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DEEP LEARNING-BASED CRACK, LOCATION AND AREA IDENTIFICATION FOR A PIPELINE BY THE CONVOLUTIONAL NEURAL NETWORK BASED ON CRACK CONTOUR NETWORK METHOD

Wael A. Altabey [1,2], Mohammad Noori [3,4,*], and Zhishen Wu[1,*]

[1] International Institute for Urban Systems Engineering (IIUSE), Southeast University, Nanjing 210096, Jiangsu, China.
e-mail: wael.altabey@gmail.com; zsw@seu.edu.cn

[2] Department of Mechanical Engineering, Faculty of Engineering, Alexandria University, Alexandria (21544), Egypt.

e-mail: wael.altabey@gmail.com

[3] Department of Mechanical Engineering, California Polytechnic State University, San Luis Obispo, CA 93405, USA.

[4] Visiting Professor, School of Civil Engineering, University of Leeds, Leeds, LS2 9JT, UK.

e-mail: mnoori@outlook.com

[*]Corresponding author: Mohammad Noori; Zhishen Wu

Abstract

In this work, the Convolutional Neural Network (CNN) algorithm is introduced in pipeline surface cracks monitoring-based image processing method for improving the efficiency and accuracy of crack type, location, and area identification. The method is used to extract the cracks area called the CNN based on crack contour network (CCN-CNNs) method from locate and extract the crack shape. CCN-CNNs is provides the accuracy rate (P%), recall rate (R%), and F-score (F%) index to assess the algorithm in the problem while identifying the cracks, and then according to the maximum F-score, we computes the crack corresponding contour area. In this work the pipeline crake images datasets are provided using an inspection drone with high definition camera. To the best of the authors' knowledge, the methodology presented in this paper for pipeline crack identification is an original contribution to the literature. This work introduces an efficient approach that also significantly reduces the time for crack type, location, and area identification of pipelines, the accuracy rate (P%), recall rate (R%), and F-score (F%) are recorded 91.8% ,86.1%, and 84.6% respectively.

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Keywords: Image processing; Convolutional Neural Network (CNN); Pipeline crack identification; Crack contour Network method.

1 INTRODUCTION

In recent decades, the rapid development of pipeline construction in various countries, play an important role in gas, water and liquids transportation over long distances. [1-5].

With the rapid development of pipelines construction, pipeline maintenance and management tasks also follow. In particular, a number of high-grade pipelines in the early stage have entered the period of intermediate or major repair, and the relevant pipelines maintenance and management departments have paid more and more attention to the monitoring of pipelines surface diseases and the collection of disease data. However, at present, there are few researches on pipelines disease detection, and the related detection equipment is seriously backward or even insufficient. Therefore, many pipelines maintenance management departments are still in the stage of traditional manual inspection. However, there are many problems in traditional manual detection, such as low detection efficiency, high labor intensity, long time consumption, and inability to guarantee detection accuracy. With the continuous increase of the scale of pipeline mileage, traditional pipelines detection methods can no longer meet the needs of pipelines disease detection. Therefore, research and development of advanced pipelines disease detection technology have become an urgent problem to be solved in pipelines development.

However, due to the harsh environment of the construction locations, pipelines always suffer from structural damage problems caused by corrosion, cracks, etc. Pipeline corrosion has been defined for decades as a major source of pipeline deterioration in transmission lines.

With the continuous development of the social economy, harsh environment of the construction locations, during the long-term operation of pipelines, various types of damages will occur. Damages such as cracks, and corrosion on the pipeline surface during pipeline operation will adversely affect environment and pipeline safety. Rapid and accurate detection of pipeline surface damages is an effective guarantee for maintaining the health and safety of pipeline surfaces [6-21].

At present, the management department generally collects the apparent image information of the pipe through the pipeline inspection drones and uses the traditional manual method to identify the damages, which is time-consuming and labor-intensive. Vision-based pipeline damages detection methods use adaptive threshold segmentation method, edge detection method, morphological method, wavelet analysis, and other algorithms for identification, but still face the following problems:

1) It is difficult to deal with the rich and diverse pipeline damage scenes;
2) Image noise interference leads to recognition the accuracy and efficiency are low;
3) The algorithm has many parameters, which require manual intervention, and the accuracy is low.

In addition, a single image of pipeline damages has high resolution and a large amount of image processing data. The current method is difficult to achieve rapid, quantitative, and refined identification of pipeline apparent defects.

With the development of deep learning technology [22-24] Convolutional Neural Network CNN has been widely used in the field of computer vision.

In recent years, some scholars have also tried to apply CNN to the apparent disease extraction of civil engineering structures. For example, Cha et al. [25] applied CNN combined with sliding window technology to crack recognition. The training data of CNN is 40,000 pictures

(256 pixels × 256 pixels), and the final verification accuracy is about 98%. The test picture size is 5888 × 3584. The test duration is 4.5s. Dorafshan et al. [26] constructed an SDNET 2018 crack image database that is convenient for engineers and technicians to use and applied CNN to crack recognition, which is different from the traditional edge detection method.

Compared with other methods, a hybrid identification method based on CNN and edge detection were proposed, and the effect was better [27]. Ni et al. [28] developed a CDN based on the CNN framework to automatically deal with structural apparent cracks through convolutional feature fusion and pixel-level classification.

Therefore, it takes a long time, and the use of CNN for target detection is generally easy to cause misidentification caused by over-fitting, and other methods still need to be used for subsequent processing. In order to solve the above problems, Girshick et al. [29] used CNN as the kernel and combined it with the Selective Search algorithm. Uijlings et al. [30] proposed a regional convolutional neural network (R-CNN) method. This method uses selective search to generate 2000 candidate regions, Then, CNN feature extraction is performed on each candidate region, and target classification is performed on each (Support Vector Machine, SVM) method. This method does not share the features of each candidate region extracted by CNN, resulting in information redundancy and long training and testing time. He et al. [31] proposed Spatial Pyramid Pooling (SPP-Net) which uses the full-image convolution shared feature map method to reduce the training and testing time of R-CNN. The target detection accuracy has also improved.

This paper introduces the local pipeline surface cracks localization and shape extraction based on CCN-CNNs methods. The location and area for the extracted disease area with borders are computed. For evaluation of the method is proposed, the accuracy rate (P), recall rate (R), and F-score index are introduced, which shows the effectiveness of the proposed approach.

2 METHODOLOGY

The process of pipeline cracks identification is shown in Figure 1. At present, the collection methods of pipeline surface images is inspection drones and other cameras that can achieve fast and non-contact high-quality image collection. The collected sample pictures are preprocessed, including cropping and segmentation of disease pictures, size unification, contrast adjustment, and image data enhancement to increase the number of samples; and then according to the classification of typical cracks in pipeline pictures, special software is used to mark the images and establish corresponding samples database; then input the training samples into the constructed CNN network, adjust the parameters, and perform deep learning on the entire network; finally, test the trained network.

For damages such as cracks, the algorithm directly outputs the bounding box and gives the cracks contour area and classification confidence. For horizontal and vertical cracks, after the bounding box is determined, the crack shape will be extracted and obtained the crack area, which makes the crack information richer and more accurate.

3 SYSTEM CONFIGURATION

3.1 CNN Architecture

As shown in Figure 2, typically a CNN model consists of both alternating convolution operation and sub-sampling operation, and the last layer is de-noted as a general multi-layer network. Interspersed with sub-sampling layers, convolutional layers are established to increase computation efficiency and further improve configural and spatial invariance. [32-34].

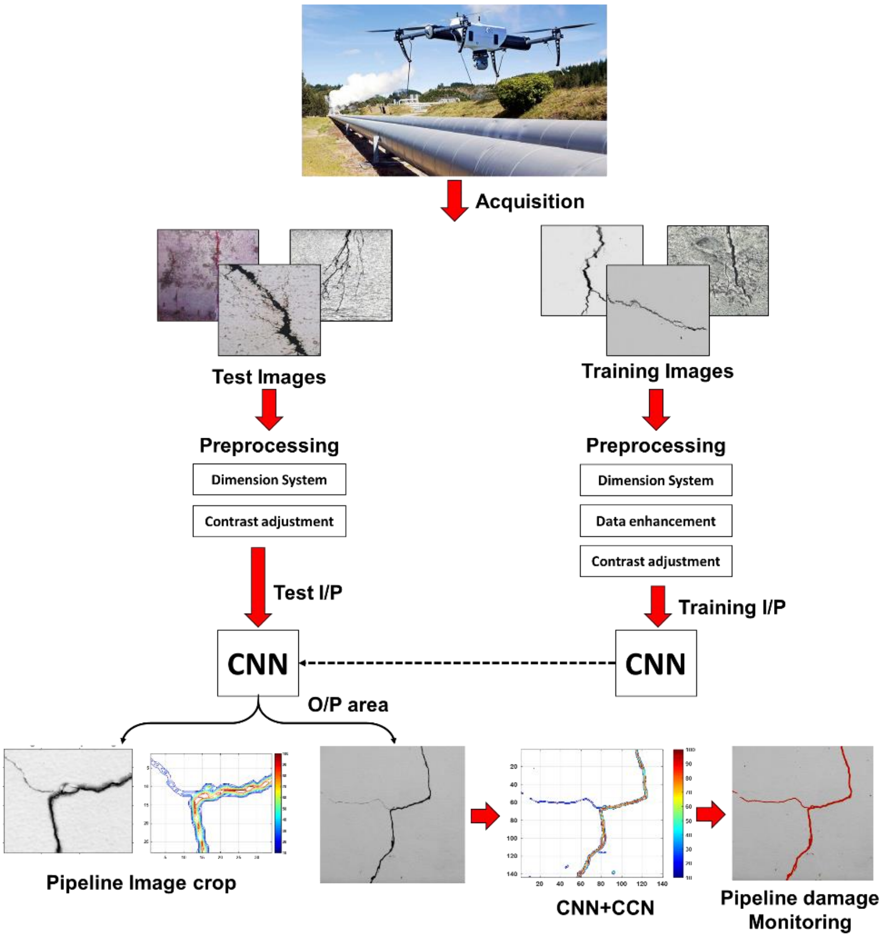

Figure 1: Illustration of the proposed method for pipeline disease identification.

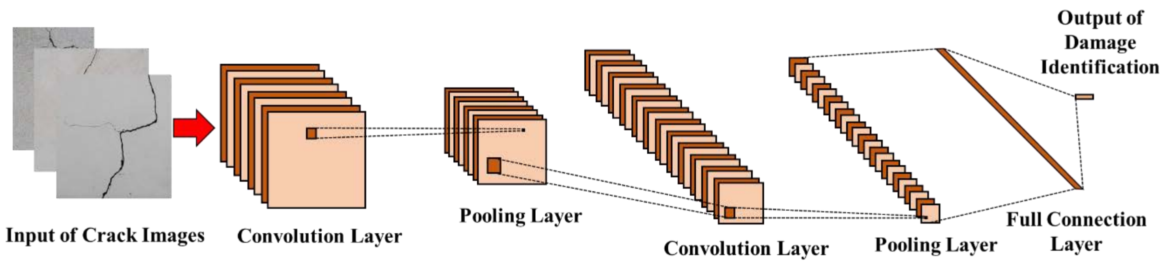

Figure 2: The architecture of a CNN model.

3.1.1 Convolution Layers

At a convolution layer, feature maps extracted from previous layers are convoluted with specific kernels and then activated to generate new feature maps. Multiple input feature maps are combined through the convolution operation until output is expressed as the following:

$$\boldsymbol{x}_j^l = f\left(\sum_{i \in M_j} \boldsymbol{x}_i^{l-1} * \boldsymbol{k}_{ij}^l + b_j^l\right). \tag{1}$$

where M_j denotes a set of input feature maps, and each output feature map is added with an additive bias b. The input feature maps are convolved with distinct kernels for a particular output feature map.

3.1.2 Pooling layer

The pooling layer is usually arranged between sequential convolution layers. It is used to reduce the feature maps locative size. This is also called undersampling, by which network overfitting can be controlled. The operations can be used for undersampling are such as maximum pooling and average pooling. It can be expressed the average pooling feature of pooling layer in Eq. (2) for assuming the pooling size is c, j^{th} is the region, and l^{th} is number of pooling layer.

$$\boldsymbol{x}_j^l = f\left(B_j^l mean\left(\boldsymbol{x}_j^{l-1}\right) + b_j^l\right) \tag{2}$$

where B_j^l is multiplicative; $mean(.)$ is average operation; The convolution and pooling layer are work together to detect the local connections and merges similar features and removes unnecessary irrelevant details.

3.2 Training, Validation, and Test Sets

In the CNN crack sample library, the cracks come from the actual collected pipeline crack pictures. The size of the source picture is 2048 × 2000 pixels. After slicing, the size of the small sample pictures is 32 × 32 pixels, and then data enhancement (rotation, mirroring, etc.) to obtain a training sample set, in which the number of samples with cracks is 15235 and the number of samples without cracks is 21642. After that, the pre-training network is used for migration learning, and all data are rotated 50 Epochs, and the final recognition accuracy can reach 95% above. Figure 3 presents the training performance using supervised mode. The key parameters for CNN training are shown in Table 1.

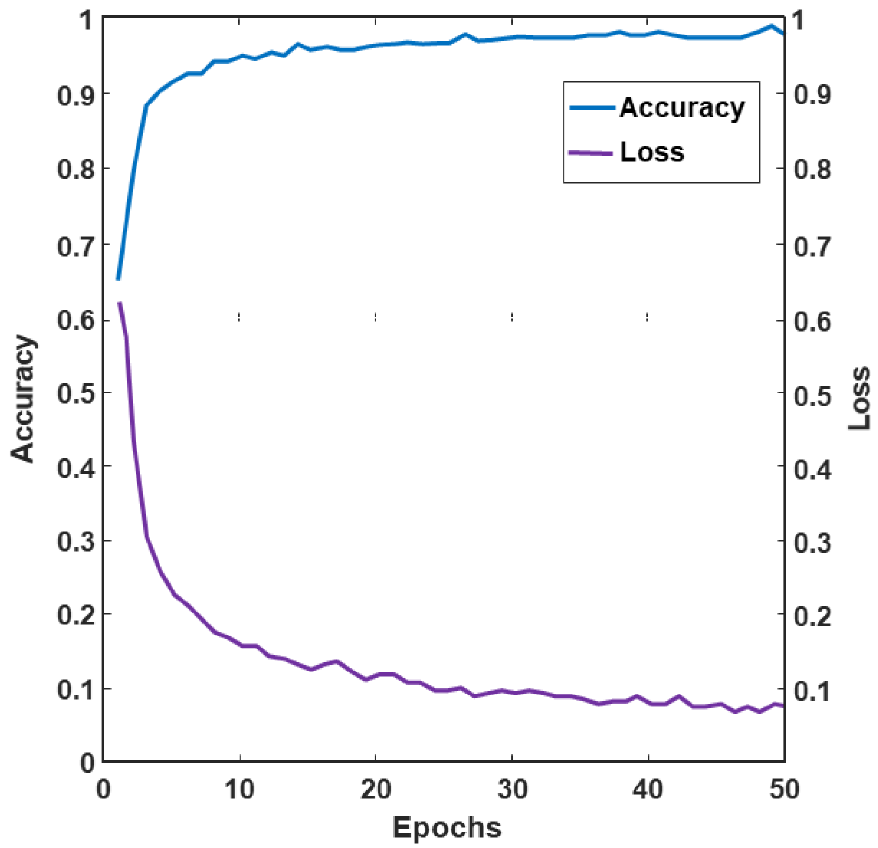

Figure 3: CNN Training Performance.

Table 1: CNN key parameters.

Training Time	Gauge	Training Rate	Attenuation Factor
50 sec	32	10^{-4}	10^{-6}

4 RESULTS AND DISCUSSION

In the previous section, CNN feature maps training, validation and test were studied for the intact and damaged pipeline system, the processing method of pipeline should be processed by the two-value image processing methods. It can be seen that the background noise is difficult to remove, and the effect is not ignored. As a result, some traditional image processing algorithms are difficult to get crack. A series of image processing operations based on shape is to extract the image component that is meaningful to express and depict the shape of the regional shape, the most essential shape characteristics of the target objects are identified, such as the contour and object areas. The typical CCN method is used for processing pipeline images, which are widely used in digital image processing. The crack shape is restored according to the minimum gray value in the bounding box area. The process is shown in Figure 4. The detection of pipeline crack can be described through the following steps in Figure 5.

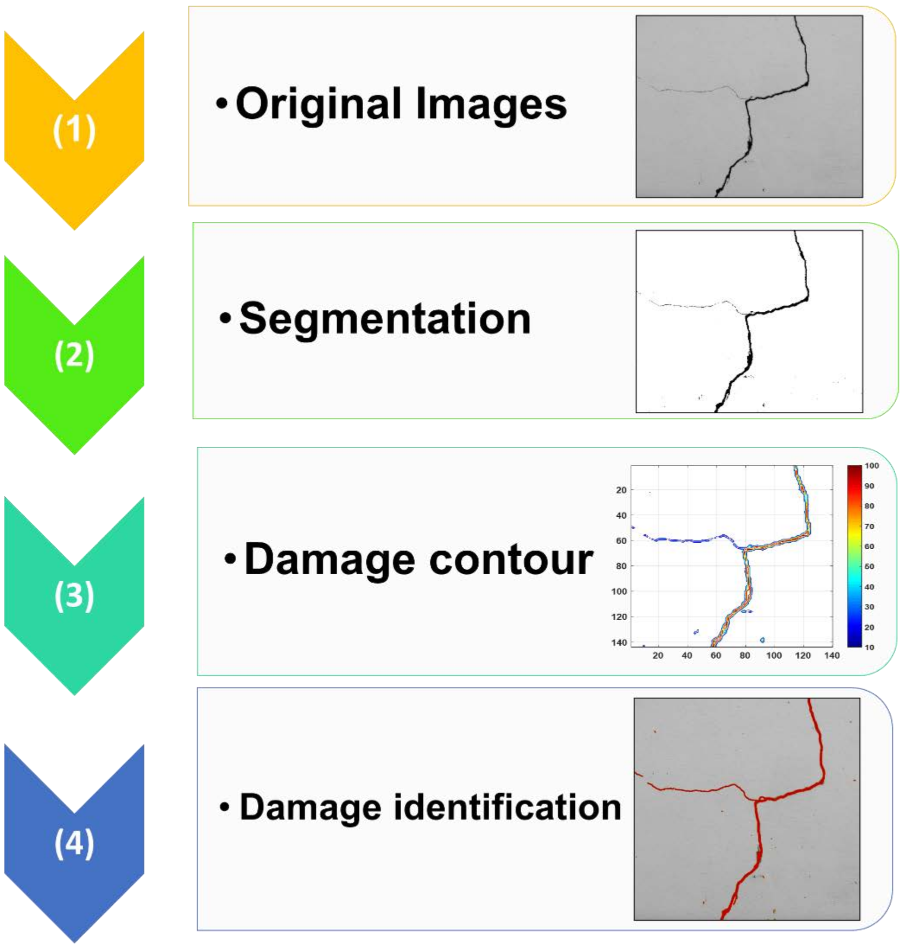

Figure 4: pipeline crack extraction flowchart.

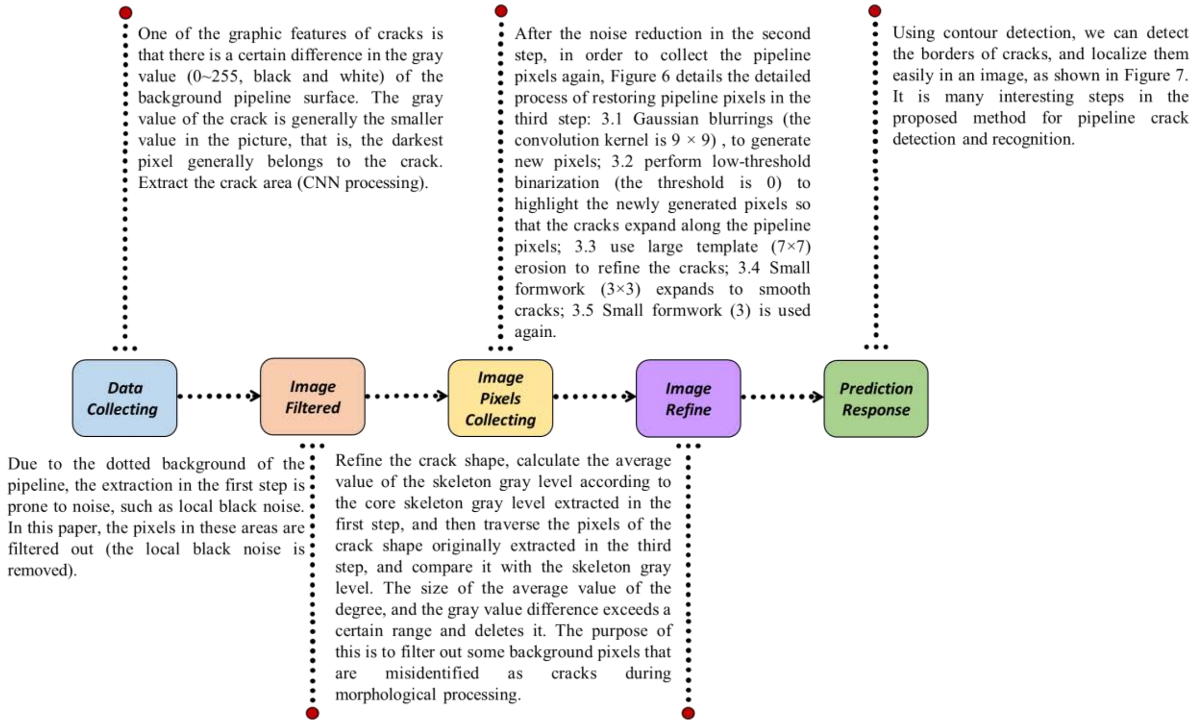

Figure 5: The steps of CCN-CNNs develop.

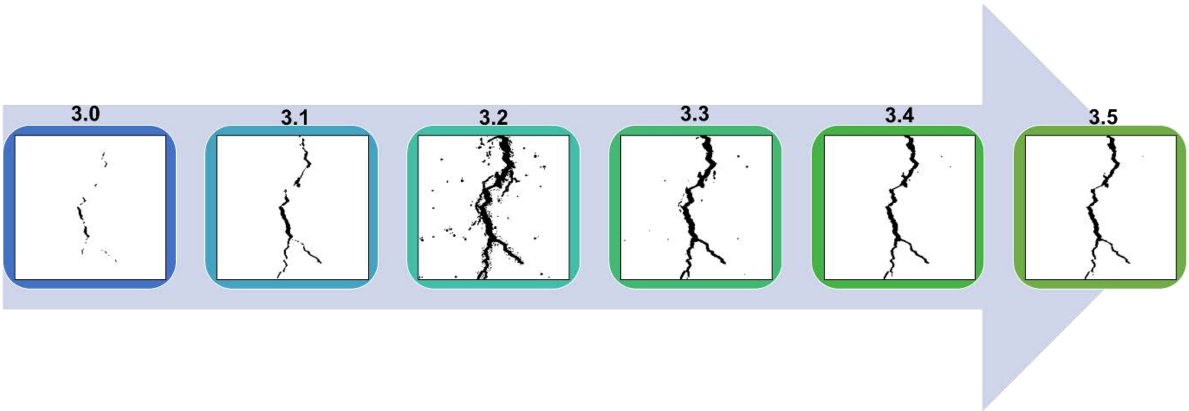

Figure 6: Collect the pipeline pixels again steps.

Four indexes that include the true-positive rate (TPR), true-negative rate (TNR), false-positive rate (FPR), and false-negative rate (FNR) are computed to estimate the proposed method performance measures for training and testing sets by calculating three indicators of the accuracy rate ($P\%$), regression rate ($R\%$), and F-score ($F\%$), these three indexes can be determined:

$$P\%, = \frac{N_{TPR}}{N_{TPR} + N_{FPR}} \tag{3}$$

$$R\% = \frac{N_{TPR}}{N_{TPR} + N_{FNR}} \tag{4}$$

$$F\% = \frac{2N_{TPR}}{2N_{TPR} + N_{FNR} + N_{FPR}} \tag{5}$$

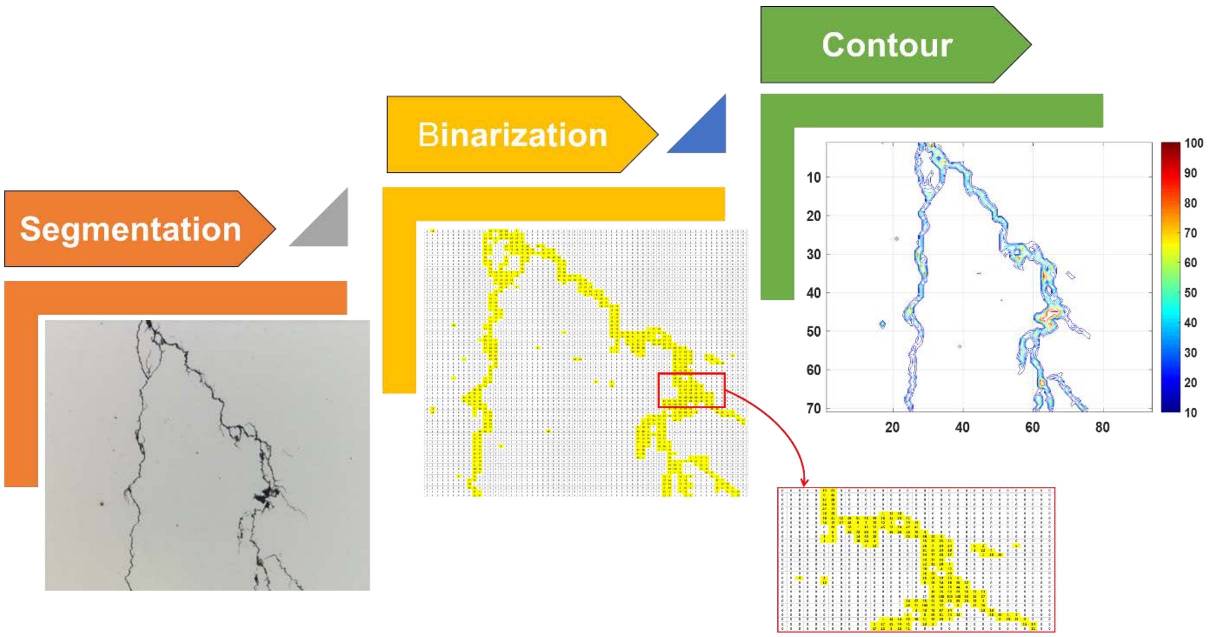

Figure 7: The crack contour extraction from pipeline Image.

Figure 8 plots the resulting accuracy (%), regression rate (%), and F-score (%) values in terms of the 50 Epochs number. In general P%, R%, and F% versus the overall performance are 91.8%, 86.1%, and 84.6%, respectively.

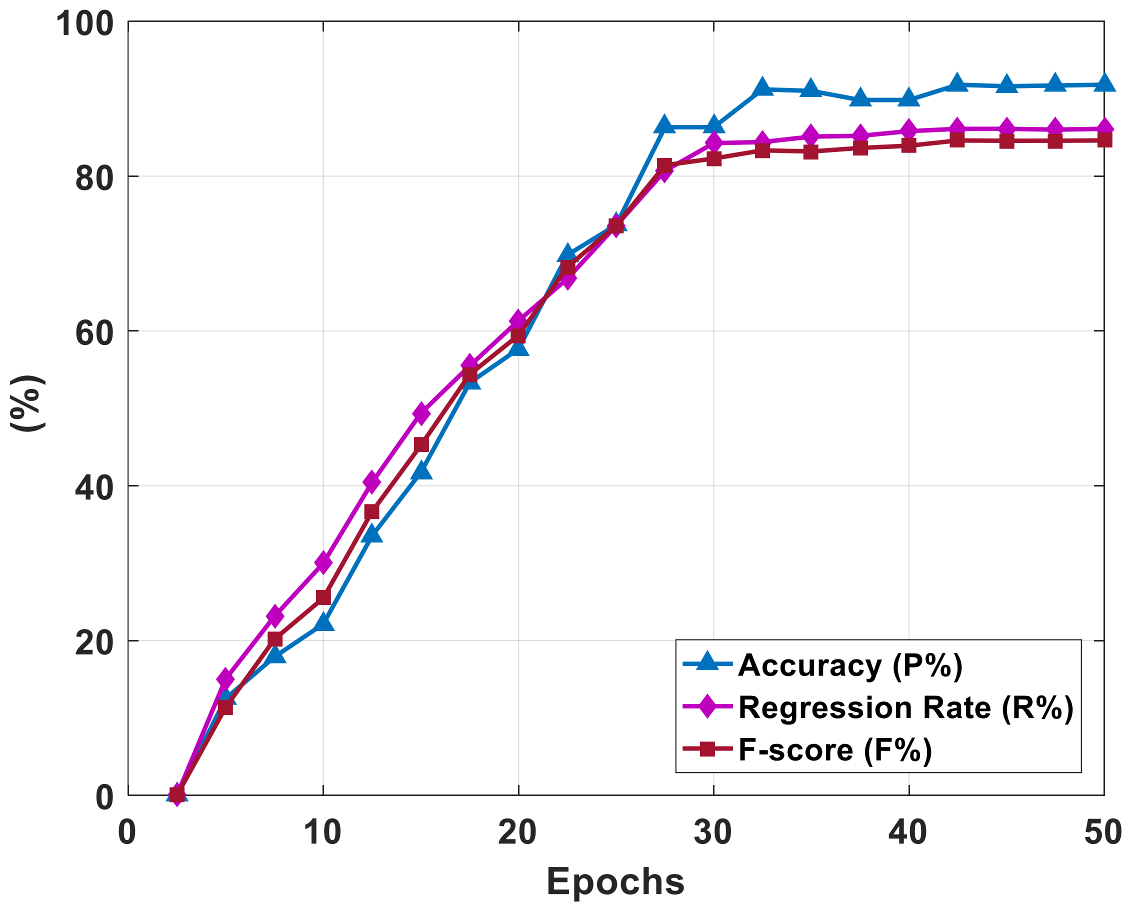

Figure 8. The training proceed comparison based on the crack identification test data.

5 CONCLUSIONS

This paper proposed the framework for pipeline crack detection method based on a learning-based model. The CNN algorithm in target detection is introduced to quickly identify the type, location, and area for the extracted disease area with borders, the CCN-CNNs method used to locate and extract the crack shape. The following conclusions can be drawn from the results:

1) The integrated method of CCN-CNNs can effectively search and locate the disease on the pictures collected by the pipeline inspection drones, and accurately extract the crack shape.
2) The test results show that its work efficiency is high, although the missed detection rate of the algorithm is low, the false detection rate is high, and it is difficult to be directly applied to the automatic detection of pipeline cracks.
3) Indexes such as the accuracy rate (*P%*), recall rate (*R%*), and F-score precision rate (*F%*) are introduced to evaluate the algorithm and determine the corresponding contour area of the disease frame according to the maximum F-score. A pipeline image was carried out by using an inspection drone with high definition camera.
4) The dataset used in this work, modeled with high *P%*, *R%*, and *F%*, and the overall performance are 91.8%,86.1%, and 84.6% respectively, highlighting the potential of using deep learning for the detection of pipeline crack.

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