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The RFID Electronic Tag Defect Detection System Based On YOLOv5 For Industrial Scenarios

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Abstract: *Recent technological progress has promoted a large number of development trends in the Radio Frequency Identification (RFID) system. RFID tag detection/identification is one of the most critical problems in successfully deploying the RFID system in various applications. However, many significant issues related to detecting RFID tag defects have not been addressed. The main problems of RFID electronic tag defect detection methods in industrial scenarios are low efficiency, low accuracy, and high labor costs. This paper analyses the characteristics of RFID tag defects based on defect samples, and a detection and prediction method related to YOLOv5 is proposed. In this experiment, a real-time RFID tag defect intelligent detection system embedded in the YOLOv5 model was developed and applied to industrial production. The results show that this system has higher accuracy in defect detection, faster detection time, and saves labor costs, which can meet industrial needs.*

Keywords: Deep learning; Machine vision system; RFID electronic tag; YOLOv5.

1. INTRODUCTION

One of the overall goals of industry 4.0 is to further select intelligent technology to help people make decisions and carry out complex work [1]. Wireless communication technology (RFID) [2] is increasingly used to uniquely identify objects. Unlike the bar code of commodities, RFID can inspect several long-distance non-visual objects simultaneously. At this stage, hundreds of millions of RFID tags have been deployed; The application of the RFID system mainly comes from its net savings, low deployment costs, and accuracy. It is believed that this figure will reach one hundred billion within seven years. This field is an ideal experimental field for integrating intelligent technology with industrial 4.0.

The RFID system comprises a reader, electronic device tags, and a data management system. The RFID electronic tag is the key to the RFID system, which is generally composed of a processing chip, tag wireless antenna, and external packaging materials. The information transmission is completed according to the processing chip that the reader loads and writes the tags of electronic devices. If the tag has defects, it may endanger the transmission of information. So, before the RFID systems can be applied to practical activities, tag defect detection is a crucial issue. Traditionally, this is mainly a manual daily task. The staff will check each tag in the database system for its flaws. Yet, due to the slow speed, low precision, and easy fatigue of manual sampling and testing, it is far from meeting the requirements of industrial production for fast, high pixel, and nondestructive testing technology. Thus, the automation technology [3][4] of the RFID tag's intelligent inspection has been promoted recently. It can be done in many ways. However, the proposed method stipulates that the staffs need to know all kinds of defects or data characteristics very well to get improved detection conclusions. It is unlikely that ordinary enterprises can achieve the remarkable effect of defect detection. So, it is necessary to propose other methods to complete the daily task of real-time detection on the factory production line. Considering that the traditional defect detection method has many defects, the method based on machine vision [5] is gradually paid attention to. Due to the improvement of industrial camera performance and the ease of use of many identification images, convolutional neural networks have a good development trend in image detection processing. According to the method of abstract features, the defects of RFID identification can be divided and detected according to various abstract features. This abstract feature is obtained by a convolutional neural network without manual control. The performance index of the method based on abstract features is better than that based on special features [6]. A globally responsive percentile threshold method based on gradient direction image is proposed in reference [7]. This method can selectively segment the defect area and preserve the defect characteristics, regardless of its size. Although this method has won excellent detection conclusions under special conditions, it is very easy to make mistakes in the complex industry scene because of the variety of sunlight effects.

According to the above work, we propose an RFID tag defect detection system based on YOLOv5 for industrial production lines [8-12]. In the experiment, we made data enhancement to ensure the diversity of the data and the accuracy of the results. YOLOv5 is used to carry out deep learning [13][14] on defect types, which can realize the detection of eight defect types in RFID electronic tags. The result proves that the system leads to great success, which proves the effectiveness of the model. Therefore, it reasonably solves the problem of flaw detection of RFID electronic tags on industrial production lines.

This article discusses three key challenges. The first challenge is how to train for defect types with small sample sizes; The second challenge is to achieve intelligent detection, reduce the input of manpower, and realize the visualization of results; The last difficulty is how to ensure that the detection time meets the beat of the industrial production line, that is, one minute can detect 15 meters of RFID electronic tag belt. The rest of the text is as follows. In section 2, we clarify the proposed methods in former years. The third section introduces the data and the RFID tag defect detection system based on YOLOv5s. The fourth section introduces the result and conclusion of our work. Section 5 summarizes our work and puts forward the content of future research.

2. RELATED WORK

Computer vision [15],[16] has always been a vital part of artificial intelligence, in which target detection is a relatively simple task in computer vision used to find a specific object in a picture. Target detection requires the type of object recognition and the researcher to mark the object's position, and the YOLO series is much faster than the previous neural network with a suggestion box. At present, the YOLO series already has YOLOv1**Error! Reference source not found.**, YOLOv2 [17], YOLOv3 [18], YOLOv4 [19], YOLOv5 [20], YOLOV6 [21], and YOLOV7 [22]. They have been widely used in various fields, bringing convenience to people's lives. For example, the YOLO series have been applied to intelligent monitoring of video content [23], quality assurance of crops [24], various products, etc. Among them, the defect detection of objects has brought great changes to quality detection, making intelligent detection replace the traditional manual detection.

In recent years, many scholars have proposed research on defect detection. First, accuracy has become an important indicator to measure technical performance. Zhixuan Zhao [25] can accurately indicate the defect area by repairing the defect area in the sample. The advantage of this study is that it does not require defective samples and manual labelling, only positive samples. In addition, this algorithm has a pretty high detection accuracy. However, it is not clear whether this method is accurate for small area defect detection. In response to this problem, Guang Wang [26] improved YOLOv5 by adding a small-size output layer to replace the original convolution with a depth-wise separable convolution. The experimental results show that small defects and insufficient feature information are effective. At the same time, because an output layer is added, the value of Frame Per Second (FPS) is 83.3, while the FSP of YOLOv5s is 111.1, and the detection speed is greatly reduced. It cannot meet the industrial requirements for real-time monitoring of products. It can be inferred from the above research that the biggest problem of the current product defect detection method is the contradiction between detection accuracy and detection speed. To achieve real-time detection while improving detection accuracy, Jiayi Liu [27] proposed to improve the convolutional layer of the backbone network and reduce the sensitivity to the initial clustering center, which can achieve fast detection while ensuring the correct rate of detection classification. Compared with the original YOLOv3, YOLOv4, and YOLOv5 models, the improved model has higher accuracy and faster detection speed. But these are not enough to facilitate workers' use of YOLOv5 to detect the quality of RFID tags in industrial scenarios.

This paper mainly takes RFID electronic tags [28] as the research object and proposes a real-time defect detection system based on the YOLOv5 model. The system is connected to the industrial production line through a communication interface to realize real-time photodetection of products. In addition, it also automatically generates charts of defect detection results for the company to analyze the results. It provides essential technical support for surface quality detection in industrial automation.

3. METHODOLOGY

This paper proposes a defect detection method of RFID tag defects based on YOLOv5, which is conducted with three steps: constructing datasets based on the taken pictures of electronic tags in the production line, training model to judge defects by pre-processed datasets, and observing the test results. Before that, we need to determine the type of defect. Defects may be visible outside or not be observed. Thus, depending on the characteristics of the defect, the detection method may vary according to the condition. The electronic tag solution processing chip is the core component of the electronic tag. The wireless antenna is responsible for receiving electromagnetic waves and sending them to the wireless receiver of wireless communication. If the production and processing of chips and wireless antennas do not meet the product quality standards during production and processing, the electronic tag cannot be used usually. This is an internal structural defect that is challenging to be recognized by human eyes. Therefore, an internal electrical test will be carried out to check whether the internal structure meets the quality. If internal damage is found, the corresponding position will be marked with ink dots for identification. Other defect types can also be observed, including the overlap of electronic tags, lack of tags, etc. After determining the method of detecting defects, how to ensure the clarity of the taken pictures is another indispensable work. The lighting and photographing system is responsible for photographing electronic tags in the production line. The system is composed of a sample lighting system and a positive coupling device (CCD) monitoring camera to record the image of the RFID tag. Because of the extensibility of the factory environment (light, etc.), we should formulate a stable lighting scheme. At the same time, considering that the frequency of camera photography should match the speed of electronic tag carbon belt movement, we need to set the time interval of camera photography.

In this experiment, RFID tags are tested by YOLOv5s. Which needs to collect and preprocess data, train the model, and finally get the results. The specific information of this part is detailed in section 3.2.

3.1 Materials

This experiment mainly studies eight kinds of RFID tag defects. Table 1 describes the composition of training and testing data for different classes. The dataset is composed of eight types of defect images, including the ink spots in part BC(BCMD), part B(BMD), part C(CMD), adhesive tape (JD), empty tag (KT), empty tag, and ink dot (KTMD), the tags overlap (CD) and poor etching (SKBL). In addition, there are unblemished tags (OK) also in the dataset. A total of 1035 images are divided into practice activities/verification and test sets according to a percentage of 6:1.

Table 1. RFID tag samples.

Data classification	Number of training sets	Number of validation sets	Total number of pictures
BCMD	325	58	385
BMD	136	24	160
CMD	236	42	278
JD	53	9	62
KT	67	12	79
SKBL	7	1	8
KTMD	79	14	93
CD	5	1	6
OK	127	23	150
Total quantity	1035	184	1219

It should be noted that it refers to selecting the defect map with the same resolution and effect; the purpose is to keep the position of the detected object unchanged in the picture and stabilize the lighting environment. These are two categories of data text documents. A) The original data image contains 1035 images, which have relatively strong posture, angle, lighting standard, temperature standard, and natural environment diversity. Such images are all JPG format files. B) Image annotation text document, containing 1035 images. The annotation is implemented manually, and the annotation value is also saved in the TXT file. We divide each file name into two subfolders: train and valid. The image is usually taken with the monitoring camera (Mindivision). Data preparation and annotation in advance [29]. First, open one image at a time in the tool here. Then, according to the relative height of the x\u center and y\u center, the square is manually set as the boundary of the direction to specify its exact position in the image. Ultimately, each overall goal has an identity, such as "BCMD" or "CMD." In labelimg, annotation values are stored as txt files in YOLOv5 format. In addition, because of the production technology, the emergence of certain flaws of RFID tags may rarely, to realize the data of the augmented, balanced uneven data, this paper proposes an algorithm to pick out the defects in several types of defective products with fewer data, and then randomly put the defects on intact electronic tags to increase the amount of data.

3.2 System Design

To propose an effective RFID tags defects detection system, we have integrated a vision system with the proposed YOLOv5s network. In this section, firstly in detail, the RFID tags defects vision system is introduced. Then, we present the backbone feature extraction network of YOLOv5 that specifies our evaluation approach.

The RFID tags defects detection system developed for this work consists of five major units, i.e, the vision system, RFID tag defect detector, serial communication system, data display, and account logins. Figure 1 and Figure 2 show the system at work, detecting the RFID tag. The whole process is as follows, including sensors connected to the product line. When the RFID processing chip reaches the designated position, the sensor pushes a signal to the Programmable Logic Controller (PLC), and the PLC receives the signal that the processing chip has reached the designated position. After the information is sent, the camera is hard turned on according to the 12V high-voltage and low-voltage, and the mobile phone software loads the photos taken by the camera. The vision system based on a camera captures the information in form of images and videos in unsupervised surveillance environments. After the RFID tags defect detector test, if it does not conform to the product quality regulations, it often pushes the termination signal to the PLC according to the dialogue box. After detecting the defect, the machine and equipment will automatically stop the disassembly and replacement of RFID electronic tag adhesive tape. Finally, we are able to get various data charts related to the types of defects and then visualize the big data of information. The system completes the instant identification and classification of the captured photos. The images and XML files of the classified results are saved to a specific path. For different products, we can train them according to the samples, save them into the program name of corresponding products, and call the test at any time after switching products. The detailed flow of working of the proposed RFID tag defect detection system is shown in Figure 3. (OK means that the test requirements are met, NG means that defective products are detected).

The RFID tag defect detector is the most important part of the proposed RFID tag defect detection system since it is responsible for detecting the defect of RFID tags therefore, efforts are required to develop effective RFID tags defect detector that can detect the defect of RFID tags in varied conditions with high detection accuracy. Next, we introduce how to build a high-performance defect detector through the YOLOv5 model.

Windows 10 operating system and the Pytorch framework were used for the training of the model. The configuration of hardware facilities is shown in Table 2. There are four basic network models for YOLOv5: YOLOv5s, YOLOv5m, YOLOv5l, and YOLOv5x. In this paper, we adopt the YOLO5s model, which is the network with the smallest depth and the smallest width of the feature graph in the YOLOv5 series. Compared with YOLOv4, YOLOv5 does not change much, but the improvement of the anchor processing mechanism makes the YOLOv5 model convergence speed fast and the training results better [29]. YOLOv5 continues to use the three main components of the YOLO series. The network structure is shown in Figure 4.

The following introduces YOLOv5 from input, backbone, and neck.

3.2.1 Input

In YOLOv3 and YOLOv4, different datasets need to be trained with separate scripts to initialize the calculation of the frame, but YOLOv5 [12] embeds this function into the whole training code, so before each separate training, it will adapt the calculation of the anchor according to the different datasets.

3.2.2 Backbone

The focus module is proposed in YOLOv5, and the input channel is expanded by 4 times. Its function is to improve the computing power without losing information. It first divides the feature map into blocks and slices, then concatenates the results, and then sends them to the following modules. YOLOv5 replaces the focus module with a 6x6 convolution layer. The amount of computation is equivalent, but for some graphic processing unit (GPU) devices, it is more efficient to use 6x6 convolution. And in YOLOv5, two Cross-Stage-Partial (CSP1_X and CSP2_X, are derived from the Cross Stage Partial Network but have been changed. The specific structure composition can be seen in Figure 4.) structures are designed. Among them, CSP1_X applies to backbones.

3.2.3 Neck

YOLOv5 has made some changes to the structure of the Feature Pyramid Network (FPN) and Path Aggregation Network (PAN). Another CSP2_X structure is used here to strengthen the ability of network feature fusion.

3.2.4 Model Evaluation Indicators

In this paper, precision rate (P), recall rate (R), and mean average precision (mAP) are introduced to evaluate the training results of the model [29]. Precision is the percentage of positive samples detected by the classifier to all positive samples predicted, that is, the proportion of correct target prediction boxes detected in the prediction boxes currently traversed. Recall rate is the percentage of correct positive samples detected by the classifier in all positive samples, that is, the proportion of correct positive sample boundary boxes detected in all truth boundary boxes.

$$P = \frac{TP}{(TP+FP)} \tag{1}$$
$$R = \frac{TP}{(TP+FN)} \tag{2}$$

Among them, True positive (TP), true negative (TN), false positive (FP) and false negative (FN) represent correctly classified positive samples, correctly classified negative samples, misclassified negative samples, and misclassified positive samples respectively. The average precision (AP) value is a crucial evaluation index to measure the performance of the target detection model classifier. The higher the AP value, the better the classifier performance is. The value of AP is equal to the area bounded by the precision-recall curve (PR-curve) and the coordinate axis. Mean average precision(mAP) represents the average AP value of all tag categories. The larger the mAP value, the better the model performance is. mAP@0.5: mAP value change curve when the intersection over union (IoU) threshold is 0.5. They are defined as follows:

$$AP = \int_0^1 P(R)\,dR \tag{3}$$
$$mAP = \frac{1}{|Q_R|}\sum_{q=Q_R} AP(q) \tag{4}$$

Where QR is the number of categories[5].

Fig. 1. The system is being prepared.

Fig. 2. The system is detecting the RFID tag.

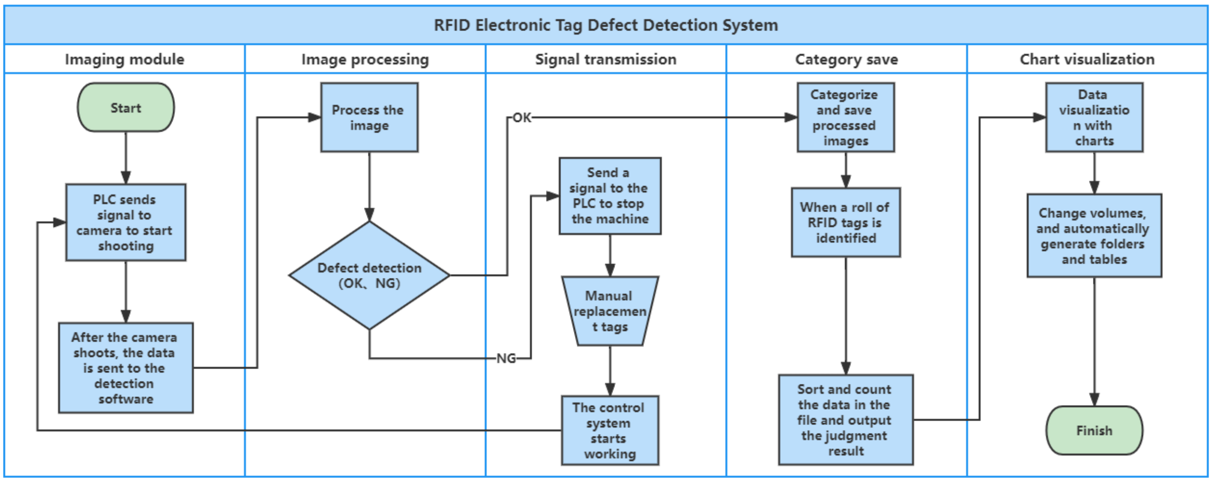


Fig. 3. RFID electronic tag defect detection system flow chart.

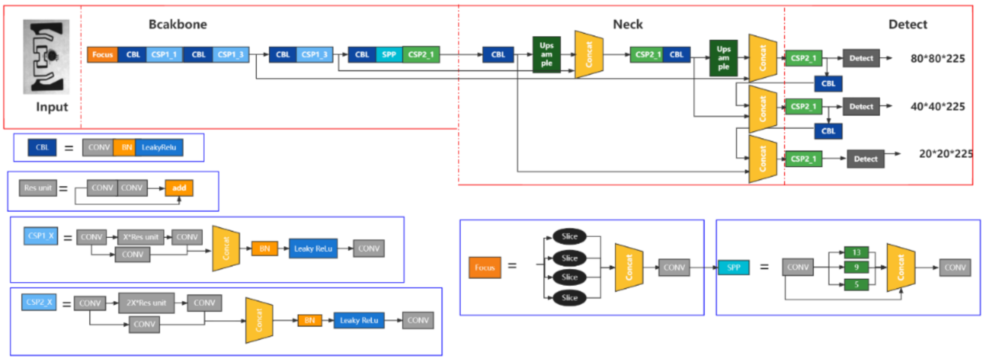


Fig. 4. YOLOv5 network structure diagram.

Table 2. Experimental hardware configuration.

Hardware Equipment	
Industrial Control Computer	IPC-615G2-Q370-P500-8400-8G-256G CPU AX Gaming Renegade RTX3060 X2W LHR graphics card
Camera	Mindvision
Light	LED light

4. RESULTS AND DISCUSSION

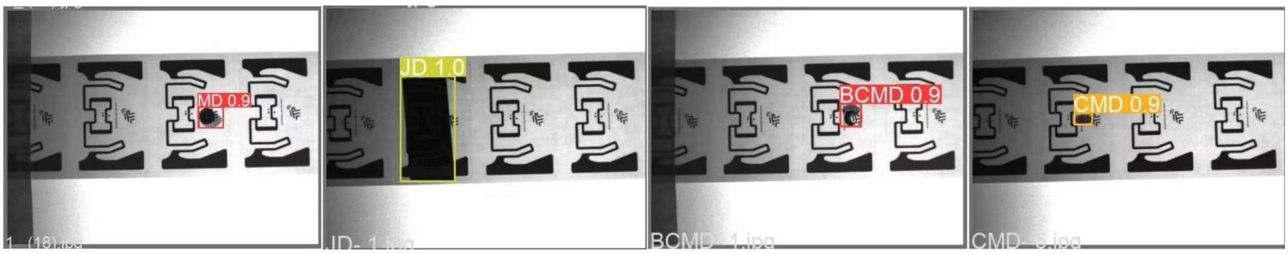
The following Figure 5 shows the YOLOv5 network in the RFID tags dataset part of the detection results, respectively, for different defect categories. The verification set detection results show that one Tag error judgment, one tag missing judgment, and the recognition rate can reach 98.9%.

In this paper, confusion matrix and mAP are used to evaluate the quality of the detection model.

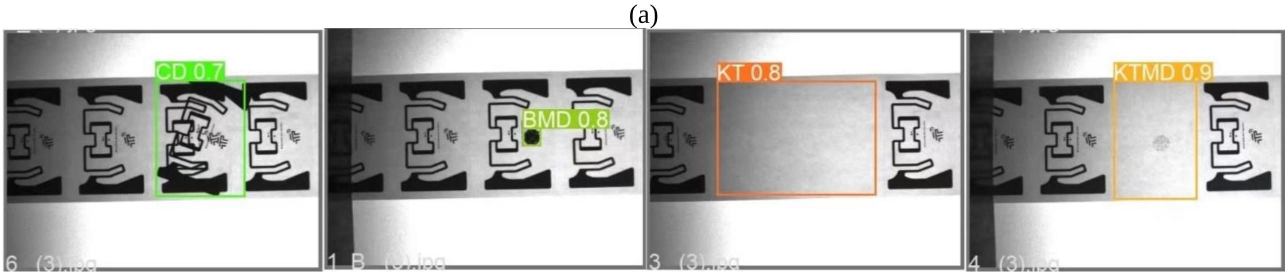
In the process of network training, the confusion matrix can directly reflect the prediction results of the multi-classification model in machine learning. In the form of the matrix, it is predominantly used to compare the classification results with the actual classification results, and the accuracy of the classification results can be displayed in the confusion matrix. The specific confusion matrix of the model is shown in Figure 6 below.

The actual defect types are represented on the horizontal axis, while the predicted defect types are represented on the vertical axis. For example, the probability of a "BCMD" defect being predicted as "BCMD" is 100%, and the prediction types of other defects are exactly the same as the real defect type, indicating that our model is highly accurate. Background FP means that the image of the background is incorrectly identified as a defect. From the Confusion matrix, 33% is on the vertical axis of BCMD, 33% is on the vertical axis of CMD, and 33% is on the vertical axis of OK. That is, the background is considered to be BCMD, CMD, and OK categories. In addition, 75% of the OK class is also considered as background FP. There are mainly because the images collected were not in a good light in this experiment, resulting in prediction errors. However, since the defect categories are accurately identified, there is no significant impact on this study.

The PR_curve is shown in Figure 7. The larger the area surrounded by the curve, the better the performance. There are ten curves in the figure, but because the area surrounded by some curves is close to 100%, they all coincide with the outer frame line, so only two curves can be seen in the figure. When the IoU threshold was 50%, mAP@0.5 of YOLOv5s was 98.1%, indicating that the YOLOv5s model had a high accuracy of defect detection. The performance of the model has largely exceeded expectations. The feasibility of this experiment is as follow:



(a)



(b)

Fig. 5. YOLOv5s to detect RFID tag defects.

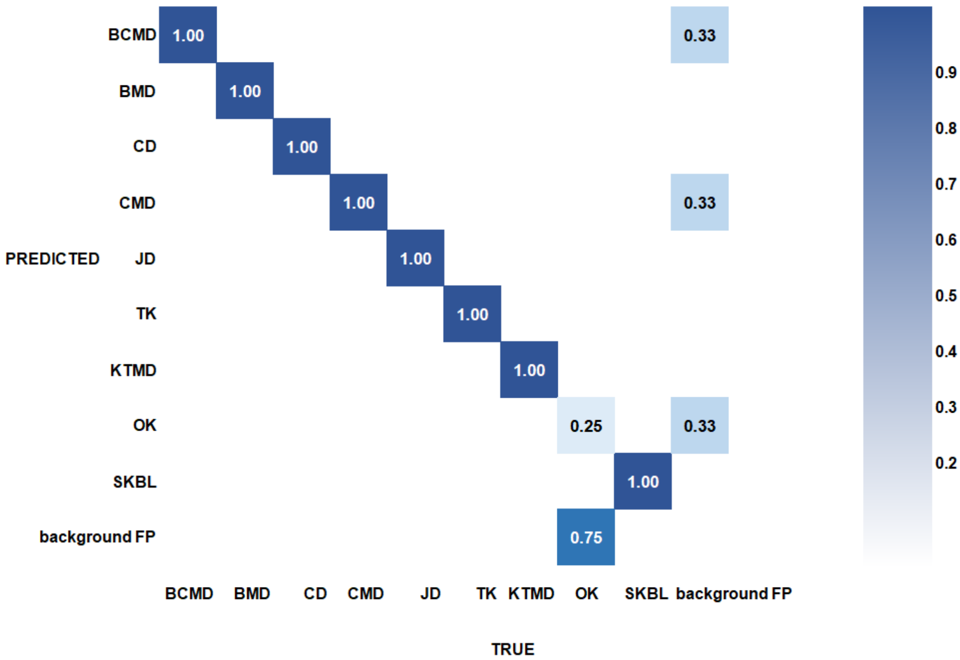


Fig. 6 Confusion matrix for RFID tag defects detection.

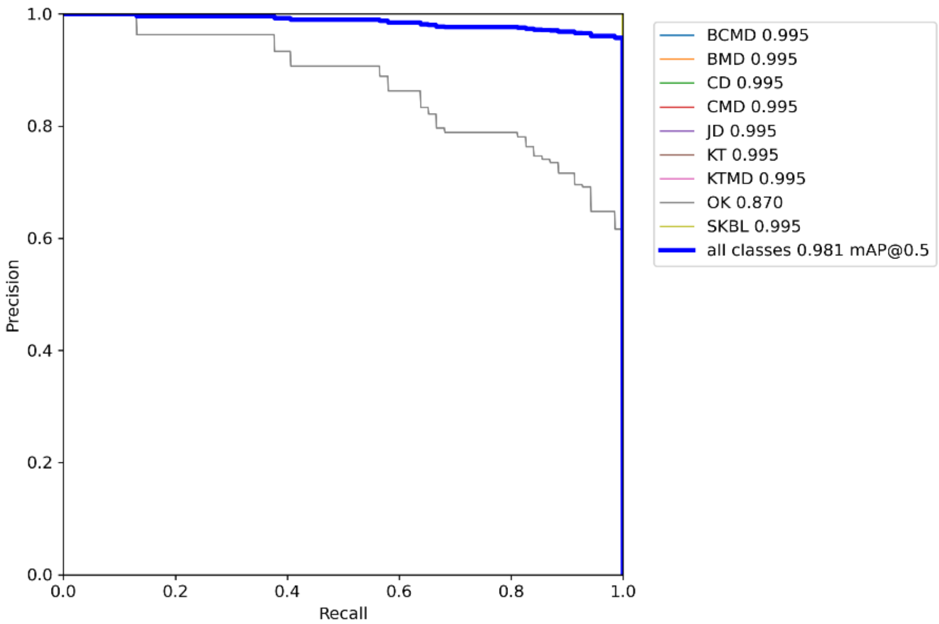


Fig. 7 PR_curve for RFID tag defects detection

- In terms of processing accuracy, the data used in the experiment are collected manually, and the pre-processing of the data is also manually calibrated. So, the lighting environment is relatively simple. In the case of an uncertain lighting environment, the detection accuracy may be reduced. However, in this experiment, we used industrial cameras and lighting schemes from different angles to ensure the quality of pictures taken in practical applications.
- In terms of processing speed, cameras need to be used to take real-time photos to meet the immediate requirements of the staff. Initially, we tried object detection models in place of models, such as segmentation or semantic segmentation. However, to detect the model in multiple targets, we decided to use YOLOv5s of the YOLO series. This model only takes 20ms to detect a picture, which can cut the mustard in industrial scenes.
- In terms of model generalization, YOLOv5s adopt the Mosaic data enhancement strategy to enhance the generalization capability and scalability of the model.

The final results show that eight defect types can be accurately predicted, and mAP can reach 98.1%. With hardware support, the system can identify a defective product in 20ms. The intelligent detection of industrial production lines is realized through the combination of YOLOv5 technology and RFID tags defect detection system, which liberates labor and reduces costs. The specific benefit analysis data are shown in the following table 3. The YOLOv5 significantly improves the detection speed and accuracy, while the real-time detection on the assembly line greatly improves the detection efficiency. The report module in flaw detection can visually display flaw detection results. The system can take photos and classify different kinds of defects so that we can find the causes of defects to form a virtuous cycle.

Based on the above discussion, we believe that our proposed method is an effective and efficient exploration that can facilitate the development of post-production reprocessing of RFID tags. To sum up, the YOLOv5 algorithm has high value and practicability for RFID defect detection and can be used in daily defect detection tasks.

Table 3. Benefit analysis before and after the experiment.

	Before	After
Training cycle	1 week/person	1 day/person
Inspection efficiency	Overall planning:3 hours/shift	Overall planning:0 hours/shift
	Inspector:1.5hours/shift	Inspector:0.5hours /shift
	Engineer:2 hours/shift	Engineer:0.5hours /shift
	Material keeper:1 hour/shift	Material keeper:0 hours/shift

5. CONCLUSION

To realize the intelligent detection of RFID label defects, this experiment developed a system including real-time photography, detection tags, and detection results visualization. The system is connected with the camera, PLC, and an industrial computer. The connection between the hardware is achieved through signals and hard triggers of the camera, such as sending signals through serial communication to stop the machine when defective items are detected. The system only takes 20ms to detect a picture, which can meet the requirements of real-time detection in the industry. In future research, we will learn more about defects that may exist in RFID and expand the application of RFID electronic label defect intelligent detection system.

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