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Poster

Detection of impurities in wool based on improved YOLOv8

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Abstract

In the current production process of wool products, the cleaning of wool raw materials has been realized in an automated way. However, detecting whether the washed and dried wool still contains excessive impurities still requires manual testing. This method greatly reduces production efficiency. To solve the problem of detecting wool impurities, we propose an improved model based on YOLOv8. Our work applied some techniques to solve the low resource model training problem, and incorporated a block for small object detection into the new neural network structure. The newly proposed model achieved an accuracy of 84.3% on the self built dataset and also achieved good results on the VisDrone2019 dataset.

CCS Concepts

• ***Computing methodologies*** → ***Computer graphics;*** *Image manipulation; Image processing;*

1. Introduction

In the production of wool products, the material used to make wool is fluffy wool that has been cleaned and dried by a special machine. Whether the wool is pure and free of impurities directly affects the quality of the yarn spun in the later period. Therefore, the wool after cleaning and drying must be sampled and tested, and only qualified wool can be entered into the next process. In the production process of wool products, there is a technical difficulty in how to efficiently and accurately detect the content of impurities in wool. At present, the detection methods of impurities in wool mainly rely on manual methods, which are not only slow in speed and poor in reliability, but also low in automation. In order to solve this problem, this paper puts forward a new solution. We use deep neural networks to identify impurities in wool. This method fills the technical gap and realizes the purpose of improving the production efficiency of wool products. The work of this paper is based on the improved YOLOv8 model to quickly identify impurities from the test samples of wool, so as to determine whether the wool raw materials are qualified and whether the wool cleaning needs rework.

2. Related Work

When using manual methods to detect impurities in wool, the collected samples are spread as flat as possible on a black background plate. The advantage of this is that the wool to be tested can have a distinct contrast with the background, and the entanglement between impurities and wool can be eliminated as much as possible, making it easier to observe impurities. So we also used this method when collecting training data. Specifically, we took out one gram of wool and tried to flatten it onto a black board. Then, we used a high-definition camera to take photos to ensure that impurities and wool could be clearly seen in the photos. When using model inference, it is also deployed in the same scenario. A total of 60 photos were collected. Then the data annotation was completed by labelimg software. The marked data is divided into the training set and the verification set according to the ratio of 7 to 3. We used data enhancement methods such as random scaling, cropping, translation, clipping, and rotation on our self-built dataset. In addition to the above global pixel enhancement methods, there are also some more unique data enhancement methods, such as MixUp [ZCDLP17] and Mosaic [BWL20].

3. Improved to YOLOv8

YOLOv8 is a general purpose model that can be applied to image classification, object detection and image segmentation tasks. The main changes in YOLOv8 are the use of a new backbone network, a new anchor-free detection head, and a new loss function. The main work of this article is to complete this task based on the improved model of YOLOv8. The principle of an improved network is to retain the advantages of YOLOv8 and enhance the small identification capability of the model. The improved model structure is shown in Figure 1:

Backbone: On the BackBone of YOLOv8, we add the Focus module and a custom integration CConv to the data input of the model. The image input is a 3-channel picture of 1280x1280 pixels, which can be converted into four pictures of 640x640 pixels through the Focus module. The advantage of this is to retain picture information as much as possible to avoid information loss caused by resize

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operation. The custom convolution layer CConv is composed of an ordinary 3x3 convolution and a 3x3 expansive convolution in parallel. Its function is to enlarge the receptive field while extracting features. The new model retains the C2f module in YOLOv8, which greatly improves the detection accuracy and speed of the model.
Neck: In the feature fusion stage, the Neck part of the TPH-YOLOv5 model is mainly taken, which is very useful for the detection of small targets. The Transformer encoder module can capture global information and rich context information. At the same time, CBAM attention mechanism can resist confusing information and focus on useful target objects.
Head: In the detection head part, the head part of YOLOv8 is mainly retained, that is, the anchor-free policy and decoupling head of YOLOv8 are retained.

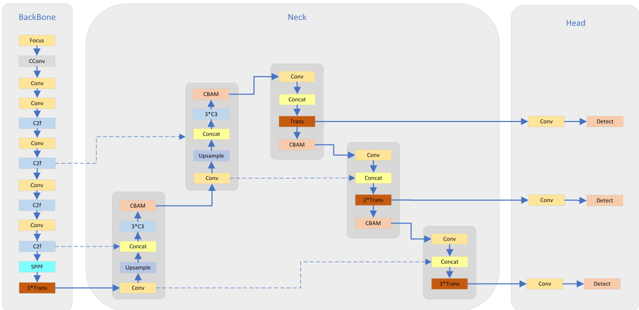

Figure 1: *The network structure of improved YOLOv8*

4. Experiments

The model is implemented with PyTorch2.0.1 and Cuda11.7, and our nework is trained using Adam as the optimizer with a total of 100 epochs on NVIDIA GTX 3080 GPU . The data sets used in the experiment are the self-collected wool data set (YMzz) and the aerial photography dataset VisDrone2019. We choose several

DataSet	YMzz			DisDrone2019		
Methods	P(%)	R(%)	mAP(%)	P(%)	R(%)	mAP(%)
SSD	69.3	70.2	70.4	71.9	72.6	73.7
Faster-RCNN	70.2	72.4	75.8	71.9	80.2	77.3
YoloV5	16.7	13.4	4.2	27.3	29.5	31.9
TPH-YoloV5	69.4	79.9	75.1	56.4	50.5	56.2
YoloV8	79.3	74.4	77.8	73.1	77.3	79.5
Ours	84.3	81.2	80.2	80.4	79.5	81.5

Table 1: *Data from comparative experiments*

different object detection models to compare the performance of the improved model. This chart sets forth the important fact that YOLOv5 has insufficient ability to identify small targets. TPH-YOLOv5 [ZLL*23] is an improved YOLOv5 model for small target detection tasks, and it can be seen that its various evaluation indicators have been significantly improved. From the comparative experiment, it can be seen that our model has significantly improved the recognition ability of small targets compared to YOLOv8 and YOLOv5. In terms of accuracy, when trained to 100 epochs using the current model, it is 84.3%, which is larger than the other three models, at least about 5%. Other indicators such as recall rate and mAP have all increased. These results indicate that the improvement of the model is suitable for small target detection tasks, as well as for detecting wool impurities.

5. Conclusion

Figure 2: *The Effect of Improved YOLOv8 Target Detection*

In this paper, in order to solve the problem of wool impurity detection, we put forward the improvement of YOLOv8. The improvement is mainly to retain the advanced modules of YOLOv8, and to add CBAM which is conducive to small-scale target detection. It can be seen from comparative experiments that our model achieves good performance in both self-built data sets and DisDrone2019. We hope that this report can help solve some problems in the production of wool products and improve the efficiency of production.

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