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A Comparative Study of YOLOv5 and YOLOv8 for Appearance Defect Detection in Polyester Fiber Yarn Packages

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Abstract—**Polyester fiber yarn packages often exhibit various appearance defects during production, including six classes: hairiness, hairiness clusters, broken thread, broken pipe, oil stains, and dust impurities. Failure to detect these defects in time during the production process can lead to significant economic losses. This highlights the importance of real-time detection of yarn packages defects during production. Currently, there are some problems with methods that rely mainly on manual testing, such as high false positive rates and poor timeliness. In order to address the increasing complexity of defect detection in the appearance of yarn packages, in this study, 2480 datasets of size 2448*512 were first collected on the production line, and defect detection was explored using the popular YOLOv5 model and the newer YOLOv8 model. The performance of the model at different scales was also evaluated. The results show that YOLOv8 is better than YOLOv5 in this task and is more suitable for industrial applications. Our study provides an efficient and accurate quality control method for the production of Polyester fiber yarn packages.**

Yarn Packages;Surface Detect Detection;YOLO; Quality Control

I. Introduction

In recent years, China has consistently been the world's largest consumer and producer of polyester fibers. However, within the conventional manufacturing process of Polyester fiber yarn packages, a range of defects, including hairiness, hairiness clusters, broken thread, broken pipe, oil stains, and dust impurities, frequently arise due to fluctuations in production equipment parameters[1]. If these defects are not promptly detected during quality inspection, it can result in a significant number of yarn packages in the same batch being scrapped, potentially entering the market, ultimately leading to substantial resource wastage and economic losses, and negatively impacting the company's reputation. Therefore, conducting real-time appearance defect detection during the yarn packages production process is of paramount importance.

Currently, quality inspection of yarn packages appearance in China heavily relies on manual labor. However, in high-output, high-speed yarn packages production lines, defects such as hairiness and dust impurities are often too small to detect, leading to the possibility of false positives and false negatives in manual inspection. According to statistics, approximately 30% to 40% of yarn packages defects go undetected on the production line. Furthermore, the elevated noise levels in the production environment are not conducive for employees to work for long hours[2].

With the advancement of deep learning technology, CNN-based defect detection algorithms have proven effective in identifying industrial defects and are now widely adopted across industries, including yarn packages appearance defect detection. Previous research has made significant progress in the field of yarn packages appearance defect detection: Wang et al[3], employed an enhanced AlexNet-based network to identify defects like broken thread, oil stains, and failure formation in yarn packages. Zhang, et al[4], modified the SSD network to detect small hairiness defects in yarn packages. Tang, et al [2], proposed an improved algorithm based on Centernet, enhancing the detection accuracy of hairiness and broken thread defects in yarn packages images.

With increasing demands in production lines, the defect categories have grown to six, and yarn packages image sizes have expanded, intensifying the complexity and difficulty of the detection task. Considering the advancements in object detection model algorithms, the most popular YOLOv5[5] model and the newer YOLOv8[6] model were used to address the complexity of yarn packages detection tasks. Benchmark tests on models of varying scales were also conducted, providing a comprehensive assessment of their accuracy, speed, and energy consumption performance.

II. Data Set and Model

A. Data Set Introduction

We utilized industrial cameras with a 2K resolution to capture a total of 2,480 BMP-format yarn packages images on the operating production line. Each yarn packages image had dimensions of 2448 x 512 pixels. Regarding defect classification, we needed to detect six types of features as illustrated in Figure 1. , which include hairiness (BF), hairiness clusters (BC), broken thread (BT), broken pipe (BP), oil stains (OS) and dust impurities (FS). The following content about defects will use abbreviations.

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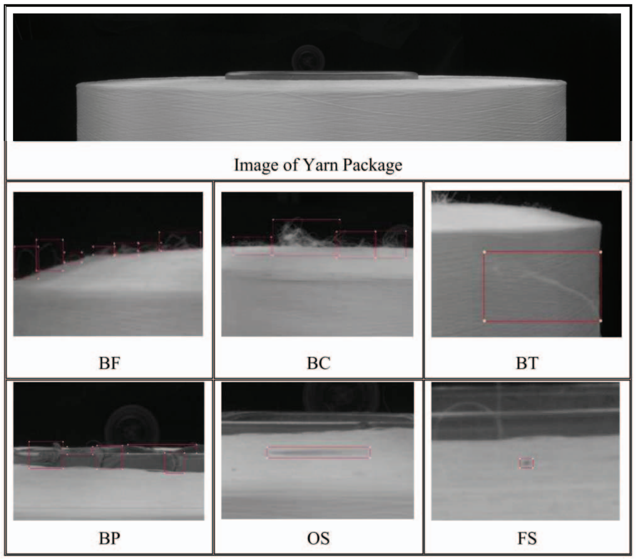

Figure 1. Dataset Sample and Defect Features.

Among the six types of defects mentioned above, BF, BC, and BT exhibit significant similarities in their feature morphology, and the difference mainly focuses on feature density and size. For instance, in terms of density, BF defects typically consist of single or small numbers of broken feather, whereas BC are characterized by a multitude of interwoven and entangled broken feather. Regarding size, small-scale BF defect may only possess a height of 4 pixels, whereas larger BT defect features can extend to 260 pixels in height. This places high demands on the model's robustness and its capability to detect multi-scale features.

B. Object Detection Model

The YOLOv5 model, launched by Ultralytics in 2020, stands as the dominant one-stage defect detection model in the industrial sector, offering fast inference speeds with high accuracy. YOLOv5 use CSPDarknet as its backbone network and PANet as the neck [7]. YOLOv5 surpasses the v4 version with improved data enhancement algorithms and the introduction of a K-means based auto-learning bounding box anchor [5].These enhancements notably boost the model's training and inference performance, particularly for smaller datasets and Multiscale datasets.

Meanwhile, YOLOv8, released by Ultralytics in 2023, represents the latest SOTA model. As shown in Figure 2. , YOLOv8 uses a lighter and more efficient C2f module with richer gradients of information flow in the backbone compared to the C3 module of YOLOv5[8]. Additionally, YOLOv8 introduces an anchor-free detection head, breaking free from the limit of prior bounding box. It also decouples classification from bounding box regression, thereby enhancing the model's flexibility and detection capabilities, especially on customized datasets[6][9].

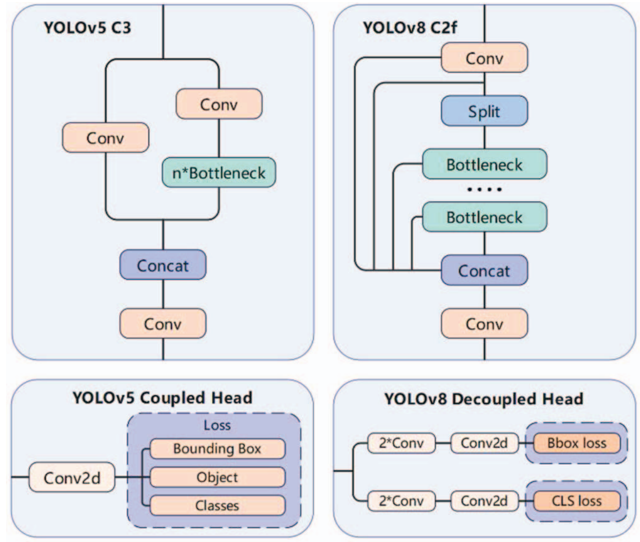

Figure 2. Differences Between YOLOv5 & YOLOv8 .

Both YOLOv5 and YOLOv8 come in various scale versions, ranging from nano to extreme (n,s,m,l,x). As the model's layers going deepen and widen, there's a gradual improvement in mean average precision (mAP) on public datasets[10]. However, this enhanced performance demands more computational resources and lowers speed. Therefore, in real-world applications, selecting the right model version should align with specific needs and compute resource limitations.

III. Training Process and Methods

Regarding the model's input, we opted to train it directly using BMP format images with a resolution of 2448 x 512 pixels, without using image cropping or compression methods. There are several reasons for this decision.

Firstly, although image cropping can reduce memory requirements during training and enhance small object detection performance, as mentioned earlier, BF and BT defects share a similar morphology, with their primary distinction being in size. Consequently, cropped images may lead to a small portion of BT being incorrectly detected as BF. While this issue can be mitigated by setting overlap regions and performing cross-category global non-maximum suppression (NMS) on merged images [11], it may also result in some BF defects being mistakenly removed.

Another concern is that image cropping and reassembly in post-processing demand substantial computational resources, negatively impacting I/O efficiency and significantly extending the detection time, thereby affecting real-time defect detection.

Lastly, we chose to train and infer using BMP format images instead of compressed formats like PNG or JPEG to ensure the accuracy of model predictions. This choice is particularly crucial for tiny BF defects, which may have diameters as small as 1-2 pixels, as compression in JPEG or PNG formats can introduce noticeable distortion and blurring.

Our yarn packages dataset was trained on an NVIDIA GeForce RTX 4090 GPU. We trained five models of varying sizes for both YOLOv5 and YOLOv8 using the same parameters. During the training process, we disabled mosaic, copy-paste, and multi-scale augmentation. The reason is that these data enhancement methods can make it challenging for the model to differentiate features closely linked to density and size, such as BF, BC, and BT.

IV. Results and Discussion

To assess the effectiveness of different-sized YOLOv5 and YOLOv8 models in the six-category yarn packages appearance defect detection task, this paper employs the following metrics to evaluate model performance: Mean average precision at IoU0.5 threshold ($mAP_{0.5}$) and frames per second (FPS). Where the area enclosed by the PR curve plotted in terms of precision(P) and recall (R) is the Average precision (AP) of the class, and averaging the AP over all classes yields mean average precision (mAP)[12].

TABLE I. Average Percision of Class

Model	Classes / AP						
	BF	***BC***	**BT**	**BP**	**OS**	**FS**	**mAP**
YOLOv5n	0.721	0.799	0.503	0.317	0.001	0.471	0.469
YOLOv5s	0.717	0.757	0.463	0.638	0.001	0.267	0.474
YOLOv5m	0.721	0.759	0.527	0.712	0.004	0.512	0.539
YOLOv5l	0.747	0.744	0.572	0.662	0.348	0.365	0.573
YOLOv5x	0.733	0.750	0.677	0.763	0.002	0.491	0.569
YOLOv8n	0.747	0.803	0.421	0.617	0.430	0.453	0.579
YOLOv8s	0.759	0.767	0.595	0.665	0.396	0.449	0.605
YOLOv8m	0.786	0.785	0.593	0.603	0.148	0.586	0.584
YOLOv8l	0.719	0.831	0.312	0.449	0.334	0.517	0.527
YOLOv8x	0.756	0.810	0.341	0.585	0.399	0.562	0.576

TABLE II. FPS on Different Platforms

Model	Platform / FPS		
	Pytorch	**ONNX**	**TensorRT**
YOLOv5n	133.3	38.5	102.0
YOLOv5s	100.0	36.8	81.3
YOLOv5m	52.1	29.8	57.5
YOLOv5l	32.5	22.6	37.7
YOLOv5x	19.3	16.7	25.3
YOLOv8n	72.5	33.9	69.9
YOLOv8s	56.8	32.2	56.2
YOLOv8m	31.7	24.5	39.8
YOLOv8l	22.3	18.7	26.1
YOLOv8x	15.1	15.0	20.7

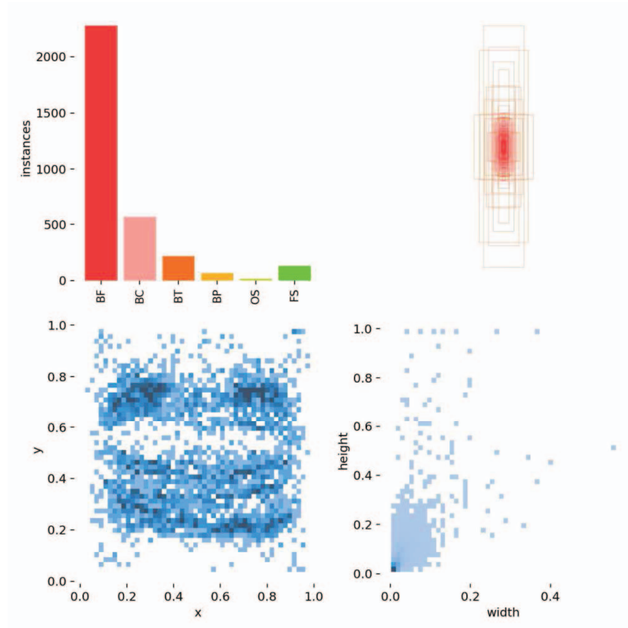

Figure 3. Sample Distribution in the Dataset

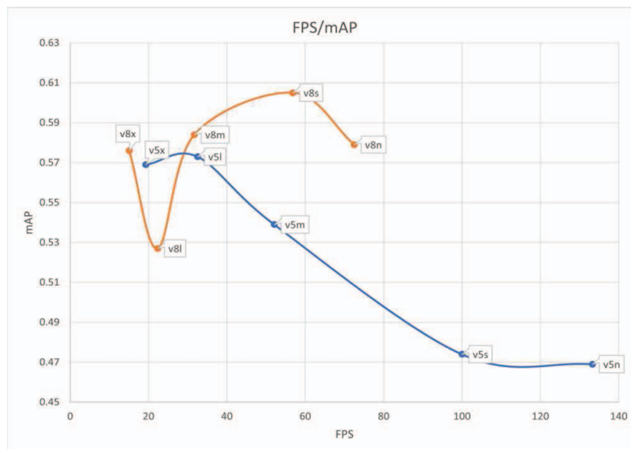

Figure 4. mAP/FPS Curve on Pytorch Platform

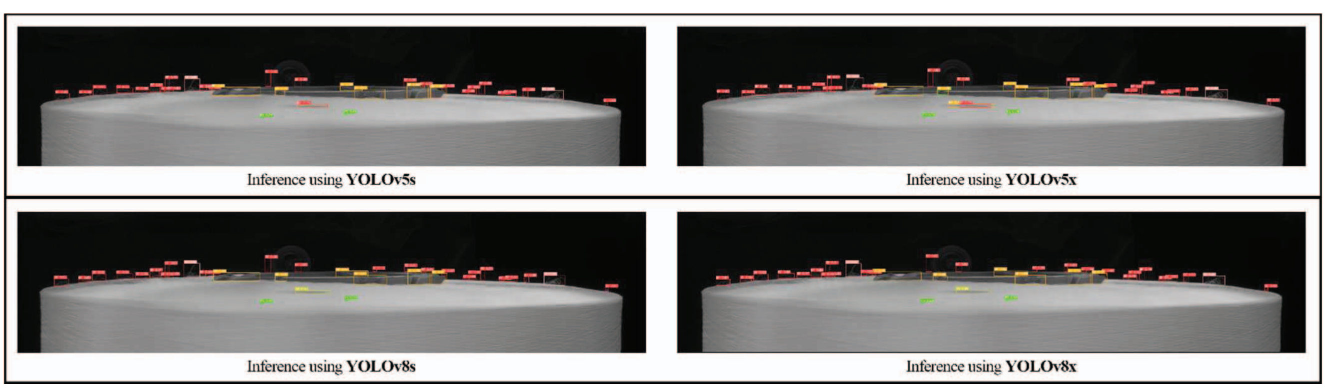

Figure 5. Inference Result

From TABLE I. , it is evident that both BF and BC reached 0.7AP, indicating a high level of performance. BT, BP, and FS can also be achieved at about 0.4 AP. However, the performance of the OS class is the poorest, especially in the YOLOv5 model. This phenomenon can be attributed to the issue of datasets imbalance, as depicted in the Figure 3. BF and BC defects account for over 80% of the training samples, while BT, BP, and FS defects occupy the remaining 20% of samples. In contrast, the proportion of OS defect samples is barely 1%, making it highly susceptible to overfitting due to the limited number of samples or even rendering gradient descent infeasible.

As shown in TABLE I. , YOLOv8 shows an overall mAP improvement of 0.07 to 0.13 compared to YOLOv5. Notably, there is a significant improvement in oil stain category detection in small samples, highlighting YOLOv8's excellence in trainability and generalization performance, as confirmed by Figure 5. In terms of different-scale models, the YOLOv5 model experiences a 0.1 increase in mAP from size n to x. Conversely, the mAP of the YOLOv8 model only sees a 0.026 increase from size n to x, which means the YOLOv8 reached great performance in a smaller size.

Based on TABLE II. , Figure 4. and Figure 5. when there's no significant mAP improvement, especially when YOLOv8 performs well at the nano-level model, increasing model parameter size leads to a notable drop in FPS and a substantial reduction in energy efficiency. Thus, models beyond the small-level are unsuitable for the six-category yarn packages appearance defect detection task. Considering real-time production line needs and the trade-off between defect detection accuracy, opting for YOLOv8 n-level or s-level models is a comprehensive and optimal choice.

V. SUMMARY

We collected and constructed a moderately-sized yarn packages image dataset containing six different types of defects from the production line. This dataset presented challenges in both image size and feature dimensions. We conducted testing and evaluation using YOLOv5 and YOLOv8 object detection models of varying scales. Throughout this process, we emphasized the necessity of training and inference using uncompressed BMP images without cropping, which mitigated the risk of false negatives between broken thread and hairiness, as well as the loss of accuracy due to distortion in small hairiness features.

Our research achieved the following results: (1) The cutting-edge CNN-based object detection models have demonstrated excellent performance in categories such as hairiness (0.79 mAP), hairiness clusters (0.83 mAP), broken thread (0.68 mAP), broken pipe (0.76 mAP), and dust impurities (0.59 mAP), achieving satisfactory mean average precision. (2) In the six-class yarn packages appearance defect detection task, YOLOv8's nano-level and small-level models have emerged as the most comprehensive and optimal solution in terms of inference accuracy and speed performance. This is because the minimal consumption of computational resources while achieving sufficient accuracy is essential for real-time deployment on production lines. (3) We have also provided an efficient and accurate quality control method for polyester fiber yarn packages production, with the ability to reduce resource wastage, economic losses, and enhance a company's reputation.

However, detecting oil stain defects poses challenges due to limited sample quantities and sample distribution imbalances. Therefore, future research will focus on addressing sample distribution imbalances, further optimizing model performance, and improving model inference speed to meet a broader range of industrial application demands.

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