Defect Detection of Mechanical Design Products Using Deep Neural Network

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Research Article

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Defect Detection of Mechanical Design Products using Deep Neural Network

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Abstract: In industrial production, defect detection is one of the key methods to control the quality of mechanical design products. Although defect detection algorithms based on traditional machine learning can greatly improve detection efficiency, manual feature extraction is required and the design process is complicated. With the rapid development of CNN, major breakthroughs have been made in computer vision. Therefore, building a surface defect detection algorithm for mechanical design products based on DCNNs plays a very important role in improving industrial production efficiency. This paper studies the surface defect detection algorithm of mechanical products based on deep convolutional neural network, focusing on solving two types of problems: defect recognition and defect segmentation. Aiming at the problem of defect recognition, this paper studies a defect recognition algorithm based on fully convolutional block detection. This algorithm introduces the idea of block detection into the ResNet fully convolutional neural network. While realizing the local discrimination mechanism, it overcomes the shortcomings of the traditional block detection receptive field. Compared with the original ResNet image classification algorithm, this algorithm has stronger generalization ability and detection ability of small defects. Aiming at the problem of defect segmentation, this paper studies a defect segmentation algorithm based on improved Deeplabv3+.

Keywords: Mechanical product; Defect detection; Defect segmentation; Convolutional Neural Network

1. Introduction

All countries are using information technology to promote the era of industrial transformation. Prior to this, the development of industry has experienced the steam engine era, the electrification era, and the information era. China is a major manufacturing country. In 2017, the government proposed to accelerate the development of advanced manufacturing. In 2019, the government proposed to build an industrial Internet platform, expand intelligence, and empower the manufacturing industry to transform and upgrade. Artificial intelligence is actually serving the manufacturing industry. Driven by this situation, China and the world urgently need a large number of artificial intelligence projects to be applied in the industrial field. Among them, deep learning is the core of artificial intelligence, and it is the mainstream technology that enables artificial intelligence to achieve prosperity from concept to prosperity [1-5].

In industry, in the manufacturing process of mechanically designed products, surface defects will inevitably occur. On the one hand, these defects will cause the product to bring people an unsightly experience, on the other hand, it will affect the

performance of the product or even fail to work normally. Therefore, surface defect detection is a key method to control product quality. Early detection of product defects can reduce the risk of product damage and thus reduce costs.

The early detection of surface defects of mechanical products mainly relied on manual detection, but this method relied on the experience of the inspector and was easily affected by its subjective factors. With the advancement of science and technology, manual detection methods are gradually eliminated. At present, the defect detection methods in the industry mainly rely on some vision software and traditional image processing technology. This traditional defect detection method mostly relies on experienced experts to find features, including considerations from various aspects such as shape, color, and length. In the end, a series of rules are formulated for defect detection. This process is quite complicated and time-consuming. This type of detection method performs well in some simple examples, but it is difficult to apply to some features that are difficult to quantify directly by the human eye or other more complex features. And for different types of products and defects, different rules and algorithms need to be designed [6-10].

Deep learning technology is advancing by leaps and bounds and is widely used. Compared with traditional technologies in all directions, it shows significant advantages. Artificial intelligence projects have landed one after another. Megvii Technology's urban brain uses city management, communities, and transportation as application scenarios, combined with cameras and other hardware as sensors, and uses deep learning technology to analyze perception data. It provides an integrated solution for urban public IOT scenarios. SenseTime's wisdom and health apply deep learning technology to medical images to provide decision support for clinical diagnosis of various diseases and improve medical results. Yuncong Technology's Universiade Huoyan portrait big data system combines deep learning and big data to achieve real-time monitoring and trajectory retrieval. For mechanically designed products, the background of surface defects is complex, and there are many types of defects. Various types of defect characterization forms are different, and the same type of defect characterization forms are also different. It is difficult to capture all effective features through manual features. Deep learning convolutional neural network has a strong ability to extract image features independently, so it is of research significance to introduce deep learning into workpiece surface defect detection [11-15].

2. Related Work

Surface defect detection algorithms based on traditional image processing methods include threshold segmentation, template matching, edge detection, and frequency domain transformation. Literature [16] proposed a new automatic detection system for surface crack defects of magnetic tile workpieces. The system is based on fast discrete curve transformation to decompose and reconstruct the collected magnetic tile workpiece image to obtain a low-noise image, which can remove noise such as background texture to a certain extent, and combines edge detection algorithm to realize the surface defect detection of the magnetic tile workpiece. Literature [17] proposed a real-time detection algorithm for steel surface defects, which segmented the steel area

of interest from the collected original images, and segmented the steel surface defects based on the local ring contrast. Literature [18] realizes the segmentation of workpiece surface defects based on improved Otsu, which solves the problem that the defect image tends to be unimodal or close to unimodal image Otsu's segmentation effect is not ideal. In literature [19], aiming at the problem that the grayscale histogram of welding small defect images is close to the unsatisfactory classification threshold of the single-peak histogram distribution, an improved Otsu segmentation algorithm is proposed to realize automatic detection of welding surface defects. Literature [20] realizes automatic detection of surface defects of mobile phone screen glass based on an improved fuzzy C-means clustering algorithm. The system first performs graphics registration based on contours, which solves the problem of image misalignment caused by rotation and displacement caused by graphics acquisition vibration.

The workpiece surface defect detection algorithm with machine learning can generally be divided into two phases. The first phase is to artificially extract effective image features, and the second phase is to classify workpiece surface defects based on machine learning algorithms. Literature [21] combines wavelet transform, discrete cosine transform and other methods to extract three-dimensional features to describe the defect of the workpiece, and combines with the Bayesian classifier to realize the surface defect detection of the blank. Literature [22] is based on the HotEye image acquisition system to obtain rich a priori information such as defect aspect ratio, defect longitudinal position, defect transverse position and defect severity, combined with support vector machine classifier to realize automatic detection of surface defects in steel hot rolling process. Literature [23] improved Complete Local Binary Pattern [24] and proposed the AECLBPs feature extraction algorithm, and combined the nearest neighbor and SVM to realize the automatic detection of multiple types of hot strip steel surface defects. Literature [25] proposed an automatic optical detection system for defects in thin film transistor arrays, which combines 9 image area features and combines with BP neural network to classify 5 common defects. Literature [26] proposed a steel surface defect detection system. The system integrates LBP, GLCM, HOG and wavelet transform algorithms to fully extract image information, and uses multiple SVM classifiers to make full use of these features, and finally uses bayes to merge the classification results of SVM to form an integrated classifier.

The workpiece surface defect detection algorithm with deep learning uses convolutional neural networks to automatically extract effective image information, and has strong feature extraction capabilities. Literature [27] proposed the realization of track fastener defect recognition with CNN. The classification accuracy of the system reaches 95.02%. Literature [28] based on Generativte Adversarial Networks proposed a new semi-supervised hot-rolled strip workpiece surface defect recognition algorithm, the recognition accuracy reached 96.7%. The algorithm uses the convolutional automatic encoding-decoding module to realize unsupervised learning of features, and introduces the trained automatic encoding module with a classification layer as a discriminator into the GAN model, which improves the classification accuracy of defects under limited training samples. Literature [29] proposed to realize bearing fault diagnosis with neural network, with highest classification accuracy of 95%.

3. Defect Recognition Algorithm Based on Fully Convolutional Block

Different from the classification task, there is a small defect detection problem in the defect recognition task. There is no obvious difference between small and normal area pixels, and the area ratio is very small. The existing convolutional neural networks for image classification tasks generally make judgments from the entire image. Applying this overall inspection strategy directly to defect identification tasks often makes the detection rate of small defects very low. For local small defects, block detection is a common and effective method. By dividing into blocks, the proportion of defects in the area of the image block to be inspected can be enlarged, so that small defects can be found more easily. However, the traditional block detection strategy completely discards the overall information, which is easy to cause misjudgment. This work proposes a defect recognition algorithm with full convolution block, and introduces the idea of block detection into a full convolution network, which overcomes shortcomings of traditional block detection strategy.

3.1. Advantages and Bottlenecks of Traditional Block Detection

Block detection is a common method in defect detection algorithms. The traditional block detection strategy has the following three advantages. 1) Through block detection, the proportion of the defect area can be expanded, thereby improving the detection accuracy. 2) It is easy to obtain massive training samples through block division. Deep learning models are driven by data and require massive training samples. After the block detection strategy is adopted, since the input of the recognition algorithm becomes an image block, the training samples can be expanded by block division to reduce over-fitting. 3) Blocking can prevent accidental factors from destroying the classifier learning process. The block detection strategy can clearly tell the classifier which areas are defective areas and which areas are normal areas, so as to avoid accidental factors from destroying the learning process.

However, traditional block detection methods have limitations due to insufficient receptive fields. Therefore, this article combines the characteristics of the fully convolutional neural network to improve the traditional block detection strategy.

3.2. Block Detection with Fully Convolutional Network

The receptive field is an important concept in CNN, which represents range of original image of neurons. The recursive calculation of the receptive field is:

$$a_n = a_{n-1} + (b_n - 1) \prod_{i=1}^{n-1} c_i \tag{1}$$

The traditional block detection strategy is directly applied to CNN. The disadvantage is receptive field of neuron can only cover the image block to be tested at most, and the information around the block to be tested and global information cannot be obtained. The drawbacks of traditional block detection can be solved by using a fully convolutional neural network. It can make the last extracted feature map have a one-to-one correspondence between the original image and the reserved space. After the multi-layer convolutional neural network extracts features, each pixel of the last feature map of the full convolutional network contains a feature vector, which corresponds to the

information of the corresponding area of the original image. Different from traditional block detection, the receptive field of each pixel of the last feature map covers the area around the image block to be tested, and can even cover the entire image. This method can judge whether the image block is defective or not based on the local information and the global information at the same time.

The network structure adopted by the defect recognition algorithm in this paper is illustrated in Fig. 1. The backbone uses ResNet-50 network, fully connected layer at the end of ResNet network is replaced by a convolutional layer to form a fully convolutional neural network. The input image size is normalized to 224×224 by bilinear interpolation, and the prediction image is obtained after the fully convolutional neural network. Each pixel in the prediction image corresponds to a 32×32 image block in the original image, and its receptive field covers the entire input image. The algorithm expects that the output corresponding to the defective image block is (0,1), and the output of the normal image block is (1,0). Because the defect recognition task has the characteristics of small data, this paper chooses the ResNet-50 network with relatively small parameter as the backbone network.

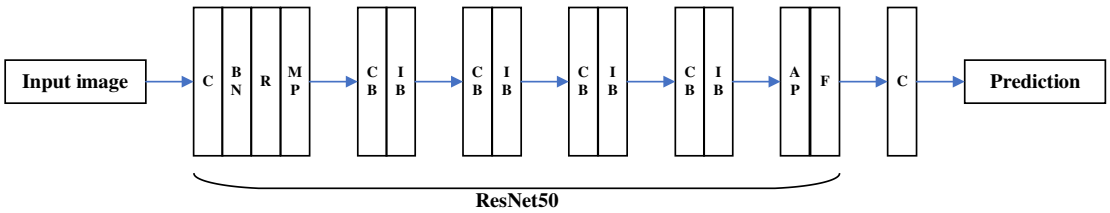

Fig. 1. Defect recognition network.

3.3. Optimization Goal and Training Strategy

In this paper, Logistic cross-entropy is applied as loss, L2 regularization is used, and the Adam optimization algorithm is used to optimize the network. Logistic cross-entropy is:

$$CE(d_e(x), y) = \begin{cases} -\log\big(d_e(x)\big), & y = 1 \\ -\log\big(1 - d_e(x)\big), & y = 0 \end{cases} \tag{2}$$

Under the training strategy of stochastic gradient descent, the loss of a batch containing N image blocks is:

$$L_1 = \frac{1}{N}\sum_{i=1}^{N} CE(\hat{y}_i, y_i) + \lambda \sum_{w \in W} w^2 \tag{3}$$

In order to expand the sample and increase the randomness of the network to reduce the over-fitting phenomenon, in the training phase, this paper does not use all the image blocks to calculate the loss, but adopts a strategy of randomly selecting a small number of positive and inferior image blocks. This strategy allows the training samples to be expanded during the training process. For the network model, the samples observed in each iteration are almost different, so the diversity of the samples can be increased. The image block selection strategy in this paper is as follows. For each defective sample, a genuine sample is randomly selected to correspond to it. Defective blocks and normal

blocks are randomly selected from defective samples and genuine samples.

3.4. Data Enhancement

The diversity of training samples will affect the effect of the deep learning model. Data enhancement is particularly important in defect recognition tasks where the training sample size is only tens or hundreds. In order to increase the sample diversity as much as possible and reduce over-fitting, this work adopts the following data enhancement methods.

Rotation is a simple and effective method of data enhancement. Rotation transformation can introduce rotation invariance to the model. This is very beneficial for defect recognition of round objects such as buttons. The image is rotated by angle θ around the origin as follows:

$$\begin{bmatrix} x_1 \\ y_1 \end{bmatrix} = \begin{bmatrix} cos\theta & -sin\theta \\ sin\theta & cos\theta \end{bmatrix} \begin{bmatrix} x_0 \\ y_0 \end{bmatrix} \tag{4}$$

Perspective transformation is also a common data enhancement method. A slight perspective transformation will not change the overall structure of the original image. The perspective transformation formula is:

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} a_{11} & a_{12} & a_{13} \\ a_{21} & a_{22} & a_{23} \\ a_{31} & a_{32} & a_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \tag{5}$$

Since the final transformation needs to be mapped in the plane, the following transformations need to be done:

$$x' = X/Z \tag{6}$$

$$y' = Y/Z \tag{7}$$

The color space transformation includes the transformation of chroma, saturation, and brightness. In this paper, saturation transformation and brightness transformation are used.

4. Defect Segmentation Algorithm Based on Improved Deeplabv3+

As a general semantic segmentation algorithm, the Deeplab series of algorithms have achieved success in the semantic segmentation of natural images. Considering the difference between the defect segmentation task and the natural image segmentation, this paper studies the defect segmentation algorithm based on the improved Deeplabv3+. Aiming at the characteristics of the defect detection task, the network structure and training strategy of Deeplabv3+ are improved.

4.1. Deeplabv3+ Semantic Segmentation Algorithm

Deeplab series [30-31] semantic segmentation algorithm is one of the most successful algorithms in the field of semantic segmentation. For the problems of semantic feature extraction, resolution restoration and multi-scale, the Deeplab series of algorithms all propose unique solutions. The Deeplabv3+ algorithm framework consists of backbone network and decoding network.

In backbone network, algorithm uses ResNet-101 or Xception network. After the backbone network, the feature map size is reduced to 1/16 of the original size. Hollow

convolution is used in backbone to expand receptive field. In addition, algorithm uses ASPP pooling layer to deal with multi-scale problems. The ASPP pooling layer uses different ratios of hole convolution, 1×1 convolutional layer and global pooling to extract features to obtain multi-scale features. Use 1×1 convolution to fuse these features. This multi-scale feature extraction and fusion mechanism can deal with objects to be segmented at different scales. The decoding network part uses bilinear interpolation to enlarge the resolution. Different from direct interpolation and amplification, the decoding network uses two interpolation and amplification to gradually restore the resolution. After the first interpolation and amplification, the decoding network obtains the low-level feature information in the backbone network. After the feature fusion, perform the second interpolation and enlargement. This method combines deep global features and low-level features, and can obtain fine segmentation results.

4.2. Improved Deeplabv3+ Network

The Deeplab series of algorithms are designed for the semantic segmentation of natural images. The defect segmentation task is different from the natural image semantic segmentation, and the differences are mainly in the following points. 1) The semantic information of defect segmentation is simpler. Compared with semantic segmentation of natural images, in surface defect detection tasks, common defect categories such as stains, scratches, cracks, pits, etc. are often expressed as defects of normal background information in the image, and their semantic information is far from natural images. The prospects are rich in information. In addition, the pattern features exhibited by normal regions are often similar. Compared with the complex background in natural images, the background in defect detection segmentation is much simpler. 2) There are weak defects similar to the background in the defect segmentation task. In natural images, the distinction between foreground objects and background is more obvious. However, in the task of defect segmentation, some weak defects often appear, even so weak that it is difficult to recognize. Some weak defects slowly transition from the normal area, and there is no obvious dividing line from the normal area. 3) The scale of defects in defect segmentation tasks is generally small and relatively fixed. In defect detection, the scale of the detection target is smaller than that of foreground targets of different sizes in natural images. In addition, considering that the internal and external parameters of the camera are fixed during inspection, the scale of the same type of defect is also fixed. Therefore, there is no multi-scale problem of the same type of foreground. 4) Training samples for defect segmentation tasks are even more lacking. Generally speaking, for a semantic segmentation model, a large number of pixel-wise labeled foreground images are required for model training. In the task of defect segmentation, the defect is the prospect to be segmented, so the defect data is often more important than the genuine data. However, in practice, the difficulty of collecting defective samples is much higher than that of genuine samples, resulting in a lack of defective samples. The number of samples available for general defect detection tasks is far less than that of natural image semantic segmentation tasks.

Considering the above differences, this paper proposes the defect segmentation

network structure shown in Fig. 2.

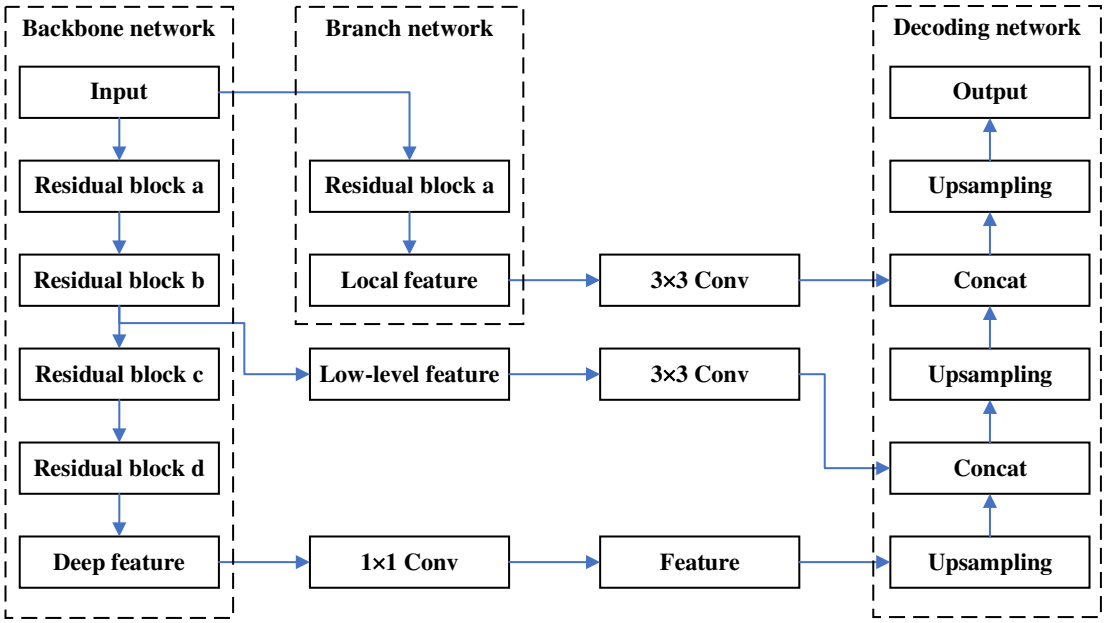

Fig. 2. Defect segmentation algorithm framework.

Local characteristics are more commonly used to segment small-scale defects and weak flaws in the defect detection task. Most feature maps have higher resolution and more complete local position information if they are at a lower level. Therefore, this paper introduces a branch network based on Deeplabv3+ for the extraction of fine low-level local characteristics. Large kernel convolution and ResNet-50's first residual block structure are used to build the branch network. Image resolution is reduced by half after branch network, however local position information is adequately maintained. Using the branch network, this article combines low-level features of the backbone network, deep-level global semantic features, and local data extracted by the branch network, and gradually restores resolution through three upsampling steps. This research uses the ResNet-50 network as the backbone network since it has fewer network layers and is easier to optimize due to the simplicity of the semantic information in the defect segmentation task. This work also removes the ASPP pooling layer which is mentioned early for multi-scale feature extraction because the scale of the same sort of defect is fixed.

4.3. Optimization Goal and Training Strategy

To increase the network's unpredictability and improve its ability to extract local characteristics, this study uses local images as input. The global image is fed into the backbone network during training. A random picture block from the global image is used as input for the branch network. A segmented picture block of equal size to the input image block will be the output of the network at this point. Only the segmented picture block's loss function and back propagation are calculated during optimization.

The following are some of the advantages of this method. First, the branch network is compelled to concentrate on local aspects because of the lack of resources. With only

a local image to work with, the branch network will be limited to learning only the features found in the image. Even though the branch network only has access to local information, the decoding network can nonetheless make judgements that are consistent with the global semantics provided by the backbone network. Second, by boosting the network's randomness, the network's ability to generalize is enhanced. To reduce model overfitting when there are no defective training data, a blocking technique is comparable to implicitly amplifying the samples. Third, the branch network's calculation amount is reduced throughout the training process, improving training efficiency. Because the branch network retains a large image resolution, the calculation amount of the residual block in the branch network is four times that of the residual block in the backbone network. Adopting a block strategy can effectively reduce the amount of branch network calculations, thereby improving training efficiency.

Under the training strategy of partial image input, the optimization goal of the segmentation algorithm is:

$$L_2 = \frac{1}{N}\sum_{i=1}^{N} CE(\hat{y}_{ci}, y_{ci}) + \lambda \sum_{w \in W} w^2 \tag{8}$$

The training process is: 1) Initialize network parameters randomly. 2) Randomly select n genuine samples and n defective samples from the training sample set, and select the corresponding mark from the mark set. 3) According to the local image input strategy, randomly select the image block, and select the marker block from the corresponding marker map. 4) Input the entire image set and image block set into the segmentation network to obtain the prediction result. 5) Calculate the loss. 6) Update the network parameters according to the Adam optimization algorithm to minimize the loss. 7) Repeat until the loss converges

5. Experiment and Discussion

5.1. Dataset and Evaluation Metric

This work uses two self-made mechanical design product datasets to evaluate algorithm. These two datasets are MDPA and MDPB. Different datasets contain different training samples and testing samples. The specific distribution is illustrated in Table 1. TRPS is training positive samples. TRNS is training negative samples. TEPS is testing positive samples. TENS is testing negative samples.

Table 1. Details of sample sizes in different datasets.

Dataset	TRPS	TRNS	TEPS	TENS
MDPA	236	267	165	186
MDPB	316	327	218	240

In defect recognition, this work uses TPR (true positive recognition), TNR (true negative recognition) and ACC (accuracy) to evaluate the accuracy of defect recognition algorithms. The indicator is calculated as follows:

$$TPR = \frac{N_{TP}}{N_{TP}+N_{FN}} \tag{9}$$

$$TNR = \frac{N_{TN}}{N_{TN}+N_{FP}} \tag{10}$$

$$ACC = (TPR + TNR)/2 \tag{11}$$

In defect segmentation, this article evaluates the accuracy of defect recognition algorithms based on PR (precision), RE (recall) and F1 scores, which are defined as:

$$PR = \frac{TN}{TN+FN} \tag{12}$$

$$RE = \frac{TN}{TN+FP} \tag{13}$$

$$F1 = (2\times PR\times RE)/(PR + RE) \tag{14}$$

5.2. Evaluation on Defect Recognition

This section compares the detection results of the algorithm and the ResNet-50 image classification algorithm on the two datasets. Due to the small number of experimental samples, the experimental results between multiple experiments may fluctuate greatly. In order to ensure the reliability of the experimental results, a cross-validation experiment is carried out. The experiment is divided into five cross-validation groups, and each group of experiments randomly selects the original training samples and test samples according to Table 1. The experimental results are shown in Fig. 3 to Fig. 5.

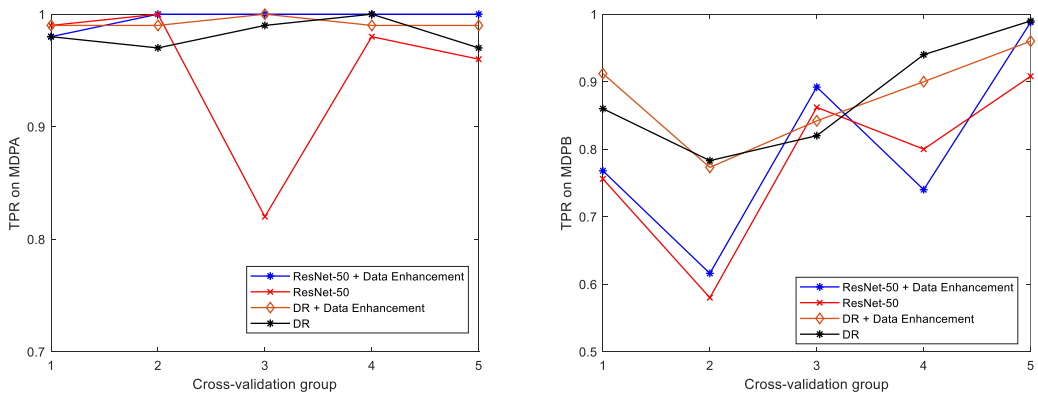

Fig. 3. TPR in defect identification.

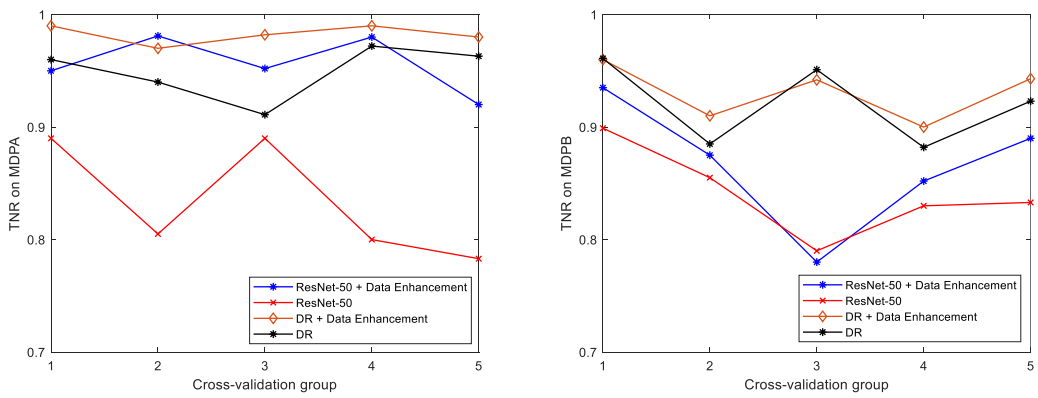

Fig. 4. TNR in defect identification.

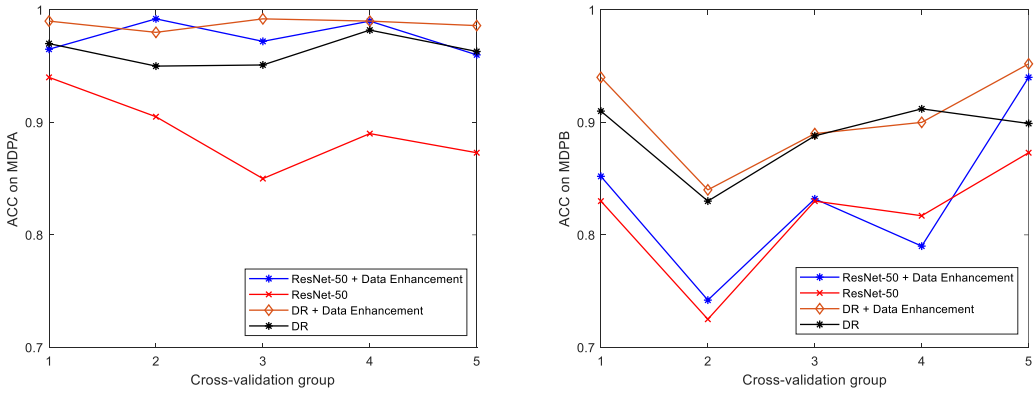

Fig. 5. ACC in defect identification.

On the whole, the detection of defective products is significantly improved on the basis of the ResNet-50 image classification method. Regarding the data enhancement strategy, it can be seen from the experimental data that the data enhancement strategy can effectively improve the accuracy of the defect recognition algorithm, and the improvement of the ResNet-50 image classification method is more obvious. Even if the data enhancement strategy is not adopted, the accuracy of the algorithm has declined on the three datasets. Compared with the ResNet-50 image classification method, the algorithm adopts a full-convolutional network block strategy for the lack of defective data, so that the algorithm can maintain a better detection effect even when the data diversity is lacking.

For defect recognition algorithms, small defects are often more difficult to detect than general defects. There are two main reasons for this. First, the proportion of small defects in the area of the input image is smaller than that of general defects, and the impact on the overall image is smaller. Second, if the defect is too small, its pattern may be close to the noise pattern of the genuine area, which makes it difficult to distinguish. The detection rate of the algorithm for small defects is also an important index to evaluate the defect recognition algorithm. In the experiments in this section, the defect samples with a total defect area of less than 100 pixels are defined as small defect samples. This section uses the same cross-validation experiment as the previous section. The total test results on the five cross-validation test groups are shown in Table 2.

Table 2. Small defect recognition experiment results.

Dataset	ResNet-50			DR (Ours)		
	TPR	TNR	ACC	TPR	TNR	ACC
MDPA	0.992	0.850	0.924	0.996	0.945	0.977
MDPB	0.980	0.913	0.951	0.985	0.942	0.979

The experimental results show that the detection effect of this method on small defects is significantly improved compared with ResNet-50, and the overall accuracy rate is increased by 5.3% and 2.8% respectively. The experimental results show that the method has a higher detection accuracy for small defects than the original ResNet-50

image classification method.

5.3. Evaluation on Defect Segmentation

This section compares detection effects of our method and Deeplabv3+ algorithm on the two datasets. Due to the small number of samples in the dataset, in order to avoid the influence of accidental factors and improve the reliability of the experiment, this section adopts a cross-validation experiment, and the experiment is divided into 5 groups of cross-validation groups. The results are shown in Fig. 6 to Fig. 8.

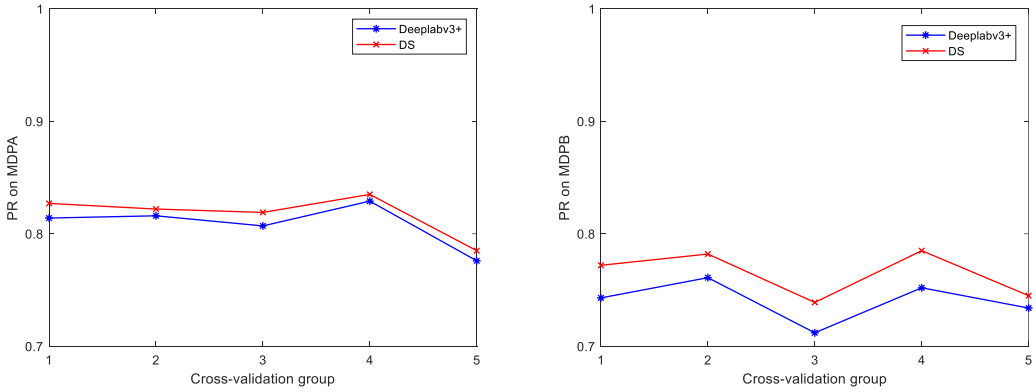

Fig. 6. PR in defect segmentation.

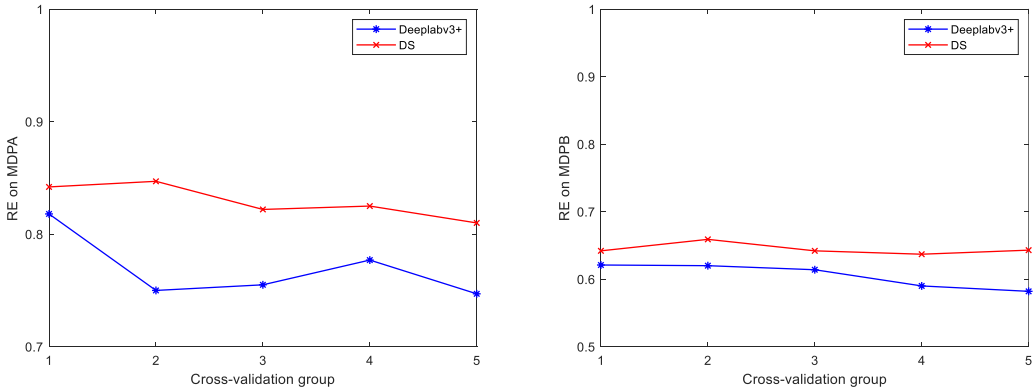

Fig. 7. RE in defect segmentation.

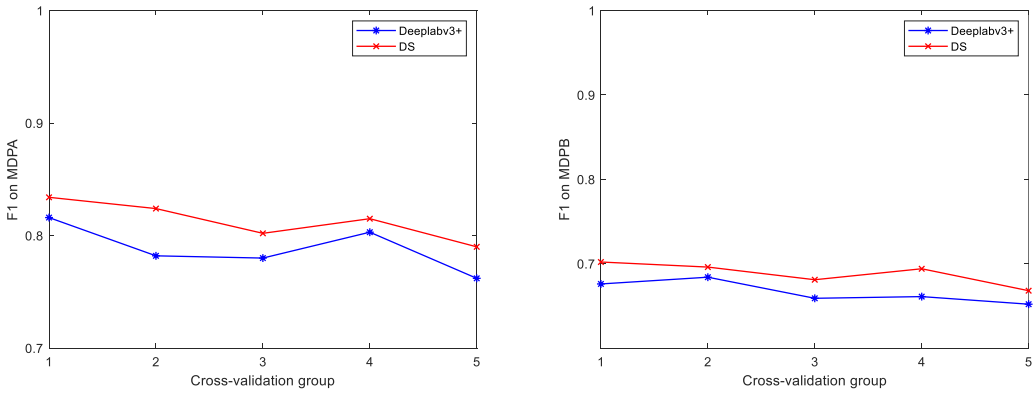

Fig. 8. F1 in defect segmentation.

6. Conclusion

This paper focuses on the automatic visual inspection of surface defects of mechanical design products, and studies a set of general defect detection schemes based on deep learning, including defect recognition algorithms and defect segmentation algorithms, focusing on solving the problem of defect recognition and defect segmentation. In order to verify the effect of the algorithm, this work has carried out experimental verification. The main contributions of this paper are as follows: 1) Aiming at the problem of defect recognition, this paper improves the ResNet image classification algorithm, and studies the defect recognition algorithm based on full-convolutional block detection. The algorithm combines the advantages of the block detection strategy and the fully convolutional neural network. Through block detection, the difficulty of detecting small defects is reduced. The use of full convolutional network overcomes the shortcomings of traditional block algorithm. After the improvement, compared with the original ResNet-50 image classification algorithm, the accuracy of the algorithm has been improved. 2) Aiming at the problem of defect segmentation, this paper studies the defect segmentation algorithm based on the improved Deeplabv3+. Aiming at the characteristics of the defect segmentation task, this paper strengthens the extraction and utilization of local features on the basis of the Deeplabv3+ network structure.

Availability of data and material

The datasets used during the current study are available from the corresponding author on reasonable request.

Ethical approval

My paper does not deal with any ethical problems.

Conflict of interest

The author declared that he have no conflicts of interest to this work.

Informed Consent

I declare that I have informed Consent.

Reference

[1] Yuan Q, Cheng C F C, Wang J, et al. Inclusive and sustainable industrial development in China: An efficiency-based analysis for current status and improving potentials[J]. Applied Energy, 2020, 268: 114876.

[2] Liu Y, Zhang X, Pan X, et al. The spatial integration and coordinated industrial development of urban agglomerations in the Yangtze River Economic Belt, China[J]. Cities, 2020, 104: 102801.

[3] Su T, Zhao D, Khodadadi M, et al. Lignocellulosic biomass for bioethanol: Recent advances, technology trends, and barriers to industrial development[J]. Current Opinion in Green and Sustainable Chemistry, 2020, 24: 56-60.

[4] Fan Y, Fang C. Assessing environmental performance of eco-industrial development in industrial parks[J]. Waste Management, 2020, 107: 219-226.
[5] Ryser L, Halseth G, Markey S. Moving from government to governance: addressing housing pressures during rapid industrial development in Kitimat, BC, Canada[J]. Housing Studies, 2021, 36(10): 1618-1643.
[6] C. F. J. Kuo, C. T. M Liu, et al. Automatic inspection system of LED chip using two-stages back-propagation neural network[J]. Journal of Intelligent Manufacturing, 2014, 25(6): 1235-1243.
[7] H. Lin, B. Li, X. Wang, Y. Shu, et.al. Automated defect inspection of LED chip using deep convolutional neural network[J]. Journal of Intelligent Manufacturing. 2019, 30(6): 2525-2534.
[8] D. M. Tsai, C. T. Lin, J. F. Chen. The evaluation of normalized cross correlations for defect detection[J]. Pattern Recognition Letters. 2003, 24(15): 2525-2535.
[9] H. Jia, Y. L. Murphey, J. Shi, et al. An intelligent real-time vision system for surface defect detection[C]. Proceedings of the 17th International Conference on IEEE, 2004, 239-242.
[10] A. Giaquinto, G. Fornarelli, G. Brunetti, et al. A neurofuzzy method for the evaluation of soldering global quality index[J]. IEEE Transactions on Industrial Informatics, 2009, 5(1): 56-66.
[11] Su B, Chen H, Chen P, et al. Deep learning-based solar-cell manufacturing defect detection with complementary attention network[J]. IEEE Transactions on Industrial Informatics, 2020, 17(6): 4084-4095.
[12] Pei J, Zhong K, Li J, Xu J, Wang X. ECNN: evaluating a cluster-neural network model for city innovation capability[J]. Neural Computing and Applications, 2021, 1-13. https://doi.org/10.1007/s00521-021-06471-z.
[13] Kim J, Ko J, Choi H, et al. Printed circuit board defect detection using deep learning via a skip-connected convolutional autoencoder[J]. Sensors, 2021, 21(15): 4968.
[14] Liu M, Cheung C F, Senin N, et al. On-machine surface defect detection using light scattering and deep learning[J]. JOSA A, 2020, 37(9): 53-59.
[15] Yin X, Chen Y, Bouferguene A, et al. A deep learning-based framework for an automated defect detection system for sewer pipes[J]. Automation in construction, 2020, 109: 102967.
[16] A X L, B H J, A G Y. Detection of surface crack defects on ferrite magnetic tile[J]. NDT & E International, 2014, 62(2): 6-13.
[17] Li W B, Lu C H, Zhang J C. A local annular contrast based real-time inspection algorithm for steel bar surface defects[J]. Applied Surface Science, 2012, 258(16): 6080–6086.
[18] Yuan X, Wu L, Peng Q. An improved Otsu method using the weighted object variance for defect detection[J]. Applied surface science, 2015, 349: 472-484.
[19] Malarvel M, Sethumadhavan G, Bhagi P C R, et al. An improved version of Otsu's method for segmentation of weld defects on X-radiography images[J]. Optik, 2017, 142: 109-118.
[20] Jian C, Gao J, Ao Y. Automatic surface defect detection for mobile phone screen

glass based on machine vision[J]. Applied Soft Computing, 2017, 52: 348-358.
[21] Pernkopf F. Detection of surface defects on raw steel blocks using Bayesian network classifiers[J]. Pattern Analysis & Applications, 2004, 7(3): 333-342.
[22] Agarwal K, Shivpuri R, Zhu Y, et al. Process knowledge based multi-class support vector classification (PK-MSVM) approach for surface defects in hot rolling[J]. Expert Systems with Applications, 2011, 38(6): 7251-7262.
[23] Song K, Yan Y. A noise robust method based on completed local binary patterns for hot-rolled steel strip surface defects[J]. Applied Surface Science, 2013, 285: 858-864.
[24] Guo Z, Zhang L, Zhang D. A Completed Modeling of Local Binary Pattern Operator for Texture Classification[J]. IEEE Transactions on Image Processing, 2010, 19(6): 1657-1663.
[25] Yang S W, Lin C S, Lin S K, et al. Automatic defect recognition of TFT array process using gray level co-occurrence matrix[J]. Optik-International Journal for Light and Electron Optics, 2014, 125(11): 2671-2676.
[26] Xiao M, Jiang M, Li G, et al. An evolutionary classifier for steel surface defects with small sample set[J]. EURASIP Journal on Image and Video Processing, 2017, 2017(1): 48.
[27] Gibert X, Patel V M, Chellappa R. Deep multitask learning for railway track inspection[J]. IEEE transactions on intelligent transportation systems, 2016, 18(1): 153-164.
[28] Di H, Ke X, Peng Z, et al. Surface defect classification of steels with a new semi-supervised learning method[J]. Optics and Lasers in Engineering, 2019, 117(6): 40-48.
[29] Duong B P, Kim J. Non-Mutually Exclusive Deep Neural Network Classifier for Combined Modes of Bearing Fault Diagnosis[J]. Sensors, 2018, 18(4): 1129.
[30] Chen L C, Papandreou G, Kokkinos I, et al. Semantic image segmentation with deep convolutional nets and fully connected crfs. arXiv preprint arXiv:1412.7062, 2014.
[31] Chen L-C, Zhu Y, Papandreou G, et al. Encoder-decoder with atrous separable convolution for semantic image segmentation. in: Proceedings of the European Conference on Computer Vision, 2018, 801-818.