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Computer Vision Recognition Method for Surface Defects of Casting Workpieces

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Abstract. To improve the recognition efficiency of surface defects in castings, this article first uses median filtering algorithm to denoise the defect image to distinguish between defects and background. Then, gray threshold method is used to segment the image, and the processed image is sent to the improved RefineDet network structure. Improving the RefineDet network structure mainly improves the network depth and incorporates dataset augmentation algorithms. Finally, an experimental platform was built to train, recognize, and compare the collected image dataset. The results show that the accuracy of detecting porosity, blowhole, and flaw defects is 95.6% and 97.3% and 98.15%, the method proposed in this article is accurate and efficient.

Keywords: casting defects, deep learning, computer vision

1 Introduction

Computer vision casting is the technology of casting liquid metal into a closed cavity, forming and solidifying to obtain the required workpiece. Casting is the foundation of equipment manufacturing, and the vast majority of large workpieces are manufactured with a casting process. China is a major casting country, and according to statistical data, 45% of the global casting production comes from China.

During the casting process, due to the influence of liquid metal type, environmental temperature, casting type, and cavity shape, the metal cannot be accurately controlled during the filling and solidification process, resulting in a large number of casting defects. Casting defects are the main defects in the casting process, and precise and rapid identification is required to ensure the product's qualification rate.

With the development of computer vision and artificial intelligence, probabilistic judgments based on data operations have gained the favor of scholars. Therefore, this article uses improved deep learning algorithms based on computer vision technology to identify surface defects in castings. The work done is as follows:

(1) Firstly, preprocess various forms of images, use median filtering algorithm for noise reduction, and use grayscale threshold method for image segmentation;

(2) Improved image recognition algorithm by adding recognition depth and detail recognition to the RefineDet network structure model;

(3) The number of data samples is relatively small, and through data augmentation and expansion, the number of sample datasets for casting defects has been increased, improving the performance of the model.

This article is mainly composed of 6 chapters. Chapter 2 mainly introduces the relevant research results at home and abroad. Chapter 3 discusses image preprocessing methods. Chapter 4 mainly discusses the process of establishing an image recognition model. Chapter 5 verifies the ability of the method to identify casting defects through an experimental platform. Chapter 6 is the conclusion section, which summarizes this article and lists the shortcomings of this study to prepare for further research.

2 Related Work

Pastor López iker proposed a classification method for workpiece surface recognition. In order to verify the ef-

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fectiveness of the method, a training dataset containing inclusions and cold cracks was created. After experimental verification, the recognition accuracy of casting surface defects reached 91.305% [1]. Ulisses Galan identifies the surface defects of metal parts produced in the casting process by acquiring the binary image of the bright and dark areas on the surface of the casting workpiece and designing an algorithm to convert the binary image into corresponding pixels [2]. Thong Phi Nguyen used convolutional neural networks to detect defects such as blowholes, chips, and cracks in casting products, and repeatedly annotated them based on the order and defect presence, improving recognition accuracy [3]. Fan Chang conducted research on computer vision recognition of defects, using grayscale curves to quickly locate defect locations, and then using edge detection algorithms to determine defect categories. After experimental verification, the method effectively improved the accuracy and efficiency of defect detection [4]. Xiansheng Zhao used DR images to collect surface defect information of workpieces, and then used an improved yolov5 algorithm to recognize feature information. Finally, the improved method was applied to the recognition of side frame castings of high-speed vehicles, and the results showed that the average detection accuracy could reach over 92% [5]. Tingwu Lin, preprocesses the workpiece image by using the gray transformation method and Bilateral filter image adaptive segmentation method, then extracts the gradient histogram features of the image, and finally uses the improved Adaboost RF algorithm to identify the defect type. The experimental results show that the method has a high generalization ability [6].

3 Preprocessing Process of Workpiece Defect Images

The image of casting defects is collected through an industrial vision camera and then sent to a neural network for judgment. The collected image needs to be processed in order to be better recognized.

There are various types of surface defects on workpieces, including pores, sand holes, cracks, etc., with obvious differences in their respective shapes. The pore defects are spherical pores, the sandstone is irregular depressions, and the cracks are elongated grooves [7]. The typical defect characteristics are shown in Fig. 1.

(a) Flaw (b) Blowhole (c) Shrinkage cavity

Fig. 1. Typical characteristics of casting defects

3.1 Visual Image Denoising Processing

Image acquisition is susceptible to interference from various factors such as electromagnetic fields and light, which are called noise. This paper uses the median filtering method to denoise the collected image. The median filtering is a nonlinear smoothing technology based on the mathematical statistics theory. It sets the gray level of each pixel as the median of all pixel gray levels in the neighborhood window of the point [8]. The gray level of the central pixel obtained after the median filtering is expressed as:

$$g(x, y) = Med\left\{f(m,n)\right\},(m,n \in S). \tag{1}$$

In the formula, $f(m,n)$ is the grayscale of pixel (m, n), x and y are the coordinates of the pixel, $x, y = 0,1,2,\cdots,N-1$, S are the set of pixel coordinates in the neighborhood of point (x, y). Generally, 3×3 or 5×5 panes are used to slide in the image. The filtering process is shown in Fig. 2.

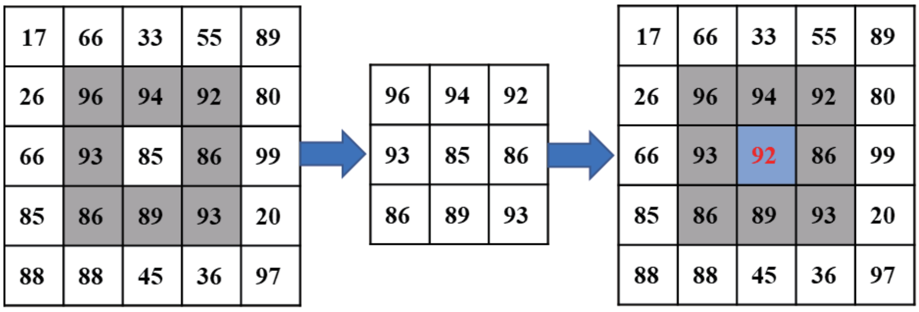
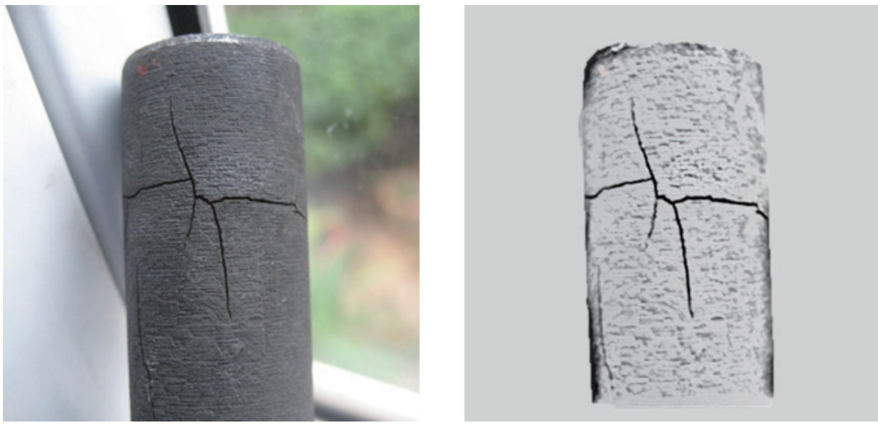


Fig. 2. Image filtering

The median filtering algorithm can effectively suppress pulse noise and has high execution efficiency. Taking a workpiece crack as an example, the image before and after filtering processing is shown in Fig. 3.



(a) Before noise reduction (b) After noise reduction

Fig. 3. Comparison image before and after noise reduction treatment

3.2 Image Segmentation of Casting Defects

Image segmentation of casting defects is the process of detecting and segmenting the surface defects of castings from the collected images. It is an important part from image processing to image analysis. After sampling the defects, the image is segmented using the grayscale threshold segmentation method [9]. The grayscale threshold segmentation expression is:

$$g(i,j)=\begin{cases}0 & f(i,j)<T\\ 1 & f(i,j)\geq T\end{cases}. \quad \textbf{(2)}$$

In the formula, a fixed grayscale threshold T is set. When the grayscale value of the image element is greater than T, $g(i,j)=1$, and when the grayscale value is less than T, $g(i,j)=0$. Therefore, determining an appropriate threshold can effectively separate defects and backgrounds, compare the grayscale values of each pixel with the threshold, and perform pixel segmentation in parallel for each pixel. Finally, the processed image area is obtained. Therefore, the flowchart of the image preprocessing process is shown in Fig. 4.

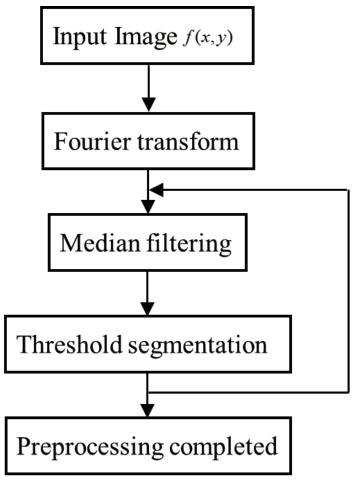


Fig. 4. Comparison image before and after noise reduction treatment

4 Establishment of A Casting Defect Detection Model

This article uses an improved RefineDet [10] to identify casting defects. RefineDet has the characteristics of high accuracy and efficiency, consisting of two interconnected modules, namely the refinement module and the object detection module. The refinement module is used to remove negative samples from the sample set, reduce the search space of the classifier, and roughly adjust the position and size of the detection block to provide better initialization conditions for subsequent regression processing. The purpose of the object detection module is to use the adjusted detection block as input, and further obtain more accurate target positions and predict multi-level labels through regression processing. To establish a connection between the refinement module and the object detection module, a transmission connection block is introduced in the network to convert the different layer features of the refinement module into the required form of the object detection block, so that the two share features and improve the accuracy of detection. Furthermore, the purpose of predicting the position, size, and category labels of defects in the object detection block can be achieved.

4.1 Image Segmentation of Casting Defects

The improvement process of the algorithm is to introduce a two-stage object detection algorithm in the basic network, which moves from coarse-grained information to further regression to obtain more accurate box information for candidate region boxes. At the same time, the detection network introduces feature fusion, which can effectively improve the detection efficiency for small targets. In order to better detect smaller defects such as cracks, sand holes, and shrinkage cavities. The low-level $conv3\_3$ feature map and high-level feature map are fused to enhance the Semantic information of small defects. The feature map at the bottom layer has clear local detail information in the image, which is beneficial for improving the detection accuracy of small-sized defects. The improved RefineDet network structure is shown in Fig. 5.

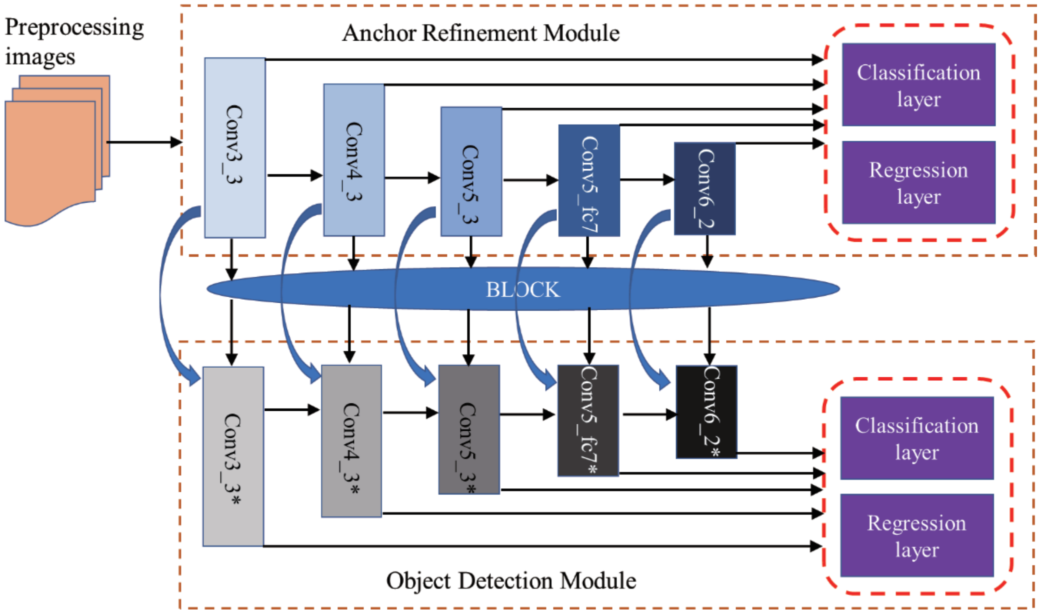


Fig. 5. Improved recognition network structure

The network model includes a VGG16 convolutional network model, which converts the fully connected layers A and B in the original network into C and D, and adds extension layers E and F. The feature maps generated by layers G, H, I, J, and K are selected as the detection layer in the network. The feature maps generated by the refinement module are input to the target detection module through transmission connection blocks, and the high-level and low-level features are fused, so that the low-level features have high-level semantic level features, Improve the accuracy of defect detection at different scales.

The improved RefineDet network enhances the connections between different layers through feature fusion, allowing the feature maps in the detection network to fuse features of different scales and semantic levels, which is conducive to the detection and recognition of defects with different shapes. Firstly, the feature maps generated by $conv6\_2$ are transmitted through three convolutional layers to obtain the corresponding size of $conv6\_2*$, and then the feature maps generated by $conv\_fc7$ are transmitted through the corresponding size of $conv\_fc7*$ through the transmission connection blocks, At this point, a deconvolution operation was added throughout the entire process. This article takes the process of $conv6\_2$ generating $conv6\_2*$ as an example, and inputs the feature maps $conv\_fc7$ and $conv6\_2$ in the refinement module. $conv6\_2$ generates a feature map of the same size as J through the deconvolution operation, where the deconvolution kernel size is $conv\_fc7$. The step size is 2, the number of channels is 256, and then $conv\_fc7$ is obtained by adding and fusing with the convolutional 4×4 -feature map, with a number of channels of 256. The conversion process of the connection block is shown in Fig. 6.

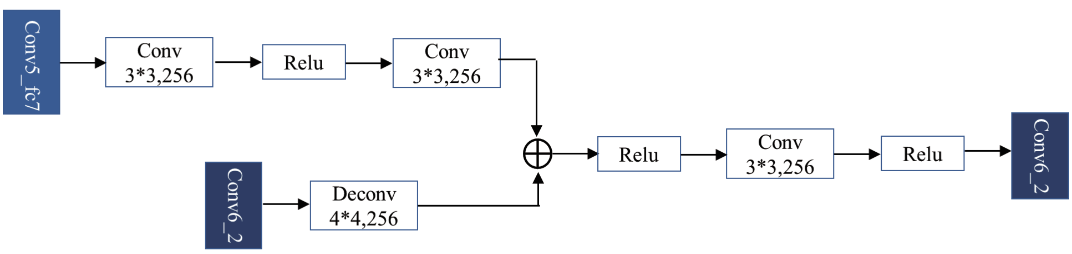


Fig. 6. Connection block conversion

4.2 Selection of Loss Function

The improved RefineDet network adopts end-to-end training mode, and the loss function of the whole network consists of two parts, namely, refinement module and detection module. The refinement module consists of two parts: the second category loss function and the regression loss function, while the detection module consists of the multi category loss function and the regression loss function. The loss function of the whole network is expressed as:

$$\begin{aligned}
&L(\{p_i\},\{x_i\},\{c_i\},\{t_i\}) = \\
&\frac{1}{N_{ARM}}\left(\sum_i L_{bcls}(p_i,[l_i^* \geq 1]) + \sum_i [l_i^* \geq 1] L_{reg}(x_i, g_i^*)\right) \\
&+\frac{1}{N_{ODM}}\left(\sum_i L_{mcls}(c_i, l_i^*) + \sum_i [l_i^* \geq 1] L_{reg}(t_i, g_i^*)\right).
\end{aligned} \quad \textbf{(3)}$$

In the formula, l_i^* is the true category of the i -th detection object, g_i^* is the true position of the i -th detection object, p_i is the confidence level of the refinement module to predict whether the i -th detection object is a target, x_i is the position coordinate of the i -th detection object after refinement, c_i is the category of the candidate region box predicted by the detection module, t_i is the position coordinate of the candidate region box predicted by the detection module, and N_{ARM} is the number of positive sample detection objects in the refinement module, N_{ODM} is the number of positive samples in the detection module.

4.3 Dataset Augmentation

Due to the small number of defect samples, which is insufficient to support the training of the model, it is necessary to expand the existing sample data and expand the sample size of the dataset. The Mosaic data augmentation strategy can achieve the stitching of four images, which can concatenate single defect images into new images and input them into the neural network for learning. The main process of the method is:

Step 1: Randomly select 1 image and arrange it in quadrants;

Step 2: Select a size with a height of and a width of as the output image size, and divide the image into four different regions;

Step 3: Select vertices farther from the segmentation line as overlapping features;

Step 4: Use the histogram equalization method to enhance the data of locally missing details. The schematic diagram of data augmentation is shown in Fig. 7.

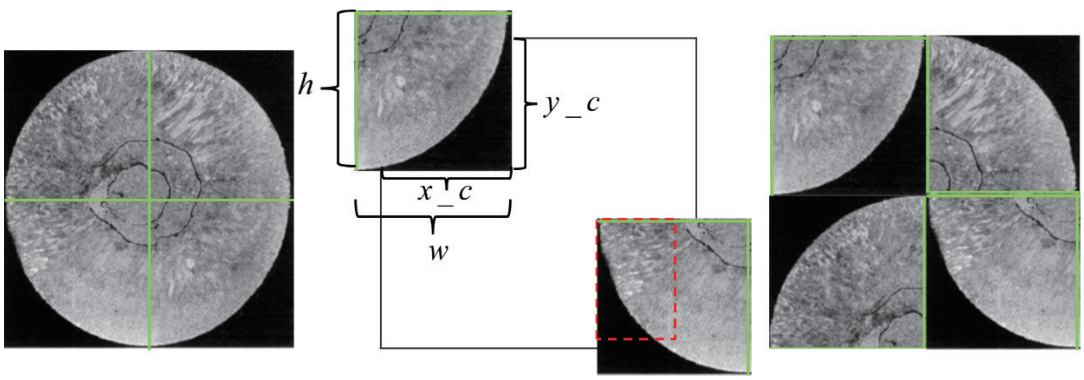


Fig. 7. Schematic diagram of data augmentation

5 Experimental Results and Analysis

5.1 Experimental Data

The experimental platform includes light sources, industrial cameras, and industrial lenses. The software used for image collection uses NI Vision, and the computer GPU used for data analysis uses NVIDIA's RTX3090 graphics card with 32GB of graphics memory and Cud9.0 Python framework. 1000 images of casting workpieces were collected using an industrial camera as experimental data. The size of each photo was $768ps \times 672ps$ and manually labeled with defect labels in the experimental data. The dataset was divided into training, testing, and validation sets according to proportion. Therefore, the number of training set photos was 600, testing set images were 300, and validation set images were 100. Using the Mosaic data augmentation strategy and method to expand the dataset, and scaling the image size to $640ps \times 640ps$, we ultimately obtained 9000 images.

5.2 Analysis of Defect Detection Results

The processed image dataset is fed into the improved RefineDet network. In order to facilitate subsequent description, the improved RefineDet is collectively referred to as I-RefineDet. The model is trained in Python and the environment. The deep learning framework is PyTorch, and the model is trained 2000 times. The number of samples selected for each training is 4, and the initial learning rate is set to 0.01. Accuracy and Loss rate are used as evaluation indicators to measure the performance of the model, Choose the RefineDet before improvement and the RefineDet after improvement for training comparison, The convergence results of the model are shown in Fig. 8.

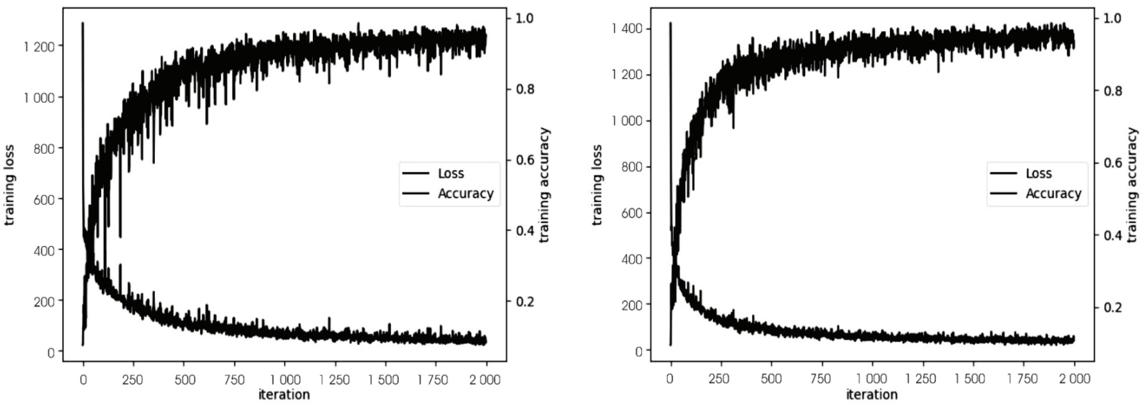


Fig. 8. Schematic diagram of data augmentation

As shown in the figure, as the number of iterations increases, the average detection accuracy reaches over 80%. When the IoU value is 0.5, the average accuracy approaches 1, reaching 99.6%. At the same time, the iteration process performs more stably. Taking actual image recognition as an example, the recognition results are shown in Fig. 9.

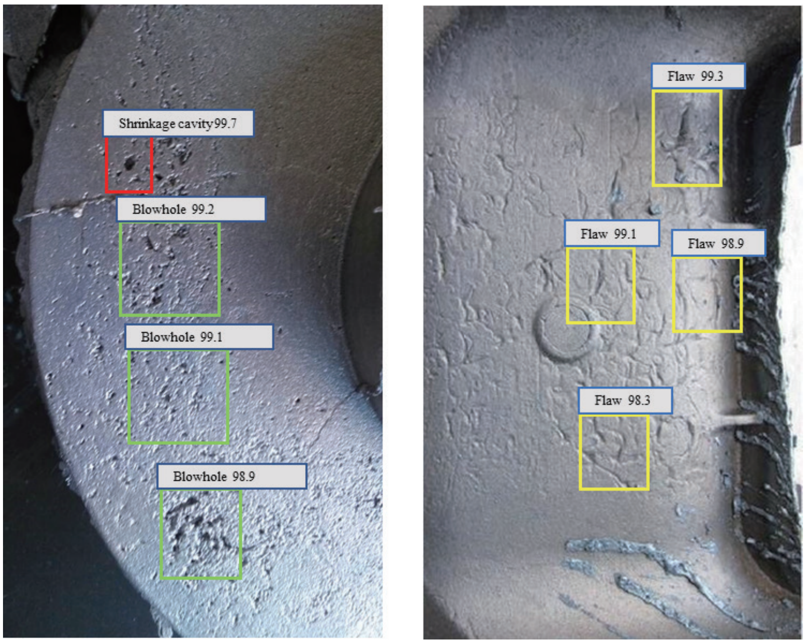


Fig. 9. Image recognition results

5.3 Analysis of Defect Detection Results

At the same time, the dataset was fed into the classic YPOLOv5 for training, with consistent parameter settings and 2000 iterations. The sample was selected as 4, and the training results were compared using FPS (detection of real-time frames) and mAP (average accuracy). The comparison results are shown in Fig. 10.

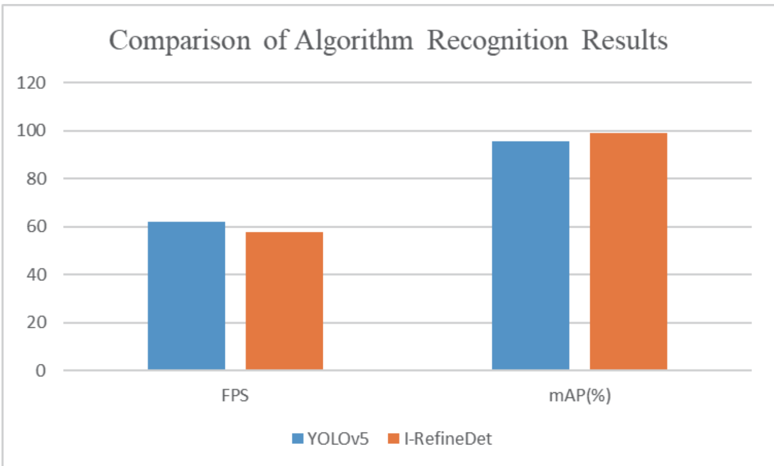


Fig. 10. Comparison of algorithm recognition results

After the above steps, it can be proven that the algorithm proposed in this article can meet the real-time and high-precision detection requirements for defects in images, with a detection accuracy of 99.2% and a real-time frame count of 57.9, which can meet the requirements of pipeline operations. Therefore, the algorithm proposed in this article has high effectiveness.

6 Conclusion

After analysis, this article has achieved the expected goals and there is still room for improvement. The summary is as follows:

(1) By using image denoising and filtering methods, as well as Mosaic data augmentation strategies, image enhancement and expansion were completed, enhancing image complexity and improving the accuracy of model training.

(2) The recognition network model has been improved, and a series mechanism has been constructed between the refinement module and the object detection module, resulting in an overall improvement in the recognition performance of the model.

(3) Compared to the original network, the average detection accuracy of common porosity, sand hole, and crack casting defects has been improved by 3.8%, which can achieve automatic detection of multiple types of defects in castings. This method has good generalization ability.

7 Acknowledgement

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