DOI: 10.54254/2755-2721/53/20241344

Application of big data analysis in water pollution monitoring

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Abstract. Contemporarily, the quick development of an abundant amount of big data analysis technologies has brought great convenience to individuals' everyday existence. In terms of environmental protection, especially water pollution monitoring, this technological progress is particularly critical. As the global demand for clean water resources grows and global industrialization intensifies pollution of the water environment, the adoption of advanced data analysis technologies has become critical. Among the vast array of machine learning architectures, three particularly stand out due to their significance and widespread adoption: the artificial neural network (ANN), which serves as a foundational pillar in understanding complex data patterns; the multi-layer perceptron neural network (MLPNN), a sophisticated evolution that allows for deeper computations and learning; and the adaptive neuro-fuzzy inference system (ANFIS), which brilliantly combines neural and fuzzy logic principles for intricate problem solving. These models not only have high accuracy due to their wide application, but they still have their own limitations. This article aims to introduce the methods, basic principles, and application scenarios of these models. In addition, this article also compares the advantages and limitations of these machine learning models, thereby providing some new ideas for future improvements and innovations in model algorithms, application scenarios, and integration.

Keywords: Big data, Machine learning, Water pollution, Monitoring.

1. Introduction

Water, being the lifeblood of our planet, serves as a fundamental natural resource underpinning the existence and advancement of humanity. As the global economy has witnessed significant growth over the past several years, there has concurrently been a noticeable surge in water consumption, both for industrial endeavors and daily domestic activities. This amplification in utilization underscores the pivotal role water plays in socio-economic development. However, the increasing demands have concurrently spotlighted the imminent challenge of ensuring the availability of high-quality water resources. The significance of this issue is not confined to a particular region; rather, it has emerged as one of the most pressing global concerns [1]. In this century, water pollution remains a major challenge, affecting socio-economic growth and posing risks to public health [2]. Therefore, developing precise and effective methods to track pollutant sources and ascertain the locations, timings, and quantities of pollutants discharged into rivers is essential [3]. Moreover, as computer technology advances, artificial intelligence, machine learning, and big data analytics emerge as the most impactful technologies. Consequently, intelligent solutions are being incorporated into an ever-expanding array of real-life applications. For example, the use of AI in vehicular technology in the driving environment which is complex [4] and large global medical data analysis using deep learning [5].

Within the broad domain of environmental monitoring, the specific niche of water quality monitoring and prediction has seen a paradigm shift with the infusion of cutting-edge technologies. Notably, the advent of artificial intelligence (AI) technology has played a transformative role in this arena. AI, with its array of sophisticated learning algorithm models, has been successfully deployed, paving the way for enhanced accuracy, efficiency, and predictive capabilities in water quality assessments. Such integrative approaches promise to not only revamp traditional methodologies but also offer data-driven insights that can significantly inform and influence policy-making and sustainable water management strategies. Zhu and Heddam used the MPLNN model to analyze and model the aquatic purity records of four city rivers in the remote place area of the Three Gorges Reservoir in China [6]. Elkiran and his team used the ANFIS model to analyze and model Yamuna River Dissolved Oxygen (DO) data [7]. Haribowo, along with his dedicated team of researchers, leveraged the capabilities of the ANN model. They aim to meticulously analyze a range of metrics from the Surabaya River. This included the Biochemical Oxygen Demand (BOD), Chemical Oxygen Demand (COD), DO levels, pH balance, water temperature, and several other pertinent data points to understand the river's ecological health and overall water quality [8].

This study delves into the application of certain algorithmic models of neural networks for big data analysis in the domain of water quality monitoring, assessment. Centered around recent research advancements, this investigation showcases the progress and breakthroughs in this field. Inquiries of this nature are of paramount importance, not only serving as a rich information reservoir for scholars and professionals but also guiding them towards innovative solutions through interdisciplinary avenues. The study is a significant contribution to this paper on the utilization in neural network algorithm models within the context of water quality monitoring, especially against the backdrop of water pollution. This encompasses a brief overview of the scenario descriptions used, the methodologies behind the models, their foundational principles, and the resulting findings. Moreover, the primary objective is to consolidate the current status of the existing knowledge base, pinpointing both common threads and gaps. It lays the groundwork for unveiling new, challenging, effective, and meaningful research directions.

2. Basic descriptions

In the continually evolving landscape of water quality monitoring and prediction, the integration of Artificial Intelligence (AI) has introduced transformative benefits. Among these, one of the most salient advantages is the unparalleled speed and efficiency brought forth by AI-driven approaches. Moreover, the sustainability of AI-based methodologies ensures minimal environmental impact while guaranteeing optimal results. Furthermore, AI systems inherently possess the capability for real-time water quality forecasting, offering timely and proactive interventions, a phenomenon corroborated by the findings of Yetilmezsoy and his team [9].

The utilization of artificial intelligence in monitoring water purity and evaluation can be traced back to the early 1990s [10]. Over the past few decades, there has been a notable stream in the application of innovative technologies in the realm of water quality and monitoring. A testament to this development is the expansive range of its applications. Notably, these technologies have been effectively utilized in various aquatic environments, including water reservoirs, as evidenced by the comprehensive study undertaken by Allawi and his team. in 2018 [11]. In a similar vein, the research undertaken by Hasan and his associates highlights the successful application of these technologies in monitoring river water quality [10]. Additionally, lakes have not been an exception to this trend, with the research of Zaji and Bonakdari showcasing their implications in lake monitoring [12]. Furthermore, the vast and intricate marine ecosystems of seas have also been under the purview of these technological advancements, as delineated by the findings of Ceccaroni and his team in 2018 [13].

Based on a meticulous review and detailed statistical analysis of accumulated scientific works, it becomes abundantly clear that technologies like MLPNN, ANFIS, and ANN have not just been theoretical concepts. Over the last ten years, they have been actively and effectively harnessed for practical applications, especially in the realm of water quality evaluation and ongoing surveillance. Their widespread adoption highlights their reliability and significance in this vital sector [14].

3. Application in water quality monitoring

To gain a holistic understanding of the capabilities and effectiveness of artificial intelligence-driven learning models in the context of water quality monitoring, it is crucial to assess models that are emblematic of the broader landscape of these AI technologies. In light of this, the present study was conceived with the intent of evaluating and potentially earmarking models for future, more nuanced water quality monitoring endeavors. Accordingly, MLPNN, ANFIS, and ANN were selected for investigation.

3.1. ANN

First, Haribowo and his team modeled predictions of water quality conditions using artificial neural network (ANN) methods using data from the Surabaya river. Their investigative approach was particularly comprehensive, focusing on discerning the influence of various environmental parameters such as precipitation, watershed region, and distinct land utilization trends on key water quality indices, namely BOD, COD, DO, pH, and temperature. In order to guarantee the reliability and robustness of their findings, the phase of data gathering was divided into two distinct periods. For the calibration phase, data spanning from 2006 to 2014 was used, while the validation phase relied on more recent data collected from 2015 to 2017. The technical analysis was meticulously carried out using the ANN method, the network type utilized is feedforward back propagation, with Matlab R2014b software serving as the primary computational tool.

The training function they utilize is a function of TRAINCGF (Backpropagation using the conjugate gradient method with a Fletcher-Reeves restart, the conjugate gradient technique is a repetitive approach used to tackle systems of linear equations and nonlinear minimization problems.). LEARNGD is used for the adaptation of the learning function (LEARNGD is used to implement gradient descent learning of weights and bias values. Gradient descent is an optimization algorithm used to iteratively minimize an error function. In the context of neural networks, this error function is usually the overall error of the network. It has the advantages of simplicity and universal use and the disadvantages of slow convergence and low autonomy.), while MSE (mean square error which is easy to calculate, but also has the disadvantages of being sensitive to outliers and unintuitive.) is used for the performance function.

The activation function employed is TANSIG (TANSIG is a commonly used function in the field of neural networks, representing the hyperbolic tangent sigmoid function. It is nonlinear, with an output range of -1 to 1), with the final layer utilizing PURELIN (PURELIN represents the linear transfer function and does not transform its input in a bounded or nonlinear manner. This linear function can be particularly useful in certain layers of a neural network, especially in regression tasks where the desired output is not necessarily constrained within specific values). During the network development, iterative testing revealed the optimal model configuration. This was achieved by setting the training data allocation at 75% and utilizing 5 hidden layers in the network, with an upper limit of 2000 epochs for training. The results of this rigorous analysis were compelling. The relative errors (RE) which It has the advantages of being independent of scale and easier to compare, but it also has the disadvantage that it is undefined when the true value is 0 and readers are easily misled observed for BOD, COD, DO, pH, and temperature stood at 7.80%, 6.33%, 6.83%, 1.92%, and 1.05% respectively, yielding an average RE of 4.79%. When the refined model was subsequently validated using datasets from the unused years, the overall RE was a closely matching 4.85%, reinforcing the model's accuracy and reliability.

ANNs are powerful computational models inspired by the structure and function of biological neural networks. One of their main strengths is their ability to model complex, nonlinear relationships between inputs and outputs. Given the right number of neurons and the appropriate architecture, ANNs can approximate virtually any continuous function to a high degree of accuracy. This flexibility is due to the network's ability to learn from data. As an ANN is exposed to training data, it adjusts its synaptic weights

– essentially the strength of connections between neurons, i.e., to minimize the difference between its predicted outputs and the actual outputs. This dynamic fine-tuning ensures that the network optimally represents the data it is trained on. Moreover, ANNs demonstrate a degree of robustness; even if some neurons in the network are malfunctioning or if the input data is noisy or imperfect, a well-trained ANN can still produce accurate outputs. However, ANNs are not a panacea. One of the key challenges with them is their "black box" nature. Once a network is trained, understanding, or explaining how it arrives at a particular decision can be incredibly difficult. This lack of interpretability can be a significant hindrance in situations where transparency and accountability are crucial. Another limitation is the data dependency. For an ANN to achieve its best performance, it often requires a vast amount of labeled training data, which might not always be available or feasible to obtain. Additionally, ANNs, particularly deep networks, can sometimes be prone to overfitting. This means they might perform exceptionally well on the training data but fail to generalize to new, unseen data.

3.2. ANFIS

Elkiran and his team, in a study showcased in the Journal of Hydrology, adeptly amalgamated the Backpropagation Neural System (BPNN), the Support Vector Framework (SVM), ANFIS, and the Linear ARIMA model, the researchers integrated three unique ensemble techniques. These methodologies comprise the straightforward average ensemble (SAE), the consideration-based average ensemble (WAE), and the ensemble with a neural network foundation (NNE). These varying methods offer diverse strategies for data processing and prediction, maximizing the potential for accurate outcomes, they crafted models predicting both short-term and extended periods for DO levels in India's Yamuna River. Against this backdrop, information related to DO, BOD, COD, Water Discharge (Q), pH levels, ammonia concentration (NH_3), and water's thermal readings (WT) were gathered from three separate locations. Specifically, the datasets from three key locations: Hazni Kund (SL1), Nizamuddin (SL2), and Udi (SL3), as meticulously documented by the Central Pollution Control Board, were harnessed for the study. These data sources provided a comprehensive view of the environmental conditions across different regions. The model's performance accuracy was determined using two methods: Determination Coefficient (DC) and Root Mean Square Error (RMSE). The computational results from individual models suggest that the precision effectiveness of the ANFIS approach surpasses the other three models, enhancing the average accuracy for SL1 and SL2 by 7% and 19% respectively. Fig. 1 offers a comprehensive visual representation, showcasing the overarching structure and components of an ANFIS [15]. If ‘x’ and ‘y’ serve as the entry and 'f' represents the output for an inference system based on fuzzy logic, The Sugeno type of first order adheres to these regulations. (Eqs. (1) and (2)).

$$if\ \mu(x)\ is\ A_1\ and\ \mu(y)\ is\ B_1: f_1 = p_1x + q_1y + r_1 \tag{1}$$

$$if\ \mu(x)\ is\ A_2\ and\ \mu(y)\ is\ B_2: f_2 = p_2x + q_2y + r_2 \tag{2}$$

For the specified inputs 'x' and 'y', the researchers denote the membership functions as A_1, B_1, A_2, B_2, The specifications for the outlet functions are p_1, q_1, r_1, p_2, q_2, r_2, The 5-layer ANFIS structure and layout are outlined as follows. The function for this layer, as described in Equation (3), represents an adaptive node i.

$$Q_i^1 = \mu_{Ai}(x)\ for\ i = 1,2\ orQ_i^1 = \mu_{Bi}(x)\ for\ i = 3,4 \tag{3}$$

Here, Q_i^1stands for membership grade for ‘x’ and ‘y’ inputs and The Gaussian membership function was chosen due to its effectiveness in minimizing errors during the forecast phase. Layer 2: Every input layer connects to an operator known as T-Norm, which is implemented using the 'AND' operator, as described in Eq. (4):

$$Q_i^2 = w_i = \mu_{Ai}(x).\quad \mu_{Bi}(y) for\ i = 1,2 \tag{4}$$

Layer 3: The final from this layer is known as 'Normalized firing strength', and every node is identified as 'Norm'.

$$Q_i^3 = \overline{w_i} = w_i/(w_1 + w_2) \quad i = 1, 2 \tag{5}$$

Layer 4: The subsequence rules are performed by each node as an adaptive node in this layer

$$Q_i^4 = \overline{w_i}(p_i x + q_i y + r_i) = \overline{w_i} f_i \tag{6}$$

The irregular parameters p_1, q_1 and r_1, are referred to as subsequent parameters. Layer 5: The overall final layers use Eq. (7) to calculate the product of each of the incoming transmissions.

$$Q_i^5 = \overline{w_i}(p_i x + q_i y + r_i) = \sum_i \overline{w_i} f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{7}$$

Continuing from the preceding discussion, it becomes evident that ANFIS boasts several notable advantages. Firstly, its adaptability stands out as a prominent feature, primarily because it possesses the capability to autonomously adjust its model parameters based on incoming data, rendering it suitable for a diverse array of data types and characteristics. Secondly, ANFIS exhibits a commendable proficiency in tackling challenges associated with uncertainty and fuzziness, thereby excelling in solving intricate real-world problems. What further sets it apart is its foundation in fuzzy logic, upon which ANFIS model rules are constructed. This foundation simplifies the interpretation and comprehension of the decision-making process, thus enabling its practical application across a myriad of domains, including but not limited to pattern recognition, control systems, and time series analysis. Nevertheless, it is important to acknowledge that the ANFIS model is not without its limitations. The processes of training and inference can prove to be rather intricate, particularly when confronted with large-scale datasets, necessitating substantial computational resources to execute effectively. Additionally, the model demands a significant volume of training data and features multiple hyperparameters that require fine-tuning—a task that has the potential to consume both time and resources when striving to optimize model performance. Furthermore, there are limitations regarding the breadth of application domains within which ANFIS can genuinely provide effective solutions.

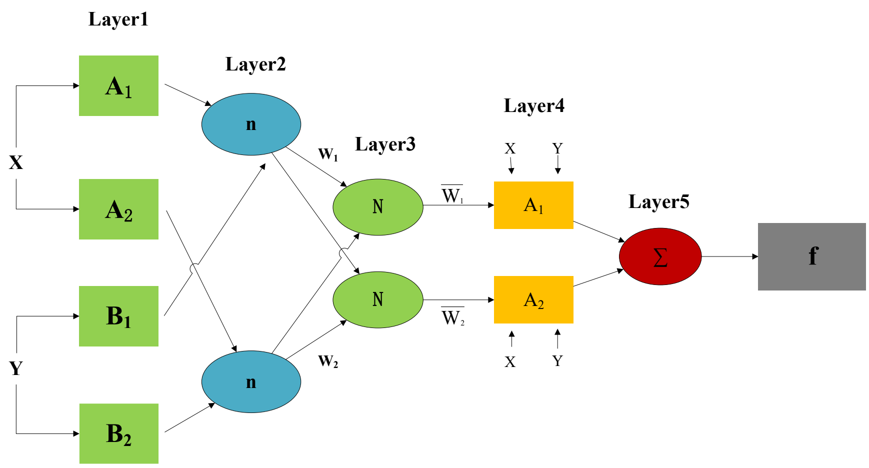

Figure 1. General structure of ANFIS [15].

3.3. MLPNN

In a comprehensive study spearheaded by Zhu and Heddam, the duo delved into the potential of nonlinear mathematical modeling. They introduced two groundbreaking models, namely the extreme learning machine (ELM) and the MLPNN. Their primary aim was to adeptly forecast the daily concentrations of DO in water bodies. To ensure the robustness of their research, data from four urban rivers was used by them, all strategically situated in the backwater regions of China's renowned Three Gorges Reservoir, a testament to the country's engineering prowess. The dataset they meticulously

DOI: 10.54254/2755-2721/53/20241344

analyzed contained not just any ordinary measurements, but detailed daily water quality assessments. These evaluations included rudimentary parameters like water temperature and pH levels. However, they also delved into more intricate indicators. These consisted of the permanganate index, which offers insights into the water's organic content; ammonia nitrogen levels, highlighting potential pollution sources; electrical conductivity, providing a glimpse into the mineral content of the water; the chemical oxygen demand, indicating the organic pollutant amount; total nitrogen and total phosphorus, which are essential for understanding nutrient loads; and, crucially, the DO (Dissolved Oxygen) levels, a key metric in assessing aquatic health. To thoroughly evaluate the efficiency and accuracy of their newly crafted ELM model, especially when pitted against the time-tested MLPNN, they turned to a set of robust error statistical metrics. This suite of tools comprised the root mean square error, which assesses the model's overall prediction error; the mean absolute error, a direct measure of prediction accuracy; the coefficient of correlation, determining the linear relationship between predicted and actual values; and, not to be overlooked, the Wilmott consistency index, a widely accepted metric for model consistency and reliability. Their in-depth analysis bore fruit, shedding light on some critical insights. Both ELM and MLPNN models showcased noteworthy performance, particularly in their predictions for the Wubu River. Similarly, the Yipin River data analysis reinforced the robustness of the models. The Huaxi River, however, presented a moderate performance output. Interestingly, the model's application on the tributaries of the Huaxi River didn't yield the expected results, indicating a performance that was below par. Delving deeper into their results, a pattern emerged. There was a pronounced inverse correlation between the accuracy of the model predictions and the pollution levels present in the respective rivers. It's worth emphasizing that in the specific task of forecasting DO concentrations, the MLPNN model demonstrated a marginal advantage over the ELM.

Typically, ANN models consist of three distinct layers. The primary entry layer, integrating the handpicked water quality metrics, serves as the foundational step for the DO model and is symbolized as x_i. The architecture might include one or more hidden layers that process and transmit the information. Culminating in the terminal layer, its primary role is to reflect the dependent variable. It translates to the concentration of DO, represented as y. When the linkage among the neurons is one-way, this specific type of ANN model is referred to as a feed-forward neural network (FFNN). In the MLPNN model structure, the neurons located within the hidden layers are pivotal. These neurons fulfill two primary responsibilities. Firstly, they capture and process signals from the input layers, represented by the xi variables. The processing involves computing a scaled combination where each input parameter (x_i) is multiplied by a corresponding weight factor (w_i). To this result, a bias term (δ_i) is added. Secondly, after determining this sum, it is then channeled through an activation function, ensuring that the outcome is forwarded to the neural unit of the subsequent layer. The singular neural unit found in the final layer functions similarly to the neural unit in the intermediate layer. However, its triggering mechanism is predominantly linear or identity. The exact count of neural units in the hidden layer is typically arrived at through an iterative process of experimentation. A pivotal challenge is identifying the optimal collection of weight values and bias values for the MLPNN framework, which is accomplished using the backpropagation (BP) algorithm:

$$Y = f_2\left[\sum_{j=1}^{n} w_{jk}\left[f_1\left(\sum_{j=1}^{n} x_i w_{ij} + \delta_j\right)\right] + \delta_0\right] \tag{8}$$

where, x_i denotes the input parameter. w_{ij} signifies the weight connecting input i and concealed neural unit j. δ_j represents the bias associated with concealed neural unit j. The sigmoidal activation function is given by f_1 and can be seen in Equation (9). The weight linking neuron j within the intermediate layer to the singular neural unit k in the final layer is represented by w_{jk}. $\delta_0$is the bias related to the output neural units k and $f_2$stands for a straight-line triggering mechanism specific to the neural unit present the final layer.

$$f_1(x) = \frac{1}{1+e^{-x}} \tag{9}$$

An MLPNN that incorporates a single interior layer has 'n' neural units, while its output layer contains just one neural unit, as illustrated in Fig. 2 [6]. Moreover, MLPNN boasts a multi-layered architecture comprised of nonlinear processing units, a characteristic that proves highly effective in capturing and modeling intricate nonlinear relationships. Its versatility extends across a broad spectrum of tasks, encompassing classification, regression, pattern recognition, and function approximation. This adaptability is a result of its innate capacity to autonomously discern and extract crucial features from input data. Additionally, MLPNN leverages parallel computing across multiple processing units, a feature that significantly enhances both training speed and overall performance. Nonetheless, it is important to acknowledge the inherent limitations of MLPNN. First and foremost, optimal performance often necessitates copious amounts of data, rendering it less suitable for scenarios with limited datasets. Moreover, the susceptibility to overfitting poses a constant challenge, requiring vigilant regularization techniques. Additionally, the training process can be protracted and potentially unstable, demanding substantial computational resources. Furthermore, the opaqueness of the model's internal operations can hinder interpretability, making it challenging to elucidate its decision-making process. In the context of high-concentration polluted water data, these limitations become particularly pronounced. The intricate and nuanced nature of water quality data demands more robust and explainable models to ensure accurate handling and informed decision-making.

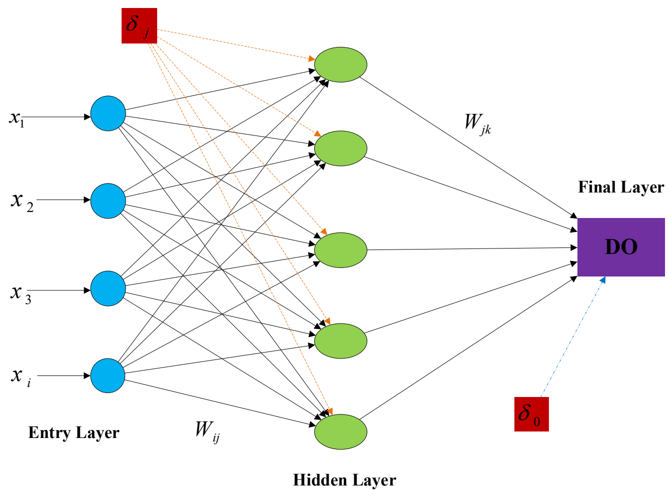

Figure 2. MLPNN architecture [6]

4. Limitations and outlooks

To offer an all-encompassing perspective, it's essential to acknowledge that the three machine learning models we've delved into each possess distinct strengths and weaknesses. First and foremost, ANN model, while undeniably robust in its overall performance, isn't without its areas of potential improvement. Notably, it exhibits room for enhancement, especially concerning its precision in the domain of water quality surveillance. While it's undoubtedly a powerful tool, fine-tuning its accuracy in this specific context could make it an even more formidable asset. On the flip side, ANFIS model, although quite capable, does occasionally face limitations in terms of reliability, particularly when compared to the SVM model. This occasional shortfall in reliability becomes evident in certain situations and scenarios. Therefore, while ANFIS has its strengths, there's a need for a careful consideration of its deployment in specific circumstances to ensure optimal results. Lastly, MPLNN model displays impressive versatility, particularly in the context of monitoring DO levels in relatively unpolluted rivers. Its ability to handle such scenarios with minimal pollution is noteworthy. However, it's important to recognize that its effectiveness may come under scrutiny when applied to the modeling of DO levels in water bodies suffering from severe pollution. This implies that the choice of model should align with the specific environmental conditions and challenges posed by the task at hand. In conclusion, while each of these machine learning models brings unique strengths to the table, a comprehensive understanding of their strengths and limitations is crucial when deciding on the most appropriate model for a given application in the realm of water quality assessment. As a result, future applications of large-scale data technology within the realm of water quality monitoring ought to give primary attention to the refinement of the fundamental algorithms employed by machine learning models. Moreover, there exists ample opportunity for improvement in data acquisition methodologies. To illustrate, the data regarding water quality, gathered through monitoring instruments, can be systematically archived within databases, subsequently serving as an automated input to these algorithmic models. Through the integration of detection mechanisms, data gathering procedures, data analysis processes, and model advancement within a unified system, the efficiency of water quality monitoring can be substantially elevated.

5. Conclusion

To sum up, the integration of big data analysis techniques into various sectors of human life and production has marked a transformative shift. This incorporation has resulted in a notable increase in the efficiency and accuracy with which tasks are executed. Particularly, the realm of environmental conservation, specifically water pollution monitoring, has benefited significantly. The employment of machine learning models like ANN, MPLNN, and ANFIS has offered invaluable technical support, making it easier for researchers to gather data and for governmental bodies to make informed decisions. These machine learning models have the capability to continuously monitor and predict potential surges in water pollution levels, ensuring that timely interventions can be deployed to safeguard or enhance aquatic ecosystems. Nonetheless, it's vital to recognize that the journey of perfecting these big data techniques is ongoing. Some models, under circumstances of extreme pollution, might not yield the desired accuracy. Another challenge is the need for a more cohesive system, where monitoring, prediction, and actionable interventions are harmoniously integrated. The essence of this study, therefore, is not just to highlight the strides made but also to underscore areas ripe for innovation. In essence, while we've made commendable progress in harnessing big data for water pollution monitoring, there's still a significant distance to cover in fully actualizing its potential.

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