Journal of Computers Vol. 34 No. 1, February 2023, pp. 199-210
doi: 10.53106/199115992023023401015

An Improved Recognition Method of EMU Surface Apron Board Defects Based on Depth Learning

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Received 1 January 2023; Revised 18 January 2023; Accepted 19 January 2023

Abstract. EMUs play an important role in the rapid development of China's economy, so ensuring the safety of high-speed EMUs has been a research issue for relevant experts and scholars. Because the defect change of the motor car apron will lead to the stability of the whole motor car running on the side, this paper takes the motor car apron defect as the recognition object, and proposes to add feature reasoning module to the typical convolutional network model to improve the ability to identify occlusion defects by solving the problem that the traditional recognition model cannot identify the features of occlusion and stacking and the status quo that cannot be identified under a small number of samples, Then the meta learning mechanism is incorporated into the model to realize the recognition under the condition of few samples in the dataset. Through experimental comparison, it is proved that the performance of the improved recognition network algorithm in recognition accuracy and recognition speed is improved as a whole.

Keywords: apron board, defect detection, Metalearning, deep learning

1 Introduction

Since the Chinese government put forward the railway development idea of "market for technology" in 2003, China's high-speed railway has developed rapidly. By the end of 2021, the world's largest high-speed rail network, namely the "eight vertical and eight horizontal" trunk line, has been built. Among them, the high-speed rail line is 38000 kilometers, and more than 2655 pairs of EMUs are operated every day. Therefore, high-speed rail plays a decisive role in the development of the national economy, serves the rapid development of China's economy, and makes "morning and night" possible in the vast land of China. The National Development and Reform Commission calls a train with a speed of more than 250km/h as a high-speed railway. Therefore, how to ensure the operation safety of EMUs at high speed has become the top priority. Any minor failure may lead to major safety accidents. Faced with the pressure of high-speed development of the railway and the increasing number of daily trains, the traditional manual visual inspection can no longer meet the requirements of reliability and efficiency. Therefore, this paper proposes machine vision defect detection based on deep learning to ensure the efficiency of daily maintenance of EMUs and improve the accuracy of detection.

During the operation of EMUs, when the EMUs meet, the air pressure on the train surface will change greatly when passing through the tunnel. Under the strong crosswind environment, the integrity of the EMUs apron is particularly important. The motor car apron and the car body are connected by high-strength bolts. With the increase of service time, the bolts may become loose, broken, worn and fall off, thus threatening the safety of the motor car. Therefore, this paper takes the motor car apron defects as the detection object, and the work done is as follows:

(1) First, an improved recognition model is proposed. By adding a feature reasoning module at the end, it can realize the recognition of occluded or stacked defects of different classes, and improve the recognition accuracy.

(2) A recognition model based on few samples is proposed. Aiming at the actual problem of sample missing in practical tasks, a meta learning method is proposed to improve the model's ability to predict defects in a few samples way.

The second chapter introduces the current development of related work and the development status of EMU defect identification; In the third chapter, the implementation process of the improved model is proposed, that is, the implementation process of adding the feature reasoning module to the model; Chapter 4 introduces the process of adding meta - learning methods to the model; In the fifth chapter, the experimental analysis and compar-

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ison of each improved algorithm are carried out, and the recognition is verified by using the actual apron image; The sixth chapter summarizes the article and discusses the shortcomings, and then puts forward further research plans.

2 Related Work

Li Jing and others put forward a method for locating and identifying the key bolts of motor train based on the direction gradient histogram and support vector machine by using the image acquisition equipment at the track edge. The accuracy rate reaches 90%, and the recognition accuracy rate has much room for improvement [1]. Xavier Gibert proposed a multi task learning method based on deep convolutional neural network, which improved the detection efficiency of railway rail tie fasteners [2]. Junhua Sun used binocular vision camera and convolutional neural network to realize the detection of key bolt looseness, which is only the detection of multiple bolt looseness, without involving other damages [3]. On the basis of Faster R-CNN, Bing Zhao and others proposed a dual channel defect detection framework combining component detection and defect classification process to classify the defect images of key components of EMUs collected by TEDS [4]. Yu Feng Shu proposed a method to detect and identify commutator surface defects. YOLOv3 target detection is applied to the detection and recognition of commutator surface defects. On the premise of not significantly reducing the detection accuracy, the model size and number of parameters are reduced, and the detection effect is enhanced [5]. Siyu Zhang proposed a new method combining neighborhood adaptive and adaptive convolution neural networks, which shows its advantages in steel surface defect detection [6]. Jinmin Zhang proposed a defect detection method based on Weber local descriptor and local phase quantization feature fusion for the fault image of the center plate bolt of the freight car to realize the bolt location and recognition. The results show that the detection speed is fast [7]. Jiahong Tang proposed a defect detection method based on the improved Faster-CNN algorithm, which uses the deep residual network to extract the defect features, and uses the feature pyramid model with content-aware reorganization to fuse the special images at all levels, which can improve the accuracy and speed of defect detection [8].

3 Improved Network Model Implementation Process Word

Aiming at the two defects of SSD network: ignoring the context information around objects in the image and being unable to detect small objects and occluded objects, this paper uses a more powerful basic network, and then improves the feature fusion method and the relationship between objects to achieve the balance between defect detection speed and detection accuracy, and improves the detection speed and detection accuracy to an ideal level at the same time.

The classic SSD structure is shown in Fig. 1, which consists of three parts: the convolution layer, the target detection layer, and the NMS filtering layer. The convolution layer uses ResNet as the basic network to complete the task of feature extraction.

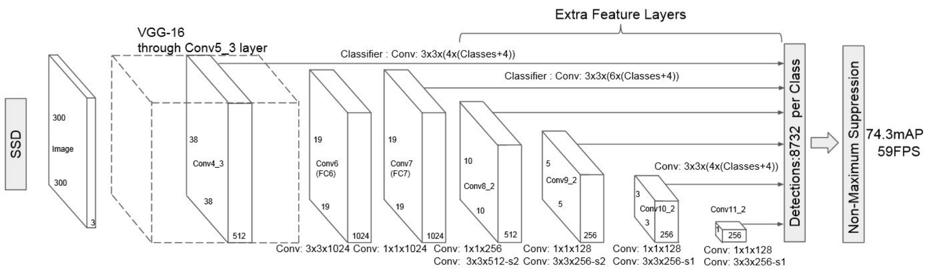

Fig. 1. SSD structure diagram

Therefore, due to the defects of the classic SSD network, its network structure is first changed to a network that contains two-way transmission of feature information and feature fusion. Secondly, in order to detect occluded or stacked detection targets, feature reasoning module is added at the end of SSD network. In this way, the bidirectional improvement of detection accuracy and speed is achieved through feature reasoning technology and improving the feature fusion relationship between different output layers. The specific steps include three aspects:

(1) Select a more appropriate basic network with performance as the main driving factor;
(2) Improving feature fusion strategy in the model;
(3) Add feature reasoning module at the end of the network.
The schematic diagram of the improved SSD network structure is shown in Fig. 2:

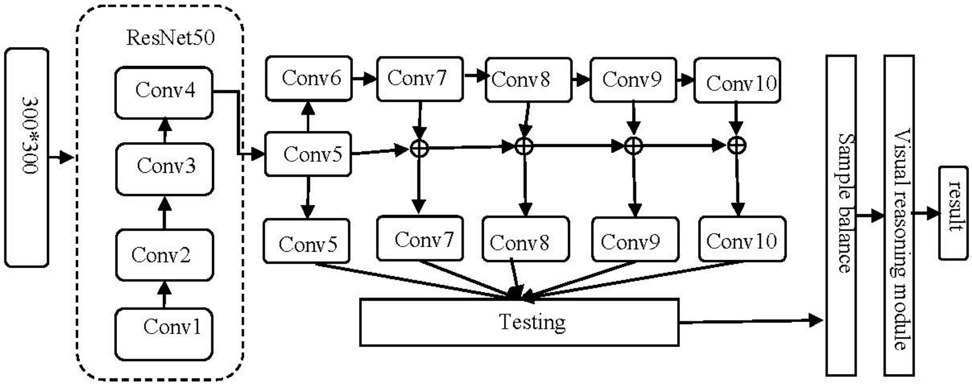

Fig. 2. SSD improved algorithm structure

3.1 Selection of Basic Network

The traditional SSD network includes the basic network and the target detection network. With the continuous improvement of the network, the network degradation is very serious. ResNet as the network itself, contains residual modules, which can well resolve the degradation problem. Therefore, compare each basic network in the experiment, and select the basic network with good detection accuracy and speed. After the experiment, the experimental data of each network is shown in Table 1:

Table 1. Comparison of basic network performance for SSD

Basic network	mAP	fps
VGG-16	0.8263	15.201
DarkNet	0.8543	22.312
ResNet101	0.9203	7.812
ResNet50	0.9101	13.001

3.2 Improved Strategy of Feature Fusion between Layers

In traditional SSD networks [9], each layer contains special information, the bottom layer contains rich details, and the top layer contains rich semantic information. Therefore, an effective strategy is adopted to fuse the original layers, and the newly generated layer will contain rich details and semantic information. According to Fig. 2, feature fusion is carried out after the CONV5 layer, and prediction is completed from the classification confidence and prediction frame compensation obtained from the additional layer to realize two-way transmission of information. The fusion structure is shown in Fig. 3. The fusion process includes up sampling, down sampling and fusion. When implementing the upper and lower sampling process, in order to improve the calculation effect and speed, this section adopts the bilinear interpolation and maximum pooling method. In terms of fusion techniques, the feature mapping of the target layer is given the maximum weight by using the sum of elements to ensure that the fused features do not disappear. Take a feature layer as an example, let the middle layer contain low-level and high-level information, and then use the feature map of the same size to adjust the shape of each feature layer by sampling up and down.

The details of improved feature map fusion are shown in Fig. 3. First of all, in order to get the same shape $2H \times 2W$ as the middle layer, the *reise* strategy is used for the lower and higher layers. Secondly, the channel size is unified to 512 through 1×1 convolution layer. Since the distribution of eigenvalues in each layer is quite different, normalization operation is required before fusion.

According to the requirements of dimensions, this chapter uses the method of batch normalization to operate. Based on this, the feature map fusion is completed, and a feature layer with rich details and full semantic information is obtained.

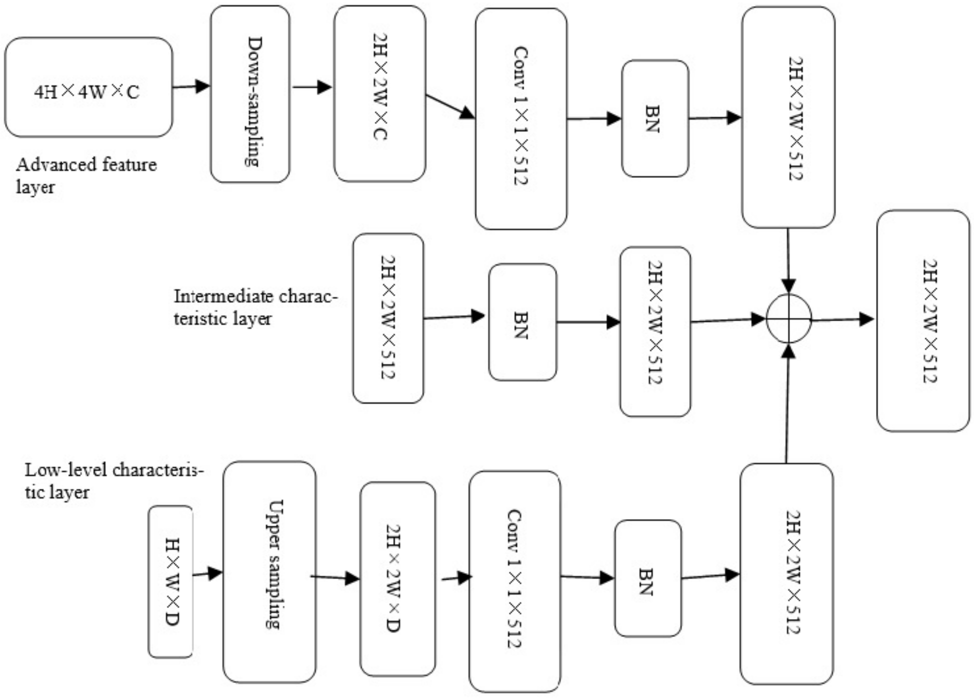

Fig. 3. Feature fusion module structure

3.3 Creation of Feature Reasoning Module

Feature reasoning module is used to solve the problem of defect recognition capability that is occluded or stacked together. Due to the complexity of the actual defects of the motor car apron, the superposition or repetition of different types of defects is inevitable, and the effect of relying solely on feature recognition is not ideal. Therefore, for the target with fuzzy judgment, infer the logical relationship between defects from the defect generation mechanism, and judge from the scene around the defects and related things, which is feature reasoning, that is, use the target with high confidence to judge the fuzzy target. The inference mechanism is as follows [10]:

Assuming that there are apron defects in picture i, the set of defects is set as $\left[O_1, O_2, \cdots O_k\right]$, where *k* represents the number of defects. In order to identify all defects in the picture, the objective function of the training model is expressed as follows:

$$\arg\min_{M} L = \log P(O_{UK} \mid M, I) . \tag{1}$$

In the formula, *M* represents the maximum value of the logarithmic probability model *L*, and O_{UK} represents $\left[O_1, O_2, \cdots O_k\right]$.According to the correlation between objects, formula (1) is transformed equivalently:

$$\arg\min_{M} L = \log P(O_{UK} \mid M, I) = \sum_{UK} \log P\left(O_{UK} \mid M, I\right) \tag{2}$$

The feature reasoning module is integrated into the objective function, and the approximate formula is as follows:

$$\arg\min_{M} L \approx \sum_{n=UK} \log P\left(O_K, \middle| S_{K-1}, M, I\right). \tag{3}$$

Here, the design of feature reasoning module includes two steps. The first step is to create the association between different defects. Suppose there is a defect type, build a relationship matrix:

$$E = \left(e_1, e_2, \cdots, e_n\right) \in R^{n \times n}. \tag{4}$$

The above relational matrix is the decisive factor for model detection. The relationship between different defects can be calculated by the following formula:

$$\begin{aligned} e_{ij} &= \sum_{n=1}^{N} I_n(i,j) \\ I_n(i,j) &= \begin{cases} 1 & if, d_{ij} < T \\ 0 & else \end{cases} \end{aligned}. \tag{5}$$

In the formula, element e_{ij} represents the relationship between type i and type j defects, N represents the number of training samples, d_{ij} represents the distance between two defect centers, and T represents the threshold value of *ROI*.

Second, build an auxiliary judgment mechanism based on confidence. First, use the improved SSD algorithm to detect all defects in an image based on confidence. For the defects to be detected, if the confidence value is greater than, they are considered as reliable targets. Then use these reliable results to re evaluate the recognition results with confidence values between. If the recognition results are considered unreliable, The confidence value will be updated according to the following formula.

$$\begin{aligned} s_i(x) &= s_i(x) + \lambda \frac{e^{k_i(x)} - e^{-k_i(x)}}{e^{k_i(x)} + e^{-k_i(x)}} \\ k_i &= \sum_{j \in D} e_{ij} - C\left(e_{ij} = 0\right) \end{aligned}. \tag{6}$$

In the formula, $s_i(x)$ represents the confidence value that defect x belongs to class i, and λ represents the balance parameter between feature reasoning module and detection module, D is a list of defects with high confidence distributed around defect x, k_i is the probability that the defect belongs to class i, and C is the number of times $e_{ij} = 0$ returns. The value of confidence degree indicates that whether a defect is a type defect depends not only on its own characteristics, but also on the attribution of surrounding defects. Therefore, in this way, those occluded or superimposed defects can also be accurately identified. After using the feature reasoning module, the defect recognition effect is shown in Fig. 4.

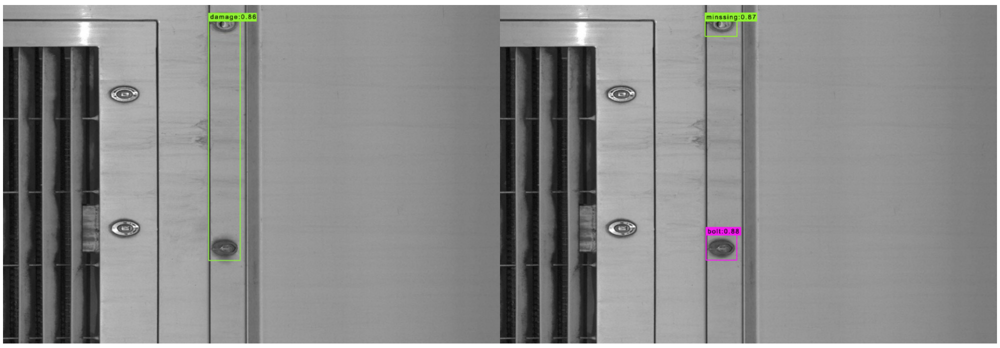

Fig. 4. Comparison of inference module effects

4 Research on the Method of Small Sample Recognition based on Meta Learning

When identifying defects, for any special task, it is necessary to identify large-scale sample data sets of objects. However, the actual situation is that many tasks do not have enough data, and the undersized data sets lead to the collapse of the identification model [11]. Therefore, this paper uses meta learners to learn features and realize knowledge feature transfer, so as to guide the detector to recognize new classes when the number of target object samples is small. The identification system diagram is shown in Fig. 5.

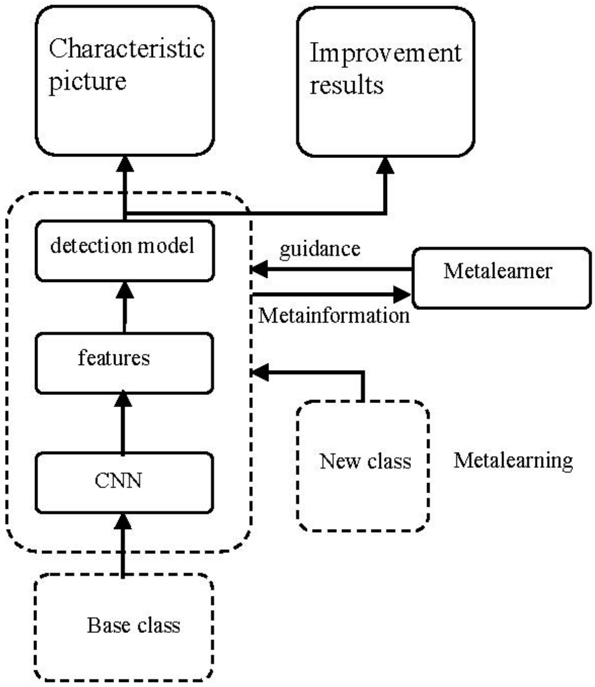

Fig. 5. Small sample learning

In order to solve the problem of meta learning to improve the level of generalized recognition in the case of extreme imbalance of data, the target detector based on meta learning is equipped with a predictor to reconstruct the network, so as to improve the ability to recognize generalized recognition.

4.1 Meta Learning Theory Model

In this paper, we use the learning optimizer method in meta learning to train the tasks in the model learning training set during the learning process, and two optimizations are at work: learner and meta learner. Among them, the learner is used to learn new tasks, and the meta learner is used to train the learner, so that the learner can learn to update automatically. The specific process is that the meta learner continuously displays a variety of supervised learning tasks to the learner, so that the learner can learn to acquire experience in learning other tasks [12]. In the training stage, C classes are randomly selected from the training set, and each class includes k samples.

4.2 The Construction of a few Sample Learning Model Framework

Target detection network SSD and meta learning are combined as a new target detection network, at the same time, the detector reconstruction network is added to realize the generalized recognition with few samples. The basic idea is to effectively combine time convolution with attention mechanism. Time convolution provides high bandwidth access at the cost of limited context information, and attention mechanism provides unlimited accurate access to context information. This paper selects information channel level features for each RoI feature to help the meta learner learn valuable information quickly without being limited by the number of experiences. Therefore, the model framework is shown in Fig. 6.

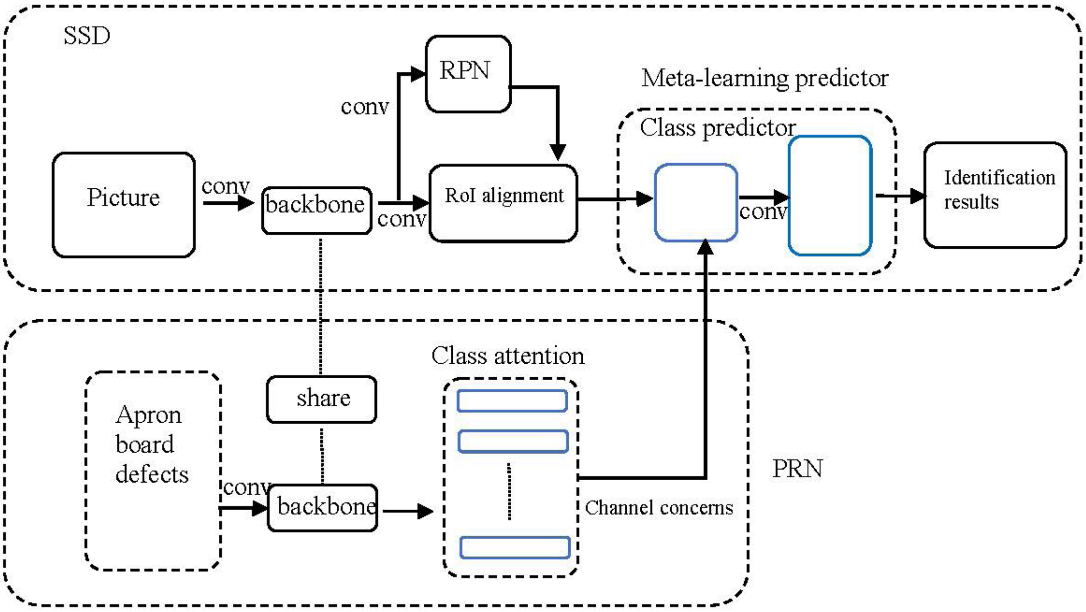

Fig. 6. Small-sample learning framework

This model trains the meta learner from the sub tasks of target network SSD, which enables the experienced meta learner to guide the detector to quickly update its own network, so as to realize the recognition of few samples.

4.3 Target Detector Creation

After the meta learner completes a series of base class defect training tasks, it should be able to quickly adapt to new tasks with fewer samples of new types of defects, and teach the network how to quickly adjust parameters (only updated once). This is obviously different from the supervised learning method in which the evaluation object is "sample". The training and evaluation object of meta learning is "task" rather than "sample", as shown in Fig. 7.

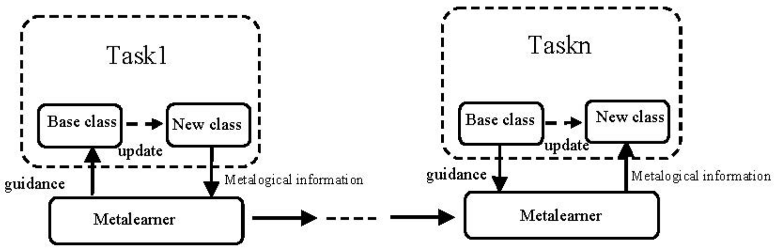

Fig. 7. Metalearning principle

The data set includes training set and test set. The meta learner guides and adjusts its parameters according to the feedback of the training set in each task, and updates them through the meta information of the test set in a batch of tasks. After learning M tasks, the meta learner has learned how to quickly adapt to the update of new tasks.

4.4 Predictor Rebuild Network

The predictor reconstruction network is represented as A, and each RoI feature in image B is represented as C [13], meeting the following formula:

$$h(\hat{z}_{i,j}, D_{meta}; \theta') = h(\hat{z}_{i,j} \otimes v^{meta}, \theta) = h(\hat{z}_{i,j} \otimes f(D_{meta}; \phi), \theta) . \quad \textbf{(7)}$$

In the formula, θ, ϕ represents the parameters of the target recognition convolution network and target detector, and $\theta' = \{\theta, \phi\}$, represents the information channel multiplication operator, The predictor reconstruction network reconstruction $h(\cdot, \theta)$ is based on $h(\cdot, D_{meta}; \theta)$, which can achieve end-to-end joint training with the corresponding part of the target detection network Faster R-CNN.

Assume that x_i is the target detection image of the small sample learning network. After the alignment of the area of interest of the recognition module is completed, it becomes a group of RoI features $\{\hat{z}\}_{i,j}^{\hat{n}_i}$. The predictor reconstruction process is as follows:

(1) Class attention vector inference: the predictor reconstructs the network with all targets in the dataset as input, D_{meta} is a list of targets of class *C* in the image, and each type of defect in D_{meta} is a 4-channel input. Assuming that *m* is the scale of C_{meta} , the predictor reconstruction network receives the defect input of channel $m \times 4$ in each reasoning process. In order to reduce the calculation, the input space is unified as 224×224 . Before aligning each defect feature in the region of interest, the shared backbone is imported into the second layer of the corresponding target recognition network SSD. The feature generates its target attention vector v through the information channel level attention layer to achieve the alignment of regions of interest. To this end, the predictor reconstructs the network to encode *mK* objects in D_{meta} into *mK* defect attention vectors, and then uses average pooling to obtain the attention vector v_c^{meta} , as shown below:

$$v_c^{meta} = \frac{1}{k} \sum_{j=1}^{k} v_k^{(c)}, (\forall c \in C_{meta}) . \quad \textbf{(8)}$$

Where, $v_k^{(c)}$ represents the attention vector derived from Class *C* defects, and each class has *k* samples.

(2) Reconstruction predictor: after obtaining the attention vector $v_k^{meta} (\forall c \in C_{meta})$, it is used to pay attention to the information channel level of each region of interest feature $z_{i,j}$,The predictor reconstruction network realizes the recognition of all *C*-type defects in image x_i through continuous updating and iteration, so each $z_{i,j}$ will produce *m* binary detection results about the class in C_{meta} ,by using the proposed method, $z_{i,j}$ is divided into Class *C*, and then defects are located through $z_{i,j} \otimes v_c^{meta}$. If the confidence obtained is lower than the set threshold, the region of interest will be discarded as the background. Therefore, the whole process of meta learning optimization is shown in Fig. 8.

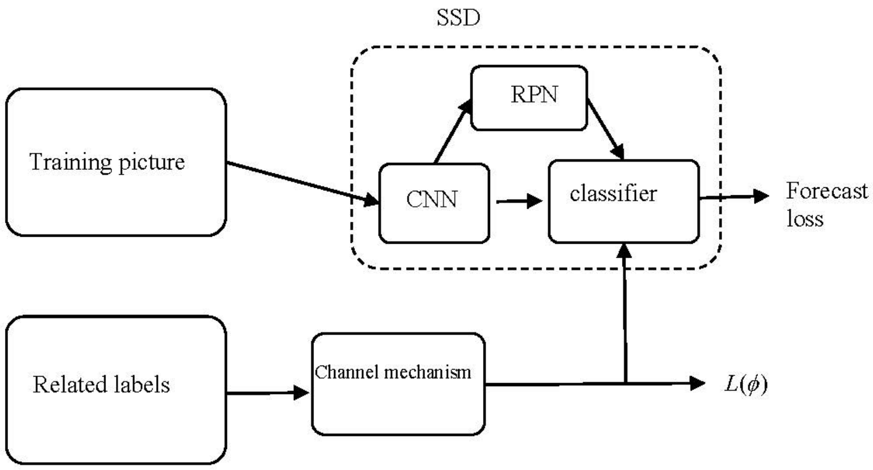

Fig. 8. Meta-learning optimization process

The above completed the feature reasoning process.

5 Model Test and Comparative Analysis

The experimental server is configured with Intel i9-9920K CPU and 48GB of running memory (RAM), and the parallel computing device is three RTX 2080Ti with 11GB video memory. Set the threshold value of SSD positive sample to 0.7, the threshold value of negative sample to 0.3, the maximum training batch to 12, the learning rate to 0.0025, the gradient decline momentum to 0.9, and the weight decay coefficient to 0.0001. Log in to the server remotely through SSH, enter the Docker container, and execute the training task through the terminal command.

5.1 Recognition Accuracy Experiment and Analysis

Firstly, the recognition ability of SSD model with feature reasoning module is explained. For the sake of illustration, it is called SSD+R model. In this paper, YOLOv3 data set is selected for comparison experiment, and the resolution of the images inputted into the network is changed to, comparing the detection classification of the normal apron and the apron bolt loss samples, as shown in Table 2 and Table 3:

Table 2. Experimental results of YOLO3

YOLOv3	TP	NP	FN	P	R
bolt	316	25	21	92.67%	93.77%
missing	297	19	17	93.99%	94.59%

Table 3. Experimental results of SSD+R

SSD+R	TP	NP	FN	P	R
bolt	325	17	12	95.03%	96.44%
missing	304	12	10	96.20%	96.82%

Faster R-CNN and Faster R-CNN * are added as comparison objects, and the comparison of recognition accuracy mAP and recognition speed is shown in Table 4:

Table 4. Algorithm comparison results

Detection algorithm	AP%		mAP%	FPS
	bolt	bolt_lost		
YPLOv3	93.02%	94.05%	93.54%	77.7
SSD+R	95.14%	96.18%	95.66%	77.1
Faster R-CNN	94.11%	95.16%	94.64%	31.1
Faster R-CNN*	93.86%	95.19%	94.53%	24.3

It can be seen from the table that the calculation speed is below 80%, which means that the increase of graphics resolution will reduce the calculation speed, but it can ensure that the resolution remains at a high level. The SSD+R proposed in this paper achieves 95.65% of the mAP value, which is the highest among the compared algorithms. Although the detection speed decreases slightly, the recognition accuracy and speed comprehensive ability of several algorithms are the best.

5.2 Experiment and Analysis on the Recognition Ability of Few Samples

For the convenience of discussion, the model added with meta learning method in Chapter 4 is called SSD+R+M. According to the C-way K-shot ($C = 4, K = 1,3,5,10$) experimental scheme, the first phase of the experiment uses $100K$ training images and $30K$ verification images for joint training, and the remaining $15K$ images for evaluation. In the second stage, K samples in each new class have structural labels, and $2K$ samples in each base class have structural labels for training. The VOC2007 dataset is used for training. The experimental results are shown in Table 5:

Table 5. The experimental results

	Group 1				Group 2				Group 3			
K value	**1**	**3**	**5**	**10**	**1**	**3**	**5**	**10**	**1**	**3**	**5**	**10**
FRCN	5.6	6.0	10.8	21.5	4.4	7.8	9.0	16.1	3.6	8.5	9.0	11.5
FRCN+	11.5	28.5	33.7	44.1	25.2	26.1	30.5	39.3	6.8	22.0	29.2	42.0
SSD+R+M	13.2	34.1	46.3	49.0	19.0	29.5	35.3	44.9	11.5	26.8	42.1	49.5

Among them, FRCN is a supervised learning model. The FRCN detector is jointly trained by base class objects and new class objects, using the same number of iterations as SSD+R+M. FRCN+ adopts a two-stage training strategy: in the first stage, only base class objects are used to train FRCN. In the second stage, the network is fine tuned by combining base class and new class objects, and the number of iterations is the same as SSD+R+M. It can be seen from the above table that with the increase of K value, the recognition rate is significantly improved. When the K value is 5, the detection rate of SSD+R+M is 31.4 percentage points higher than the FRCN result, and the average accuracy of the new class is 10.3 percentage points higher than the FRCN+ result. When $K = 10$, the MFRC detection rate is 31 percentage points higher than the FRCN results, and the average accuracy of the new category is 5.7 percentage points higher than the FRCN+. The experimental results show that the combination of meta learning method and target detector can significantly improve the recognition rate of new type targets, and this method is effective for the task of small sample recognition of parking apron surface defects.

5.3 Analysis of Image Recognition Results of Motor Car Parking Apron

The camera is used to detect the motor train apron image, and SSD+R and SSD+R+M are used for identification and comparison respectively. The identification results are shown in Fig. 9.

(a) SSD+R identification result

(b) SSD+R+M identification result

Fig. 9. Meta-learning optimization process

Both models can identify the defect of missing apron bolts. For the unified input image, SSD+R+M identification is more accurate and has high confidence than SSD+R. Therefore, SSD+R+M can be used as the target detection algorithm in the second stage, which is specially responsible for proposing a suggestion box close to the target location and size, SSD+R is responsible for predicting the central coordinates of the bounding box. The combination of the two can improve the accuracy and speed of recognition when the object is occluded and there are few samples.

6 Conclusion

This paper introduces two improvements based on the existing recognition network model, and the following effects are achieved through improvement:

(1) To detect occluded or stacked detection targets, feature reasoning module is added at the end of SSD network, so that the detection accuracy and speed can be improved in both directions through feature reasoning technology and improving the feature fusion relationship between different output layers.

(2) In this paper, meta learners are used to learn features and realize knowledge feature transfer, so as to guide the detector to recognize new classes when the number of target object samples is small.

Based on this, for the defect identification of motor train apron, at present, only the identification of bolts on the surface of the apron has been realized. In fact, there are many kinds of defects in the apron. Therefore, the future research direction is the identification of all kinds of defects in the motor train apron to ensure the safety of motor train operation.

7 Acknowledgement

Science Research Projects of Colleges and Universities in Hebei Province in 2023: Research on Encryption Technology of 5G Train ground Wireless Transmission in Rail Transit(Subject No.: QN2023078).

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