Book Chapter

Application of Artificial Intelligence in the Management of Coagulation-Flocculation Process

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Abstract

In this paper, the application of artificial intelligence, especially neural networks, in the field of water treatment is comprehensively reviewed, with emphasis on water quality prediction and chemical dosage optimization. It begins with an overview of machine learning and deep learning concepts relevant to water treatment. Key advances and challenges in using neural networks for coagulation processes are thoroughly analyzed, including the automation of coagulant dosing, dosage level optimization, and efficiency comparisons of modeling approaches. Applications of neural networks in predicting pollutant levels and supporting water quality monitoring are explored. The review identifies avenues for improving coagulation-based modeling with neural networks, such as enhancing data quality, employing feature engineering, refining model selection criteria, and improving cross-validation methods. The necessity of continuous monitoring and adaptive optimization strategies is emphasized. Challenges such as the complexity of coagulation processes, feedback control signal acquisition, and model adaptability from simulations to real-world settings are discussed. Cost control and resource management in water treatment are also highlighted, emphasizing the optimized chemical dosage to reduce expenses while maintaining water quality compliance. In summary, this review provides valuable insights into the current state of neural network applications in water treatment and highlights key areas for further research and development. Integrating AI into coagulation processes has the potential to enhance the efficiency and sustainability of drinking water treatment.

Keywords:

Drinking Water; Coagulant; Artificial Intelligence; Neural Networks; Deep Learning; Transfer Learning

Abbreviations

AI-Artificial Intelligence; ANN-Artificial Neural Network; FNN-Feed Forward Neural Network; RNN-Recurrent Neural Network; CNN-Convolutional Neural Network; MLP-Multi-layer Perceptron; BP-Back Propagation; ANFIS-Artificial Fuzzy Neural Network; RBF-Radial Basis Function; RBNN-Radial Basis Neural Network; MMPC-Multi-Model Predictive Control; LSTM-Long Short-Term Memory; PSO-Particle Swarm Optimization; DCNN-Deep Convolution Neural Network; RSM-Response Surface Methodology; ENN-Edited Nearest Neighbors

1. Introduction

With the rapid development of the information age, AI, as a cutting-edge technology, is profoundly changing our life and work with its unlimited potential and diverse applications. From healthcare to finance, from transportation to entertainment, AI is demonstrating amazing innovation and impact in various fields. Its excellent self-learning and adaptive ability enables it to handle complex tasks and large-scale data, thus achieving remarkable results in prediction, classification, optimization, and other tasks. However, in this wave of advances in AI, few areas are in as urgent need of technical support as water treatment [1]. Since its inception, drinking water treatment has remained a primary focus of the water industry [2,3]; ensuring that our drinking water remains uncontaminated is a focal point of natural and urban water systems, carrying significant social responsibility [4,5]. Traditional drinking water treatment processes, including coagulation, sedimentation, filtration, and disinfection, have been widely employed since the early 20th century and have remained effective water treatment technologies [5-7]. However, excess nutrient runoff from agricultural land around the world has adversely affected water bodies, primarily through the presence of excess fertilizers, including nitrogen and phosphorus. In addition, it has been observed that increased pollution loads from pharmaceuticals, dyes, pesticides, heavy metals, microplastics, and other pollutants in industrial wastewater exacerbate the pollution burden of aquatic ecosystems [8]. With the rapid economic growth and the enhancement of societal productivity, the extensive consumption of products has inevitably led to lax control over pollutants, resulting in water pollution. The most significant issue is that the persistent presence of pollutants in drinking water poses risks to human health [9-12]. Furthermore, the widespread increase in water consumption or the decline in water quality increases the consumption of pollutant capacity. Additionally, dosages and energy consumption are bound to increase, leading to economic demands [13,14]. Therefore, in order to promote the efficient operation and management of drinking water and maintain the safety of water quality, smart technology opportunities for drinking water or wastewater treatment plants are becoming increasingly urgent [5,15,16]. In this context, the application of AI is gradually permeating all stages of water treatment, providing new possibilities for improving treatment efficiency, optimizing resource utilization, and solving complex problems [17]. Artificial intelligence neural networks are used in various fields with powerful capabilities, such as predicting the amount of water produced by water treatment plants [18], forecasting drinking water quality deterioration[19], predicting oxidant demand in water treatment plants [20], anticipating disinfection byproduct formation in drinking water[21], evaluating pressure gradients in oil–water pipelines [22], assessing pollutant treatment [23,24], and forecasting residual chlorine levels in wastewater [25]. At present, in the realm of coagulation water quality prediction, the combination of artificial intelligence and models breaks the limitation of traditional forecasting methods. Through leveraging extensive data and complex algorithms, it efficiently predicts the concentration of organic substances [18]. This precise predictive capability empowers decision-making in water treatment plants, optimizing operational strategies during the coagulation phase and enhancing water quality treatment effectiveness. On the other hand, in automatic dosing prediction, the integration of artificial intelligence and models enables water treatment systems to automatically predict the appropriate dosages based on real-time data and complex variables [26]. This greatly enhances the automation level of water treatment systems, reduces the need for manual intervention, and improves dosing accuracy, better addressing water quality fluctuations and changes.

Despite the progress made in applying AI to water treatment, a significant gap remains in the existing research—particularly concerning the integration of AI for pollutant prediction and dosing control during the coagulation phase in drinking water treatment. This review aims to address this gap by examining both the practical applications and theoretical foundations of AI in these critical areas. The focus is on predicting organic substance concentrations during coagulation and optimizing dosages in automatic dosing systems. This field is highly scrutinized and urgently requires innovation, as it directly impacts public health, resource management, and environmental preservation.

Through a comprehensive examination of the both practical applications and theoretical foundations of artificial intelligence (AI) in coagulation water quality prediction and dosing prediction, this review paper underscores the profound impact these advancements have had on the water treatment sector. This exploration fosters technological advancements in water treatment, while simultaneously providing novel perspectives and strategies to tackle pressing challenges in environmental protection and resource management. Figure 1 presents a straightforward approach to managing water treatment engineering systems, such as chemical dosing, leveraging AI technology. This framework illustrates how AI can streamline processes, enhance efficiency, and ultimately contribute to more sustainable water management practices. The system combines empirical data processing with AI-based image analysis to create an intelligent coagulant dosing control solution. In terms of empirical data processing, the system monitors parameters such as coagulant type, dosage, mixing time, settling time, pH, turbidity, and temperature, allowing it to accurately track water quality changes. Based on these data, the system monitors suspension turbidity and energy consumption, enhancing data quality and providing early warnings for potential water quality issues, thereby improving the effectiveness of water treatment.

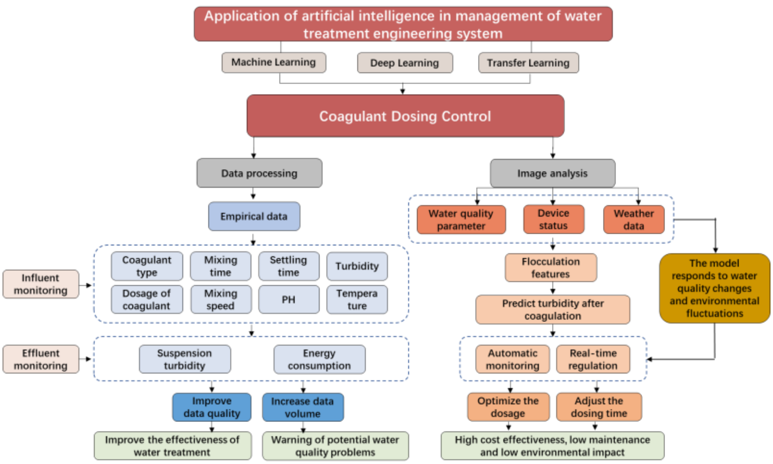


Figure 1: Research route (e.g., chemical dosing).

2. Concepts and Principles

AI is a discipline dedicated to enabling computer systems to mimic human intelligent behavior. It encompasses technologies such as machine learning, deep learning, and transfer learning that allow algorithms to learn, infer, and perform tasks from data. Machine learning is the core of AI, which enables computers to continuously optimize models with numerous data, thereby enhancing their performance in specific tasks. Deep learning is a subset of machine learning that simulates the structure of neurons in the human brain to efficiently process and analyze complex data through hierarchical processing and feature extraction. In the field of water treatment, AI technologies offer new ideas and methods for tackling complex prediction and optimization problems.

2.1. Machine Learning

Machine learning is a subfield of artificial intelligence that employs statistical and computer science methods to enable computer systems to learn from and improve with data. The goal of machine learning is to automatically learn and perform tasks such as prediction, classification, recognition, and clustering, by analyzing and understanding patterns and structures within data. It achieves this by learning patterns and structures from vast amounts of data, automatically adjusting and improving models to adapt to different data and tasks. Machine learning involves manually identifying data types, encoding application-specific data features, and then applying computer-based learning analysis [27]. During the training process, model parameters are adjusted, and the trained model is evaluated using metrics like accuracy, recall, F1-score, etc., to optimize the model for subsequent tasks.

Machine learning can be divided into three types by analyzing the unresolved problems and the available effective data—supervised learning, unsupervised learning, and reinforcement learning [28]. Supervised learning refers to training a model using pre-labeled data (the correspondence between input and output) and then using it to predict the output for new unlabeled data. Common supervised learning algorithms include linear regression, logistic regression, decision trees, etc. Seppo Linnainmaa introduced the "automatic differentiation of reverse mode" in 1970, which is a form of the backpropagation (BP) algorithm [29]. In 1995, Vapnik and Cortes introduced the support vector machine (SVM), which produces precise results [30]. In 1997, Freund and Schapire developed weak classifier ensembles, integrating multiple decision trees, each created from a random subset, called the Random Forest (RF) algorithm [31], known for its improved stability [32]. Unsupervised learning involves modeling and analyzing unlabeled data to discover hidden structures and patterns within these data. Prominent unsupervised learning techniques encompass clustering algorithms for grouping data, dimensionality reduction methods for simplifying data complexity, and association rule mining for discovering patterns, among others. Reinforcement learning involves learning through interaction with the environment, optimizing decision strategies through trial and error and reward mechanisms. Common reinforcement learning algorithms include Q-learning, deep reinforcement learning, and others.

2.2. Deep Learning

Deep learning is a method within machine learning that utilizes multi-layer neural network models to learn and extract features from data. Deep learning employs a cascade of layers with non-linear processing units for feature extraction and transformation [33, 34]. Data input progresses from lower layers, where simple features are gradually learned, to higher layers, where more complex features are derived, creating a hierarchical and powerful feature representation. This makes deep learning well-suited for analyzing and extracting valuable information from large and diverse datasets. In comparison to traditional machine learning, it offers several advantages [35-37]: the selection of features does not require manual extraction, as the machine autonomously extracts them; it exhibits sparse interactions, parameter sharing, and equivariant representations, resulting in fewer learned network parameters; and it leverages transfer learning principles, enabling the transfer of knowledge from the source task to the target task with limited labeled data, as shown in Figure 2. Overall, water systems encompass a vast array of objects characterized by intricate features, often posing challenges for precise identification and straightforward calculations. Deep learning offers a solution to tackle this intricate issue.

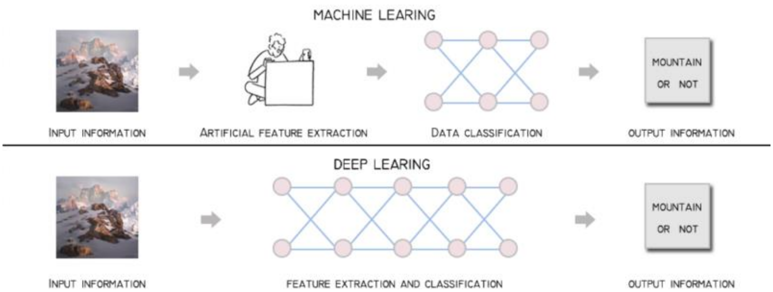


Figure 2: Machine learning vs. deep learning.

Deep learning systems outperform traditional machine learning systems in areas such as image processing, computer vision, and pattern recognition [32]. The model principle of image analysis and processing based on a CNN is shown in Figure 3. The principle of matrix and number variation in the figure embodies the core step of convolutional neural networks (CNN) in processing image data. In the convolutional layer, the filter slides over a 3x3 input matrix to perform weighted summation operations on each local region. The pooling layer further compresses the feature map through operations (such as maximum pooling or average pooling), selecting the maximum or average value in a local area as the output. The pooled eigenmatrix is flattened into a one-dimensional vector and input to the fully connected layer. The fully connected layer further processes the flattened features and generates the final classification or prediction results by assigning different weights and biases. The changes of these matrices and numbers reflect the process of extracting and transforming image features layer by layer in CNN, from the original input to the final output, to realize the step-by-step abstraction and recognition of complex image data.

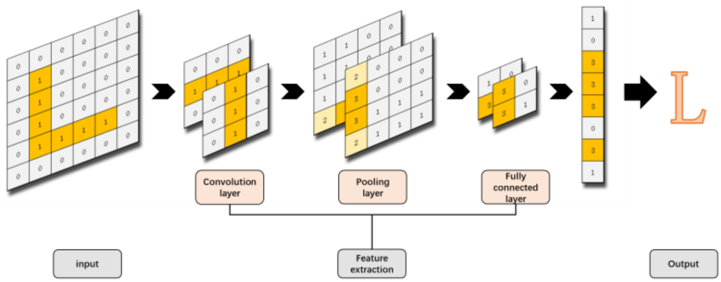


Figure 3: A simple flow chart for the principle of convolutional neural network (CNN).

Among all categories of neural network models based on network structure, the most fundamental main categories are feed-forward neural networks (FNNs) [38], recurrent neural networks (RNNs) [39], and convolutional neural networks (CNNs) [40]. These three models serve as the foundation for most neural network models, with other neural network models being improvements and extensions of them. For instance, the Deep Belief Network is an enhancement based on the feed-forward neural network, the Long Short-Term Memory Recurrent Neural Network is an improvement on the recurrent neural network, and the Deep Convolutional Generative Adversarial Network is an advancement based on the convolutional neural network. The deep neural network architecture invented by Goodfellow in 2014 [32] has also been influential. Common categories and characteristics of neural network models are presented in Table 1.

Table 1: Common category and characteristics of neural network models.

Category	Network Structure	Representative Models	Pros and Cons	Application Areas	Reference
Feedforward Neural Network (FNN)	Each layer is only connected to the immediately subsequent layer.	Multi-layer Perceptron (MLP), Improved Multi-layer Perceptron (BP, RBF, DBN), Fully Connected Neural Networks	It is parallelizable, making it suitable for processing various data types efficiently. However, a potential drawback is its proneness to overfitting.	Classification, Regression, Clustering, Image, Speech, Natural Language Processing	[38, 41, 42]
Recurrent Neural Network (RNN)	It enables information to propagate cyclically through the network, making it suitable for processing sequential data.	Elman Network, Jordan Network, Long Short-Term Memory Network (LSTM), Gated Recurrent Unit (GRU)	It is particularly suitable for sequential data, capable of modeling long sequences effectively. It can be vulnerable to the issue of gradient vanishing, which may hinder the training process.	Speech, Text, Natural Language Processing	[43-45]
Convolutional Neural Network (CNN)	It reduces the number of parameters by leveraging local connections and weight sharing, rendering it ideally suited for spatial feature processing.	LeNet, AlexNet, VGG, GoogLeNet, ResNet	It excels in image recognition tasks, and the use of parameter sharing significantly reduces the total number of parameters required. However, it is not naturally suited for processing sequential data.	Image, Video, Natural Language Processing	[46-48]

2.3. Transfer Learning

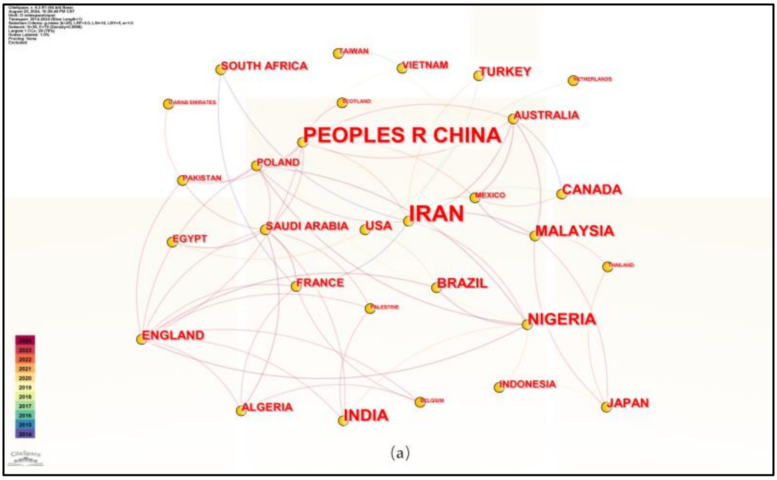
Transfer learning is a machine learning method that aims to improve the performance of learning tasks by discovering and transferring underlying knowledge. Transfer learning models utilize existing knowledge to address learning problems in a target domain that lacks labeled sample data. When there is a certain level of similarity or correlation between the source and target domains, data are transferred from the source domain to the target domain, expediting the learning process, enhancing generalization capabilities, and reducing the need for samples. Transfer learning is a crucial tool in machine learning to address deficiencies in training data [32,49]. Through the transfer method and theory, CNNs can transfer the model knowledge obtained in the laboratory or simulated environment to the training of production models with limited labeled data, avoiding starting from scratch, saving resources, and improving the model's applicability.

The effectiveness of transfer learning depends on transfer scenarios, learning structures, etc. [49-51]. Different scenarios may have different features, resulting in varying transfer effects. The principles of transfer learning encompass the following: (1) Leveraging similarity in data distribution, tasks, and scene features between source and target domains for optimal results. (2) Effectively adapting source domain knowledge to the target domain is paramount. (3) Minimizing data interference between domains with inherent similarities and differences enhances effectiveness. (4) Utilizing multi-task learning with shared features and parameters across correlated tasks boosts efficiency. (5) Incrementally incorporating target domain data facilitates information fusion and improves performance. Tailoring methods to specific transfer scenarios and learning structures is crucial for overcoming limited data challenges.

In water treatment systems, the significance of transfer learning lies in the fact that many practical applications within water engineering heavily rely on referencing data from diverse scenarios. For instance, laboratory data are often leveraged to inform and guide production data, and water engineering systems in one region can serve as a reference for another water treatment project. Currently, there may not be a universally precise method to seamlessly correlate these diverse entities. Transfer learning, however, offers a promising approach. It enables knowledge transfer across domains, adapting models trained on abundant data for new or scarce scenarios. This accelerates solution development, leveraging existing knowledge and minimizing the need for extensive data collection and training.

3. Research Statistics and Analysis

The preceding section provided foundational knowledge on neural networks, framing them within the broader contexts of machine learning, deep learning, and transfer learning. The subsequent section presents a statistical analysis of research papers pertaining to neural networks and their application in the flocculation industry within the water treatment sector. The analysis comes from the Web of Science core database; after searching the words related to artificial neural networks, flocculation, and coagulation in the core database of Web of Science, the selected authoritative articles will be data exported. The analysis was performed using data analysis software CiteSpace V6.1R6. Figure 4 encapsulates this examination, with Figure 4a–c offering an insightful view into the integration of neural networks within the flocculation technology domain.



(a)

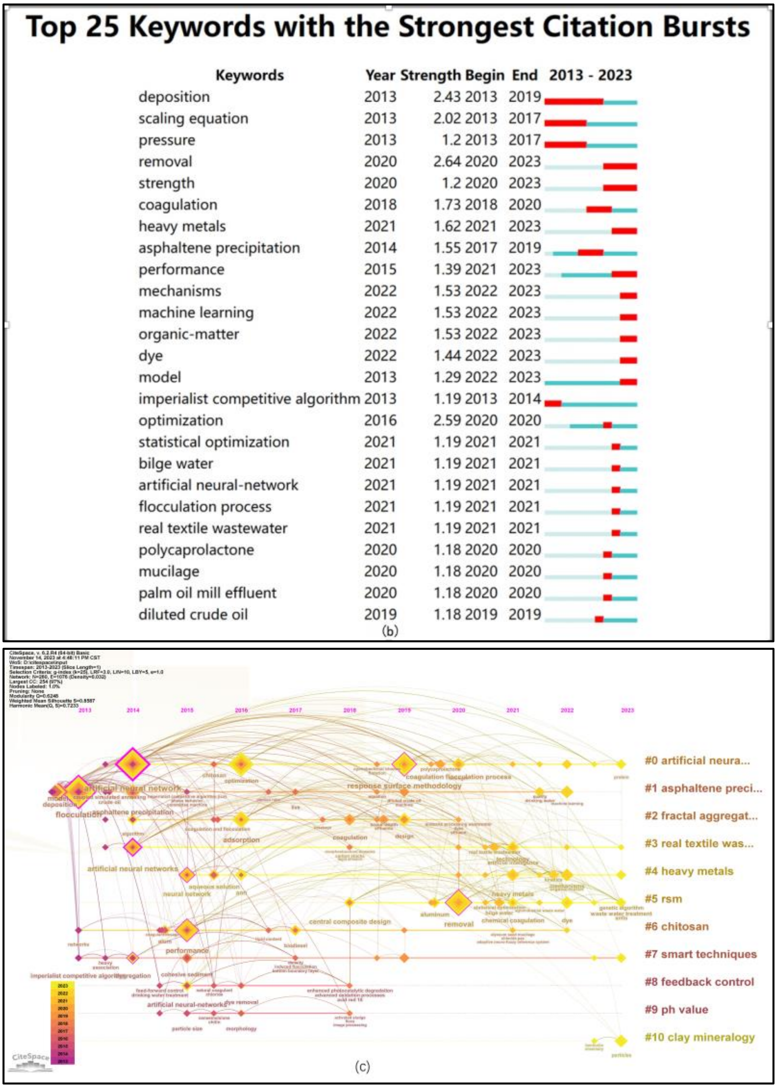


Figure 4: (**a**) National distribution of research achievements in neural networks and agglomeration-related research. (**b**) Distribution of the top 13 keywords in agglomeration neural network research. (**c**) Keywords appearing in research papers on agglomeration neural networks.

Figure 4a provides a detailed distribution of research achievements in the field of neural networks and agglomeration across various countries. It is clear from the figure that Iran and

China are the two most prominent countries in the field of aggregation and neural network integration. These two countries have contributed the most to research in this field, followed by the United States, Nigeria, Indonesia, Japan, India, Poland, Canada, and others. Although these countries produce less research compared to Iran and China, they are still significant contributors to core research areas. There are also some contributions from Malaysia, Vietnam, Brazil, Germany, and Australia, whose authority is less evident due to their relatively limited cooperation with other countries. The colors of the nodes in the graph indicate that China has been particularly active in related research in recent years, while other major countries have had higher research output in previous years. In addition, Canada and India have increased their research output in recent years.

Figure 4b analyzes the keywords in aggregated neural network research papers, showing the frequency of the top 25 keywords over time. For example, in the core database of Web of Science, the keyword "deposition" exploded in research papers on clustered neural networks before 2013, decreased in frequency in 2019, but continued to appear in subsequent research papers. Presented in the picture is the timeline on the far right, you can see that the red segment is the peak of the frequency of occurrence, while the darker blue is the occurrence but not much time, and the light blue is the absence.On the other hand, the most recent keyword to emerge is “heavy metals”, which has significantly increased its occurrence in research papers, especially in 2021 and continuing through 2023.

Figure 4c displays the occurrence of keywords in aggregation neural network research papers. The rightmost column represents the cluster labels, which are summary terms automatically generated by the algorithm for all the keywords on the left. These labels can represent the common themes between related keywords. For instance, the first keyword “turbidity” is displayed on the horizontal axis, next to several high-frequency keywords and the trend of their occurrence times. The frequent appearance of the keyword ‘chitosan aqueous solution’ suggests a strong association with the domain of ‘turbidity’, implying a potential link or effect on turbidity properties. This keyword primarily appeared before 2019, with a peak in 2015–2016. It often appears in conjunction with other keywords such as "adsorption", "artificial neural network", and "scour depth algorithm", as shown in various connection lines. This keyword also co-occurs with keywords from other cluster labels in the keywords of the same paper.

The comprehensive analysis of Figure 4a–c reveals significant trends and key features in international research on neural networks and agglomeration. First, Iran and China emerge as the most active and prolific countries in this field. Second, the United States, Nigeria, Indonesia, Japan, India, Poland, and Canada exert significant influence in this domain. Figure 4b highlights keyword trends, pointing out keywords that have garnered research attention in different periods, such as "coagulant dosage" and "heavy metals". Finally, Figure 4c provides insights into keyword associations, aiding in understanding common themes and collaboration relationships in the research field. This section aims to map the research landscape and identify key trends and features in the field. Figure 4a–c highlight, in particular, the geographical distribution of research results, the frequency of changes in popular keywords over time, and the associations between keywords. This analysis helps to identify which countries are leading in research, the evolution of research topics, and common themes or collaborations. Overall, this section aims to gain insight into the global research dynamics of neural networks and their applications in coagulation processes. It also sets the stage for subsequent discussions linking research trends to the practical application of AI in water treatment, thereby contributing to understanding this area of research and determining future directions.

4. Application of Neural Networks in Coagulation

Water treatment and coagulation play a vital role in ensuring water quality safety and sustainable water resource management [52]. In recent years, the rapid development of AI technology has brought new possibilities and opportunities to this field. The applications of artificial intelligence in water treatment and coagulation are extensive and diverse [53, 54]. First, AI can optimize dosing levels by analyzing water quality monitoring data and historical information, achieving a balance between optimal turbidity removal efficiency and chemical cost-effectiveness. Secondly, using predictive models, AI can accurately forecast water quality changes and provide strong support for the formulation of governance strategies. During actual treatment processes, AI employs real-time monitoring and control to automatically adjust parameters such as dosing levels and mixing speeds, ensuring stable and efficient treatment outcomes. Additionally, AI technology can identify anomalies in the treatment process and issue early warnings, providing a strong basis for emergency response. Energy management and conservation are also areas where AI is applied in coagulant dosing. By optimizing energy consumption during the treatment process, AI further enhances treatment efficiency and economic benefits. AI-based decision support systems provide real-time recommendations and strategies to operators, assisting them in making wiser decisions. The conventional coagulation process usually includes four aspects: the addition of chemicals and coagulants, the formation of coagulants and flocs, the precipitation and clarification of flocs, and the collection and treatment of clarified water. The conventional coagulation process is shown in Figure 5.

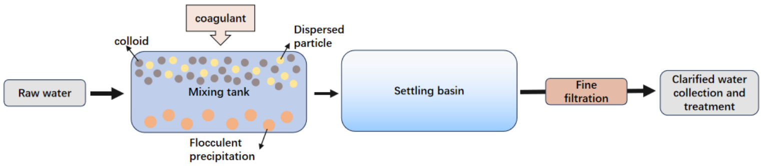


Figure 5: Diagram of the coagulation process.

In addition to optimizing the coagulant dosing, factors affecting coagulation efficiency include the timing and location of coagulant addition, monitoring of suspended solid concentration and turbidity in the water, and the detection of process anomalies. By incorporating AI model algorithms into process supervision and control, the goal is to maximize coagulation efficiency.
Currently, numerous advanced methodologies grounded in artificial intelligence, machine learning, and mathematical modeling have been devised for predicting coagulant dosage.

While notable advancements have been achieved, there persist challenges and limitations that necessitate further attention. Notably, the precision and stability of prediction models can be influenced by the variability and intricacies of raw water quality, the dynamic fluctuations in process conditions, and the intricate interactions between coagulant properties and process variables. In essence, the utilization of AI in the realm of water treatment and coagulation is anticipated to enhance water treatment outcomes, decrease operational costs, and minimize manual intervention. Additionally, it presents novel opportunities for sustainable water resource management and conservation. Consequently, this section delves into coagulation neural networks, with a primary focus on dosing control and pollutant prediction. By examining diverse applications of machine learning and deep learning, this exploration aims to impart a clearer comprehension of neural networks and their pivotal function in refining coagulant dosage predictions. Although automation technology has made significant progress in other industrial areas, there are still many challenges in the application of water treatment. These challenges are found not only at the technical implementation level, but also concern how to ensure the stability and reliability of the system under complex and variable water quality conditions. Therefore, the in-depth study of these problems will provide an important theoretical basis and technical support for the intelligent development of the future water treatment industry.

4.1. Coagulant Dosing Control System

With the increasing demand for the refined operation and management of drinking water plants, along with the need to ensure improved water quantity and quality, the potential to leverage extensive operational system data to save energy and improve efficiency has become a hot research topic [18, 55]. Currently, most facilities are still in their infancy when it comes to the automatic dosing of domestic water treatment plants. They rely on excessive dosing and manual dosing to meet the water quality requirements of the treated water. This relatively outdated method deviates significantly from modern production and water supply standards. There are problems such as high chemical consumption, poor economic benefits, unstable water quality, and high labor intensity of workers [56-58]. Therefore, it is necessary and urgent to study the automatic coagulant dosing control in the water treatment industry. In this section, we introduced the concept of an automatic model for coagulant dosing, and subsequently conducted an analysis of the simulation process, model optimization methodologies, and performance comparisons among various models.

4.1.1. Automatic Coagulant Dosing Control Modes

Automatic coagulant dosing control modes represent a technological advancement in the field of drinking water treatment. They are innovative applications based on modern computer technology and artificial intelligence algorithms. The mode combines sensors and real-time data collection systems with advanced algorithms like deep learning and neural networks to achieve the automatic monitoring and real-time adjustment of the coagulation process. Through the continuous collection and analysis of water quality parameters, weather data, and equipment status, automatic coagulant dosing control models can quickly respond to water quality changes and environmental fluctuations. They automatically adjust the dosage and timing of coagulants to ensure the stable quality of drinking water. The model mechanism is shown in Figure 6.

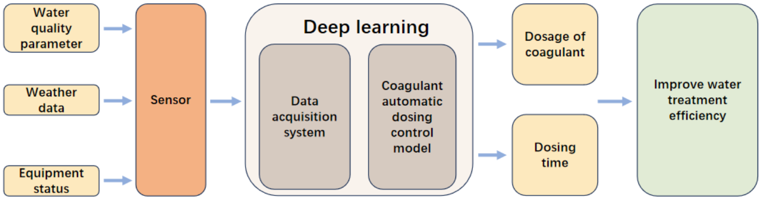


Figure 6: Schematic diagram of automatic coagulant dosing control model.

Automated coagulant dosing control can be divided into three basic modes: feed-forward control, feedback control, and hybrid control [58,35,]. Hybrid control consists of both feed-forward and feedback control, with the feedback signal of turbidity or intermediate parameters fine-tuning the setpoint of feed-forward control to meet the requirements of the entire treatment process. It is the most widely used [59]. Current signals, light signals, and image signals are the most commonly used feedback signals [60, 61]. However, there are issues such as causality problems between dosing points and water quality, susceptibility to environmental interference, and frequent equipment maintenance. Image signals typically use coagulation floc characteristics as the basis for dosing control. This approach is simple, cost-effective, and requires less equipment maintenance. However, the complexity of aquatic environments poses a significant challenge, as the characteristic identification of image signals is heavily influenced by environmental factors, and current technologies are yet unable to guarantee precise feature recognition amidst such variability. Additionally, the need for a floc transfer device introduces significant latency issues [62-64]. Therefore, research on new methods and techniques of image feature extraction can improve the quality of feedback signals. Although automated coagulant dosing control systems have demonstrated their potential to improve the efficiency and stability of water treatment, there are still technical bottlenecks in their implementation. For example, how to better deal with the impact of complex environmental conditions on sensor data, and how to improve the response speed and accuracy of the system through algorithm optimization, are still important directions of current research. In addition, with the development of data-driven technology, how to effectively use big data analysis and machine learning to further improve system performance will become the focus of future research.

4.1.2. Coagulant Dosing Optimization

A common method to determine the optimal dosage of the coagulant is the jar test (JT) tank test. However, due to their huge cost and time requirements, as well as the complex relationship between factors such as turbidity, temperature, pH, and alkalinity, these experiments face some limitations in assessing the results of sudden changes in inlet water quality [65]. Aiming at the limitations of traditional techniques, Haghiri et al. [66] used a single hidden layer artificial neural network (ANN) multi-layer perceptron (MLP) to model the jar test experiment. The mean square error (MSE) and coefficient of determination (R^2) were used to evaluate the performance of the model. The results show that the model has high accuracy in estimating water quality characteristics and optimal coagulant dosage. This method not only achieves the purpose of predicting the dosage of the coagulant, but also reduces the experimental cost and time. Asmel et al. [67] proposed an alternative to the pot test for the real-time determination of the optimal alum usage in the coagulation–flocculation unit of a water treatment plant. They used a radial basis neural network (RBNN) to predict the turbidity and pH of water treatment wastewater. When the required effluent turbidity and pH are known, the RBNN can effectively estimate the optimal amount of alum for the coagulation–flocculation unit of the water treatment plant, which reduces the cost, effort, and time required for the manual jar testing process. Regarding coagulant dosing, Bello et al. [68] described a multi-model predictive control (MMPC) strategy for coagulation in water treatment plants. This strategy effectively targets chemical dose units in different local operating areas during coagulation. By controlling the flow rate of chemical reagents and the surface charge and pH value of treated water, waste can be reduced, coagulant utilization efficiency can be improved, operating costs can be reduced, and the quality of public drinking water can be improved. Narges et al. [26] collected influent pH, turbidity, alkalinity, temperature, and conductivity as input data. They used an artificial fuzzy neural network (ANFIS) method with subtractive clustering (SUB) to determine the optimal dosage of coagulants in water treatment plants. The SUB method not only improves the model accountability and intelligent model recognition but also regulates the number of rules and interconnections. It is beneficial for adjusting the control variables and their relationships, resulting in good model outcomes. Chantaruk et al. [69] presented a model that uses Long Short-Term Memory (LSTM) neural networks to predict the dosage and concentration of coagulants. The amount and concentration of coagulants added directly impact the settling rate and turbidity of sugarcane juice. The input data included green cane, burnt cane, turbidity, and rainfall, and the output data included the quantity and concentration of coagulant. Luo et al. [70] established a BP model for predicting coagulant dosage using both feed-forward and feedback signal data, studying the impact of the particle swarm optimization (PSO) algorithm and data types on model simulation performance. The results showed that parameters like learning factor, population size, and generation significantly affected simulation results. Using hybrid data, PSO, and weak time-delay data, the new structured neural network was capable of predicting coagulant dosage. Lin et al. [71] utilized ten years of long-term data combined with weather influences to develop a Graphic Attention Multivariate Time Series Forecasting (GAMTF) model to determine coagulant dosages. The GAMTF model considered hidden relationships among features, improving prediction accuracy and demonstrating the first successful application of multi-variable time series deep models. These advanced optimization methods not only improve the accuracy of coagulant dosing, but also significantly reduce the operating cost and experimental time. However, the effectiveness of these models may vary under different water quality conditions, so it is necessary to consider the adaptability and robustness of the models under different working conditions in practical applications. In addition, with the increase of data, the complexity of the model is also increasing, so the problem of how to simplify the model calculation on the premise of ensuring the prediction accuracy is worth paying attention to.

4.1.3. Multiple Model Comparison

Kim and Parnichkun [72] proposed a method that combines k-means clustering and an Adaptive Neuro-Fuzzy Inference System (k-means–ANFIS) to predict the coagulation efficiency and optimal dosage. This model categorizes raw water quality properties into four classes and develops sub-models separately based on each class dataset. It achieved adaptive and robust models that outperformed single ANFIS models and seasonal models of ANN in terms of more accurate and consistent predictive capabilities across five evaluation criteria. Zhang and Ai [73] investigated a multi-input, single-output modeling approach based on BP and Radial Basis Function (RBF) neural networks. By clearly reflecting the influence of dosage on zeta potential changes in wastewater, the zeta potential model captured the actual coagulation process in wastewater. This neural network prediction model enabled optimal zeta potential prediction with good real-time and generalization capabilities, providing a rapid and efficient response to coagulant usage efficiency. Comparing the two models, RBF networks exhibited superior performance with lower errors, reduced computational requirements, and shorter cycles, making RBF neural networks an effective modeling method. During their research, Arab et al. [74] employed intelligent soft sensors using various machine learning algorithms to control and predict coagulation and flocculation processes. By comparing different ML methods, including Random Trees, RF, ANN, Quinlan's M5 regression function algorithm (M5P), Linear Regression (LR), Simple LR, and Gaussian methods, the models were evaluated for estimating and controlling Chemical Floc Precipitation (CFP) in wastewater treatment plants. These models effectively controlled coagulant usage, operation time, and optimized energy consumption for coagulant mixtures. Most machine leaning models are effective and applicable. Wang et al. conducted a study utilizing water quality parameters from the Suzhou Baiyangwan Waterworks as samples. They established four representative models based on various machine learning techniques: Multiple Linear Regression (MLR), Radial Basis Function Neural Network (RBFNN), Least Squares Support Vector Machine (LSSVM), and a proposed Enhanced Neural Network (ENN). The findings of their research indicate that the ENN model outperforms the other three models in terms of forecasting performance. Notably, the ENN model incorporates the characteristics of time-varying behavior and periodicity, which are essential for accurately predicting water quality data. Consequently, it achieves the best forecasting effect on the water quality dataset, demonstrating its superiority and potential for practical applications in water treatment and monitoring. The multi-model comparison method provides a flexible and efficient solution for coagulant dosing control, especially under complex water quality conditions. However, the implementation of this method often requires high computational resources and a complex algorithm design, so the problem of how to strike a balance between model performance and computational cost in practical applications is a problem that needs further research.

4.1.4. Parameter Control

Qin et al. [75] utilized an IMLT system to obtain voltage changes during different coagulation stages with varying coagulant dosages and coagulant sizes. They managed the coagulant dosage, detection voltage, and coagulant size using a CNN method to enhance the accuracy of their correlation. By regulating dynamic indicators during the coagulation process based on the relative changes in multiple values, they found that particle size and voltage were inversely proportional. A larger voltage R-value indicated better coagulation and settling effects, effectively reflecting the impact of coagulants on coagulation, settling, stability, and dynamics in the coagulation system. Onen et al. [76] used an MLP-based ANN model to determine optimal conditions for various coagulants and flocculants. Input variables or independent variables included the type and dosage of coagulants/flocculants, mixing time, mixing speed, settling time, and pH, while the output variable or dependent variable was the estimated turbidity of marble suspensions. This estimation allowed them to predict the final turbidity of treated wastewater. Anionic coagulants performed the best with a coagulation efficiency of 97%, and $FeCl_3{\cdot}6H_2O$ was the best-performing coagulant with an efficiency of 86%. Zheng et al. [77] predicted the coagulation efficiency using a RBF neural network. The results demonstrated a good predictive capability. Under optimal conditions, an increase in the fractal dimension of flocs led to an improved COD removal efficiency and increased floc density. Various operational variables that might affect PPAC coagulation behavior, such as the P/Al molar ratio, initial wastewater pH, coagulant dosage, and stirring speed, were experimentally tested. The efficiency of treatment was assessed by measuring the reduction in Chemical Oxygen Demand (COD) and residual turbidity. Parameter control plays an important role in the automatic coagulant dosing system, but its effect often depends on the accuracy and real-time performance of the model. In practical applications, the variability of environmental variables and operating conditions may affect the effect of parameter control, so the problem of how to maintain the accuracy and stability of parameter control in complex environments is the focus of future research.

4.2. Prediction and Analysis of Contaminants

The importance of artificial intelligence in predicting contaminants in water treatment cannot be underestimated. With the continuous growth of the population and accelerated industrialization, water resource scarcity and pollution have become increasingly severe, making water treatment a critical concern [78]. Traditional water treatment methods often struggle to cope with the growing complexity and variability of contaminant characteristics, necessitating smarter and more accurate approaches to address this challenge. Artificial intelligence, through techniques such as deep learning, data analysis, and model building, can extract patterns from large-scale data and precisely predict fluctuations and trends in contaminant concentrations. Compared with traditional methods, this prediction method based on big data and artificial intelligence not only improves the accuracy of pollutant prediction, but also can respond to complex polluted environments in time, providing a more forward-looking basis for water treatment decisions. Figure 7 shows the model prediction principle. This not only helps water treatment plants develop more scientifically informed treatment strategies but also provides early warnings of potential water quality issues, offering strong support for resource management and environmental protection. Therefore, the application of artificial intelligence in predicting contaminants in water treatment not only enhances the effectiveness of water treatment but also contributes significantly to safeguarding public health and sustainable water resource management, carrying substantial societal and environmental significance.

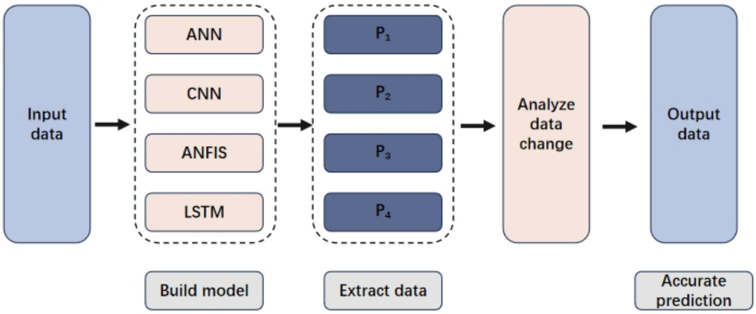


Figure 7: Schematic analysis of model prediction.

4.2.1. Monitoring of Inlet and Outlet Water

Two modeling methods, Multiple Linear Regression (MLR) and ANN, were employed to predict the minimum value of the Water Pollution Index. Through the analysis of 12 physicochemical parameters of the WPI, including turbidity (Tur), pH, electrical conductivity (EC), total dissolved solids (TDSs), total hardness (TH), potassium (K^+), sodium (Na^+), magnesium (Mg^{2+}), calcium (Ca^{2+}), alkalinity (Alk), chloride (Cl^-), and sulfate (SO_4^{2-}), Abdulkareem et al. [79] determined that the ANN-SA method, under optimal parameters, resulted in the lowest minimum WPI value, which was 0.373. Igwegbe et al. [80] optimized the treatment of wastewater turbidity using a pomegranate flower extract (coagulant) through a Response Surface Methodology (RSM) and ANN techniques. Factors such as time, pH value, and coagulant dosage were found to have a significant impact on turbidity reduction. Wang et al. [81, 82] analyzed the removal efficiency of THMs and DOM and their correlation from the perspectives of water quality conditions, metal salt coagulant dosage, and morphology. They predicted the coagulation effectiveness based on input water quality parameters and coagulant dosage information, which helps to evaluate the effectiveness of different dosing schemes and guides subsequent operations. Zhang and Stanley [83] used a neural network process control system to control coagulation, flocculation, and sedimentation processes. An artificial neural network model was established based on nearly 2000 sets of process control data, forming a crucial component of the software feed-forward controller. This analysis affected control parameters and requirements and developed a feed-forward neural network control scheme that identifies different patterns and trend changes based on existing data characteristics, allowing for timely optimization adjustments of chemical reaction effects. Other studies [72, 84] established multi-input multi-output (MIMO) and multi-input single-output (MISO) models based on BP networks, and then developed a BP artificial network. By comparing the relative error values using the root mean square error method, the predictive capability of water quality at the inlet and outlet was inferred, providing a rapid preliminary assessment of wastewater quality prediction in the coagulation process. Pouresmaeil et al.

[85] used an ANFIS to predict energy consumption and outlet turbidity based on inlet turbidity and ferric chloride as a coagulant in the coagulation and flocculation unit of a wastewater treatment plant. The high consistency of determined values (over 80%) indicated a reliable correlation between inputs and outputs. Deng et al. [86] further investigated nearshore water quality prediction using two different machine learning methods (ANN and SVM) to establish dynamic relationships between water quality consequences and various nearshore system conditions and environmental factors. This modeling and prediction aimed to predict algal growth trends and scales in Tulu Harbor. Researchers [88,89] used a backpropagation neural network with the Mann–Kendall test to comprehensively evaluate Wuhan's urban drinking water quality. These studies not only demonstrate the potential of artificial neural networks in predicting complex water quality indicators, but also reveal the relative advantages of different methods in treating different environmental conditions, which provides an important reference for future water treatment technology development, including prediction, temporal/spatial analysis, and pollution source identification. They created an adaptive water quality index approach that is applicable globally. Separately, Shetty et al. [90] employed commercial neural network software to accurately forecast pollutant concentrations and predict municipal water quality during nanofiltration under different conditions. Although these modeling methods have achieved remarkable results in predicting water quality, their scope of application is still limited by data quality and model adaptability. Further research should focus on improving the generalization ability of the model to adapt to complex changes under different water quality conditions and improve its practicability in different environments.

4.2.2. Image Processing of Inlet and Outlet Water

Suzuki et al. [87] predicted the post-coagulation turbidity with a deep convolutional neural network (DCNN) using floc images from the jar test. They developed a system to control water purification processes using a prediction model without using chemical parameters. Instead, they used images of the flocculated matter, referred to as a "float" as inputs for the DCNN to predict the post-coagulation turbidity from images of "flocs" generated from bottle tests, enabling a more efficient assessment of coagulation effectiveness. This method demonstrates the powerful ability of image processing combined with deep learning to obtain key indicators directly from visual data, which provides a new direction for intelligent monitoring and optimization in water treatment in the future. Zhu et al. [88] developed a tensor diagram and deep learning model to optimize the flocculation process, achieving over 98% accuracy in pollutant classification, thereby enhancing the efficiency and speed of commercial water treatment. Through the introduction of deep learning models, the study significantly improves the automation level of the traditional flocculation process, not only reducing the need for manual intervention, but also improving the accuracy and consistency of pollutant treatment, laying the foundation for the intelligent operation of large-scale water treatment plants. Yu et al. [89] established a digital image analysis system to measure the particle size distribution, equivalent diameter, total area, total volume, and fractal dimension during coagulation. Using two real industrial wastewater samples, coagulation and flocculation processes were conducted in batch reactors with different doses of polyaluminum chloride. The experimental results showed that using digital image analysis (DIA) to measure the particle aggregation combined with a Back-propagation Neural Network (BPN) model could accurately predict the removal efficiency of suspended solids and outlet concentrations after chemical coagulation. This study further highlights the potential of digital image analysis in water treatment, not only providing a more accurate assessment of particle properties, but also enabling the efficient prediction and control of processing processes by combining neural network models, showing the great potential of image processing and machine learning fusion. Panckow et al. [90] employed a CNN for particle detection based on image analysis. This approach was trained for particle detection and used to develop an experimental method to characterize the fluid dynamic stresses of particles in a laboratory stirred-tank reactor. It provided high-quality particle recognition for the subsequent size and shape analysis of coagulation processes under various experimental conditions. Through the accurate detection and analysis of particulate matter, the CNN model shows its unique advantages in particle control and the optimization of water treatment and provides an important reference for improving coagulation efficiency and treatment effects.

5. Challenges and Prospects

5.1. Optimization of Coagulation Neural Network Models

Optimizing the network model is the key step to ensure the efficient operation of the water treatment process. In the coagulation stage, the fine tuning of the model can improve the coagulant dosing precision, reduce energy consumption, and improve water quality. With the increasing demand for water treatment, the need to optimize the model is more prominent. By optimizing the neural network model, we can not only improve the accuracy and stability of predictions, but also better cope with complex water quality changes and operating conditions, resulting in more efficient and sustainable water treatment.

5.1.1. Improvement in Data Quality and Quantity

High-quality data are the basis for building accurate models. Therefore, the primary task is to ensure that the collected data are accurate, comprehensive, and representative. The number and frequency of sensors can be increased to improve data quality. In addition, this ensures that the data collected cover variations in various operating conditions to better reflect real-world scenarios. Yamamura et al. [91] used a camera to record floc images during jar testing and constructed a model to predict the clarity of a supernatant based on recorded floc images and turbidity levels as the training dataset. Subsequently, they studied the overfitting levels by inputting test data into the model. The maximum prediction accuracy of all models exceeded 96%. The models achieved a maximum accuracy of 99.6% in learning from floc images within the initial 100 s, demonstrating that images captured during the rapid mixing process are sufficient to ensure model reliability. This study shows that capturing high-quality image data at an early stage can significantly improve the prediction accuracy of the model, and data diversity and representativeness are crucial to avoid overfitting the model.

5.1.2. Feature Engineering

The performance of the model can be improved by analyzing the key features that affect the flocculation process. This includes operational variables like temperature, turbidity, pH, as well as the type and dosage of coagulants. Proper feature selection and engineering can reduce the complexity of the model and improve the prediction accuracy. Kusuma [92] modeled and optimized the removal of turbidity in simulated wastewater using a sweet potato leaf extract. They elucidated the interaction between process factors and compared the relative efficiency of the RSM and ANN. The results show that although the RSM model performs well, the artificial neural network has a higher correlation coefficient (R), R^2 value, and adjusted R^2 values, and a lower mean square error (MSE), standard error of prediction (SEP), mean absolute error (MAE), root mean square error (RMSE), and average absolute deviation (AAD). Hu et al. [93] proposed a prediction model with an attention mechanism based on LSTM neural networks. The model correlated current sensor data with historical data, extracted multi-dimensional features, and focused on critical information while ignoring redundancy. In the context of nonlinearity, multiple input factors, uncertainty, and time-dependent characteristics, the authors compared commonly used models such as BP, RNN, and LSTM in predicting semi-annual coagulant dosages for water treatment plants. The proposed model demonstrated high accuracy. Through reasonable feature engineering, the model can extract the key factors related to water treatment more effectively, which enhances the prediction performance and applicability of the model.

5.1.3. Model Selection

Selecting appropriate neural network architecture is crucial for model performance. Different flocculation problems may require different types of neural networks, such as MLP, CNNs, RNNs, and others. The most suitable model can be chosen based on the problem's characteristics and the data structure. Igwegbe et al. [80] synthesized a green coagulated seed extract from Garcinia kola nuts and used it to reduce the turbidity of aquaculture effluents. They employed the RSM and Central Composite Design to model and optimize the process. The study demonstrated that adsorption kinetic data best fit the PSO model, providing better predictive reliability compared to other kinetic models. Abdalrahman et al. [94] utilized two different ANN architectures, MLP and ENN, to develop the optimal model. They selected the best model by evaluating three stages: selecting the optimal data partition, choosing the best model, and determining the best combination of input parameters based on multiple performance criteria. The choice of neural network architecture should be based on specific application scenarios and problem characteristics. Through proper selection, the model can better adapt to the diversified water treatment needs and improve the application effect.

5.1.4. Cross-Validation

Utilizing cross-validation techniques can provide a better assessment of the model's generalization performance. The dataset is divided into a training set and a validation set, and the model is trained multiple times to ensure its stability across different subsets of data. Hadjisolomou et al. [95] studied the optimal k-fold cross-validation when constructing artificial neural networks using a small water quality dataset, yielding improved outputs with a relatively shorter computational time. Asadollahfardi et al. [96] used RBF, ANFIS, and fuzzy regression analysis to investigate the performance of predicting the removal of Acid Red 14 removal from reactors. In order to reduce overfitting in the training process, k-fold cross-validation was adopted. The results indicated that the ANFIS performed more suitably compared to the fuzzy regression model. Cross-validation not only prevents model overfitting, but also evaluates the robustness of the model under different conditions, guaranteeing performance in the final application.

5.1.5. Continuous Monitoring and Optimization

The quality of water and operating conditions during the coagulation process may change over time. Therefore, it is essential to establish continuous monitoring and adaptive mechanisms for the model, allowing real-time adjustments to adapt to changing conditions and ensuring its continuous optimization. Arab et al. [74] overcame the challenge of data scarcity with an eight-year experimental database. They developed a Petri-Net conceptual model to intelligently manage water treatment insights. Continuous monitoring and adaptive optimization not only improve the long-term effectiveness of the model, but also deal with unexpected problems and improve the overall efficiency and reliability of the water treatment system.

By employing the optimization methods mentioned above, it is possible to continually enhance the accuracy and stability of coagulation neural network models, enabling them to play a more significant role in water treatment. This, in turn, facilitates more efficient and sustainable drinking water treatment processes. Continued model optimization will enable more efficient and sustainable drinking water treatment processes to support future water management.

5.2. Various Challenges in Neural Networks for Coagulation

5.2.1. Information Structure Issues

Although research on tailoring data structures to suit neural networks is relatively scarce, there have been notable advancements made in this area so far. A significant drawback of the “black box” artificial neural networks is the difficulty in explaining the knowledge acquired within the neural network. Therefore, introducing the information capacity within the neural network can significantly impact the network’s performance. Studies have shown that input information has a substantial impact on network systems, which is crucial for subsequent coagulation problem analyses [18,97]. Coagulation is characterized by challenges such as large delay, time-varying behavior, nonlinearity, and multiple disturbances [98,99]. Furthermore, there is no unified definition of the structural framework of coagulation impacts, as different coagulants and coagulation substances are involved. However, in drinking water coagulation systems, hydraulic conditions (H), metal salts (metal coagulants, M), and water quality (W) [100-102] are all key factors affecting coagulation. These factors reflect the structural framework of coagulation effects [100,101,103]. Included in these essential factors are simple variables, such as pH, coagulant dosage, mixing speed, coagulation reaction time, and conductivity. All of these play crucial roles in discussing coagulation control. The interaction of these factors can result in regions with a large number of unknown coagulation effects, where coagulation characteristics and mechanisms may vary. Although neural networks are excellent at handling complex data, their "black box" nature makes it difficult to interpret the knowledge in the network. This problem significantly affects the information transfer and application in the coagulation process. Although the existing research has made progress in the custom data structure, more in-depth exploration is still needed, especially in the variability and complexity of coagulation systems.

5.2.2. Feedback Control Signal Acquisition and Feedback Mechanism

From the point of view of solving the key problems of dosing control, the acquisition of a feedback control signal and feedback mechanism is one of the urgent problems to be solved. At present, feedback signals are mainly divided into three types: current signal, optical signal, and image signal [104]. However, the research and application of a feedback-signal-based dosing control system at home and abroad still have great limitations.

The Streaming Current Detector (SCD) is a commonly used automatic control method worldwide, which controls dosing amounts based on the positive correlation between the streaming current magnitude and the zeta potential of the colloids in water [105]. This method has the advantages of single operational factors, simple operation, less investment, overcoming lag, and realizing on-line detection and control. However, it performs poorly in regulating high-molecular-weight polymer coagulants, mainly due to their adsorption-bridging mechanism. Additionally, the electrical resistivity of water changes with components, temperature, flow rate, etc., leading to reduced detection accuracy over time [106]. As high-molecular-weight coagulants are widely used in water treatment plants, and water environmental conditions become increasingly complex, the application of electric current signals is severely restricted.

Monitoring turbidity through an optical signal is a convenient control method. However, there is a significant time delay between the point of administration and the effluent turbidity. The Flow Perturbation (FP) method is a common form of automatic control used worldwide, relying on the principles of photoelectricity to detect changes in coagulation particle size and quantity, subsequently controlling dosing amounts [104]. This method calculates the degree of fluctuation in light intensity passing through the suspension, which reflects relative changes in particle size. It achieves online coagulation control and detection based on the stochastic fluctuation characteristics of the particle composition in flowing suspensions. However, this method has limitations in maintaining stable and responsive R-values, requiring high standards for the detection and sampling system. Other methods reflecting the particle's physical properties through optical signals include particle counting detection, dual-wavelength particle analysis, laser analysis, etc. These methods are mainly applicable in laboratory settings.

In contrast to the optical signal, the image signal directly captures particles in water and uses the characteristics of the particle images as the basis for coagulation dosing control. An example is the Display Coagulation Dosing (FCD) control method. FCD primarily consists of three parts: raw water flow pre-control, coagulant fractal dimension control, and effluent turbidity feedback regulation. It utilizes feature parameters of the particle images, turbidity signal, and flow rate signal to form the signal of the dosing control system [107]. Nevertheless, the calculation of image fractal dimensions and turbidity testing both introduce issues related to time delays. Currently, image signal feature selection primarily relies on manual specifications, necessitating systematic analysis, complex calculations, increased human effort, and the prevention of issues like particle breakage and blurring [62-64].

Current feedback control methods face many limitations in practical applications. For example, although the current signal is simple to operate, it does not perform well when dealing with high molecular weight coagulants, and the detection accuracy is easily affected by environmental changes. Optical signals and image signals provide new control ideas, but time delay and high requirements for detection systems limit their wide application. This shows that in the field of water treatment, the existing feedback control signal acquisition and application technology still needs to be further optimized to improve the robustness and adaptability of the system.

5.2.3. Transfer Learning Challenges

In terms of knowledge transfer, researchers encounter two significant challenges when attempting to apply prior knowledge gained under simulated conditions [35]. Those models obtained through experiments in laboratories or simulated field conditions often come with high implementation costs when transitioning to real production. Currently, there is no viable mechanism for transferring these models to practical production settings. Machine learning assumes that training and testing data are drawn from the same data distribution. However, experimental data can change over time, space, and location, making it impossible to treat new training data with the same data distribution. Additionally, limited training samples can lead to issues like the cold start problem and overfitting, hindering effective generalization to production scenarios.

Transfer learning is a popular machine learning paradigm for addressing these challenges. Its core idea involves borrowing labeled data or extracted knowledge from related domains to assist machine learning algorithms in achieving better performance in the target domain [108]. Reusing learned models eliminates the need to reacquire training data or perform relationship inference on complex data representations, making model-based transfer learning more efficient and capable of capturing high-level knowledge from the source domain [109]. Therefore, researchers can apply transfer learning to coagulation studies, which holds significant academic and engineering practical value, by establishing complex simulators to transfer models trained in simulated environments to real-world settings.

5.2.4. Real Production Challenges

In the production of purified water, there are several specific challenges to contend with. These include difficulties in adjusting coagulant dosages compared to laboratory conditions, such as pH control. Drinking water plant quality parameters (turbidity, temperature, pH, etc.) tend to remain relatively stable over certain time periods, resulting in limited labeled data [110]. This imposes significant constraints on factor adjustments. In the production process, dosages are often based on experience, making it challenging to pinpoint precise dosing points [111]. Models constructed through methods like beaker tests and on-site simulations may differ from actual production, making it difficult to accurately assess production conditions. Furthermore, there are objective factors at play, such as the instability of the incoming water quality, the impact of changing weather conditions on coagulation effectiveness, the cost and stability of the coagulant supply, and resource and energy management at water treatment plants. The instability of incoming water quality encompasses daily and seasonal fluctuations in the concentrations of various pollutants in the source water, complicating the optimization of coagulation processes. Changes in weather conditions, such as variations in rainfall and temperature, can significantly affect coagulant dosages and coagulation effectiveness [112]. Additionally, the cost and stability of the coagulant supply are critical for the economic operation of water treatment plants [113]. Finally, resource and energy management issues require water treatment plants to more effectively manage resources such as water, electricity, and chemicals, in order to achieve both environmental and economic objectives. Addressing these challenges necessitates the integration of advanced technologies, including artificial intelligence and modeling, to enhance the automation and efficiency of water treatment processes. This ensures the provision of safe, stable, and sustainable drinking water supplies [111].

5.2.5. Analysis of Cost Control Issues

When discussing cost control in drinking water treatment, the key focus typically revolves around two crucial aspects: optimizing and improving model quality and enhancing the quality of manually collected data. Both of these aspects hold significance at various stages of drinking water treatment and are essential for maintaining cost-effectiveness.

First, optimizing and improving model quality is a vital strategy for cost control. Coagulation is the most critical phase in the drinking water treatment process, involving numerous complex physical and chemical phenomena to maintain acceptable water quality and efficient plant operations. Moreover, the dosage of coagulants is nonlinearly related to the characteristics of the raw water, such as turbidity, conductivity, pH, temperature, and more. Modeling can be employed to overcome these limitations [114]. However, mathematical models often lack a macroscopic understanding of the overall dynamics, making it challenging to fit the widespread nonlinear relationships in drinking water treatment (DWT) [115-117]. Such an approach may lead to health risks associated with drinking water, particularly during unexpected pollution events or seasonal variations in source water quality. Additionally, due to the lack of timely and accurate high-precision prediction models, specific operational decisions may depend on manual intervention in some cases [53]. If the quality of these models is not high, their predictive accuracy can be compromised, resulting in poor coagulation efficiency and wastage of coagulants. Therefore, improving and optimizing these models to enhance their predictive accuracy is crucial. This may involve using more advanced algorithms and technologies such as deep learning neural networks [42] and generative adversarial networks (GANs) [118] to better capture the complex relationships among water quality data. By improving model quality, costs can be controlled more effectively, reducing the overuse of coagulants and, consequently, dosing costs.

Second, improving the quality of manually collected data is also an integral part of cost control. In drinking water treatment, a substantial amount of water quality data are required to support model training and predictions to derive final results [18]. However, if the quality of these data is not high, misleading results may be generated [119]. Hence, ensuring the collection of abundant, diverse, timely, accurate, and valuable data becomes crucial [120]. This can be achieved by enhancing data collection equipment, increasing data collection frequency, strengthening data quality control, and more. High-quality data not only enhance model accuracy but also reduce unnecessary testing and experimental costs, thereby helping to control overall costs.

Cost control is a critical component of drinking water treatment, and optimizing and improving model quality, as well as enhancing the quality of manually collected data, are two key strategies for achieving cost control. By enhancing both model and data quality, it is possible to more effectively manage dosing costs while ensuring high standards and compliance with water quality. This contributes to cost control, reduces unnecessary wastage, and maximizes the assurance of safe drinking water for residents.

5.2.6. Application of Neural Network in Drinking Water Treatment

Neural networks possess the capability to perform complex pattern recognition and prediction utilizing data-driven methods, offering distinct advantages in optimizing parameter control, pollutant detection, and water quality forecasting in water treatment processes. Nevertheless, their application encounters several challenges, notably poor model interpretability, significant data dependency, and suboptimal performance in the absence of large-scale labeled datasets. Additionally, compared to traditional methods, neural network models tend to rely excessively on the quality and quantity of training data, leading to unreliable performance when confronted with small datasets or changes in data distribution. Furthermore, neural network models are often regarded as “black box” operations, lacking transparency and interpretability, which hinders their widespread adoption in highly regulated sectors requiring high transparency, such as drinking water treatment. Since neural networks learn from training data, the presence of biases or flaws in the data can inadvertently introduce similar biases into the decision-making process. Variations in water treatment facilities can also exacerbate model uncertainty, particularly in cross-regional or cross-device applications. To address these issues, greater emphasis should be placed on data sources, model validation, and uncertainty analysis during the model development and application stages. Furthermore, the introduction of diversified testing methodologies and robustness analyses is crucial [121,122]. By doing so, we can enhance the reliability, transparency, and applicability of neural network models in water treatment processes.

6. Conclusions

This paper provides a comprehensive overview of the application of artificial intelligence, particularly neural networks, in the field of water treatment, with a focus on water quality prediction and chemical dosage optimization. By outlining the fundamental concepts of machine learning and deep learning, it emphasizes their relevance to water treatment processes. A detailed analysis of neural network usage in coagulation processes highlights advancements and challenges. Discussions encompass the automation of coagulant dosing, optimization of dosage levels, and modeling approach comparisons. The paper also explores neural network applications for pollutant level prediction, supporting water quality monitoring and image analysis. It identifies areas for improvement, such as data quality, feature engineering, model selection criteria, and cross-validation methods. The importance of continuous monitoring, adaptive optimization, cost control, and resource management is stressed. However, the effectiveness of these models largely depends on the quality and quantity of data, so accurate data collection and feature engineering are key components of successful implementation. In addition, choosing the right neural network architecture and using cross-validation techniques are critical to obtaining reliable results. Practical applications also face some challenges, such as adapting the model to fluctuating conditions and overcoming structural and cost-related obstacles. Future research should focus on addressing these challenges, improving data collection methods, and developing adaptive models that can optimize the coagulation process in real-time, ultimately contributing to more efficient and cost-effective water treatment. In summary, this review offers insights into neural network applications in water treatment and outlines key research directions.

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