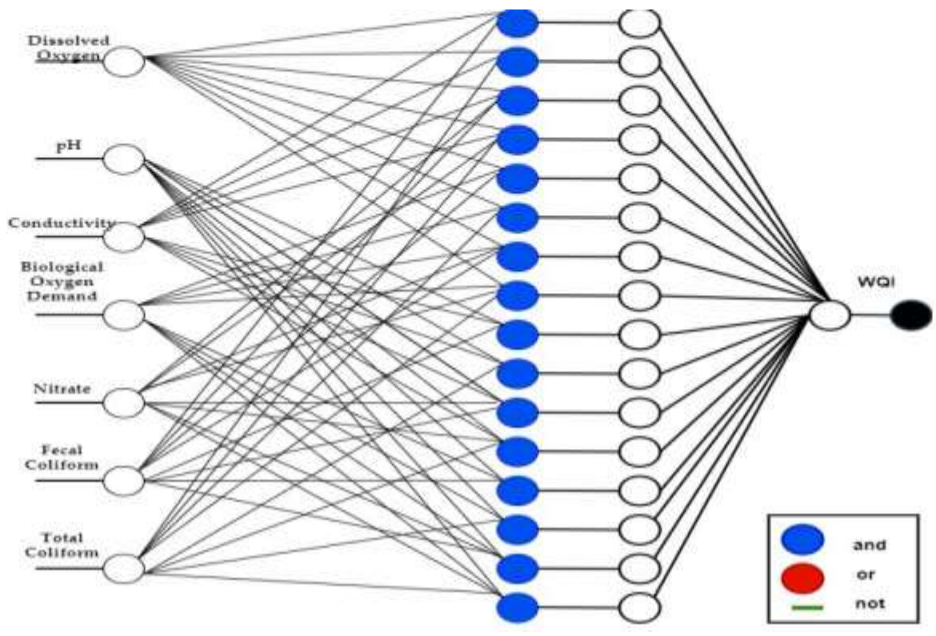

Figure 1: Proposed framework for ANFIS to predict WQL

3.1 Water Quality Index Calculation

The WQI, which is calculated using several parameters that affect WQ [32], was used to measure water quality. The performance of the proposed system was evaluated on the published dataset, with seven important water quality parameters. The WQI was calculated using the following formula:

$$WQI = \frac{\sum_{i=1}^{N} q_i \times w_i}{\sum_{i=1}^{N} w_i}$$

where N denotes the total number of parameters included in the WQI formula, qi denotes the quality estimate scale for each parameter i calculated by Formula (2), and wi denotes the unit weight of each parameter in Formula

$$q_i = 100 \times \left(\frac{V_i - V_{Ideal}}{S_i - V_{Ideal}}\right)$$

where Vi is a measured value that refers to the water samples tested, VIdeal is an ideal value and indicates pure water (0 for all parameters except OD = 14.6 mg/L and pH = 7.0), and Si is a standard value recommended for parameter I, where K denotes the constant of proportionality, which is calculated using the following formula:

$$w_i = \frac{K}{S_i} \quad K = \frac{1}{\sum_{i=1}^{N} S_i}$$

In general, ANN models are used as very powerful machine learning algorithms for time series prediction of different engineering applications. The ANN model consists of an input layer, hidden layers, and an output layer. Each hidden layer has weight and bias parameters to manage neurons. To transfer the data from the hidden layer into the output layer, the activation function is used. The learning algorithms are used to select the weights within the NN framework. The weight selection is based on minimum performance measures, such as mean square error (MSE). Figure 4 shows the architecture of FFNN for the classification water quality WQC.

4. Results & Discussion

This section presents the results of the classification algorithms used to predict the WQC. The performance of the FFNN model was superior compared to that of the KNN algorithm. The accuracy, specificity, sensitivity, precision, recall, and F-score of the FFNN algorithm were 100%, 99.61%, 99.61%, 99.61%, and 100%, respectively. Notably, the performance of the FFNN outperformed that of the KNN algorithm. Figure 2 shows the confusion matrix of the FFNN model used to classify WQ. To validate the proposed system, we divided the dataset into 70% training and 30% testing. The numbers of false positives, false negatives, true positives, and true negatives were reported using a confusion matrix. The total number of samples of data was 1679, and we divided the data into 1119 samples as training, 280 as testing, and 280 as validation. It is observed that all sample data in both phases' classification were true positive. The x-axis values represent class target and the y-axis values denote class output. The classes are categorized into 1 (excellent), 2 (good), 3 (poor), and 4 (very poor).

Figure 2: Confusion Matrix for FFNN Algorithm

The ROC for measuring the validity of the FFNN model based on the real standard dataset. All graphs for the testing, training, and validation of the system are presented. The last graph shows the overall ROC of the system. Notably, the detection rate was very high, and dataset. is study attempted to prove that the SES-BiLSTM and SES-ANFIS models are effective tools for forecasting water quality and may be used to construct integrated water protection systems while applying appropriate environmental management practices. e proposed models have several advantages over the computational approach when it comes to forecasting WQI. A minimum of four different water quality measures must be calculated and then transformed into partial indications to use the second technique. WQI is calculated using a formula that relies heavily on subindices. As a result, implementing an existing ANN model based on raw data is substantially simpler because no new calculations are required. To develop the model, certain water quality characteristics are needed, minimizing the cost of water quality monitoring, among other things.

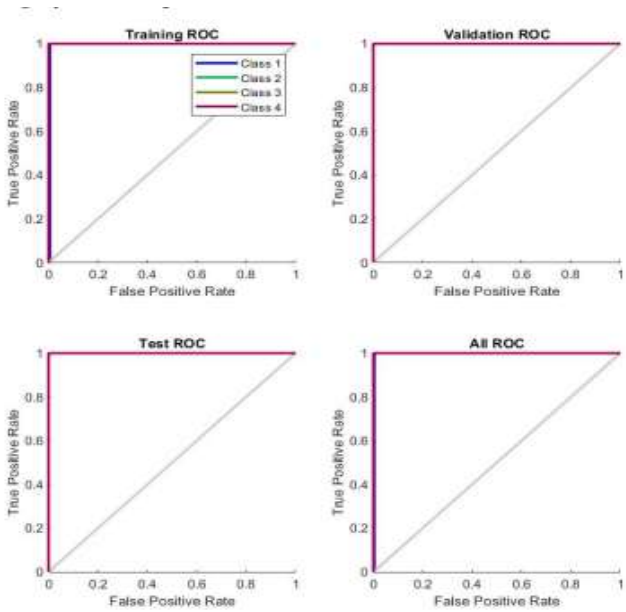

Figure 3: ROC curve for FFNN Model

5.Conclusion

The integration of Artificial Intelligence (AI) into water quality monitoring systems represents a transformative advancement in environmental resource management. This study demonstrates that AI models—particularly machine learning and deep learning techniques—can accurately predict key water quality parameters such as pH, dissolved oxygen, turbidity, and chemical concentrations. These predictive capabilities enable more proactive, data-driven decision-making in managing water resources. By leveraging large datasets from sensors, satellites, and historical records, AI not only enhances the precision of water quality assessments but also facilitates early detection of contamination and ecological degradation. Moreover, AI models can operate in real time, allowing for continuous monitoring and adaptive responses to environmental changes, which is essential for sustainable water resource management in the face of climate change and urbanization.

However, challenges remain, including data availability, model interpretability, and the need for interdisciplinary collaboration. Addressing these will be critical for scaling AI-based solutions and integrating them into existing water management frameworks.In conclusion, AI holds significant promise for improving the efficiency, reliability, and sustainability of water quality monitoring. As technology and data infrastructure continue to evolve, AI-driven tools will play an increasingly vital role in safeguarding freshwater ecosystems and ensuring clean water access for future generations.

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