Research on Pipeline Video Defect Detection Based on Improved Convolution Neural Network

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Abstract. At present, the existing drainage pipeline defect detection methods cannot meet the use standards. This paper proposes an image classification method based on improved convolution neural network. By adopting multi-scale convolution kernel and splitting convolution kernel, pipeline image features can be fully extracted and accurate image classification can be realized. The data set used in this method is 6 kinds of pipeline defects collected under real scenes, including residual wall, deposition, root invasion, foreign body penetration, obstacles and hidden connection of branch pipes. Through a large number of comparative experiments, the accuracy rate of the method proposed in this paper is as high as 90.2%, which can effectively solve the complicated problem of pipeline defect classification. The method proposed in this paper has greatly improved its accuracy and efficiency, which has laid a solid foundation for efficient and accurate detection of pipeline defects.

1. Introduction

With the continuous advancement of urbanization, more and more residents gather in urban areas, and water supply and drainage pipelines are under great pressure. Drainage pipes can remove domestic wastewater, sewage and rainwater, and are an indispensable and important part of residents' sunrise life. With the increasing flow of people, the drainage pipeline system has been damaged to varying degrees, which cannot eliminate domestic sewage in time and rainwater in time when rainstorm strikes, seriously affecting people's daily life and urbanization construction. In order to find the problems in the drainage pipeline in time, it is necessary to check the drainage pipeline frequently, find the problems and repair them in time.

Traditional pipeline defect detection methods are very complicated⁠[1]⁠. The operation process is to use the robot to carry the camera into the drainage pipe to take pictures and record the environment inside the pipe and the condition of the pipe. The video taken will be watched manually and problems will be found. This will make the workload of the staff heavy, and long-term work will make the staff's judgment error. Therefore, pipeline defect detection based on machine vision will become a trend. The traditional image processing method can't meet the use standard when dealing with the complicated scene of pipeline defect detection. In this paper, depth neural network is combined to detect defects in pipeline images. Convolution neural network is mainly used to extract image features, and SVM is used to classify the extracted features. The method combined with deep neural network can extract more abundant pipeline image features, further strengthen the accurate identification of pipeline defects, and secondly reduce the workload of staff.
2. Related Work
With the development of machine vision, image classification tasks have been widely popularized and used. Many scholars at home and abroad have studied image classification tasks and achieved some results. SINHA[2] uses morphological method to preprocess the image, then extracts image features including texture, edge and other features, and finally uses KNN algorithm to classify defects in pipeline images. Yang[3] uses wavelet transform and co-occurrence matrix to extract pipeline texture features, and finally uses SVM algorithm to classify pipeline images. Li Bofeng[4] extracts roundness, compactness and concavity and convexity as feature vectors, and then trains BP neural network to classify pipeline defects. CNN[5] has made great achievements in Imagenet competition. CNN can be used to extract image features to classify pipeline defects. Zhang[6] identifies pipeline defects through target detection, and obtains defect location and category information by extracting features for Anchor location prediction and regression. Therefore, deep neural network provides a direction for pipeline defect detection. However, the pipeline scene is very complex and affected by different interference factors, resulting in the pipeline defect detection accuracy not meeting the use standard. The existing methods cannot solve this problem well. On the one hand, the extraction ability is limited and the accuracy is low; On the other hand, the method is inefficient and flexible.

This paper proposes a method based on improved convolution neural network to classify images in drainage pipeline video. The first choice is to convert video data into image data and build an image library. Secondly, data labeling is carried out, multiple SVM classifiers are trained to detect and classify each frame of image, the results returned by each neural network are counted, the defect type of the video frame is determined, and finally the results of the whole video frame are counted.

3. Improved Pipeline Video Defect Detection Algorithm
The pipeline defect detection method proposed in this paper refers to the use of multiple CNN models to detect defect types in drainage pipelines. Each neural network learns a specific defect, and the image is classified as containing or not containing a specific type of defect for learning during training. The detection process takes the pipeline CCTV video as the input. Firstly, the video is cut into continuous image frames, and then each frame is sent into 6 trained convolution neural networks for two classifications. The classification results only include the presence of a specific defect and the absence of defects. Finally, the return values of each neural network are combined to determine the detection results. The flow of pipeline video defect detection is shown in Figure 1.

![Figure 1. Overall flow chart.](image-url)
3.1. Improved Convolution Neural Network Model

Traditional convolution neural networks extract features through a multi-level structure. Because such networks pay too much attention to the details in the local receptive field, they are easily limited by the image itself. When the targets in the image are relatively small, they cannot accurately describe the targets only by details. Therefore, this paper improves the detection effect by adding global features[7-8]. In this paper, two different levels of network structures are designed and the defect detection of drainage pipelines is realized by connecting the two neural network structures in parallel. Using the global features learned from the shallow network structure to supplement the deep features can not only make up for the problem of insufficient feature extraction, but also grasp the global features and detailed features of the image as a whole. At the same time, a $1 \times 1$ convolution layer[9] is added to reduce the dimension of the input features, greatly reducing the network training parameters and accelerating the network calculation speed. The model network structure is shown in Figure 2:

![Network structure diagram](image)

**Figure 2.** Network structure diagram.

3.2. ReLU, LReLU and ELU functions

ReLU activation function is a simple maximum function, which can only be derived in the positive interval, thus solving the problem of gradient disappearance. However, when the activation function is in the negative interval, the activation function will fail and the neurons will not update their parameters, thus affecting the model training. In addition, the ReLU function also has the problem that the output mean value is not 0. As shown in Equation (1).

$$y = \max(x, 0) = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{else} \end{cases}$$

Aiming at the hard saturation problem, the LReLU[10] activation function is proposed. As shown in formula (2), the LReLU function has a relatively small slope at the negative end, which makes the zero gradient no longer appear in the whole activation region and alleviates the problem that hidden layer neurons are abandoned.

$$y = \begin{cases} x & \text{if } x \geq 0 \\ \frac{x}{a} & \text{else} \end{cases}$$

Recently, ELU[11] is proposed to correct linear elements. For example, in Formula (3), ELU can get negative values, which makes the activation mean value of the elements closer to 0, similar to the
regularization effect. ELU has soft saturation when inputting small values, thus improving robustness to noise. Therefore, ELU is selected as the activation function in this paper.

\[
y = \begin{cases} 
  x & x > 0 \\
  a(\exp(x) - 1) & x \leq 0 
\end{cases}
\]  

(3)

3.3. Stochastic Pooling

Common pooling methods include maximum pooling and average pooling. In order to improve the generalization ability of classification network, this paper adopts stochastic pooling method. On the one hand, maximization ensures the value of the maximum value; On the other hand, it ensures that all elements will not be taken as the maximum value, causing excessive distortion. Stochastic pooling allocates the probability of being selected according to the size of feature points. The calculation steps are as follows: the first step is to calculate the statistical sum of the pooled regions; The second step is to divide each pixel in the pooled region by the sum of the regions to obtain the probability value of each pixel; The third step is to randomly sample according to the probability value.

4. Experiment

4.1. Datasets and Evaluation Metrics

The experimental data in this paper come from Beijing Institute of New Technology Application. As shown in Figure 3, there are 6 types of defects, including residual wall, deposition, root invasion, foreign body penetration, obstacles and hidden connection of branch pipes. Defect definition refers to CJJ-181-2012-Technical Regulations for Inspection and Evaluation of Urban Drainage Pipelines [12]. In this paper, k-fold cross-validation method is used to optimize the network model. At the same time, Precision, Recall and F1 are used to evaluate the performance of the model.

![Figure 3. Pipeline defect image.](image)

4.2. Experiment Results

In order to verify the effectiveness of the method proposed in this paper, a large number of comparative experiments have been carried out, as shown in Table 1. The traditional defect detection method based on HOG + LPB + HSV has limited feature extraction, with an accuracy rate of 65.3%. Based on CNN, Cui-CNN and Deng-CNN, the highest accuracy rate is 86.7%, and the extraction feature is single and inefficient. The method proposed in this paper grasps the global features of the image as a whole, which helps CNN to grasp the characteristics of pipeline defects more fully when learning. At the same time, the 1 × 1 convolution layer is added to reduce the model parameters, accelerate the calculation speed, and the recognition accuracy is as high as 90.2%. Compared with the above representative algorithms, the effectiveness and superiority of this method are further demonstrated.
Table 1. Comparison test results

| Methods                | Precision | Recall | F1    | Time/s |
|------------------------|-----------|--------|-------|--------|
| HOG+HSV+LBP[13]        | 65.3      | 63.4   | 64.3  | 1.8    |
| CNN[14]                | 84.1      | 80.8   | 82.4  | 0.43   |
| Cui-CNN[15]            | 85.5      | 82.3   | 83.9  | 1.3    |
| Deng-CNN[16]           | 86.7      | 83.9   | 85.3  | 0.45   |
| Proposed CNN-ReLU      | 88.7      | 84.7   | 86.7  | 0.4    |
| Proposed CNN-LReLU     | 89.4      | 85.2   | 87.2  | 0.4    |
| Proposed CNN-ELU       | 90.2      | 85.9   | 88.2  | 0.4    |

5. Conclusions and Future Work
In view of the complex pipeline scene, the accuracy of defect judgment is low. In this paper, an improved convolution neural network defect detection method is proposed, which can accurately judge the defects of pipeline images. However, this method still has some shortcomings, such as limited features of extracted images. In the next step, we will improve and optimize the model. On the one hand, we will increase the diversity of data sets so that the data sets are evenly distributed; On the other hand, we will reduce the influence of background on defects and further improve the effect of the model.

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