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RESEARCH ON SURFACE DEFECT DETECTION METHOD OF METALLURGICAL SAW BLADE BASED ON YOLOV5

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As a typical cutting tool with good performance and high processing efficiency, metallurgical saw blades are widely used in various industries, but surface defects are inevitably generated in the manufacturing process. To solve this problem, this paper proposes a YOLOv5-based surface defect detection model for product quality, which can distinguish three common metallurgical sawblade surface defects with mAP value of 96,1 % in each defect category detection of metallurgical sawblades and detection time of 139,8 ms per image.

Keywords: metallurgical saw blade, surface defects, target detection, YOLOv5

INTRODUCTION

In the production process metallurgical circular saw blade as a cutting tool is widely used in the manufacturing industry, the demand in the metallurgical industry and machinery industry are very large. Some of these defective metallurgical saw blades, if not found in time, can affect the cutting performance of metallurgical circular saw blades and even cause serious safety accidents and harm to the users of metallurgical circular saw blades. Classifying and locating defects in metallurgical saw blades allows for better problem detection and provides a method to assist in improving the production process.

Traditional manual visual inspection methods are not applicable to the current stage of metallurgical saw blade manufacturing. Currently, most manufacturing companies are gradually adopting computer vision methods to replace manual defect detection, making the application of computer vision in metallurgical saw blade defect detection more accurate. In this paper, we propose a product quality defect detection model based on YOLOV5. The detection of surface defects includes three types of defects, namely cracks, scars and pitting corrosion.

RELATED WORK

The detection of surface defects in strip steel has become one of the important aspects to ensure the quality of steel production, and for the current problems such as the accuracy of strip steel defect detection algorithm to be improved, [1] Proposed an improved algorithm model MT-YOLOV5 based on YOLOV5 network, which combines the Transformer layer with BiFPN network structure to further enhance the image shallow feature information and deep feature The fusion of the information enhances the feature extraction of the backbone network, and finally adds a prediction layer to detect targets of different scales to better achieve detection speed and detection accuracy. [2] In order to meet the balanced requirements of detection accuracy and detection speed in practical engineering, a surface defect detection algorithm YOLOV5s_Attentinn based on channel space attention is proposed as a baseline in the paper, which can better meet the balanced requirements of detection accuracy and detection speed in defect detection engineering. In [3], for the problem of poor performance of the traditional YOLO algorithm for detecting metal surface defects such as patches, cracks, scratches, etc., an improved YOLOV5 algorithm for metal surface defect detection is proposed to solve the situation that the algorithm cannot detect for fine defects, and for the situation that the detection image resolution is too large, the YOLT algorithm is borrowed in the subsequent detection by decomposing the detection image into multiple small images for detection, which improves the average accuracy and better detection performance of the algorithm. [4] For the problem of low accuracy of detecting small size defects on the surface of metal work pieces, the YOLOV5 network surface defect detection algorithm is proposed to increase the weight of defect-related information and reduce the interference of useless features, thus improving the detection accuracy of the target. The network significantly improves the accuracy of detecting defects on the surface of metal workpieces. [5] Proposed an improved YOLOV5-based defect detection method for hot-rolled strip steel for defect detection with small target size, unclear features and mismeasurement and omission problems. The accuracy of the anchor frame is improved, a new feature

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extraction module is designed, the scale of detection is increased and a nonlinear convolution module is added to strengthen the semantic information of the target defects, the confidence loss function is improved for a stronger stable generalization of the model convergence, the detection speed is faster and the error and miss detection rate is lower.

The above in metal surface defect detection method based on YOLOV5 successfully completes the task of detecting defective targets. For the metallurgical saw blade defect detection in the metallurgical industry, this paper proposes a study of the YOLOV5-based metallurgical saw blade surface defect detection method to achieve the task of detecting defects in the manufacturing process of metallurgical saw blades, which improves the qualification rate of manufacturing enterprises and the quality of products.

METHODOLOGY

Currently, there are four versions of the YOLOV5 algorithm: YOLOV5s, YOLOV5m, YOLOV5l, and YOLOV5x. In this section, YOLOv5s will be used as an example to introduce in detail its structural principle, which is based on the original network topology improvement to improve the performance of the network. Figure 1 shows the complete network architecture of the YOLOV5s target detection algorithm.

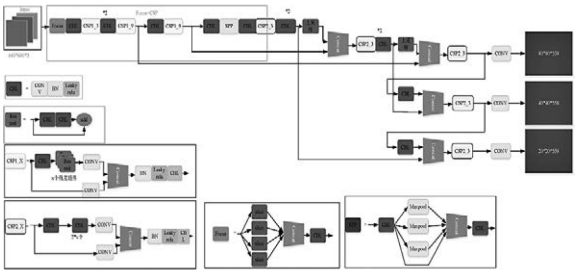


Figure 1 YOLOv5 detection framework diagram

YOLOV5 is the most advanced model in the field of single-stage target detection algorithms, which has the advantages of small memory consumption, easy training, easy deployment and high applicability. the network framework of YOLOV5 contains many components, such as CBL module, Focus module, SPP module and CSP1_X and CSP2_X modules. Among them, the SPP module performs maximum pooling of the input at four different scales, and then stitches the pooled results as the fused feature output. such a structure allows the network to receive input images of random sizes, which is robust to the detection of large and small targets. the Focus module can effectively split the image into multiple channels to reduce the amount of operations in the down sampling process and concentrate the width and height information into one The YOLOV5 structure can obtain a fuller hierarchy by using the CSP1_X and CSP2_X modules, which greatly reduces the amount of operations. CSPNet, on the other hand, improves the learning ability of the convolutional neural network by segmenting the gradient stream so that it can be passed along distinct network routes, which not only reduces the amount of operations and memory consumption, but also increases the efficiency of logical inference, thus improving the accuracy of logical inference.

The sample image data needs to be preprocessed before training, including three steps: data labeling, label conversion, and data storage. First, labelImg software is needed to label the data information. The labelImg software is used to frame the position of the target in the sample image, and the saved xml format file contains seven important data items. These include the four positions of the target frame on the sample image <xmin>, <xmax>, <ymin>, and <ymax>, the width and height of the sample image <width>, <height>, and the sample image category <name>. The specific representation of the label data on the sample image is shown in Figure 2.

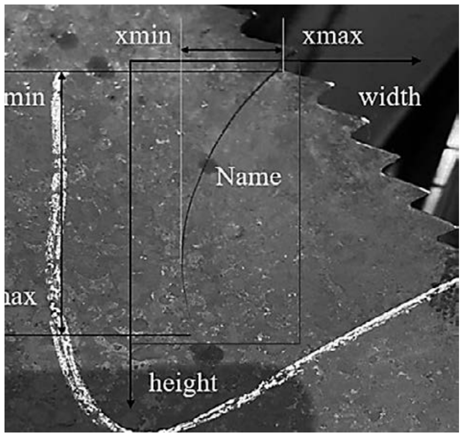


Figure 2 Image annotation style

Unlike the label information provided by the labelImg software, the label information required by the YOLO algorithm is the coordinates of the center point of the target frame in the sample image and the width and height of the target frame, so it is necessary to convert the xml label file, and the specific steps are as follows:

Calculate the YOLO-type annotation data: Let the coordinates of the center point of the target frame in the sample image be (x, y), and the width and height of the target frame be w and h, respectively. According to the known <xmin>, <xmax>, <ymin> and <ymax> four data can be expressed by (1) equation:

$$\begin{cases} w = (xamx) - (x\min) \\ h = (y\max) - (y\min) \\ x = (x\min) + \dfrac{w}{2} \\ y = (y\min) + \dfrac{h}{2} \end{cases} \tag{1}$$

Normalization: Let the width normalization factor be dw height normalization, and the factor be dh where as shown in equation (2):

$$dw = \frac{1}{width} \, dh = \frac{1}{height} \tag{2}$$

Data normalization requires multiplying the x coordinate of the center point of the target box and the width w of the target box with the width normalization coefficient dw, and multiplying the y coordinate of the center point of the target box and the height h of the target box with the height normalization coefficient dw, as shown in equation (3):

$$\begin{cases} \hat{x} = x \bullet dx \\ \hat{y} = y \bullet dh \\ \hat{w} = w \bullet dw \\ \hat{h} = h \bullet dh \end{cases} \tag{3}$$

The YOLOV5 model consists of four major units: End Input, Backbone, Neck, and Prediction. YOLOV5 efficiently processes the input data through adaptive image compression, Mosaic information enhancement, and adaptive anchor frame operations to improve the model's measurement of "small targets" and transform the training results into a dataset of images that can be used for target detection. Mosaic data enhancement can effectively overcome the difficulties associated with "small targets" and thus improve the detection accuracy of the model.

Backbone is a large-scale convolutional neural network architecture based on fused feature maps, which uses the CSP + SPPF architecture and the FPN + PAN architecture to provide three sets of fused feature maps at various resolutions. This not only saves the use of parameters and the computation of FLOPS, but also greatly speeds up the process of logical inference, making the results more accurate and reliable.

In order to evaluate the performance of the classification and detection model, the calculation of mAP is used. Before calculating the mAP value, it is first necessary to calculate the Precision and Recall values, by calculating the average of the Precision values corresponding to each Recall value is called AP see Equation (4), where ri is the Recall value corresponding to the first interpolated value of the Precision interpolation segment in ascending order. The AP of all categories is mAP, and the calculation of mAP is shown in Equation (5) where k is the number of categories.

$$AP = \sum_{i=1}^{n-1} (r_{i+1} - r_i) P_{inter}(r_i + 1) \tag{4}$$

$$mAP = \frac{\sum_{i=1}^{k} AP_i}{k} \tag{5}$$

EXPERIMENT AND ANALYSIS

The object of the target defect detection study is a metallurgical saw blade, and the defect data set is shown in Figure 3.

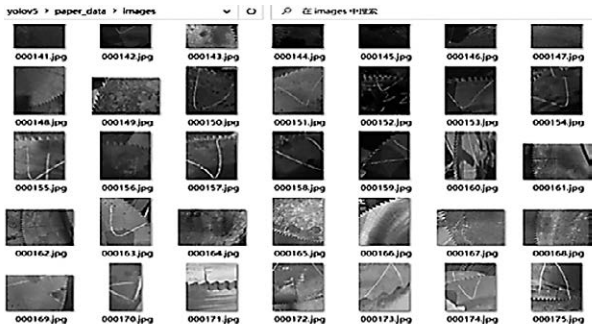


Figure 3 Some experimental data shown

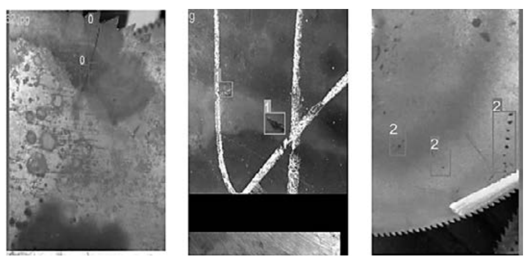
In order to effectively identify metallurgical saw blade defects, a dataset that detects the presence of saw blades is used in this paper to prevent the situation that training cannot converge due to too much negative data, and to remove the markers of other classes of objects. In order to better refer to the annotation format of Data dataset, the markers are set to txt text files containing only the contents of [upper left coordinate system, upper right coordinate system, lower right coordinate system and lower left coordinate system sawblades], in order to express the characteristics of sawblade crack targets more intuitively and to avoid the interference of irrelevant contents as much as possible to achieve the best recognition effect. The metallurgical saw blade dataset needs to be formatted for better identification, and the original dataset tagging is computationally transformed into the YOLO format.

Compared with traditional model calculations, YOLO has a more cumbersome network architecture, requires a large amount of data to understand, has many network parameters, can reach hundreds of millions of operations, is time-consuming, and requires higher hardware performance.

This study is implemented on the Windows 10 operating system using the PyTorch framework in Pycharm. The device hardware is Intel(R) Core(TM) i7-7 700 HQ and the GPU model is GTX 1050 Ti. The software environments are CUDA11.2 and Python 3,8.

The metallurgical saw blade dataset is a dataset containing 2 218 images of metallurgical saw blades with defects in 3 categories with defect category labels. Defects included are cracks, pitting rot, and scars. The results of manually annotating the defect locations in this dataset are shown in Figure 4.

The size of 640 training sets was normalized and the training convolutional layer parameters were prede-



crack pitting corrosion scab

Figure 4 Annotation sample

fined on the ImageNet dataset. During the training process, the learning rate was designed to be 0,001, and a total of 200 epochs were trained.

The constructed YOLOV5 model utilizes the Focus+SSP network for high quality detection and also applies the normalization algorithm for high quality detection. 640 epochs were input into the network model and the 200 epoch weight files trained on train were used for the exercise, and the learning rate was set to 0,001. The effect of image pre-processing was checked by visualization before the exercise started to ensure the success of the training.

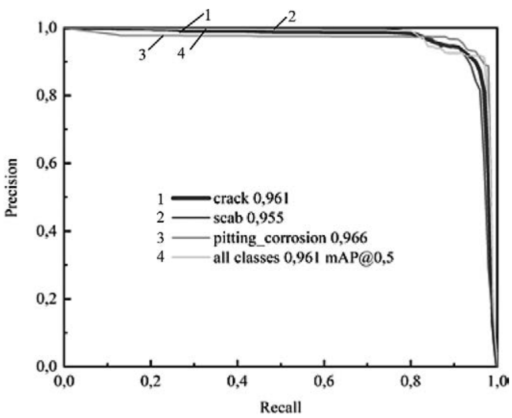


Figure 5 Torque curve of flipping

(a) The Label results (b) The prediction results

Figure 6 Defect prediction results

Ten percent of the images not involved in the training set were selected as the test set. Figure 5 shows the Precision-Recall curves and mAP values for each category, as well as the average values for the selected predictions with an intersection ratio greater than 0,5. The mAP values for cracks, crusts and pitting corrosion are 96,1 %, 95,5 % and 96,6 %.

In terms of inference speed, the method is able to analyze each image with the GTX 1 050 at an average speed of 139,8 ms, which is sufficient for the detection of surface defects in operation. It is able to meet the needs of surface defect detection during the operation of a metallurgical saw blade production line.

The actual operation of the model is shown in Figure 6, where Figure. 6(a) represents the visualization results of manual annotation of some images in the dataset, and Figure. 6(b) represents the visualization results of defect location and category information output. Figure. 6(b) represents the visualization results of defect location and category information output from these images after passing through the model.

CONCLUSION

The YOLOv5-based metallurgical sawblade surface defect detection has good performance in terms of detection speed and accuracy. In the homemade metallurgical sawblade surface defect dataset, the mAP value of three common metallurgical sawblade surface defects classification results is 96,1 %. In terms of detection speed, the average time required per image is 139,8 ms, which can be applied to meet the needs of surface defect detection in the production process of metallurgical saw blades and effectively solve the problem of timely classification of surface defects in the manufacturing process of metallurgical saw blades.

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Note: The responsible translator for English language is C. H. Wang – North China University of Science and Technology, China.