Research on the Water Quality Intelligent Monitoring System of River Gushing Based on Federal Learning

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Abstract: Intelligent video surveillance technology is increasingly widely used in social production and life and plays an important role in economic development and environmental protection. This paper focuses on the field of water quality monitoring, and aims at the problems of traditional river gushing including difficulty of water quality monitoring, poor timeliness and insufficient automation, and proposes the intelligent water quality monitoring method from the perspective of intelligent image treatment. A federated learning system combined with a NVIDIA Jetson TX2 edge nodes is constructed by HD cameras deployed at various monitoring points of the gushing. On this basis, based on the convolutional neural network technology, the identification and monitoring of the river gushing water quality can effectively reduce the operation amount and water quality monitoring automation degree under the case of ensuring the accuracy.

1. Introduction
Due to historical reasons, many urban rivers in China have become discharge channels for domestic sewage, industrial waste water and some agricultural sewage, resulting in their pollution to varying degrees. Since the 18th National Congress of the CPC, President Xi Jinping has put forward the concept of ecological civilization construction from an overall perspective, and monitoring the water quality of river gushing has become an important work to carry out urban water environment governance. The traditional river gushing water quality monitoring mainly relies on manual regular inspection and takes site sampling from relevant rivers, and then uses chemical analysis to take water quality analysis. This practice has two disadvantages: one is limited by human and traffic reasons, the existing inspection and testing frequency is limited, there is a large supervision timeliness problem; the second is that the surrounding environment of urban river gushing is complex, so taking personal sampling is accompanied by personal safety risks.

For the above problems, some researchers have proposed water quality monitoring methods based on online methods.\(^1\) The method is integrated with water quality sensor which is as the core, combined with embedded, software, electromechanical control and fluid sampling technology, which is essentially the specific application of Internet of Things technology. Chrommatography is an important water quality feature in this approach. The water images taken based on real-time locations contain rich chromatic information and intuitively reflect the degree of water pollution. With the increase of water monitoring image data volume and the wide application of deep neural network, deep learning models for temporal historical data and a large number of monitoring image data can also be used in water quality monitoring systems.\(^2\) This paper proposes a water quality color analysis model based on federal learning, which pretreatments a series of collected water image data and then uses the idea of distributed processing to construct a federated learning model, and analyzes the
collected water image data based on convolutional neural network technology, and then infers the water quality in the time and place represented by the image data.

2. Federated Learning Algorithms

2.1. Federal Learning Concepts

Federated learning is a machine learning model based on distributed data training proposed by Google that can well solve the data island problem and ensure data security. The federated learning architecture mainly includes clients (such as tablets, mobile phones, IOT devices) and central servers (such as service providers), which coordinate model training based on a mechanism. Different from the traditional and their learning algorithms that need to upload the user source data to the cloud servers with high computing power for centralized training, the client is responsible for training the local data and obtaining the local model. The central server is responsible for the weighted aggregate local model to obtain the global model. In this process, the original data participating in federated learning is retained in the local client, interacting with the central server is only the model update information, and the weights of the model jointly trained by the participants will be shared by all parties. A typical federated learning architecture is shown in Figure 1:

![Figure 1 Typical Federal Learning Framework](image)

2.2. Federal Learning and Training Process

An iterative process of federated learning is as follows:

1. The client device K downloads the global model which is formed after iterations from the server through t-1 times;
2. Client device K trains the local data to get the local model \( P(w_{t,k}) \);
3. Each client uploads the local model to the central server;
4. The central server receives the party data for weighted aggregation operation to obtain the global model \( F(W_t) \) after t times iterations.

During the training process of federated learning, assuming a total of n client devices participate in the training, the data quantity of the Kth device is \( d_k \). The local target function for the Kth device is \( \varphi_k(w) \), then the target function of the central server is:

\[
\Phi(w) = \sum_{k=1}^{n} \frac{d_k}{D} \varphi_k(w) \tag{1}
\]
Among them, \( D_n = \sum_{k=1}^{n} d_k \)  \( (2) \)

In general, optimal weights can be found using the bulk gradient descent algorithm,\(^5\) which trains the loss function through the local client model, multiplying the learning rate \( \eta \) to calculate a new round of weight updates by the learning rate.\(^6\) As shown in the formula (3):

\[
W_{t+1,k} = W_{t,k} - \eta \Delta \phi_k(w) \quad (3)
\]

After the weights of the Kth device are obtained by formula (3), the weights of all client devices are weighted according to the amount of data of a single device, obtaining the weights of the central server. As shown in the formula (4):

\[
W_t = \sum_{k=1}^{n} \frac{d_k}{D_n} W_{t,k} \quad (4)
\]

Therefore, after multiple rounds of iterations, a distributed model that approaches the results of the centralized convolutional neural network model is finally obtained. On the basis of ensuring the effectiveness, the privacy risk problem and insufficient computing power of the source data aggregation caused by the traditional convolutional neural network methods are partly solved.

3. Water Quality Intelligent Monitoring System Design Based on Federal Deep Learning

According to the structure and training principle of federal learning, this paper designs a river quality monitoring system based on federal learning. The system consists of a central server and several edge nodes. According to the actual monitoring needs, the edge nodes are arranged at different river gushing water quality monitoring points, and each monitoring point is equipped with an edge computing module connected to the central server. The edge computing module is connected to the camera of the monitoring point which can process and train the water image data collected by the camera. The overall structure of the whole water quality intelligent monitoring system is shown in Figure 2.

![Figure 2 Architecture of Intelligent Water Quality Monitoring System](image)

3.1. Edge Computing Module Deployment

In the water quality intelligent monitoring system, the NVIDIA Jetson TX2 embedded development board is selected as the edge computing module, connected to the high-definition camera arranged at
the river gushing monitoring point for data collection and processing. The role of the NVIDIA Jetson TX2 platform is to process the water image data collected by HD cameras and train the models distributed by the central server. The NVIDIA Jetson TX2 platform has the advantages of small volume, strong computing power and low power consumption, which is very suitable for deployment in the actual monitoring environment. Software such as Ubuntu 16.04 system and CUDA9.2, cuDNN7.4, OpenCV3.4 is configured to establish an operation platform, which is then connected to the high-definition camera to collect the high-definition camera data. As shown in Figure 3.

![Figure 3 Schematic Diagram of the Connection between the NVIDIA Jetson TX2 Edge Node and the High-Definition Camera](image)

3.2. Deploy Water Quality Intelligent Monitoring System
High-definition cameras distributed in various monitoring nodes collect the video data of the local river gushing water body at that time, convert it into image data, and upload it to the NVIDIA Jetson TX2 edge node through the interface conversion circuit. The edge nodes train the pre-trained initial neural network model which is distributed, pretrained by the central server using the received water image data from the central server and upload the trained model parameters to the central server. After the central server receives the model parameters of each node, the central server trains and optimizes the water quality monitoring neural network model with the weighted sum method, and redeploy the optimized neural network model to each edge node. According to the model parameters transmitted by each edge node, the central server constantly optimizes and maintains the universal water quality monitoring neural network model deployed on the central server. The edge nodes use the optimized neural network model to deeply excavate the chromatic characteristics of the water image of the river gushing, and judge and monitor the water quality results.

4. Conclusion
This paper collects remote images for water quality monitoring, and uses artificial intelligence technology for water quality discrimination, with no secondary pollution and convenient maintenance, and not causing a personal safety risk. Multiple edge nodes perform the water quality monitoring work at the same time, and realize the synchronous optimization of the neural network model, and speed up the error decline, and achieve the same reading effect as the traditional convolutional neural network model, but greatly reduce the operation amount, and reduce the difficulty of water quality monitoring, and reduce the consumption of human and material resources, the use of intelligent image processing method to conduct water quality monitoring has a good reference value.

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