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A CLASSIFICATION AND LOCATION OF SURFACE DEFECTS METHOD IN HOT ROLLED STEEL STRIPS BASED ON YOLOV7

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Hot-rolled steel strip is widely used in production life and surface defects inevitably occur during its production process. In order to solve this problem, this paper proposes a method for classifying and locating surface defects in hot-rolled strip steel based on the YOLOV7 target detection model, which takes into account both accuracy and real-time performance. The method is capable of distinguishing seven common surface defects with an average accuracy of 84,3 % and a maximum accuracy of 99,6 % in a single category of defects.

Keywords: steel, surface defect, detection, hot rolled strip, yolov7

INTRODUCTION

In the production process the rolled strip with a thickness of 1 to 20 mm is generally referred to as hot-rolled strip. Hot-rolled strip can be used directly as hot-rolled steel sheets or can be supplied as billets for cold-rolled strip. It is widely used in the manufacturing industry and the annual production and demand is extremely high. Some of these defects, if not detected in time, will affect the performance of the steel and even pose a serious safety hazard to the steel user. At the same time, it is important to be able to classify and locate defects in the production process so that people can better understand the problems in the production line and provide greater assistance in improving the production process.

Traditional manual visual inspection methods are no longer adequate for large-scale hot-rolled strip production, and most manufacturers are now gradually adopting a combination of computer vision methods and manual sampling for defect detection. Therefore, it is particularly important to enable computers to detect defects in hot-rolled strip in a more efficient and accurate way, which is also a hot topic of research in the current academic community. This paper presents a YOLOV7-based method for real-time classification and localisation of hot rolled strip surface defects, which can detect at 83 fps defects including Red Iron, Slag Inclusion, Iron Sheet Ash, Surface Scratch, Plate System Oxide Scales, Finishing Roll Printing, Temperature System Oxide Scale and 7 common defects.

RELATED WORK

Initially, the method of detecting and classifying defects on the surface of hot-rolled steel strips using computers was mainly based on the manual generalisation of the image features of defects and the detection of defects by matching methods, of which a representative one is proposed in [1], called “Noise robust method based on completed local binary patterns”, and a set of A dataset based on the NEU-DET for surface defects in hot rolled strip is also constructed. This manual generalisation and matching of defect images often requires domain experts to analyse the defect images collected in a particular environment in order to generalise a more accurate set of features.

The increasing computing power of computers in recent years has led to attempts to use machine learning methods to enable computers to automatically perform feature extraction on defective images. A defect detection method based on the K-Nearest Neighbor (KNN) algorithm was proposed in [2], and a method based on random forests and support vector machines was proposed in [3]. Compared with traditional machine learning methods deep neural networks are more prominent in automatic feature extraction, convolutional neural network (CNN) networks have been widely used in the field of automatic image feature extraction. A CNN-based method for detecting surface defects in hot-rolled strip is proposed in [4], a method for classifying surface defects in hot-rolled strip based on the RepVGG algorithm is proposed in [5], and A dataset of hot-rolled strip surface defects named X-SDD was proposed in [5].

In a practical production environment, the production speed of hot-rolled strip can reach 400 m/min, which requires a high level of real-time defect detection, and the accuracy of the detection also greatly affects the production quality, so we propose a classification and localisation method based on the YOLOV7 [6] network that balances real-time and accuracy.

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METHODOLOGY

YOLOV7[6] is currently the most accurate target detection model on the COCO dataset (the most widely used dataset for target detection tasks, often used for training and evaluating the performance of target detection models) in the detection speed range of 5FPS-160FPS at the same detection speed. Compared to YOLOR-CSP, which previously had the best balance of real-time and accuracy on the COCO dataset, YOLOV7 has 43 % fewer parameters, 15 % less computation, and 0,4 % better AP.

The YOLOV7 network mainly consists of the feature extraction network ELANNet and the detection head PAFPN, as shown in Figure 1. The original image undergoes three convolution operations in the STEM stage to convert the n×n×3 image into, n×n×64 form, and outputs three kinds of features of 512, 1 024 and 1 024 respectively through the ELANNet structure, which are fused through the PAFPN module to output three scales of prediction frames, and finally the final prediction frames and prediction classification are obtained through the non-maximum suppression algorithm (NMS) post processing.

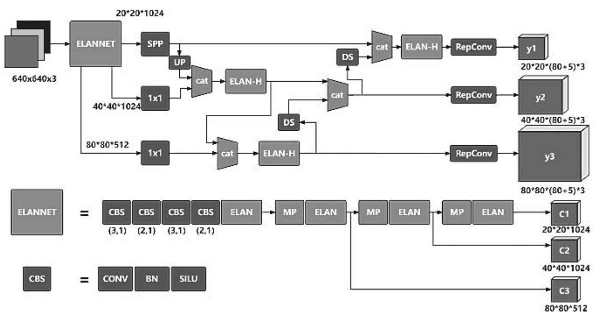

Figure 1 The network structure of YOLOV7

Before the model is trained, a number of defect images containing all the target types and labels with the defect location and category information are prepared in advance. The data set is then divided into a training set, which is used to adjust the trainable parameters of the model, and a test set, which is used to test the training effect of the model. Firstly, the trainable parameters in the model are randomly initialised. In the second step, the training set is split into several small batches of samples consisting of n defective images and input into the YOLOV7 model, and the output results are calculated with the labels to calculate the error through the loss function and adjust the trainable parameters of the model through the back propagation method, so that one operation becomes one iteration and the split training set is all involved in training into one training round. In the third step, after each training round, the trainable parameters of the model are fixed and tested using a test set to check the effectiveness of the model. Finally, steps 2 and 3 are repeated until the model no longer improves in detection and the operation is stopped.

EXPERIMENT AND ANALYSIS

The X-SDD dataset [5] is a dataset of 1 360 images of common defects in hot-rolled steel strips in 7 categories with defect category labels. The defects included are Red Iron, Slag Inclusion, Iron Sheet_Ash, Surface Scratch, Plate System Oxide Scales, Finishing Roll Printing, Temperature System Oxide Scale. It have manually annotated the defect locations in this dataset and the annotation results are shown in Figure 2.

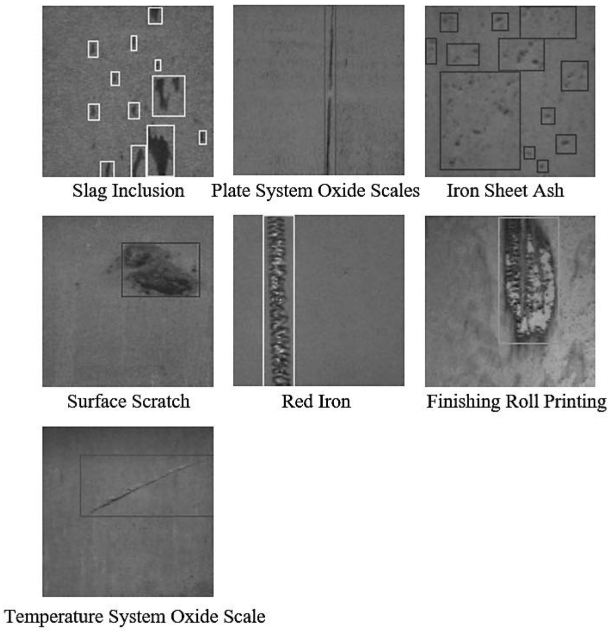

Figure 2 Annotation sample

It used the YOLOV7 model and trained it on the X-SDD dataset. During training, a stochastic gradient descent algorithm with a batchsize of 16 was used for backpropagation, the optimiser was SGD, the momentum was set to 0, 0,937 and the learning rate was 0,01. After 300 iterations, the learning rate finally decayed to 0.001, for a total of 4,5 hours of training on an RTX3080 device.

$$Pinterp\left(r_{n+1}\right) = \max_{\tilde{r}:\tilde{r} \ge r_{n+1}} P\left(\tilde{r}\right) \tag{1}$$

$$AP = \sum\nolimits_{r=0}^{1} \left(r_{n+1} - r_n\right) Pinterp\left(r_{n+1}\right) \tag{2}$$

$$mAP = \frac{\sum\nolimits_{i=1}^{k} AP_i}{k} \tag{3}$$

Where r_{n+1} represents Recall value corresponding to the first interpolation of the precison interpolation segment, $Pinterp(r_{n+1})$ represents the area under the precision recall curve.

In order to evaluate the performance of classification and detection models, the calculation of mAP is usually used. Before calculating the mAP value it is first necessary to calculate Precision, the number of correctly predicted positive classes as a percentage of the number of predicted positive classes, and Recall, the number of cor-

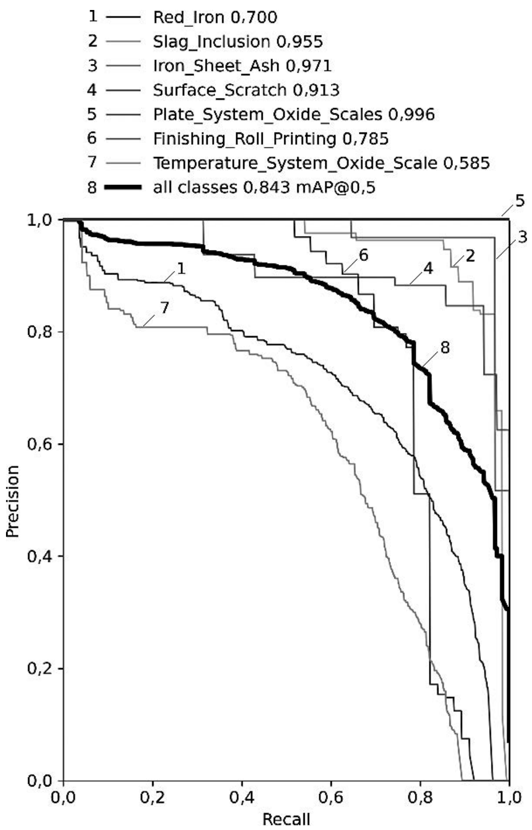

Figure 3 Precision-Recall curves for each category and mean values

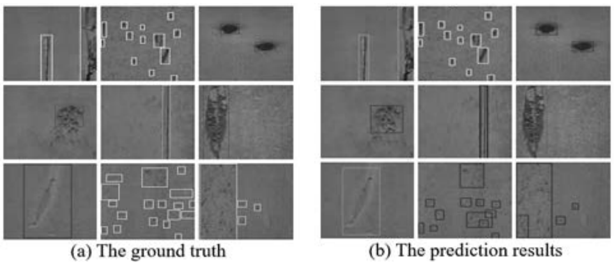

Figure 4 Defect prediction results

rectly predicted positive classes as a percentage of all positive classes in the sample. By calculating the average of the Precision values corresponding to each Recall value is called AP see Formula (1), (2), where ri refers to the Recall value corresponding to the first interpolation at the Precision interpolation segment sorted in ascending order. The mAP is calculated as in Formula (3), the AP values for each category are summed and averaged, where k is the number of categories.

It selected 20 % of the images in the training set that were not involved in the training as the test set. Figure 3 shows the Precision-Recall curves and mAP values for each category and the average value of the selected prediction frames with intersection ratio greater than 0,5. Inclusion, Iron Sheet Ash, Surface Scratch, and Plate System, the mAPs were 95,5 %, 97,1 %, 91,3 %, and 99,6 %.

In terms of inference speed, the method is able to process 83,3 images per second using an RTX3080 graphics card, analysing each image at a speed of just 0,012s, which is able to meet the needs of surface defect detection and localisation during the high-speed operation of the hot-rolled strip line.

The actual operation effect of the model is shown in Figure 4, wherein Figure 4 (a) represents the visualization result of manual annotation of some pictures in the data set, and Figure 4 (b) represents the visualization result of defect position and category information output after these pictures pass through the model.

CONCLUSION

The YOLOV7-based method for locating and classifying surface defects in hot-rolled strip has a good performance in terms of both detection speed and accuracy, with an mAP of 84,3 % in the X-SDD dataset for seven common hot-rolled strip surface defect classification and location tasks, including the Plate System Oxide Scale category. With a mAP of 99,6 %, it is worth noting that the ability to process more than 80 images per second can be adapted to the extremely high operating speed of the hot strip production line, effectively addressing the need for timely classification and location of strip surface defects in the hot strip production process.

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Note: The responsible translators for English language is J. Wang – University of Science and Technology Liaoning, China