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A Two-model Automatic Towel Defect Detection Method Based On YOLOv5

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Abstract: *For replacing error-prone, costly, incongruous, and time-consuming human operators in the textile industry, an automatic and precise fabric flaw inspection system is vital. Textile blemish detection plays an essential effect in the production of textiles in the textile industry. Researchers have proposed many algorithms for fabric defect detection. However, several important issues, including inference time consumption, data imbalance, and algorithm complexity, still need to be dealt with for application in textile industry production. This paper proposes a two-model automatic towel defect detection method based on YOLOv5 to detect the defects of towels, effectively improving the detection efficiency and significantly reducing the cost. Moreover, this method has achieved the detection speed of 10 pictures per second in the actual production.*

Keywords: deep learning; fabric; towel defect; YOLOv5

1. INTRODUCTION

The products made of fabric are widely used in clothing decoration, medical and health, aerospace, environmental protection, and other fields [1]. However, in the fabric production process, several defects can be produced on the fabric surface due to yarn problems, overstretching, improper manual operation, disturbance of the production environment, etc. More than 70 defects have been defined in the textile industry [2]. Four kinds of fabric defects are shown in Fig 1. The occurrence of defects in textiles is not in line with the requirements of textile manufacturers to produce high-quality products. The appearance of defects on textiles not only seriously affects the appearance and quality of the product but also profoundly affects the price of the product. Therefore, defect detection plays a vital role in quality control in the textile production industry.

Currently, textile enterprises mainly depend on trained human inspectors to conduct quality inspections to find all potential fabric defects. However, owing to the inborn limitations of human labor, the precision of this manual method is generally affected by human subjective factors. It is considered error-prone, costly, incongruous, and time-consuming. Thus, developing an automated system suited to fabric defect detection is of outstanding academic and pragmatic importance. A precise and automatic detection system is essential to optimize the critical process. The discussion of visual and physical characteristics of textile defects are also a hot spot in the field of target detection. For example, researchers have studied dealing with fabric defects of different sizes and shapes [3,4].

In traditional classical machine learning, various algorithms are mainly used to extract the features of target objects in images, such as Local Binary Patterns (LBP) [5], Local Binary Pattern Histogram Fourier (LBP-HF) [6], rotation invariant measure of local variance (VAR) [7], Pyramid of Histograms of Orientation Gradients(PHOG) [8]. However, due to the limitation of traditional machine learning, the application is complicated, and the generalization is poor, so the application effect is not good.

In the past two decades, deep learning methods have received great attention and have been widely used in object detection [9,10], instance segmentation [10], and image classification [11]. The advantage of using deep learning methods is that they can automatically take out efficacious features from input pictures. Nowadays, there are two categories: one-stage object detection and two-stage object detection. The operation principle of the two-stage algorithm is to input images, generate region proposals, and then send them to the classifier for classification. The two tasks are done differently.

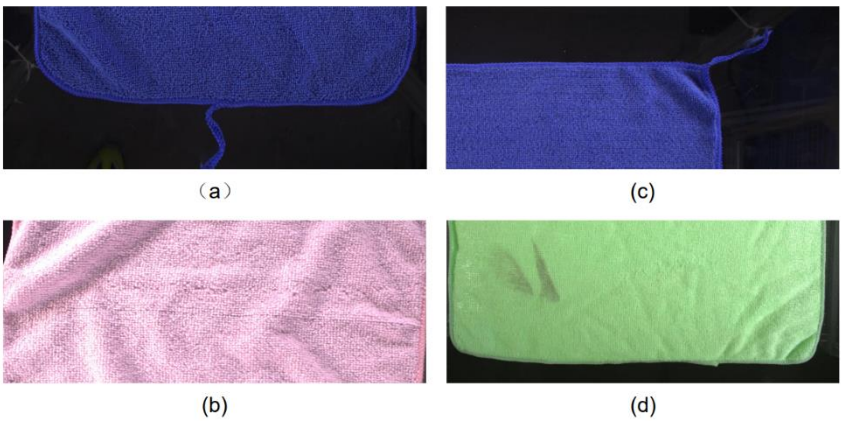

Fig. 1 Four types of fabric defects: (a) exposed stitches, (b) weft, (c) wire head (d)dirt.

Networks. The one-stage algorithm runs based on input pictures, output bounding box, and classification label completed by a network. As a result, one-stage algorithms usually run faster. The one-stage algorithm includes SSD [12], YOLO [13], YOLOv2 [14], YOLOv3, RetinaNet [15], etc.

In a real-world application, the requirement of defect inspection is highly real-time and accurate. The definition of the target object is the process of identifying a specific object in an image or video. Fabric defect detection can be viewed as a target detection issue. Some inspection methods draw on Haar [16], HOG(Histogram Of Oriented Gradient) [17], SIFT(Scale-invariant Feature Transform) [18] and final convolutional features [19]. After extracting the features, classifiers or localizers were used to recognize targets in the feature space. Lots of applications are implemented using the YOLO algorithm [20,21]. You Only Look Once is the full name of the YOLO algorithm, first proposed by Joseph Redmon in the article. The small size of the model and the fast calculation speed are the core of the YOLO object detection algorithm, which is the main reason that can realize real-time reasoning. The principle is to input all pictures in the neural network's input layer, and finally output the category and position information of the regression target box directly in the output layer. It is worth pointing out that YOLO has great generalization ability because YOLO can study fairly generalized features and transfer them to other domains.

Furthermore, YOLO uses global images during training and testing, encodes global information, and reduces the error of checking the background as a target. However, there are also some disadvantages. Its accuracy is inconsistent with the most advanced monitoring system. The second disadvantage is that the entity model revolves around the prediction boundary box based on the data provided. Therefore, the prediction will become problematic for images of different aspect ratios or image configurations. In the past several years, researchers have issued a few YOLO subsequent versions, such as YOLOv2(YOLO9000), YOLOv3, YOLOv4 [22], and YOLOv5 [23]. The speed and accuracy of them are better than the original version. Every YOLO version has its improvement measures. The main improvement methods of the YOLOv5 network contain the application of the Hardswish activation function, flexible control of model size and data enhancement.

Table 1. Number of images for test/train

Towel positive			
Class	Training Samples	Testing Samples	Total Samples
OK	612	95	707
NG	424	75	499
Towel opposite			
Class	Training Samples	Testing Samples	Total Samples
OK	401	60	461
NG	290	62	352

The towel is one of the main kinds of products in the textile industry. In this paper, we focus only on the inspection of fabric defects in towels using a deep learning approach using YOLOv5 and develop an automated towel inspection method based on YOLOv5 to inspect the fabric defects. In the experiment, we eliminated the interference of external interference factors on the detection of defects, and successfully realized the one-time detection of all defects of towels, significantly reducing the cost and effectively improving the detection efficiency.

2. RELATED WORK

Many researchers have proposed many systems and algorithms for the automatic detection of fabric defects. The key to fabric defect detection is extracting defects' features from fabric images. Here we briefly introduce some classic methods of detecting fabric defects.

Y. Ye proposed a fuzzy inductive inference method based on statistical variables of image histogram for fabric defect detection, which could not only detect defects but also identify the location of defects. However, this method is unsatisfactory for the detection of complex texture images. To solve this problem, some researchers have proposed new methods. M. Hao, J. Junfeng and S. Zebin proposed a detection algorithm that combines local binary pattern (LBP) and Histogram of Oriented Gradient (HOG) features. The algorithm can improve the detection efficiency, shorten the detection time and obtain the accurate location for six standard defect images of patterned fabric [24]. X.J. Jia proposed an edge detection method based on OpenCV, an open source computer vision library, but detecting multiple flaws is difficult [25]. M.A. Shabir, et al. proposed a new method to further segment texture data images using GLCM and Gabor filter texture detection mechanism for defective images [26]. These methods have a good detection effect for identifying defective images, but detecting the exact type of defects is difficult.

In addition, some researchers have used high-frequency features to detect flaws. X.Z. Yang et al. studied the classification and recognition training methods of six fabric defects based on wavelet transform, and successfully classified and recognized several defects. However, this method relies too much on the selection of filters and has poor performance in detecting defect images with complex textures [27]. C. Chi-ho Chan and G. K. H. proposed a defect type extraction method based on Fourier transform, which can effectively detect the structural defects of fabrics [28]. However, using Fourier transforms results in a lack of local information in the spatial domain, and these classification methods are insensitive to more minor defects. There are also model-based approaches that typically explore the relationships between fabric image pixels. Cohen et al. used Gauss-Markov fields (GMFS) to build models based on pictures of new defects for detection. However, their detection effect on minor defects is not good, and the detection efficiency is not high. Zhang et al. Proposed a new fabric defect detection method based on LGM and FCM, which can detect and segment fabric defects from various fabric defects data sets of different types and shapes [29]. Although this method is effective for fabric images with complex patterns, it takes a long computational time to

detect defects and requires too many parameters to adjust manually.
Although the traditional machine vision inspection method has detected most fabric defects, its low accuracy, low generalization degree, and high cost of manual design feature seriously affect its application in fabric inspection. In recent years, deep learning has developed rapidly and is widely used in various fields, such as object detection and speech recognition. Surface defect detection has developed even more rapidly since the introduction of AlexNet. The paper of Masci et al. introduces the method for deep learning to detect surface defects of objects is superior to the traditional machine learning method [30].
Liu et al. proposed using multilevel GAN to detect fabric defects through unsupervised data reconstruction [31]. Its significant advantage is that it can solve the challenge of multiple fabric defects. Wei et al. used faster-RCNN to detect fabric defects. It achieves satisfactory detection performance by utilizing the powerful feature engineering capability of faster-RCNN. However, its two-level target detection method makes faster-RCNN have great Spatio-temporal complexity [32]. Jing et al. adopted an improved real-time single-level target detection method, YOLOv3, to detect fabric defects and achieve better results. Rui Jin and Qiang Niu proposed a method of YOLOv5 for fabric defect detection using a teacher-student network structure. They introduced a multi-task learning strategy and focal loss and center loss constraints [23]. However, the cost of the fabric production process is not effectively reduced. This paper proposes a dual-model structure detection method based on YOLOv5, which can effectively reduce the cost of the actual deployment detection system based on entirely using the high accuracy and high real-time performance of YOLOv5.

3. METHODOLOGY

This paper designed a fabric defect detection method with a dual model structure based on YOLOv5. Firstly, we introduced the establishment of the data set and the training of the model, then briefly introduced the operation process of the whole system detection, and finally pointed out the optimization of the system by implementing the method.
The training and testing process of the model is shown in Fig 2 below.

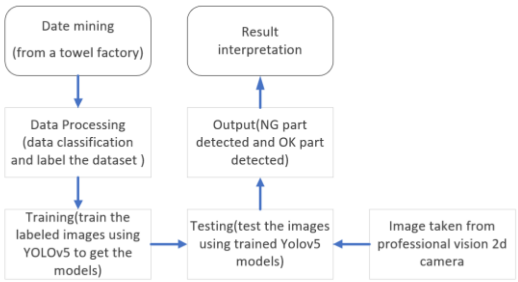

Fig. 2 Framework of proposed method

3.1 Establishment of the dataset and labeling

One of this project's most important works is acquiring high-quality datasets. We construct our datasets by designing a data acquisition system of actual factory towel production line. Firstly, we take pictures with the cameras; at this moment, we must ensure the lighting conditions and the camera angles are proper. The above work is challenging but significant and necessary to get a complete dataset. We select and label these raw images to satisfy the next model training step. The purpose of classifying the pictures is to facilitate labeling. In the labeling process, we use the software 'labelimg' to label the towel image. After successfully installing the application, we start working with image labels by drawing borders and labeling the class.
After successfully tagging the acquired images, the output includes text and class files. In order to improve speed and precision, we built two models for both sides of the towel and only divided the results into two categories: OK and NG.
Each text document includes five decimal digits. The first digit indicates the type of bounding box, and the second and third digits are center x and center y, which are also the coordinates of the central point of the bounding box. The final two digits are the total width and height of the bounding box, respectively [27]. The numbers in these text files are normalized between 0 and 1 by dividing them by the width and height. It is not hard to predict that the value of the network is in the range of 0 and 1, not a random number. The number of detected objects determines the number of lines in the text file. Labels are used for training and testing datasets. Table 1 shows the number of images used for training and testing each category. The number of bounding boxes manufactured is also shown in the text file. Table 1 illustrates the total number of images taken for training and testing for each class. Table 2 shows the classes of our project, i.e. (the class file).

Table 2. Two classes utilized for recognition

Class NO	Class
0	OK
1	NG

3.2 YOLOv5 algorithm

YOLOv5 has roughly the same structure as the previous YOLOv4 and YOLOv3. The network structure can be divided into four parts: input, Backbone, Rect, and Prediction. Compared with YOLOv3, its input adopts the same mosaic data enhancement method as YOLOv4 and randomly cuts, scales, and splices the original data to enhance its robustness. Backbone includes Focus and CSPNet (Cross Stage Partial Networks). Taking YOLOv5s as an example, compared with YOLOv4, its new Focus structure refers to multi-layer chip technology, four sliced images, and finally, 32-core convolution operation to output features. The CSPNet part retains the reusable running characteristics of Dense Net, but the gradient is throttled, reducing the running time. Through local multi-layer feature fusion, the graph is more abundant.
Rect is generally designed with YOLOv4 and is divided into SPP (Spatial Pyramid Pooling), FPN (Feature Pyramid Networks), and PAN (Path Aggregation). However, it introduces CSPnet into Neck to improve their network-fusion capabilities. SPP performs different max pooling on the segmented dimension map and

unifies the feature map specification after tensor splicing. The features of FPN and PAN are the aggregation structure of top-down and bottom-up, respectively. First, they are fused with Backbone's CSPNet output features and high-level information for sampling on transmission. Then the samples of shallow feature information are aggregated to fuse multiple layers effectively to extract image features. Its output mainly uses CIOU_Loss as the Bounding box loss function to solve the problem of distinguishing predicted box and target frame size. Finally, NMS (Non-Maximum Suppression) is used to screen multi-target boxes to improve the recognition effect of occluded targets.

3.3 Training YOLOv5 models

The YOLOv5 architecture helps improve the detection of towel defects. The architecture consists of four different models, including YOLOv5x, YOLOv5l, YOLOv5m, and YOLOv5s. The difference between these four architectures is the convolution kernel of the network and the feature extraction module. Other differences are the size of the model and the total number of model parameters, which are different for the four different architectures.

Making a training of your YOLOv5 model contains the following steps [33,34].

1- Finish the configuration to meet the conditions of training YOLOv5 models, including setting up the YOLOv5 environment and the data and the directory structure, focusing on setting the configuration file with the suffix YAML. Since to start training the YOLOv5 model, it is necessary to configure two YAML files.

2- Execute the train.py command from the computer to start training the YOLOv5 model. This step can specify hyperparameters such as batch size 8, image size 1024, lr0 0.01, and number. of epochs 200, and so on. If we apply yolov5s, the weight of the training model is only 14 MB. It is lightweight and has good mobility in practical applications. Fig. 3 represents the outcome of test data from the test dataset.

Fig. 3 OK Class and NG Class detected

3.4 Mechanical design

In order to meet industrial production needs, the camera shooting needs to be combined with the production line to form a station, and its structure is as follows in Fig 4. Two high-definition industrial cameras are used to shoot the front and back of the towel on this station. There are two light sources on the upper side and two on the lower side of the machine to meet the shooting environment. The imaging diagram is represented in Fig. 5. The working process of the towel defect detection system is represented in Fig.6. The towel will be transferred to the starting position, which is grabbed by the mechanical gripper and moved to the photo-taking position. The camera picks up an electrical signal and starts taking pictures, which it sends to software for detection. It will be detected by the detection application integrated with YOLOv5. After finishing the detection of the towel defect, the OK or NG signal will be returned to the interface. Then the mechanical gripper moves the towel to the corresponding OK and NG positions.

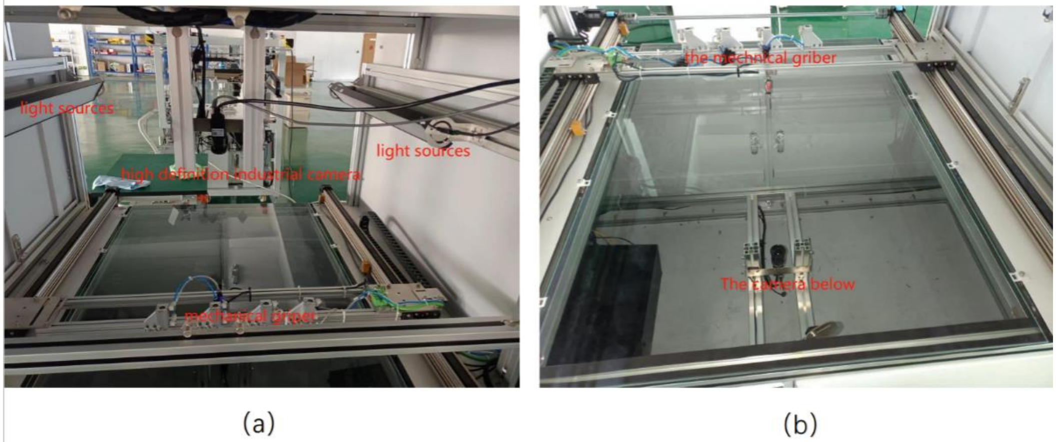

Fig. 4 Structure design of the machine

3.4 System optimization

During the implementation of the whole project, many factors should be considered. The computer configuration adopted in the experiment is presented in Table 3. Although deep learning has many benefits, it has high requirements for computer configuration. Secondly, due to the camera field of vision, towel size, and other factors, the scope of each shooting cannot be perfect, and some interference factors will affect the detection effect. The main problems are as follows.

1- The mechanical screws are identified as NG class.
2- The light source producing a green strip on the glass plate will be misidentified.
3- Since achieving a station to detect the front and back sides of the towel is needed, the problem is that the front side contains trademarks, which will be an interference factor in the detection.

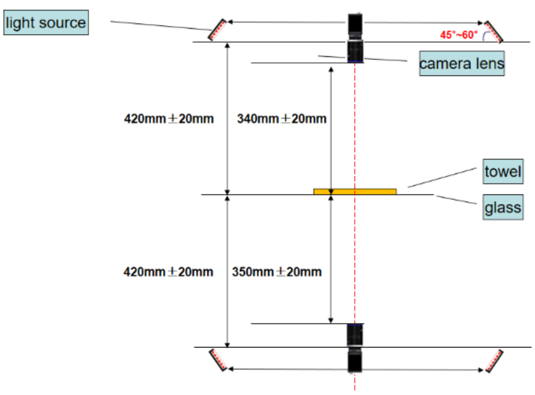

Fig. 5 Shooting and imaging diagram

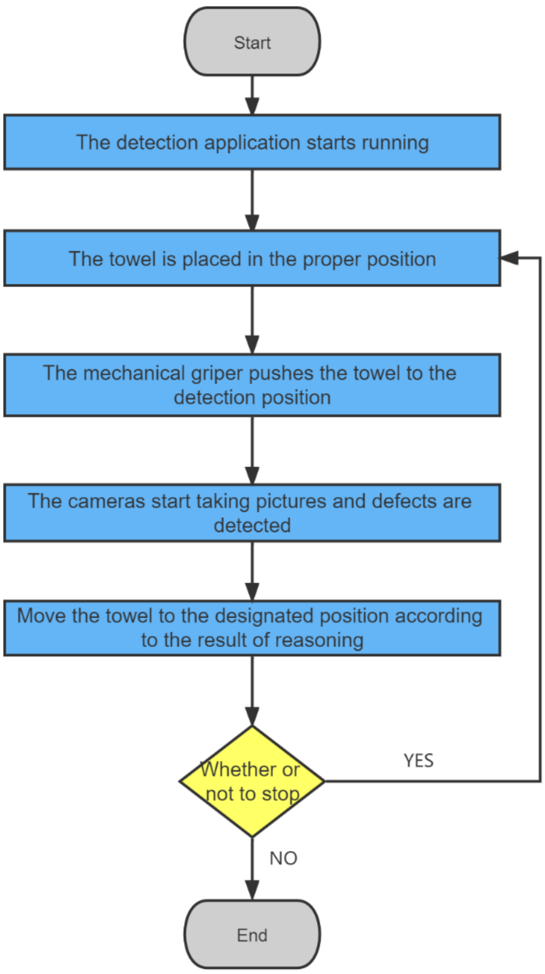

Fig. 6 System operation Flow

The machine, as mentioned earlier, screws and the said green light are located in the shooting area of the cameras. In order to exclude these interference factors, we designed the anchor box of the maximum preprocessing size according to the maximum size of the towel to be detected. The anchor box of the maximum preprocessing size can limit the image detection area of YOLOv5 by adding it to the detect.py file. On this basis, the detection error rate is reduced, and the precision rate is improved. At the same time, the inspection rate is further improved because the detection image area is reduced. After adding this limit, the detection effect is improved obviously by eliminating the influence of the above interference factors. Fig. 7 represents the anchor box of the maximum preprocessing size. Secondly, two models are used to detect a towel's front and back sides in this system. This way, towel testing efficiency is improved, and the cost is significantly reduced.

Table 3. Constitution of computer environment

Equipment	Information
Operation System	Windows 11.7
GPU	GeForce RTX 3070
CPU	Intel Core i9-10980XE
Hardware Facilitation	CUDA10.2

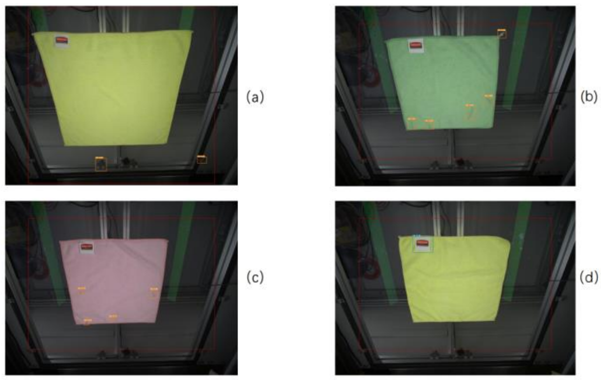

Fig. 7 Size determination and effect display of anchor frame

4. RESULTS AND DISCUSSION

In the object detection domain, the trained models are assessed for recall (R), precision (P), F1, and mean average precision (mAP) values. A standard norm of performance and reliability, this paper also uses the above evaluation, the norm to evaluate defect detection model performance.

Fig 8 shows the mAP, Precision, and Recall graphs of the train data. The graph in Fig 8 represents mAP at several 0.5 and mAP at a value of 0.5 - 0.95.. They are plotted against precision, recall, and an IoU (intersection over union) threshold of 0.2.

Two models are used to detect towel defects, and the measurement indicators of each model are shown in the figures above.

The number of towels in the OK and NG parts of the correctly identified instance is called TP(true positive).

The number of towels that misidentify the OK and NG parts of the instance is called FP (false positive).

The number of towels in the OK and NG sections that were not identified is called FN (false negative) [35].

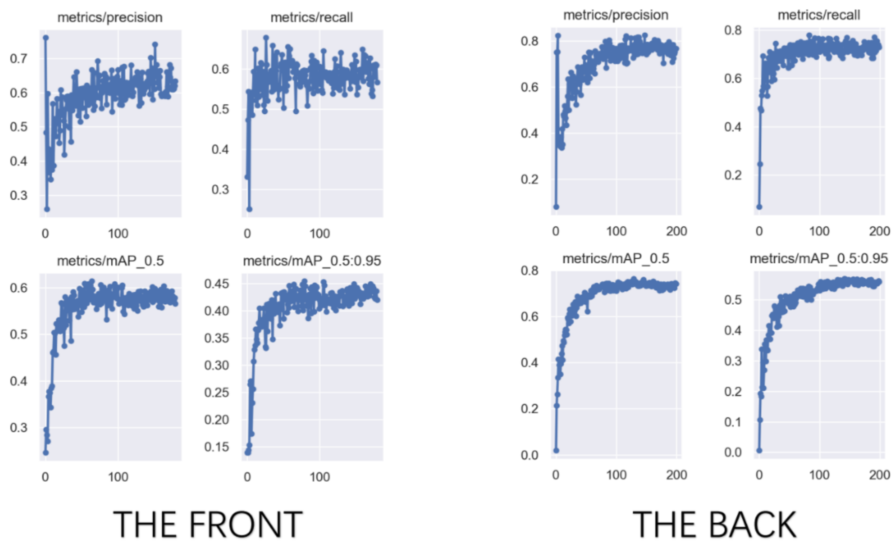

Fig. 8 mean average precision, precision, and recall after YOLOv5 network training, the front means the front side of towels, and the back means the back of towels.

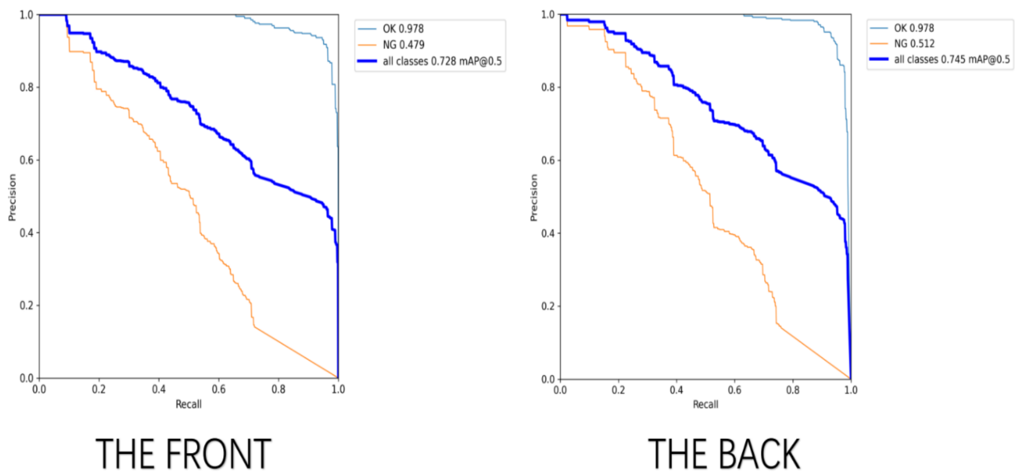

Fig. 9 Precision-Recall curve for each category included two models

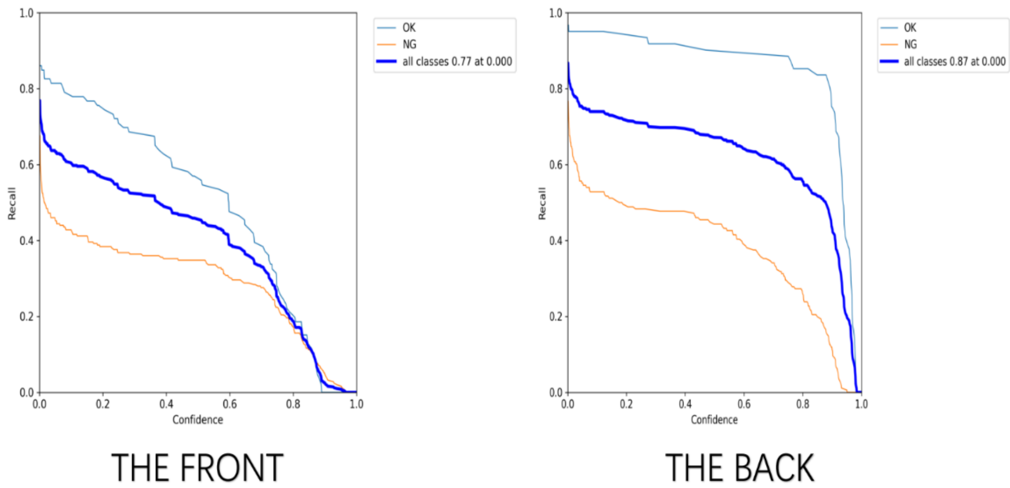

Fig. 10 Confidence Vs. R Curve

Precision(P) is the ratio of the number of correct objects detected to the sum of the number of detected objects. It is a measure of the precision of the detection model. Its calculation formula is as follows:

$$\text{precision}=\frac{\text{TP}}{\text{FP+TP}} \tag{1}$$

Recall rate is the ratio of the number of correct objects detected and the number of real objects manually identified. It measures the overall error rate of the detection entity model. The calculation method is as follows:

$$\text{Recall}=\frac{\text{TP}}{\text{FN+TP}} \tag{2}$$

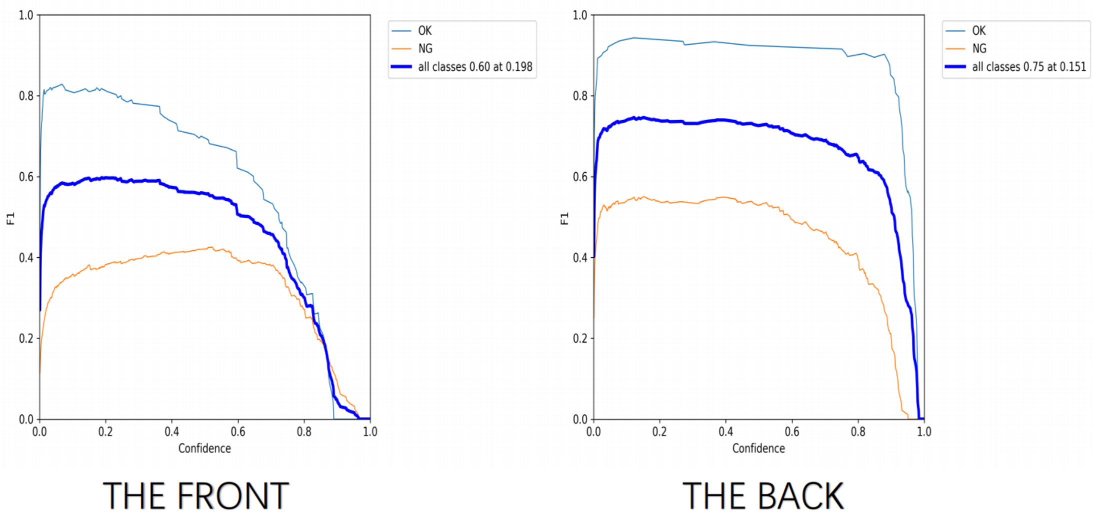

Fig. 11 Confidence Vs F1 curve

The precision-recall (PR) curve in Fig. 9 is plotted according to the corresponding curves. The area under the precision-recall (PR) curve is defined as the average precision (AP) obtained by integrating the precision-recall function. The definition of average accuracy is the average of the correct targets tested across multiple test sets.

$$\text{Average Precision}=\int_0^1 \text{P(R)dR} \tag{3}$$

The mAP can be obtained by the average precision (AP). The calculation formula of the average precision mAP is as follows:

$$\text{mAP} = \frac{\sum \text{AP}}{N} \tag{4}$$

Exploratory data analysis can be better performed with the help of correlograms. The relationships of the entire dataset can be roughly visualized. Fig. 10 is an R curve showing confidence Vs Recall, and Fig. 11 is a Confidence Vs F1 curve.

$$\text{F1}=\frac{\text{precison*2*Recall}}{\text{Recall+precison}} \tag{5}$$

What all detection algorithm models cannot ignore is the detection speed. The requirement for towel defects is to achieve high-precision real-time detection of defects. In this project, the YOLOv5 model inspection speed is calculated from the actual production inspection in the unit of FPS. It can detect ten images per second.

5. CONCLUSION

The defects of the towels are successfully detected using our method. By utilizing YOLOv5, the results acquired are exact. Since the weight file size is only 14 MB, hardware implementation becomes much more manageable. In addition, the double YOLOv5 model design are utilized to improve detection efficiency and sharply reduce the cost. It is worth pointing out that the model can also recognize defects in towels of colors not included in the training set. The system generated by this method consumes high computer resources. Further reducing the resource consumption and improving the detection efficiency will be our subsequent work.

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