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Deep Convolution Neural Network in Remote Sensing Monitoring of Water Source Pollution Sources

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Abstract: In recent years, the eutrophication of Lake Reservoir type drinking water source areas has become increasingly prominent, posing a threat to people's health and sustainable socio-economic development, and preventing and controlling Lake Reservoir pollution is extremely urgent. Only by qualitative identification and quantitative analysis of the pollution sources of lake reservoir type water sources and tracing back to the main sources of pollutants can the main contradictions and key cruxes of drinking water source pollution be clarified, scientific, effective and targeted comprehensive prevention and control countermeasures be put forward, and the safety guarantee ability and level of drinking water source areas be improved. Therefore, this paper establishes a water quality monitoring system based on the depth convolution neural network (CNN), obtains the remote sensing image of a lake by combining remote sensing technology, corrects the remote sensing image pixels through CNN algorithm, and helps to monitor the water quality of the lake area by analyzing the distribution of suspended solids, TP, TN in the image.

1. Introduction

At present, water pollution is becoming more and more serious. Remote sensing technology plays an important role in the related technologies of how to monitor and control environmental pollution, and its application is becoming increasingly popular. Therefore, remote sensing monitoring technology has become a key technology for water environment and pollution monitoring, and also plays a pivotal role in solving environmental governance problems.

There are many technologies applied to water source pollution monitoring, and some research results have been achieved. For example, some researchers believe that the water quality automatic monitoring system is a comprehensive system with the integration of automatic control, sensor technology, computer measurement and control technology and network communication technology of lake water quality and water quality analysis tools [1]. Some researchers use open source PostgresSQL, MapGuide and Ppaper to combine remote sensing and GIS technology and create a seabed water quality management system on WebGIS to support the decision-making of competent authorities or society on the management of seabed pollution [2]. Some scholars believe that it is necessary to continuously monitor the water quality, systematically assess the water quality of the basin, understand the overall water pollution situation of the basin, determine the main pollution factors and levels of water pollution, and explain the temporal and spatial distribution of water pollution characteristics in order to comprehensively control the water pollution in river pools [3-4]. In a word, the emergency response to sudden water pollution accidents can only be made by using line and technology to conduct comprehensive analysis and information processing on various environmental factors in the water source area, and timely understand the water quality of drinking water sources and the dynamic changes of pollution in the water source protection area.

This paper first introduces the hierarchical structure of depth CNN, proposes a water quality evaluation model, and then combines remote sensing technology and depth CNN to build a water source pollution source monitoring system, which can realize remote sensing data reading, water quality monitoring and monitoring results statistics. Finally, the system is applied to the water quality monitoring of a lake, and the pollutant distribution characteristics of the lake are analyzed through remote sensing images.

2. Basic Overview

2.1. Hierarchical Structure of Deep CNN

Multilayer neural networks form the structure of CNN. In the middle of general convolution and alternating grouping, each layer has different filters to understand the basic features of the bottom image and the complex features of the upper image. As the network deepens, the learned features become more and more complex [5]. CNN can process one-dimensional kernel packet audio, two-dimensional convolutional image and three-dimensional convolutional video [6]. CNN consists of the following main parts:

Convolution: Extract features from the input image to reduce the number of parameters. The key to the convolution process is the kernel, which may produce completely different results. Kernel size, step size, number and other factors affect the image output, size affects the network structure's judgment of features, and step size affects the size and number of features of the obtained image. The more cores, the more functions extracted, and the more complex the network [7-8].

Pooling: In CNN, the pooling layer is the implementation of down sampling. It can effectively reduce the size of the resource map by reducing the number of parameters that are finally inserted into the fully connected layer, avoiding excessive adjustment and speeding up the calculation [9]. The output dimension is reduced by pooling. Because adjacent pixels in an image usually have similar features, the adjacent pixels are similar by convolving the output, resulting in redundant information. Grouping layer aims to solve this problem by reducing the output size, reducing the number of exported values in the grouping layer, and retaining useful information [10-11].

2.2. Water Quality Assessment Model

The water quality comprehensive identification index method is: first calculate the single factor water quality index of each evaluation factor, then obtain the comprehensive water quality index through mathematical calculation, and finally use the comprehensive index to call the water quality classification method. The evaluation index items are the same as those of the single factor evaluation method. From the model algorithm, the comprehensive identification index method is more accurate than the single factor method of comprehensive water quality evaluation, but the single factor evaluation is superior to the comprehensive index method [12-13]. Calculation formula of comprehensive identification index I:

$$I = \sum Pi / n \tag{1}$$

$$Pi = {Ci}/{Si} \tag{2}$$

Pi is the water quality index of the ith factor, n is the number of factors, Ci is the measured quality of pollutants, and Si is the evaluation standard of pollutants.

$$Q = \max(Q_i) \tag{3}$$

Q is the comprehensive category of water quality assessed by single factor pollution index, and max represents the worst one among i water quality indicators.

3. Design of Quantitative Remote Sensing Monitoring and Inversion System for Water Source Pollution

3.1. Overall Design Framework

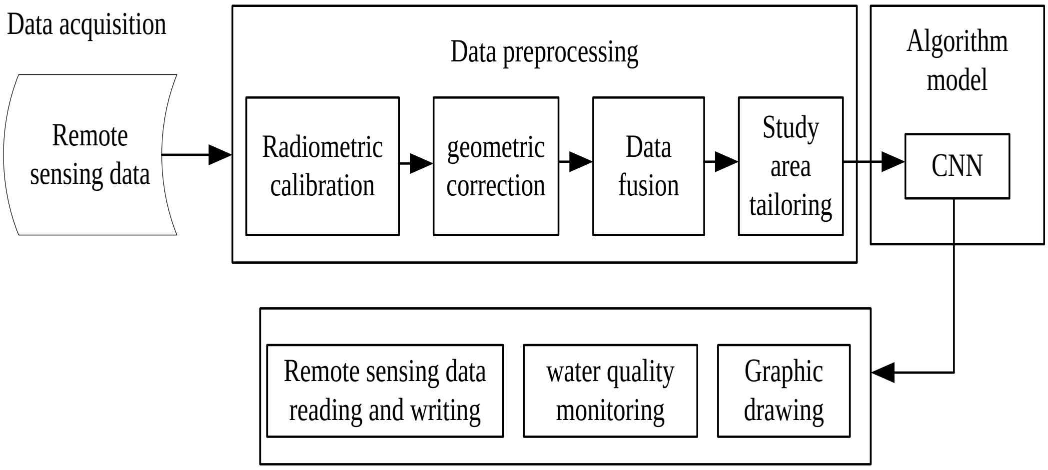

Figure 1. Framework of water quality monitoring system

According to Figure 1, a remote sensing pollution tracking system based on CNN depth is designed. The overall design of the system includes four parts: data collection, data conversion, monitoring model establishment, monitoring system design and implementation. The purpose of collecting remote sensing data is to provide data sources and practical data sources for testing and ensuring reliability; And data conversion can be used for remote sensing rotation. Only through appropriate conversion methods can the accuracy of data be ensured; Based on the characteristics of water pollution and combined with CNN depth algorithm, the establishment of system model and monitoring is the main part of the system; The system uses IDL language to design and write the complete creation program of the system [14-15].

3.2. System Module

The main functions of the system include remote sensing data reading and writing, water quality monitoring and monitoring results graphics drawing.

(1) Remote sensing data reading and writing

The remote sensing data of the system are spatial geographic entities such as water system, water source area, water quality monitoring station, etc. The remote sensing data in the specified format is read, and the data format is tif remote sensing data.

(2) Water quality monitoring

The water quality monitoring module is a monitoring indicator required for water quality assessment. It conducts visual search and questioning in various forms and schedules, and takes data and monitoring stations as units. Provide the latest real-time monitoring data issued by each water quality monitoring station, and report the behaviors and results of excessive discharge to warn of serious water pollution events [16].

The monitoring data query is based on the monitoring date and location, and the results are displayed in the form of data list to query the historical data of water quality monitoring. Monitoring data query not only supports accurate query, but also supports fuzzy query. The user specifies the date and measuring station, and precisely queries the monitoring data of the specified monitoring station at the specified time point. The user only specifies the date, not the monitoring station, and fuzzy query the monitoring data owned by the specified time point; The user does not specify a date, but only a monitoring station. Fuzzy query is performed on all historical monitoring data of the specified monitoring station [17].

(3) Statistics of monitoring results

Implement water quality monitoring indicators and draw statistical charts to intuitively reflect the change of total water quality in a given period. Statistical comparative analysis is the process of combining remote sensing information with statistical analysis methods, the process of setting specific search conditions, and the process of using statistical analysis methods for research results [18].

Statistics of water quality evaluation results: During the statistical period, each type of water quality indicators shall be calculated based on the water quality, the percentage of calculation and statistical table and the intersection plan, with the administrative region or monitoring station as the statistical unit.

Statistics of monitoring indicators: during the statistical period, take different monitoring indicators as the statistical unit, count the maximum, minimum, average and days beyond the standard of monitoring indicators of each monitoring station, and generate statistical data tables and composite broken line charts.

4. Application of Remote Sensing Monitoring System for Water Source Pollution Sources Based on depth CNN

4.1. Experimental Test

The experimental image is from the remote sensing image of a lake area obtained by Environment-1 satellite. The verification of the depth CNN algorithm uses the water quality monitoring map of the lake area as the experimental data. Only the lake suspended matter monitoring map is taken as an example to verify the correctness of the correction results of the remote sensing image. According to the suspended matter monitoring map of the lake, combined with the actual measured data, CNN algorithm is used to correct the pixel points in the image, so that the corrected image can accurately match the suspended matter distribution in the actual water area. The experimental results are shown in Figure 2.

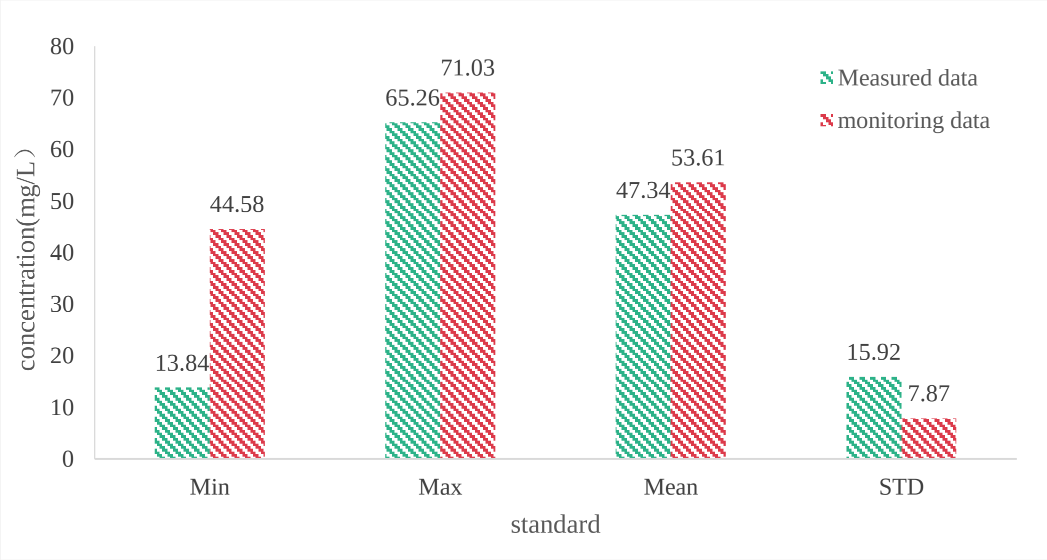

Figure 2. Concentration of suspended solids (mg/L)

The statistics of suspended solids monitored by the remote sensing image monitoring system show that the maximum value is 71.03 mg/L, the minimum value is 44.58 mg/L, and the average value is 53.61 mg/L. In the measured data, the maximum value is 65.26 mg/L, the minimum value is 13.84 mg/L, and the average value is 47.34 mg/L. It can be seen that the concentration range of suspended solids in the measured data is greater than that in the system monitoring result map, It shows that the concentration classification of suspended solids in the monitoring result map is different from the actual situation, which cannot reflect the actual water quality distribution. Therefore, CNN algorithm is used to correct the remote sensing image, so that the monitoring results can more accurately reflect the distribution of suspended solids in the lake area. The results are shown in Figure 3. The corrected image has obvious homogeneous grading property, and the concentration of suspended solids varies greatly in different areas.

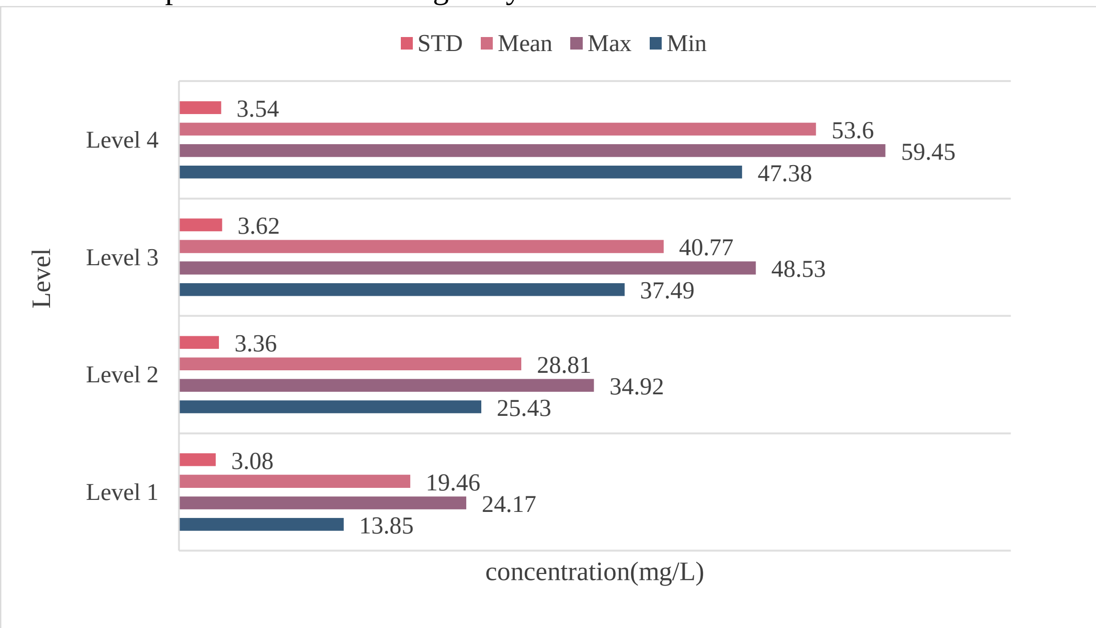

Figure 3. Grading statistics of suspended solids concentration (mg/L)

4.2. Analysis of Space-Time Distribution Characteristics of Water Quality

In order to study the temporal and spatial distribution characteristics of water quality in the lake area, TN and TP are selected as the main exceeding standard factors for analysis. The results are shown in Table 1 and Table 2.

Table 1. TN concentration distribution (mg/L)

	A1	A2	A3	A4	A5
Spring	1.12	1.46	1.37	1.00	1.72
Summer	2.36	2.35	2.18	2.89	2.51
Autumn	0.76	0.42	0.84	0.50	0.55
Winter	1.21	1.18	1.00	1.14	1.26

It can be seen from Table 1 that TN concentration in the lake is the lowest in autumn and the highest in summer. In spring, the TN concentration at most sampling points fluctuated at about 1mg/L, which was Class IV water. The total nitrogen concentration at A5 sampling point reached 1.72mg/L, which was Class V water; In summer, the TN concentration at each sampling point was the highest in the year, exceeding the Class V (2mg/L) water quality standard for surface water, which was inferior to Class V water quality; TN concentration is relatively low in autumn, and the water quality at each sampling point is basically maintained at Class III water; The water quality in winter is similar to that in spring, and the TN concentration at each sampling point is maintained at about lmg/L.

Table 2. TP concentration distribution (mg/L)

	A1	A2	A3	A4	A5
Spring	0.34	0.09	0.17	0.23	0.19
Summer	0.22	0.17	0.13	0.16	0.18
Autumn	0.26	0.27	0.24	0.21	0.23
Winter	0.07	0.09	0.06	0.03	0.04

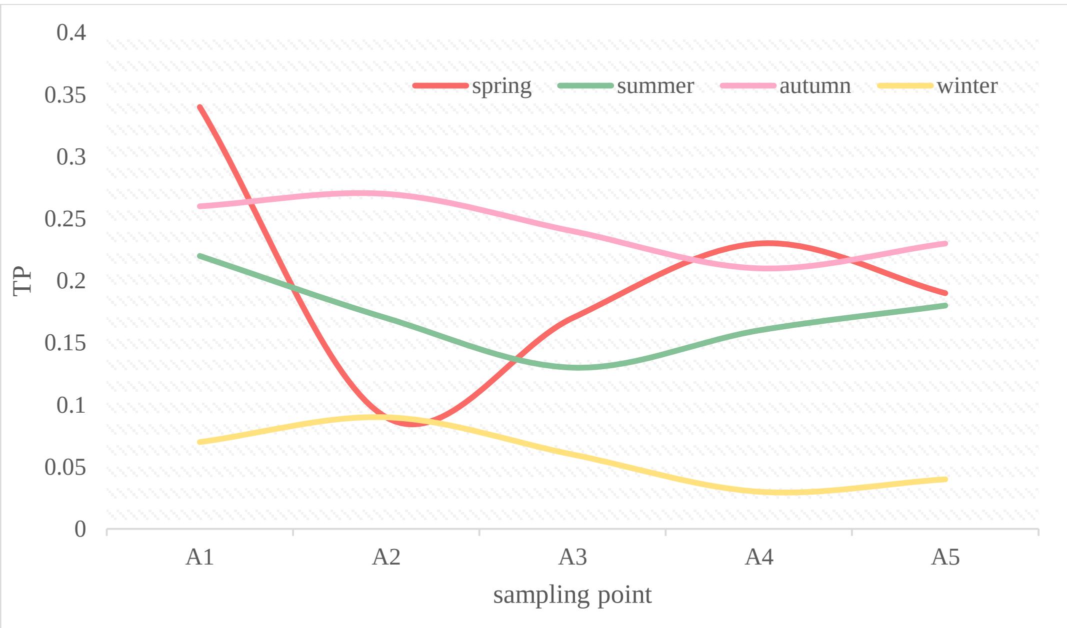

Figure 4. TP concentration in each season

As shown in Figure 4, the average concentration of TP in each season was higher in spring, summer and autumn, and the lowest in winter, which exceeded the standard for a long time during the monitoring period. In spring, the TP concentration at A1 sampling point is much higher than that at other sampling points, reaching 0.34mg/L, far exceeding the Class V (0.2mg/L) water quality standard for surface water. The total phosphorus concentration of A2 is relatively low, belonging to Class IV water quality. The water quality at other sampling points is of Class V and inferior to Class V; TP concentration in summer is basically between spring and autumn; TP concentrations at the adoption points in autumn exceeded 0.2mg/L, which was inferior to Class V water quality; TP concentration is relatively low in winter.

It can be seen that the concentration of nitrogen and phosphorus in the lake is relatively high in spring and summer, which may be due to the fact that this period coincides with the critical period of crop cultivation in the upstream of the lake, and the amount of fertilizer is increased. However, because the crops cannot absorb all the fertilizer applied in time, the utilization rate of fertilizer is low, so the rainwater carries part of the fertilizer and gradually migrates to the reservoir, causing the increase of nitrogen and phosphorus concentration in the lake area. The sampling time in autumn is October. The rainfall decreases, the loss of nitrogen and phosphorus is weak, and the concentration of TN in the lake area is low, while the concentration of TP is relatively high. The concentration of nitrogen and phosphorus is relatively low in winter. The sampling time is January. The water level in the lake area is in the dry season. The water flow in the upstream river is relatively small, and the ability to carry nitrogen, phosphorus and other pollutants is weakened. The water quality in the lake area is relatively good.

5. Conclusion

In order to solve the problem of nitrogen and phosphorus pollution in the lake reservoir type drinking water source area, we should not only focus on the external pollution in the basin, but also fully consider the internal pollution in the source area. This paper is based on CNN to identify the characteristics of pollutant images, and uses remote sensing images to analyze the sources of nitrogen and phosphorus pollution in the lake reservoir type water source, so as to clarify the priorities and primary and secondary order of pollution source treatment in drinking water source areas, and provide very effective technical assistance for scientific, effective and targeted control of non-point source pollution in water source areas, and improvement of water environment quality in lake reservoirs and other drinking water source areas.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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