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Article

Research on tire internal defect identification method based on deep learning

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Abstract: As an important part of automobile, the safety and durability of tire have attracted more and more attention. Tire defect detection is an important link to ensure tire quality, while traditional detection methods have problems such as low efficiency, high false detection rate and high labor intensity. Therefore, this study aims to develop an efficient and accurate tire defect identification and classification technique to improve the efficiency and accuracy of tire inspection. In this paper, based on YOLO (You Only Look Once) v5 algorithm, tire defect recognition and classification are studied. Firstly, the data sets containing various types of tire defects were collected and sorted out, and the data sets were preprocessed. Then, by constructing, training and optimizing the YOLOv5 tire defect recognition model, the fast and accurate recognition of tire defects was realized. Finally, the performance of the model was evaluated through experiments and compared with the existing methods. The experimental results show that the tire defect recognition and classification method based on YOLOv5 proposed in this study has high accuracy. Compared with traditional methods, this method has a significant improvement in detection speed and accuracy.

Keywords: tire; internal defect; deep learning; dataset training; YOLOv5

1 Introduction

Tire is one of the key components of automobile, and its quality directly affects the driving safety. In the manufacturing process of tires, it is easy to produce various types of defects, these defects will not only affect the normal use of tires, but also may pose a serious threat to people's life safety. Therefore, in order to ensure the safety performance of tires in the process of driving, strict and comprehensive quality inspection must be carried out before leaving the factory. Traditional detection methods often rely on artificial naked eyes for defect identification [1]. Although this method is intuitive and easy to understand, it is relatively inefficient and easy to cause visual fatigue for long hours, which affects the accuracy of detection. With the continuous development of machine learning technology, the methods based on machine learning have gradually become a research hotspot. Based on YOLOv5 algorithm, this paper does further research on the recognition and classification of tire defects. By using the advantages of YOLOv5 algorithm, we expect to realize the automatic, fast and accurate recognition and classification of tire defects, so as to improve the efficiency and accuracy of tire quality detection.

At present, the target detection algorithm can realize the location and classification of the target at the same time, which provides new possibilities for defect detection. Cui et al. [2] developed a tire texture depth detection method based on machine vision technology. This method can identify the small defects inside the tire, but the stability is poor, and the measurement accuracy is greatly affected by the measurement time. Li and Jiang used Faster R-CNN (Region-based Convolutional Network) model to detect tire defects [3]. Although certain results have been achieved, there are still defects in the application of detecting real tires. Wang et al. built an automatic detection system for the tread wear degree of automobile tires by using a camera [4]. Although the automation level is high, the detection success rate still needs to be improved. Therefore, although the existing tire defect detection technology has made some progress, it still faces many challenges in practical applications, and it still faces the problems of low detection success rate and easy to be interfered by external factors. On this basis, YOLOv5 network is used to construct an automobile tire defect recognition and classification model based on deep convolutional neural network, and the test results are predicted and analyzed.

2. Tire defect analysis and dataset construction

As an important part of the car, the tire has a decisive impact on the driving performance of the car. A qualified tire needs to have good handling, stability, comfort and safety. However, in the production process, tires may have various defects, which may affect the performance of tires and even endanger the life safety of drivers and passengers [5–9]. Therefore, the identification and classification of tire defects is particularly important.

2.1. Common types of tire defects

In the production process, the quality of radial tires is sometimes unqualified due to improper production equipment, technological process and operation [10]. According to the nature of tire defects, these defects can be roughly divided into two types: structural type defects and gray type defects [11]. This article will introduce some of the most common defects, including tire cord cracking, uneven distribution of cord, impurities, and wrong edges [12–15].

(1) Tire cord cracking

Tread cord cracking is a common tire defect. The X-ray picture of tread cord cracking is shown in **Figure 1**. As the key supporting structure of the tire, the cord inside the tire plays a vital role in coping with external forces and maintaining the shape and stability of the tire [16]. Cord cracking will lead to a significant decrease in the load-bearing capacity and deformation resistance of the tire, thus increasing the risk of tire burst during high-speed rotation.

(2) Uneven distribution of cord lines

The X-ray image of uneven distribution of cord is shown in **Figure 2**. Uneven distribution of cord will increase the risk of shoulder empty and bulging of tires, and in severe cases, it may even cause tire burst failure, resulting in premature tire damage [17].

(3) Impurities

In the manufacturing process of tires, sometimes foreign objects such as screws, rubber fragments or iron filings may be accidentally mixed into the interior of tires. The X-ray image of tire impurities is shown in **Figure 3**. The presence of these foreign substances will significantly thickensome areas of the tire, forming various shapes and prominent black block shadows on the X-ray detection image of the tire [18].

(4) wrong side of the cord

The X-ray image of the wrong edge of the cord is shown in **Figure 4**. In the cord layer of the tire, the cord is not arranged in the predetermined position or direction, and it is offset or misplaced. When driving at high speeds or bearing heavy loads, this structural weakness may cause deformation or damage of the tire, and even cause safety accidents [19].

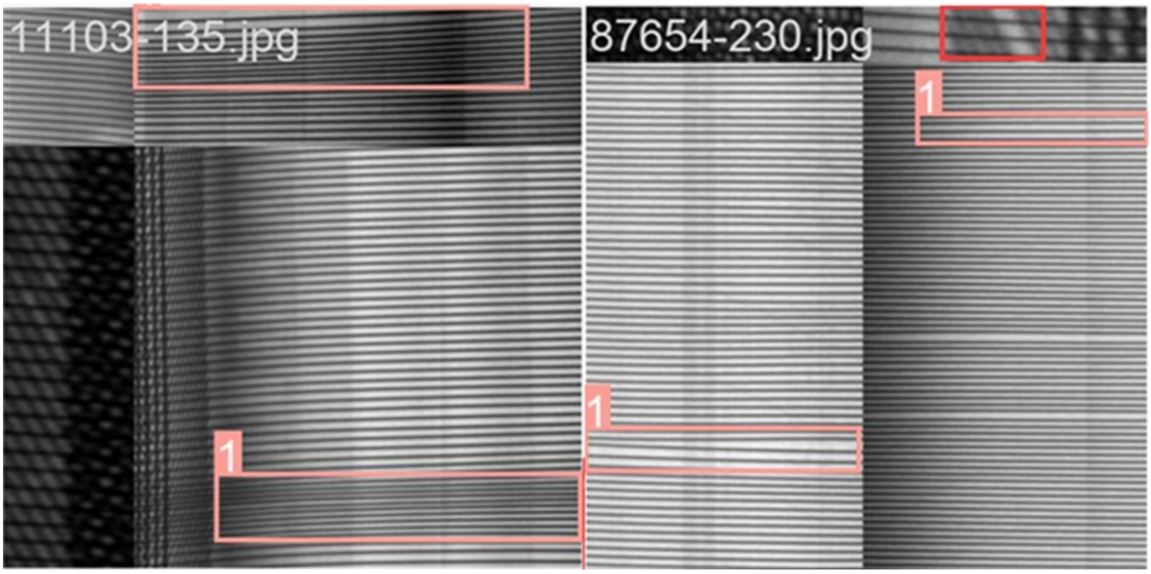

Figure 1. X-ray picture of tread cord cracking.

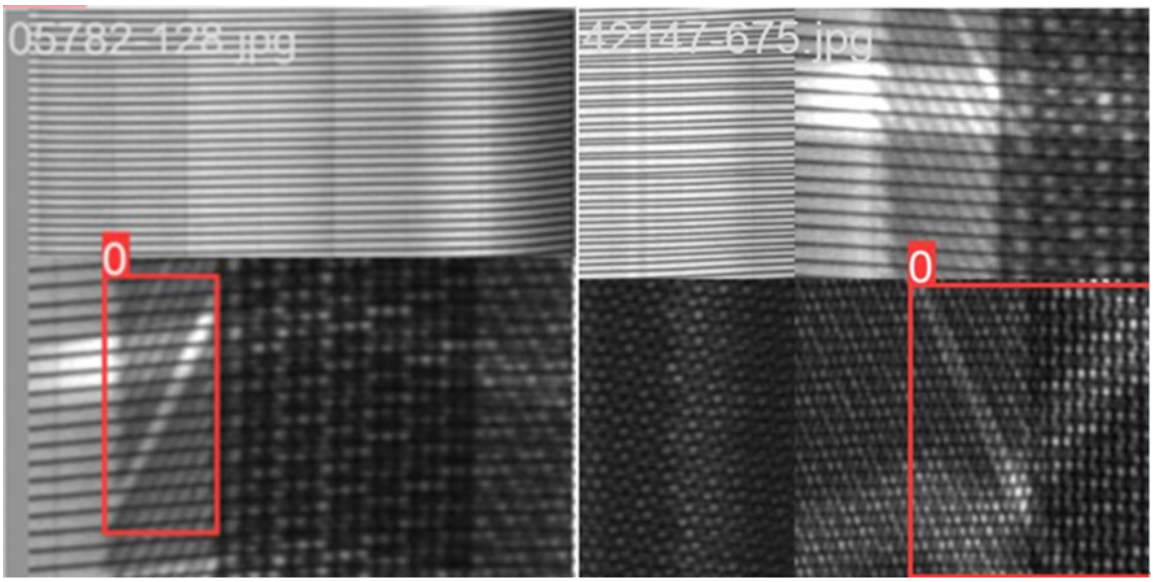

Figure 2. X-ray picture of unevenly distributed cord.

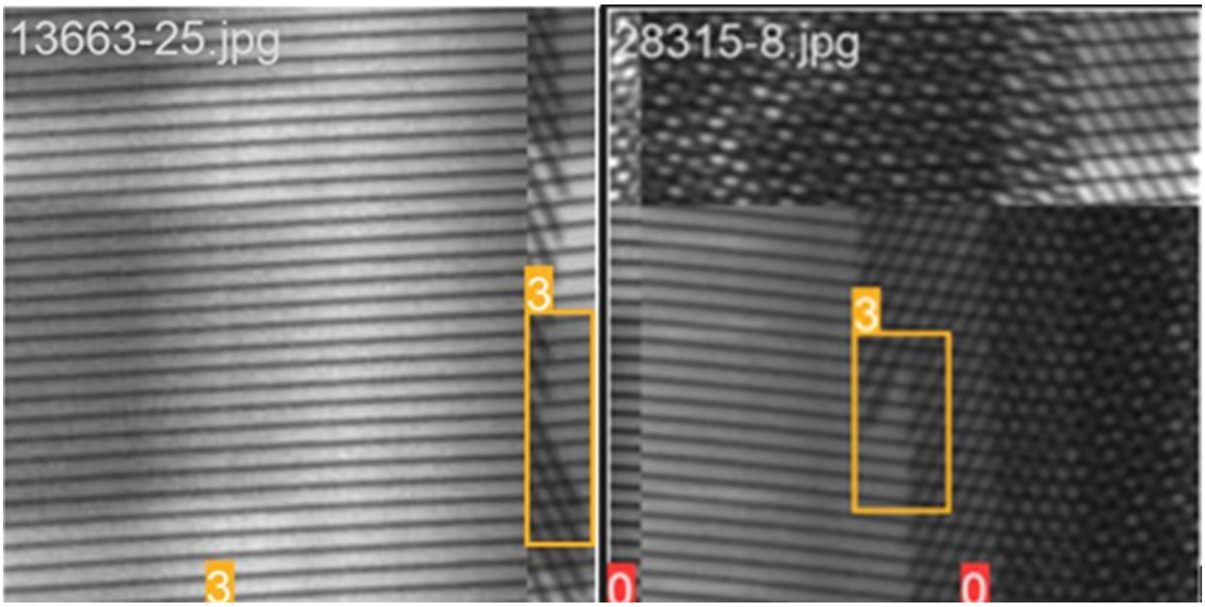

Figure 3. Tire impurity X-ray picture.

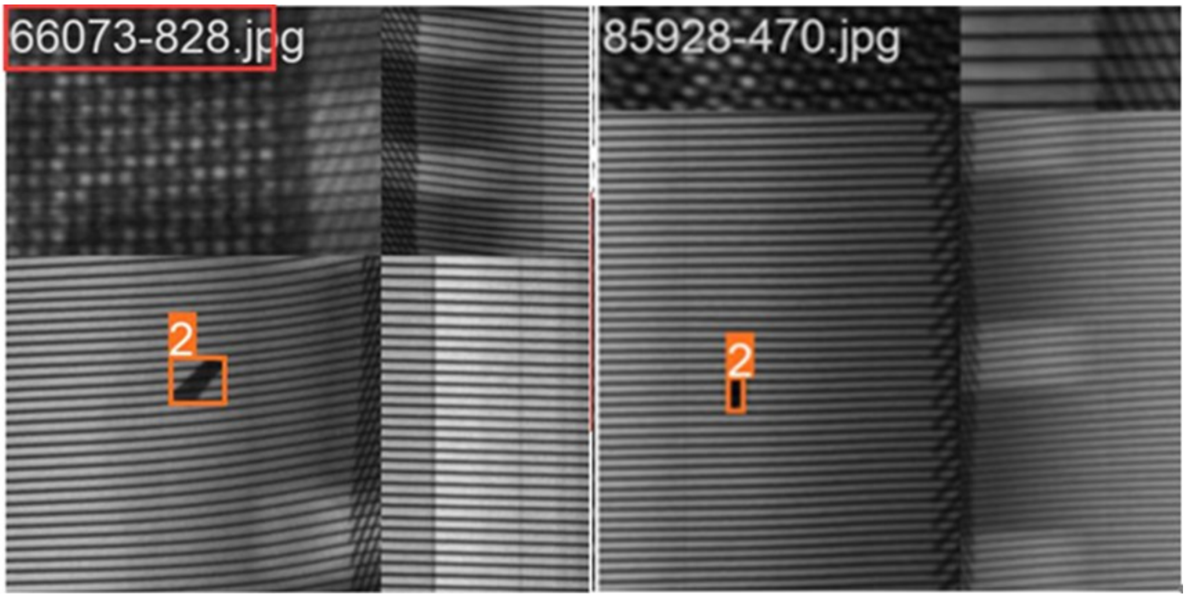

Figure 4. X-ray picture of tire cord misalignment.

2.2. Dataset construction

In order to train an efficient YOLOv5 model, the selection and annotation of the dataset is crucial, as it will directly affect the performance of the model. The data used in the experiment comes from 1905 X-ray images of radial tire defect detection provided by the Network Control Center of Shanghai University, which are 480 × 480 pixels in size and contain 4 categories in total. They are tire cord cracking (2#-open), uneven distribution of cord (cords_defects), impurity (impurity) and wrong edge of cord (belt_cuobian). The Labelimg tool is used for image annotation, and the file after annotation takes.txt as the suffix, and the file name is consistent with the image name. The Labelimg annotation interface is shown in **Figure 5**. First, select the YOLO dataset format, then press the W key to enter the annotation mode, and drag the box to completely cover the defect part. Finally, input the defect category in the pop-up window, and click the OK option to divide the dataset, and finally obtain 1142 images in the training set, 382 images in the validation set and 381 images in the test set.

The test set and validation set tire X-rays are shown in **Figure 6**, where **Figure 6 a–d** are the test set tire X-rays, and **Figure 6e–h** are the validation set tire X-rays. The confusion matrix, shown in **Figure 7**, quickly helps to analyze the misclassification of each class, so that the analysis can be adjusted in turn.

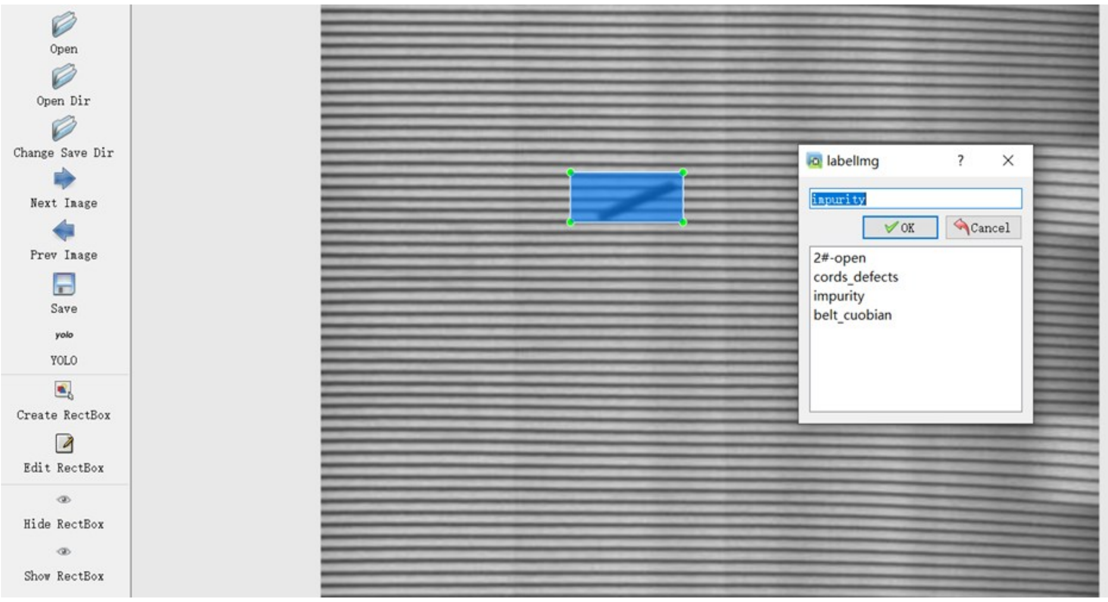

Figure 5. Labelimg annotation interface.

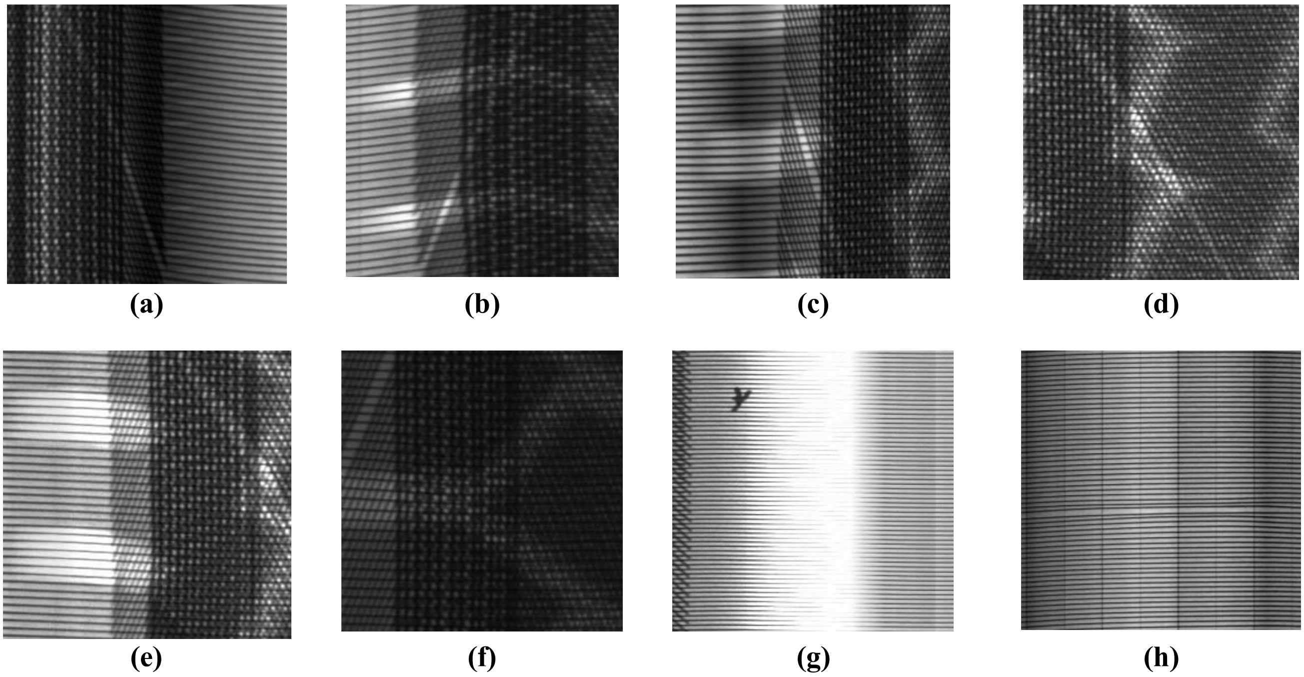

Figure 6. Labelimg annotation interface. **(a)** unevenly distributed cord; **(b)** unevenly distributed cord; **(c)** tire impurity; **(d)** unevenly distributed cord; **(e)** unevenly distributed cord; **(f)** tread cord cracking; **(g)** cord misalignment; **(h)** tread cord cracking.

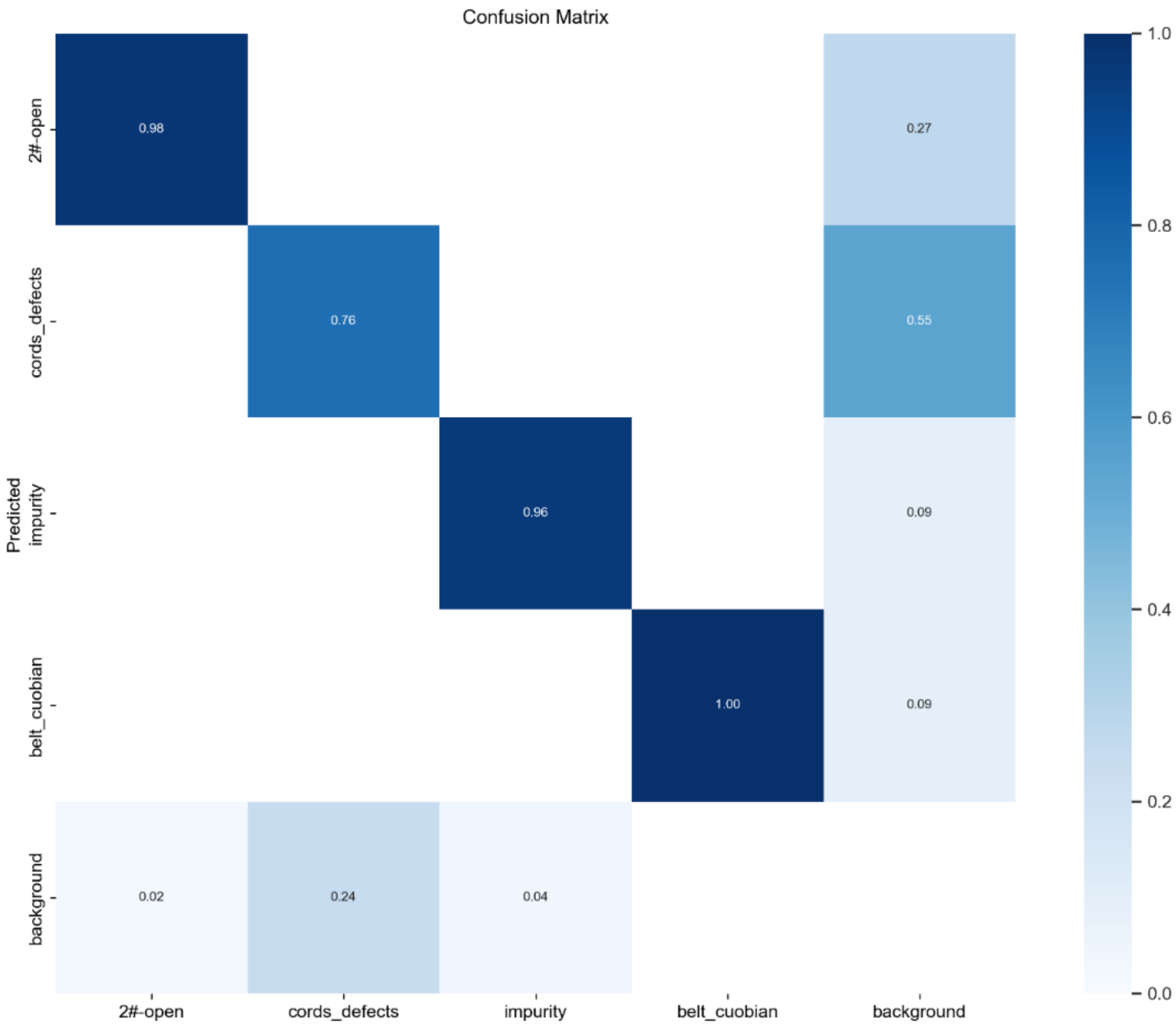

Figure 7. Confusion matrix of dataset.

3. Design of tire defect recognition method based on YOLOv5

You Only Look Once (YOLO) family of algorithms is a single-stage object detection algorithm designed for end-to-end training and real-time detection. Suitable for running in resource-constrained environments such as mobile devices and embedded systems. Its small model size and fast inference speed make it very popular in practical applications. During training, the input image is cleverly divided into $C \times C$ grids, each of which constitutes a prediction box and matches with the actual target box, so as to complete the target prediction efficiently.

3.1. Algorithm model and experimental environment

YOLOv5 uses Cross Stage Partial (CSP) and Focus slicing module on the backbone network [19,20]. The model cleverly uses the similarities existing between different levels to construct a global network structure and is trained through a deep learning process to obtain the final classification results. This design idea enables the model to make full use of the multi-scale information in the image and improve the accuracy and robustness of classification. PyTorch framework was used in the experiment environment, and Intel(R) Core (TM) i9-13900HX CPU (Central Processing Unit) and NVIDIA (An artificial intelligence computing company) GeForce RTX4050 GPU (Graphics) were used Processing Unit, using Windows11 operating system, acceleration environment is CUDA (Compute Unified Device Architecture) 11.7.

3.2. Loss function

The reason why YOLOv5 algorithm performs well in object detection tasks is inseparable from its carefully designed loss function. Specifically, the loss function of YOLOv5 consists of three key parts. These are Classification Loss, Confidence Loss, and localization loss. These three functions together make the model achieve high accuracy in identifying the target, evaluating the probability of the existence of the target, and accurately locating the target.

In YOLOv5, the classification loss and confidence loss are calculated by a binary cross-entropy loss function. The classification loss is used to evaluate the accuracy of the model in predicting the target class, and can well reflect the difference between the probability distribution predicted by the model and the true distribution. Confidence loss, which evaluates the accuracy of the model's prediction of the presence of an object, can help the model better determine whether a particular object is present in the image. Localization loss is used to measure the prediction accuracy of the model on the position of the target bounding box, and CIOU_LOSS is usually used as its loss function. In the loss calculation, CIOU_LOSS simultaneously considers the overlap area between the predicted box and the real box, the distance between the center point, and the aspect ratio, so as to measure the accuracy and precision of the predicted box more comprehensively [21]. The formula is as follows:

$$V = \frac{4}{\pi^2}(arctan\frac{w^{gt}}{h^{gt}} - arctan\frac{w}{h})^2 \quad (1)$$

$$IoU = \frac{|A \cap B|}{|A \cup B|} \quad (2)$$

$$\alpha = \frac{V}{(1 - IoU) + V} \quad (3)$$

$$\mathscr{L}_{CIoU} = 1 - IoU + \frac{\rho^2(k, k^{gt})}{c^2} + \alpha V \quad (4)$$

where w, h, w^{gt}, h^{gt} are the width and height of the predicted and true box respectively, k, k^{gt} are the center points of the predicted and true box respectively, and ρ is the Euclidean distance between the two center points. c represents the diagonal distance of the smallest closure region capable of containing both the predicted and true boxes.

3.3. Target detection evaluation index

In the field of object detection, Precision (*P*), Recall (*R*) and Average Precision (*AP*) are often used as evaluation metrics. In general, the higher the *AP* value, the better the accuracy of the model.

The formula is as follows:

$$P = \frac{TP}{TP + FP} \tag{5}$$

$$R = \frac{TP}{TP + FN} \tag{6}$$

$$AP = \int_0^1 PdR \tag{7}$$

In Equations (5) and (6), *TP* (True Positive) represents a Positive sample predicted by the model as a positive class, *FP* (False Positive) represents a Negative sample predicted by the model as a positive class, and *FN* (False Negative) represents a positive sample predicted by the model as a negative class.

By setting different thresholds, we can obtain different *TP*, *FP* and *FN* values, and thus calculate multiple sets of *P* and *R* values. Using these data points of *P* and *R*, a P-R curve can be plotted. This curve provides a visual representation of the trade-off between precision and recall, which helps us to better evaluate the performance of the model.

In object detection tasks, it is also common to compute the Mean Average Precision (mAP) to fully evaluate the performance of the model on the entire dataset. The higher the mAP value, the better the model performs in the object detection task.

4. Experimental results and analysis

In this experiment, we used the dataset mentioned above to train the YOLOv5 model. During the training process, we recorded the localization loss value, confidence loss value, and classification loss value, and plotted the loss curve as shown in **Figure 8**. By observing the plotted loss curve, we can find that with the increase of the number of iterations, the three loss values of the training set and the validation set show a decreasing trend and eventually become stable. This indicates that our model gradually learns the effective information in the dataset during the training process, and the parameter Settings are reasonable.

In order to more comprehensively show the performance of YOLOv5 algorithm on tire defect detection task, we randomly selected a certain number of tire images from the test set to detect them. Part of the inspection results are shown in **Figure 9,** showing the inspection effects of different defect types respectively. Among them, 2#-open represents the cracked tire cord, cords_defects represents the uneven distribution of the cord, impurity represents the presence of impurities, belt_cuobian represents the wrong edge of the cord, and the number after the category label is the confidence degree. From **Figure 9**, it can be found that YOLOv5 has a better recognition effect on large-size targets such as tire cord cracking and wrong edge, and a slightly worse recognition effect on small-size targets such as uneven distribution of cord.

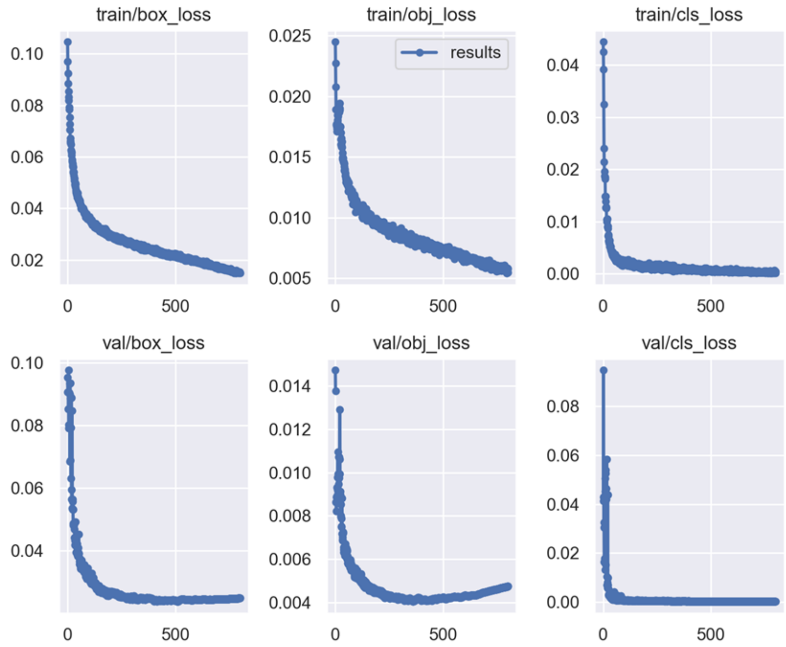

Figure 8. Loss plot.

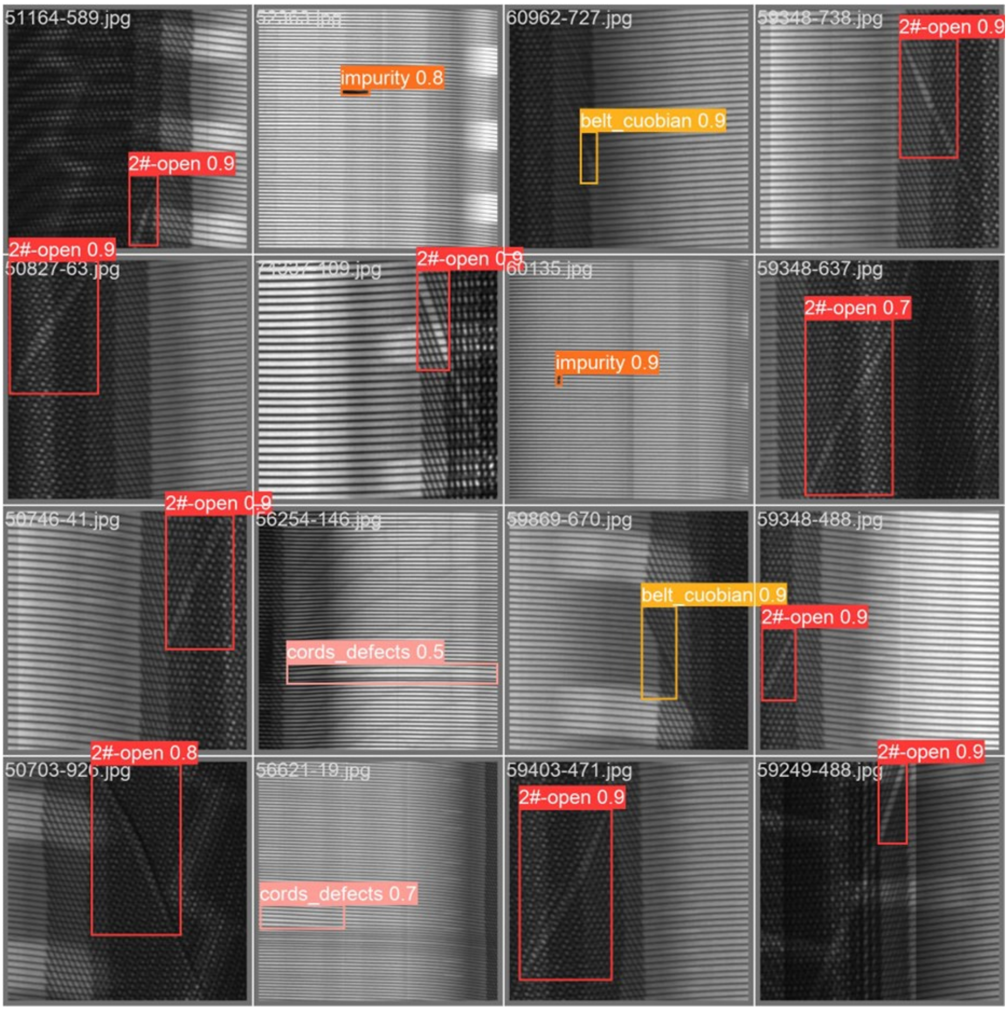

Figure 9. Partial test result.

The P-R curve of YOLOv5 model is shown in **Figure 10**. It can be intuitively seen from **Figure 10** that the area enclosed by the P-R curve with uneven distribution of the curtain line (orange line) and the coordinate axis is slightly smaller than the area enclosed by other P-R curves and the coordinate axis, that is, the *AP* value of the uneven distribution of the curtain line is slightly smaller than that of the other defects, which is also verified in **Figure 10**. The mAP curve is shown in **Figure 11**. It can be seen from the mAP curve that with the increase of the number of iterations of the model, the mean average precision gradually tends to about 95%, which proves that the YOLOv5 model can identify the location and category of the target very accurately. And compared with the traditional object detection algorithms (such as the Faster R-CNN algorithm used in literature [22], whose mAP value is 0.88, and the YOLOv3 algorithm used in literature [23], whose mAP value is 0.825), the YOLOv5 algorithm has higher detection accuracy. As shown in **Table 1**, the training speed and testing speed of the algorithm in this chapter are greatly improved compared with R-CNN, SPP (Spatial Pyramid Pooling) and Fast R-CNN, but the training time and testing time of the algorithm in this chapter are slightly higher than that of the algorithm in Faster R-CNN. And the mAP value of YOLOv5 model is significantly higher than that of other algorithms.

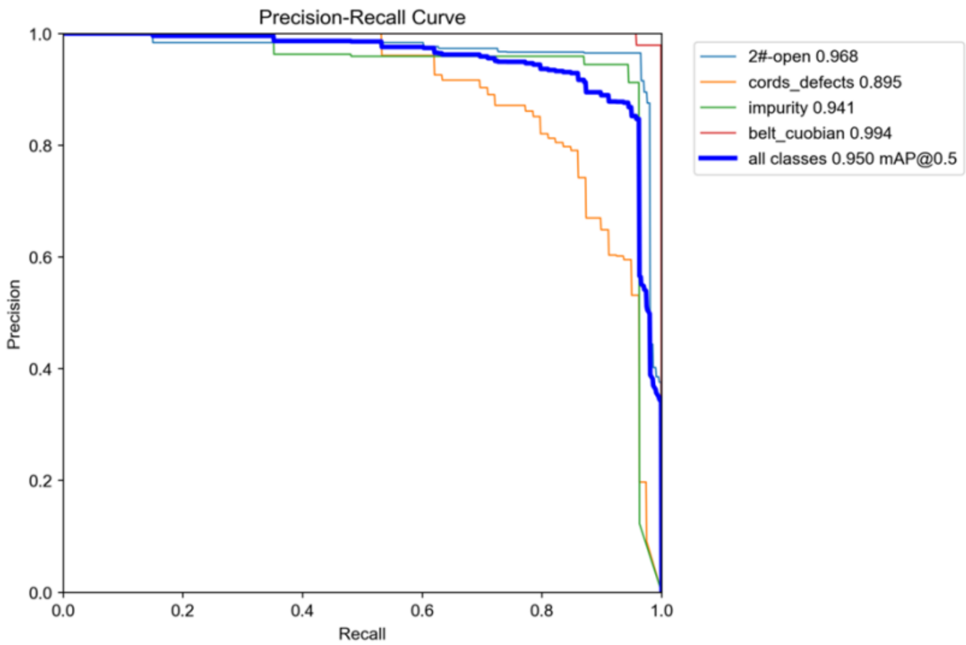

Figure 10. P-R curve.

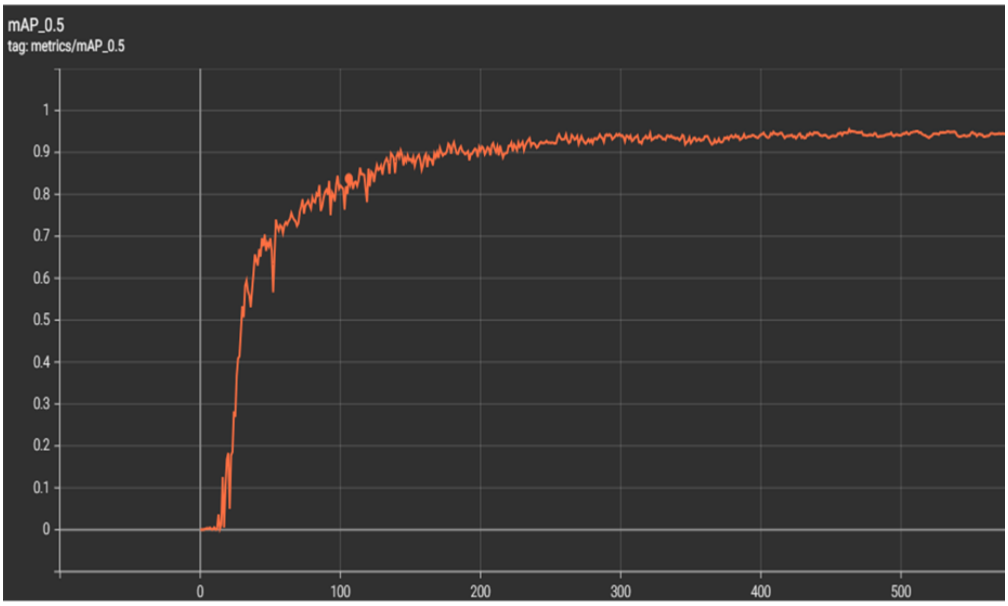

Figure 11. mAP curve.

Table 1. Performance comparison of advanced algorithms.

Algorithm	**Training Time (h)**	**Testing Time (s)**	**mAP Value**
R-CNN	27	49	0.792
SPP	4.8	2.8	0.803
Fast R-CNN	4.5	2.3	0.821
Faster R-CNN	3.7	0.26	0.884
YOLOv3	3.6	0.29	0.825
YOLOv5	4.1	0.27	0.952

5. Summary and prospect

Aiming at the problem of tire defect recognition and classification, this paper proposes the research of tire defect recognition and classification based on YOLOv5, aiming to solve the shortcomings of traditional tire defect detection methods in accuracy and efficiency. The main research of this paper consists of the following aspects:

(1) In the model construction part, this paper introduces the YOLOv5 algorithm, and introduces the basic principle and structure of the YOLOv5 algorithm. Then, by carefully building the experimental environment, this paper trains and verifies the model in detail, in order to achieve the best detection effect.

(2) Experimental design and result analysis show the performance of the proposed model in practical applications. By using the object detection evaluation index, the performance of the model is comprehensively evaluated. Through experimental verification, this method shows high accuracy and generalization ability in tire defect recognition task, and has obvious advantages compared with traditional methods.

However, this study still has some limitations, and future work will focus on the following aspects:

(1) Dataset expansion: Although this study has collected a certain number of tire

defect samples, it is still necessary to further expand the dataset scale and add more types of tire defect samples to improve the robustness and applicability of the model.

(2) Model optimization: Future work will continue to focus on the optimization of the model structure and try to introduce new modules or techniques, such as attention mechanism and multi-scale feature fusion, to improve the recognition speed and accuracy of the model.

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Conflict of interest: The authors declare no conflict of interest.

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