Research of Water Body Turbidity Classification Model for Aquiculture Based on Transfer Learning

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Abstract: Fodder, fish manure, and pond sludge will seriously affect the turbidity of the water body in aquaculture. How to quickly and online judge the turbidity of the water body is very important for realizing efficient, low-cost, and accurate control of aquaculture. In view of the shortcomings of traditional detection methods, a transfer learning method based on ResNet deep learning network model is proposed to realize water body turbidity classification, and two transfer learning methods of parameter partially frozen and completely unfrozen are designed based on ResNet18. Subsequently, the turbidity data set of aquaculture water quality was constructed, and the data set was enhanced by image cropping, image flipping, random scaling, and other methods. The experimental results show that when all parameters are not frozen, the transfer learning method can achieve the best class effect, and the accuracy rate is 0.9686, which can provide an effective method for online detection of aquaculture water body turbidity.

Keywords: water quality turbidity; aquiculture; Transfer learning; Resnet18

1. Introduction

China’s aquaculture production ranks first in the world, accounting for 65% of the global total output.[1] The change of water quality during aquaculture will directly affect the growth and harvest time of fish, and water quality is the key to the success of aquaculture.[2] Water body turbidity is the direct indicator of water quality.[3] Timely and rapid prediction of turbidity change of aquaculture
water can minimize its damage. At present, the judgment of turbidity mainly depends on the aquaculture experts. This method is not only subjective but also time-consuming and inefficient, which is not conducive to large-scale automatic production. Therefore, it is of great significance to realize intelligent, rapid, and accurate water body turbidity identification.

With the development of electromechanical engineering and modern electronic information, an online water quality monitoring system has been widely used in water quality monitoring, and automatic water quality monitoring has achieved good results. Chen[4] designed a turbidity sensor based on STM32 and used the vertical scattering method to measure the turbidity of the liquid in the low turbidity range. Yang[5] designed a water quality monitoring system based on LoRa wireless transmission technology, which can realize the on-line monitoring of dissolved oxygen content, pH value, conductivity, and temperature of the water. However, the traditional water quality detection method based on the sensor is easy to be eroded when the detection probe is in contact with air and liquid for a long time, which is short in service life, low in reliability, and hard to maintain, and few people directly identify the turbidity of the water body.

Lang[6] proposed a water body turbidity detection system based on spatial domain and frequency domain image extraction algorithm combined with the artificial neural network, which improved the accuracy of water turbidity, but the feature extraction and turbidity prediction of this method were separated, and the accuracy of feature extraction directly affected the accuracy of the results. In recent years, intelligent recognition based on machine vision has been used in agriculture and achieved great success. In the field of agriculture, many scholars study the application of agricultural intelligence based on transfer learning because of the difficulty in obtaining data sets. Xu[7] proposed a corn disease image recognition model based on transfer learning and convolution neural network. Cao[8] used the transfer learning method to recognize small-scale flower images, and achieved good results.

In this paper, We use Resnet18, a deep residual network, as the basic model, and research the method of realizing turbidity classification of aquaculture environment water based on transfer learning and propose an effective new method to realize on-line identification of turbidity of aquaculture water.

2. Water body turbidity classification model design

2.1. Convolutional neural network model

Convolutional neural networks(CNN) came into view in 1989 when Yann LeCun [9] proposed the first true CNN: LeNet 1989. Convolutional neural networks are a class of feedforward neural networks that contain convolutional computations and have a deep structure, including convolutional, pooling, and fully connected layers. The purpose of convolution is to extract the different features of the input to enhance some features of the original signal, and to reduce the noise, which reduces the amount of memory occupied by the deep network. The pooling layer can be very effective in reducing the size of the parameter matrix, compressing the data for feature downscaling, and thus reducing the number of parameters in the final fully connected layer. A classic process of the application of CNN is listed below.

\[ r = FC(Activate(Pool(Conv(X)))) \]
where the Conv denotes convolutional layer, Pool denotes pooling, Activate denotes activation function such as sigmoid or ReLu, FC denotes fully connected layer. The convolution layer, pooling layer, and activation function layer map the original data to the hidden feature space, while the fully connected layer maps the learned "distributed feature representation" to the sample mark space. The fully connected layer plays the role of "classifier" in the whole convolutional neural network. Now a lot of research used CNN in Aquaculture[10-12].

2.2. Transfer learning
Transfer learning is to transfer the weight of each node in the network from a trained network to a brand-new network, instead of training a neural network for each specific task from scratch[13-14]. In reality, most of the data or tasks are related. Through transfer learning, we can share the learned model parameters (which can also be understood as the knowledge learned by the model) with the new model, so that it can adapt to the new tasks faster, thus speeding up the convergence of the model and improving the learning efficiency of the model.

2.3. Introduction of aquaculture water body turbidity classification based on the ResNet model

2.3.1. ResNet model
Traditional convolutional or fully connected networks suffer from information loss, gradient disappearance, or gradient explosion during information transfer, making it impossible to train very deep networks. The ResNet[15] (Residual Neural Network), proposed by Kaiming He's team, is a good solution to this problem. The main idea of ResNet is to use ResNet Units to allow raw input information to be passed directly to the subsequent layer, as shown in Fig. 1 below, to protect the integrity of the information. The entire network only needs to learn the input and output differences, simplifying the learning objectives and difficulty, as well as accelerating the training of the neural network and improving the accuracy of the model.

![Residual Unit](image)

2.3.2. Transfer learning methodology design
Convolutional neural network models have numerous parameters and a large amount of data is needed to drive them in order to get a better classifier. The classification results of the models obtained from the training were less than satisfactory due to the inadequate dataset of this trial. Our team uses the
Resnet18 model pre-trained on ImageNet data set for transfer learning to improve the effect of the model.

| Layer name | Output size | 18-layer |
|------------|-------------|----------|
| Conv1      | 112×112     | 7×7,64, stride 2 |
| Conv2_x    | 56×56       | 3×3 max pool, stride 2 |
|            |             | [3×3, 64] × 2 |
|            |             | [3×3, 64] × 2 |
| Connv3_x   | 28×28       | [3×3, 128] × 2 |
|            |             | [3×3, 128] × 2 |
| Connv4_x   | 14×14       | [3×3, 256] × 2 |
|            |             | [3×3, 256] × 2 |
| Connv5_x   | 7×7         | [3×3, 512] × 2 |
|            |             | [3×3, 512] × 2 |
|            | 1×1         | Average pool, 3-d fc, softmax |

**Tab. 1** Model structure of Resnet18

This experiment was based on the original Resnet18 model and three different transfer learning models were constructed, described as follows.

a) Start From Zero (We named it as Tab. 1): Training the Resnet18 model from scratch without importing pre-trained model parameters (as shown by (a) in Fig. 2), The imported image data is first normalized and processed to allow the model to start going to learn the water quality image data, training model. Finally, modify the fully connected classification layer output categories to make them applicable to our classification tasks.

b) Frozen Convolutional Layer (We named it as Tab. 2): Firstly, when the pre-trained Resnet18 model is imported, the fc(fully-connected) layer of the model is modified to adapt to our classification task. When training the model, freeze all convolutional layers and only update the parameters of all connection layers, as shown in figure b. Secondly, during training, all convolution layers are frozen and only the parameters of all connection layers are updated, as shown by (b) in Fig. 2.

c) All layers unfrozen (We named it as Tab. 3): Import the pre-trained model and use the imported pre-trained parameters as initialization. Not freezing any of the convolutional layers as well as the fully connected layer, and updating the parameters based on the dataset during training, allowing the model to better extract valid features of the dataset, as shown by (c) in Fig. 2.
3. Experimental design and analysis

3.1. Introduction of experimental data

In this paper, a large amount of video data was collected in a different aquaculture environment, and aquaculture experts were invited to classify the water body turbidity in the videos and construct an experimental dataset. The image data categories are classified as clear, moderately turbid, and turbid, and all three categories have similar colors in the images. In addition, the background of the image data was a complex background under the pool, which also made this experiment more difficult. A total of 1293 image data were collected, and the image samples are shown in Figures 3, 4, and 5. In fact, there is a fish in the middle image of Fig.5, but due to the turbidity of the water, we cannot see it clearly.

![Fig. 2 Three transfer learning methods](image)

![Fig. 3 Clear water](image)
3.1.1. Pretreatment of Experimental Data

In order to get a better classification effect, pre-processing of the test images is needed, including redefining the image size, performing normalization process, image de-averaging, and other pre-processing operations.

In the experiment, the image size was modified to 224*224 to meet the requirements of the Resnet18 network structure.

The purpose of de-averaging a picture is to standardize the image, and the average brightness value of the image can be removed. The specific operation is as follows: the average value of pixel values of the whole training sample is subtracted from each pixel value of a given image. In many cases, we are not sensitive to the brightness of the image but pay more attention to its content. In the task of picture classification in this experiment, the overall brightness of the image does not affect what objects exist in the image, so it is meaningful to remove the average value of pixels for each data point.

Data normalization is to scale the data in proportion to a small specific interval. The treatment method for a sample is shown in formula (1).

\[
\begin{align*}
\mu &= \frac{1}{n} \sum_{i=1}^{n} x_i \\
\sigma &= \frac{1}{n} \sum_{i=1}^{n} (x_i - \mu)^2
\end{align*}
\] 

(1)
where \( x_i \) denotes the value of the i-th pixel of the sample. n is the total number of pixels in the sample; \( \mu \) is the mean; and \( \sigma \) is the variance. The formula is shown in (2).

\[
\hat{x}_i = \frac{x_i - \mu}{\sqrt{\sigma^2 + \epsilon}}
\]

where \( \hat{x}_i \) denotes the normalized pixel value of the i-th pixel of the sample.

### 3.1.2. Online data enhancement

Due to the small dataset, it is easy to overfit in the trained network, so online data enhancement is used to augment the dataset. In this experiment, a small batch of images is subjected to online data augmentation during training. The main methods include: taking images to randomly crop 200*200 areas, flipping images in the horizontal or vertical direction, random scaling, and changing colors. The image enhancement allows the model to recognize more different features and increase the generalization ability of the model. The image before the transformation is shown in Fig. 6, and after the transformation is shown in Fig. 7.
3.2. Experiment and result analysis

The experiment was conducted under Windows 7, python3.6.2, and pytorch1.3.0. The CPU used Intel(R) Core(TM) i7-7700 at 3.60GHz and the GPU using NVIDIA GeForce GTX 1080 Ti.

The dataset is divided into a training set and a test set according to 4:1. 235 images are selected as the test set, and the remaining 1058 images are training set. During the experiments, the momentum factor is 0.9, the initial learning rate is 0.001, Epochs is 1000, and the BatchSize is 16. Five experiments were conducted on each of the three transfer learning methods designed in 2.3.2, and the mean of the five experiments was taken as the final classification accuracy.

The experiment result is listed as Tab 2 and Fig.8.

(T1: Star From Zero; T2: Frozen Convolutional Layer; T3: All layers unfrozen)

|          | T1    | T2    | T3    |
|----------|-------|-------|-------|
| Training Accuracy | 0.9809 | 0.9713 | 0.9964 |
| Test Accuracy   | 0.9059 | 0.9407 | 0.9686 |

Tab. 2 Experiment result
The results show that the overall difference in training accuracy between the three learning methods is small, but the test accuracy varies greatly, and T3 transfer learning method achieves the best results. T1 mode does not use pre-training parameters to initialize the weights, although the training accuracy is high, the test set reflects the poorest result, which indicates that the model generalization is bad. The training accuracy and test accuracy of the transfer learning method with all layers unfrozen are optimal, with a test accuracy of 0.9686, which indicates that the use of pre-trained models to initialize the weights, and fine-tune the parameters through backpropagation, can make the models and parameters more suitable for the classification task, thus reflecting the best results. The transfer learning model of the frozen convolutional layer only updates the parameters of the fully connected layer, and the test accuracy is inferior to the transfer learning model without freezing all layers. According to the experimental results, when the dataset is small, the transfer learning mode of all layers unfrozen can get better results for the classification task.

4. Conclusion
In view of the need for water body turbidity identification in aquaculture, this paper proposes a turbidity classification model of aquaculture water based on transfer learning. Based on Resnet18, different transfer learning methods are designed, and the classification accuracy of the transfer learning mode of all layers unfrozen is 0.9686. In the later stage, we can consider extracting the color moment feature of the water image and fusing it with the convolution layer feature of Resnet18 to further improve the classification accuracy.

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