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Article

Application of biomechanics and deep learning models in water quality monitoring

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Abstract: This paper reviews the application of biomechanics and deep learning models in water quality monitoring, highlighting their potential to enhance the accuracy and efficiency of environmental pollution detection and prediction. Traditional water quality monitoring methods are difficult to deal with nonlinear and dynamic pollution data. This article reviews the fusion application of biomechanical models and deep learning (such as convolutional neural network (CNN), long short-term memory (LSTM)), and proves that it significantly improves monitoring accuracy (an average of 20% in cases) by simulating pollutant diffusion mechanisms (biomechanics) and mining complex data patterns (deep learning). In the future, it is necessary to establish an interdisciplinary collaboration framework to promote the deployment of lightweight models in real-time systems.

Keywords: biomechanics; deep learning; water quality monitoring

1. Introduction

Water resources are essential for human survival and socio-economic development, yet they are increasingly threatened by pollution from various sources, including industrial discharges, agricultural runoff, and urban activities. Accurate and timely monitoring of water quality is crucial for effective environmental management and public health protection. Traditional water quality monitoring methods, which rely heavily on manual sampling and laboratory analysis, are often time-consuming and unable to provide real-time data. Moreover, these methods struggle to capture the complex dynamics of pollutant distribution and transformation in water bodies.

In recent years, the rapid development of deep learning and biomechanics has opened new avenues for water quality monitoring [1–5]. Deep learning, a subset of artificial intelligence, mimics the human brain's neural networks to analyze and learn from vast amounts of data, enabling the identification of complex patterns and relationships. Techniques such as convolutional neural network (CNNs), recurrent neural network (RNNs), and long short-term memory (LSTMs) have shown promise in handling the non-linear and temporal characteristics of water quality data [6–8]. Meanwhile, biomechanics algorithms, which simulate the movement and mechanical properties of living organisms, offer unique insights into the diffusion and transport processes of pollutants in water. By integrating these two fields, researchers can develop more robust and accurate models for predicting water quality and identifying pollution sources [9].

This paper aims to provide a comprehensive review of the application of biomechanics and deep learning models in water quality monitoring. It discusses the advantages of these integrated approaches over traditional methods, highlights key research findings, and explores the challenges and future directions in this field. The review emphasizes the importance of multidisciplinary integration, model optimization, and data fusion in advancing water quality prediction and monitoring technologies. Ultimately, the application of these innovative methods holds significant potential for improving environmental decision-making and supporting sustainable water resource management. This paper reviews the application of biomechanics algorithms and deep learning models in water quality prediction, discusses key technologies such as multidisciplinary integration, model optimization, and data fusion, and looks forward to future research directions.

2. Application of deep learning in water quality monitoring

Deep learning is a type of machine learning that mimics the neural networks of the human brain, analyzing and learning from large amounts of data to identify and classify complex patterns. The application of deep learning in water quality monitoring can be divided into two aspects: First, using deep learning methods to analyze data from monitoring systems for pollution sources and regional water quality, in order to provide more accurate water quality data for governments and environmental protection agencies. Second, using deep learning methods to analyze environmental data and establish predictive models for environmental monitoring, in order to provide decision-makers with information about water quality [10,11].

In previous studies, deep learning has included: recurrent neural network (RNN), convolutional neural network (CNN), autoencoder, long short-term memory (LSTM), deep belief network (DBN), gated recurrent unit (GRU), generative adversarial network (GAN), and transformer. The characteristics of each method are as follows: CNN is very suitable for spatial analysis tasks such as image data processing, while RNN, LSTM, GRU, and transformer are more suitable for sequential tasks such as time series prediction. DBN can be used for feature extraction, for example, to identify commonalities between water bodies or water quality patterns. Transformer and GAN can generate realistic complex data, such as images and parameter maps, and can also automatically detect anomalies, such as pollution events in water supply networks. From 2021 to 2023, it was found that the emergence of water quality databases such as GEMStat, the Global Rivers Chemistry (GLORICH) database, the Surface Water Chemistry (SWatCh) database, the Global Rivers Water Quality Archive (GRQA), and the application of water quality chemical analysis have accelerated the application of deep learning in water quality [12–15].

2.1. Application of deep learning in water quality monitoring

Deep learning has an advantage over traditional methods in capturing complex patterns in data. In water quality monitoring, the data from monitoring equipment usually contains complex, non-linear data structures. Using deep learning methods can better solve the modeling problems of these data. For example, Wang et al. [16] used a deep convolutional neural network (DCNN) to analyze the chemical composition of water quality and pollution sources. To train the DCNN, researchers first used factor analysis on the data set to obtain different models of water quality components. Then, researchers used the structural similarity index to compare the results obtained from the DCNN with the actual water pollution data. The accuracy of the DCNN model is very high, indicating that the DCNN can efficiently process this complex monitoring data.

Using deep learning methods to establish environmental monitoring predictive models can predict future pollution situations. For example, Song et al. used a deep recurrent neural network (DRNN) to predict the concentrations of PM2.5 and PM10 in the Beijing-Tianjin-Hebei region. This study used the monitoring data from the previous day as part of the predictive model. It was found that the prediction accuracy of the DRNN model is much higher than other common methods. In addition, researchers also found that neural network models have the characteristic of adaptability in a short time, so they can be used to predict future pollution situations. Kong et al. proposed CNN-LSTM-Attention (CLATT), an attention-based effluent wastewater quality prediction model, which uses a convolutional neural network (CNN) as an encoder and a long short-term memory network (LSTM) as a decoder (**Figure 1**).

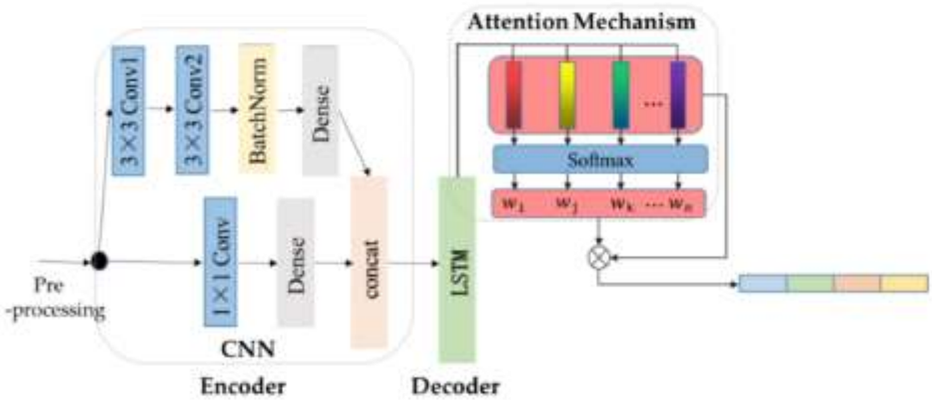


Figure 1. Overview of the proposed method called CLATT.

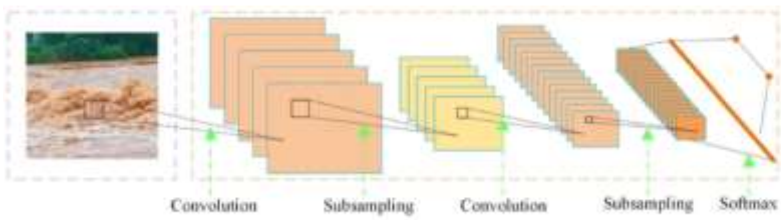
It receives a sequence of wastewater quality indicators taken from real-world wastewater treatment plants. The encoder is formed of a CNN module with a residual block. A standard LSTM module is regarded as a decoder. The attention mechanism module is used to integrate information and make predictions.

Significant progress has been made in the application of deep learning models in water quality prediction. Compared with traditional statistical methods, deep learning models are better able to handle the time-series and non-linear characteristics of water quality data, thereby improving prediction accuracy. For example, Zhang et al. showed that a hybrid model based on convolutional neural network (CNN) and long short-term memory network (LSTM) performed well in water quality prediction. In addition, some studies have proposed deep learning models combined with attention mechanisms, which further improve the accuracy and reliability of predictions. **Table 1** compares the CNN and LSTM models from four dimensions: method, data, scenario, and effect.

Table 1. Comparison of applications of deep learning models in water quality monitoring.

Model Type	Data Source	Application Scenario	Accuracy Improvement	Limitations
CNN	Chemical composition spectral data	Pollution source identification	92%	Rely on high-resolution input
LSTM	Time series sensor data	PM2.5 prediction	15% better than ARIMA	High computational complexity

In deep learning, convolutional neural networks are a class of artificial neural networks, which belong to the feedforward neural networks [13,14]. Moreover, CNNs stand out as prominent algorithms within the domain of deep learning [15], recognized for their shift-invariant or spatially invariant nature. A convolutional neural network usually consists of the following layers: the convolutional layer (Convolution Operation), the pooling layer (Subsampling Operation), and the fully connected layer (SoftMax Operation), as shown in **Figure 2a**. The convolutional neural network model was proposed by Yann Lecun of New York University in 1998 (LeNet-5), and fundamentally operates as a multi-layer perceptual machine. The success of convolutional neural networks can be attributed to their utilization of local connectivity and weight sharing. This approach not only decreases the number of weights, simplifying network optimization, but also reduces the model's complexity and the likelihood of overfitting. Recurrent neural networks are a class of recurrent neural networks designed to process sequence data. In an RNN, information cycles through the network in a sequential manner, with each node (referred to as a recurrent unit) connected in a chain. This architecture is grounded in the notion that "human cognition relies on past experiences and memories". The basic layers of an RNN include input, hidden, and output layers, as shown in **Figure 2b**. Due to their recursive structure, recurrent neural networks are adept at addressing sequence modeling challenges and find utility across diverse domains, including text generation, machine translation, and image captioning [16,17].



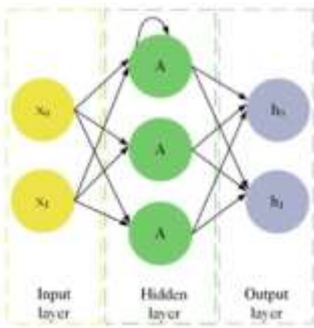


Figure 2. Structural diagrams of a CNN and an RNN: **(a)** CNN; **(b)** RNN.

3. Application of biomechanics algorithms in water quality prediction

Biomechanics algorithms, by simulating the movement and mechanical properties of living organisms, offer a new perspective for water quality prediction. These algorithms can simulate the diffusion process of pollutants in water bodies, thereby improving the accuracy of predictions. For example, Güldal et al. [18] used a biomechanics model to simulate the diffusion process of pollutants in water bodies. Through a data-driven approach, important features in the data are automatically extracted, and then validated and corrected using mechanical models. Like deep learning, biomechanics models simulate the human perception of data, thus being able to handle large amounts of complex data. With the support of molecular mechanics models, the simulation and prediction of water quality can become more convenient and accurate, which is very important for pollution prevention and control work [19–20].

3.1. Using biomechanics to analyze water quality

Using biomechanics models to analyze pollution sources is an effective method to better solve complex problems. For example, Wang et al. [21] used a method based on neural network models to identify and classify particulate pollutant sources from mobile and stationary sources. Researchers first used a generalized linear model (GLM) to conduct a preliminary analysis of the data. Then, they established a neural network-based classifier to extract more features and information from the data, in order to better identify mobile and stationary sources [22–25]. The study shows that biomechanics models are one of the effective methods for analyzing water quality pollution sources.

Molecular biology-based water quality monitoring methods mainly include PCR technology, FISH technology, and NGS technology. Li et al. [5,6] used these technologies to quickly detect pathogens, bacteria, and viruses in water samples, as well as potential microbial pathogens in water bodies.

PCR technology: Can quickly detect pathogens, bacteria, and viruses in water samples.

FISH technology: Can perform molecular hybridization detection for different target DNAs, achieving online detection of specific populations.

NGS technology: Can comprehensively detect various microorganisms in water samples, achieving a comprehensive analysis of the microbial community in water bodies.

3.2. Using biomechanics models to establish water quality monitoring predictive models

Biological monitoring methods have advantages such as sensitivity, stability, diversity, and long-term effectiveness, and can directly and effectively reflect the ecological risks faced by the water environment. Biological monitoring methods include monitoring of microorganisms, phytoplankton， zooplankton, periphyton, higher aquatic plants, and fish [26,27]. In addition to deep learning methods, biomechanics models can also be used to establish predictive models for water quality monitoring. For example, Yuan et al. used a method based on biomechanics models to predict the concentration of gaseous pollutants. Researchers collected a large amount of water quality and soil data in Wuhan, Guangzhou, and Changsha, and used biomechanics models to predict future water pollution concentrations. The results show that biomechanics models can accurately predict future water quality conditions.

4. Multimodal data analysis combined with deep learning

Multidisciplinary integration is the key to improving the accuracy of water quality prediction. Combining methods from biomechanics, physics, and chemistry can develop more comprehensive water quality prediction models. For example, a review of the research on urban water supply network water quality monitoring systems from a multidisciplinary perspective shows that the cross-integration of environmental science, computer science, materials science, and hydraulic engineering helps to promote technological innovation and progress in water supply network water quality monitoring systems. Multimodal data analysis tools used to predict the structure, dynamics, and function of biomolecules can be combined with physics-based methods, which can not only find solutions but also understand the relevant mechanisms [28,29]. In May 2021, a review article on biomolecular modeling was published in the Nature sub-journal Nat Comput Sci. The authors proposed that the combination of physics-based and knowledge-based methods may be the most effective.

4.1. Biomechanics algorithms can be combined with deep learning models

Biomechanics algorithms can be combined with deep learning models, using the powerful data analysis capabilities of deep learning to handle complex water quality data. This combination not only improves the accuracy of predictions but also effectively handles multimodal data in water quality monitoring. For example, a study on deep learning-based water quality prediction shows that hybrid models perform better than traditional models in handling complex water quality data [30]. At the same time, Chen et al. cleaned and denoised the water quality data of Huangyang Reservoir using wavelet transform, and established time series datasets for DO, pH, and TB concentrations using deep learning models and biomechanics models. Denoising the water quality data of Huangyang Reservoir using wavelet transform effectively reduced the noise in the data. The denoised dataset was then normalized, and the normalized dataset was divided into training, testing, and validation sets in a 7:2:1 ratio. Combining real-time monitoring data, historical data analysis, and water quality model predictions can help managers better understand the trends in reservoir water quality changes and take control measures in a timely manner [31,32].

4.2. Model optimization and future development directions

Currently, there are still some challenges in the application of water quality monitoring. First is the data quality issue. Since environmental monitoring data sampling and collection may be disturbed by various factors, there may be certain uncertainties and biases in the data quality. Therefore, how to process and correct the noise and errors in the data is an important direction in data analysis research. At the same time, the characteristics of biomechanics and deep learning models, combined with each other, play to the advantages of each data monitoring method.

Model optimization and data fusion are important means to improve the efficiency of water quality prediction. In recent years, the structure and parameters of deep learning models have been continuously optimized to improve the efficiency and robustness of the models. At the same time, by integrating multi-source data, such as satellite remote sensing data and ground monitoring data, the accuracy and reliability of water quality prediction can be improved. Although biomechanics algorithms and deep learning models have achieved significant results in water quality prediction, there are still some limitations. Future research directions include:

Multidisciplinary integration: Combining methods from biomechanics, physics, and chemistry to develop more comprehensive water quality prediction models. The combination of biomechanics algorithms and machine learning technologies will become an important direction for future development. Machine learning technologies can process large amounts of water quality data and automatically extract important features from the data, thereby improving the accuracy and efficiency of predictions [33,34].

Model optimization: Further optimize the structure and parameters of deep learning models to improve their efficiency and robustness. Future research will increasingly adopt multiscale modeling methods, combining quantum mechanics/molecular mechanics (QM/MM) methods to achieve multiscale simulations from the microscopic to the macroscopic level, thereby more comprehensively understanding the mechanisms of water quality changes.

Data fusion: Use multi-source data, such as satellite remote sensing data and ground monitoring data, to improve the accuracy and reliability of water quality prediction. Combining real-time monitoring data, biomechanics algorithms can be used for real-time water quality prediction and early warning systems, to timely detect water quality abnormalities and take corresponding measures.

5. Discussion

In the face of escalating environmental challenges, the integration of biomechanics and deep learning models in water quality monitoring has emerged as a transformative approach, offering unprecedented capabilities for the detection, prediction, and management of water pollution. This paper has reviewed the application of these advanced techniques, highlighting their potential to revolutionize traditional water quality monitoring practices and enhance environmental decision-making processes.

6. Significance of biomechanics and deep learning integration

The combination of biomechanics and deep learning models has proven to be highly effective in addressing the complexities of water quality monitoring. Biomechanics algorithms, by simulating the movement and mechanical properties of pollutants in water bodies, provide a detailed understanding of how contaminants spread and interact within aquatic environments. This mechanistic insight complements the data-driven capabilities of deep learning models, which excel at identifying intricate patterns and relationships within large datasets. Together, these approaches offer a more comprehensive and accurate framework for predicting water quality and identifying pollution sources.

Deep learning models, such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, have demonstrated remarkable performance in handling the non-linear and temporal characteristics of water quality data. These models can process vast amounts of data quickly and efficiently, providing real-time predictions and alerts. The integration of attention mechanisms further enhances their accuracy and reliability, allowing for more precise identification of critical factors influencing water quality.

7. Multidisciplinary integration and model optimization

The success of these integrated approaches underscores the importance of multidisciplinary integration. Combining knowledge from fields such as biomechanics, physics, chemistry, and computer science allows for the development of more sophisticated and robust models. This cross-disciplinary approach not only improves the accuracy of water quality predictions but also provides deeper insights into the underlying mechanisms of pollution dynamics.

Model optimization and data fusion are also critical factors in enhancing the efficiency and reliability of these models. Continuous advancements in deep learning architectures, such as the development of hybrid models and the incorporation of transfer learning, have significantly improved model performance. Additionally, the integration of multi-source data, including satellite imagery, ground monitoring data, and historical records, enriches the dataset and enhances the models' predictive capabilities.

8. Future research directions

Despite the significant progress made in recent years, several challenges remain. One of the primary challenges is ensuring data quality and availability. Environmental monitoring data can be noisy and incomplete, which can affect the accuracy of predictions. Future research should focus on developing robust data preprocessing techniques to handle these issues effectively.

Another area of focus should be the further optimization of deep learning models. While current models have shown promising results, there is still room for improvement in terms of computational efficiency and interpretability. The development of more efficient algorithms and the integration of explainable AI techniques will be crucial in making these models more accessible and usable for stakeholders.

The application of these technologies in real-time monitoring systems is another important direction for future research. Real-time data collection and analysis can provide immediate insights into water quality conditions, enabling timely interventions and preventing potential environmental disasters. The development of portable and affordable sensors, combined with advanced data analytics, will be essential in achieving this goal.

Finally, the integration of these technologies with other environmental management tools, such as decision support systems and policy frameworks, will be vital in translating research findings into actionable strategies. Collaboration between researchers, policymakers, and industry stakeholders will be necessary to ensure that these advanced techniques are effectively implemented and contribute to sustainable water resource management.

Future research should focus on combining lightweight models with edge computing to reduce the hardware cost of real-time monitoring systems. In addition, establishing a standardized water quality database and opening it up for sharing can promote the generalization of models across regions. It is recommended that the government and enterprises cooperate in a pilot project to embed deep learning models into existing monitoring equipment and verify their stability in actual scenarios.

9. Conclusion

In conclusion, the application of biomechanics and deep learning models in water quality monitoring represents a significant advancement in environmental science and engineering. These integrated approaches offer powerful tools for improving the accuracy and efficiency of water quality predictions, identifying pollution sources, and supporting environmental decision-making. While challenges remain, ongoing research and technological advancements hold great promise for the future of water quality monitoring. By continuing to explore and refine these innovative methods, we can better protect our water resources and ensure a sustainable future for all. It is recommended to incorporate hybrid models into national water quality monitoring standards and encourage multi-source data sharing through legislation to solve the problem of data silos.

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