WHEAT GRAIN APPEARANCE QUALITY DETECTION BASED ON IMPROVED YOLOv8n
/
基于改进 YOLOv8n 的小麦籽粒外观品质检测

Qingzhong KONG, Na MA[*)]
College of Information Science and Engineering, Shanxi Agricultural University, Taigu/China
Tel: +86-13834188480; E-mail: manasxau@163.com
DOI: https://doi.org/10.35633/inmateh-75-30

Keywords: *Wheat grains, machine vision, YOLOv8n, attention mechanism, DWR module*

ABSTRACT
Wheat grains are a common type of cereal variety, and due to their large quantity and high demand, traditional manual quality inspection requires a significant amount of labor with potentially inadequate results. To address this issue, this study focuses on intact, damaged, moldy, and shriveled wheat grains, and establishes a YOLO-wheat automatic wheat grain appearance quality detection model. First, a large number of wheat grain sample images were collected, preprocessed, and annotated. Next, YOLOv5n, YOLOv8n, and YOLOv10n wheat grain object detection models were established, and the optimal model YOLOv8n was selected as the base model for automatic wheat grain appearance quality detection. To further improve wheat grain detection performance, the Dilation-wise Residual (DWR) module was integrated into the YOLOv8n network structure to enhance feature extraction from the expandable receptive field in the higher layers of the network. Additionally, the TripletAttention attention mechanism was introduced, and this improved network was named YOLO-wheat. Experimental results showed that YOLO-wheat achieved an mAP value of 91.3% in wheat grain appearance quality detection, representing a 4.3% improvement compared to the previous version. This study provides technical support for automatic wheat quality detection.

摘要
小麦籽粒是一种常见的谷物类品种，且由于其数量多需求量大，在传统人工品质检测时耗费大量精力而效果不见得足够好。为解决上述问题，本研究以小麦完善粒、破损粒、发霉粒和干瘪粒为研究对象，建立 YOLO-wheat 小麦籽粒外观品质自动检测模型。首先，采集了大量小麦籽粒样本图像，并进行了数据预处理和标注整理。其次，建立了 YOLOv5n、YOLOv8n、YOLOv10n 小麦籽粒目标检测模型，从中选取最优模型 YOLOv8n 为小麦籽粒外观品质自动检测基础模型。为了进一步提升小麦籽粒检测性能，在 YOLOv8n 网络结构中使用 Dilation-wise Residua(DWR)模块加强从网络高层的可扩展感受野中提取特征，并引入了 TripletAttention 注意力机制，将此网络命名为 YOLO-wheat。实验结果表明 YOLO-wheat 在小麦籽粒外观品质检测中 mAP 值为 91.3%,较改进前提升 4.3% 。该研究可为小麦品质自动检测提供技术支持。

INTRODUCTION
In daily life, wheat is one of the most demanded and high-quality food products for human consumption (*Zahra et al., 2023; Shewry et al., 2023*), requiring both high quantity and quality standards. However, due to its large volume and the difficulty in distinguishing quality categories, traditional manual inspection methods are highly complex, time-consuming, and labor-intensive, often leading to unsatisfactory results. With the development of machine vision and deep learning technologies, the use of computers to achieve automated analysis of target detection images (*Dhanya et al., 2022)* has become a powerful tool to solve this problem, improving production efficiency and reducing labor costs. Therefore, machine learning and deep learning techniques can be utilized in combination with large datasets of labeled wheat grain samples to perform target detection on wheat grains through automated and intelligent methods, promoting the modernization and intelligent development of the agricultural industry. Furthermore, this can later be integrated with robotics to achieve intelligent agriculture (*Soori et al., 2024*).

Target detection tasks based on deep learning have been widely applied in agricultural production due to their high precision and rapid detection capabilities. In 2021, *Wang Qiujin et al., (2021)*, developed a wheat fusarium head blight grain recognition model based on feature band fusion images and deep learning algorithms. By comparing recognition accuracy, the optimal deep learning model was selected, enabling real-time online detection of fusarium-infected wheat grains.

In 2023, *Wang Ling et al., (2023*), proposed a wheat grain counting method based on the YOLOv7-ST model. The YOLOv7-ST model accurately and quickly detected issues such as grain occlusion and adhesion under varying degrees of dispersion, significantly improving the efficiency of wheat seed testing. In 2024, *Yu Zhaofu et al., (2024*) proposed a genetic algorithm-based optimizer designed for the YOLOv8 network, addressing the challenge of optimizing complex networks through intelligent algorithms, thus providing a better method for soybean grain recognition. *Tomáš Zoubek et al., (2024)*, conducted a comparative study of YOLO models for weed and crop recognition. By adjusting different parameters, the model was fine-tuned to address weed recognition challenges, and it was determined that different models showed improved performance for specific feature detection problems. In 2024, *Ma et al.* (*2024*), focused on wheat grains and proposed an improved YOLOv8-based wheat grain detection and counting method. Today, the applications of deep learning in agriculture are not limited to crop recognition. *Yue et al., (2024),* proposed a lightweight pest detection method based on an improved YOLOv8 model, capable of identifying dynamic pests affecting crops. This method enhanced YOLOv8's feature extraction capabilities, addressing issues like low precision in small-object detection and improving the model's suitability for embedded deployment, providing valuable insights for the lightweight model in this study. In addition, YOLO models can be repeatedly modified to make them better suited for specific detection scenarios. For instance, *Liu et al., (2024*), proposed a Fusion Transformer YOLO-based model for grape disease detection. *Sangaiah et al, (2024),* developed UAV T-YOLO-Rice, an efficient and lightweight rice leaf disease detection model; and *Ren et al, (2024*), introduced the FPG-YOLO model for detecting pollination stamens of "Yulu Fragrant" pears in unstructured environments. These studies demonstrate that target detection algorithms show excellent performance in agricultural modernization, especially in crop localization and recognition. Beyond agriculture, YOLOv8n-based models have also been improved for various applications. For instance, *Li Bohao et al.,* (*2024*), proposed an improved UAV aerial small-object detection algorithm model based on YOLOv8n. *Qin et al., (2024),* developed a cable switch fault diagnosis model based on YOLOv8n; and *Yang Ruijun et al.,* (*2024),* designed a lightweight remote sensing image detection algorithm for military aircraft using YOLOv8n. These applications highlight that visual detection using the YOLOv8n base model has found use across diverse fields, providing inspiration for this study. However, research on detecting wheat grains of varying qualities remains relatively scarce, with low recognition accuracy. Therefore, this study focuses on detecting the quality of wheat grains, specifically intact grains, damaged grains, moldy grains, and shriveled grains, using deep learning methods for intelligent quality detection.

First, a large dataset of wheat grain images was collected and annotated using labeling. The detection performance of YOLOv5n, YOLOv8n, and YOLOv10n was compared, and the YOLOv8n model was ultimately selected as the base model. To further enhance the detection accuracy of the model, the Dilation-wise Residual (DWR) module, which is more suitable for small-object detection, and the TripletAttention attention mechanism were integrated into the YOLOv8n model. The enhanced model, named YOLO-wheat, was developed to achieve automated detection of wheat grain appearance quality.

MATERIALS AND METHODS

Data Acquisition and Pre-processing

In this study, a total of 684 images of intact grains, damaged grains, moldy grains, and shriveled grains were collected (*Zhixiao et al., 2020*). These images included various scenarios such as white backgrounds, black backgrounds, different shooting angles, varying lighting conditions, different rotation degrees, and scattered stacking, aiming to realistically replicate various situations that may occur in practical application scenarios. Figure 1 shows some of the collected wheat grain images.

(a)White Background

(b)Black Background

Fig. 1 - Partial Data Collection

The images were annotated using labeling in the YOLO format. During annotation, the mouse was used to accurately draw bounding boxes on the images, ensuring that no wheat grains were missed. Each grain in the images was labeled according to its appearance quality, categorized into four classes: intact grains (denoted as "w"), damaged grains (denoted as "p"), moldy grains (denoted as "f"), and shriveled grains (denoted as "g"). The annotation results were then saved for subsequent operations.

Since images captured in a laboratory environment cannot fully reflect real-world scenarios, data augmentation techniques were applied to enrich the dataset. The collected images were further processed with random rotations, noise addition, brightness adjustments, and other image enhancement methods. These techniques were randomly combined to simulate various situations that might be encountered in practical algorithm application scenarios. Figures 2 and 3 show a comparison between the original wheat grain images and the augmented images under different backgrounds.

Fig. 2 - Comparison of Data Augmentation Effects for Wheat Grains on a Black Background

Fig. 3 - Comparison of Data Augmentation Effects for Wheat Grains on a White Background

The images were divided into a training set, validation set, and test set in a ratio of 7:2:1. The specific distribution is shown in Table 1. The dataset is categorized into two types: black background and white background. There are 348 images with a white background and 336 images with a black background. Among the white background images, the training set, validation set, and test set contain 243, 70, and 35 images, respectively. For the black background images, the training set, validation set, and test set contain 235, 67, and 34 images, respectively.

Table 1

Comparison of Experimental Parameters for Each Model

Augmented dataset	White Background	Black Background	Augmented dataset	White Background	Black Background
Training Set	243	235	Training Set	243	235
Validation Set	70	67	Validation Set	70	67
Test Set	35	34	Test Set	35	34
Total	348	336	Total	348	336

YOLOv8n Model

The YOLO algorithm series has a long history of development (*Jiang et al., 2020; Terven et al., 2023*). Among them, YOLOv8n is a state-of-the-art, lightweight object detection model capable of processing images in real-time and identifying various objects within them. It demonstrates superior performance in addressing the issues designed in this study. For instance, in real-world application scenarios, it can provide rapid feedback, allowing operators sufficient time to address problems identified after detection. This makes it highly practical in terms of both usability and accuracy.

The YOLOv8n network model primarily consists of three components: the Backbone, the Neck, and the Head. In deep learning-based object detection algorithms, these three major components have distinct roles. The Backbone is mainly responsible for increasing the feature depth and level of abstraction of the input image, transforming it into feature maps that contain various information such as the location and shape of objects in the image. The Neck is primarily designed to aggregate feature information from different levels and is situated between the Backbone and the Head. The Head is used to predict the categories and locations of objects, including their bounding boxes. The basic structure of a deep learning-based object detection algorithm follows the sequence: Input → Backbone → Neck → Head → Output.

DWR（Dilation-wise Residual）Model

The DWR module acts as a tool for extracting features at different scales in the higher layers of the network, significantly improving the algorithm's accuracy, it's structure as shown in Figure 4. First, a multi-branch structure is used to expand the receptive field, where each branch employs a dilated depthwise convolution with different dilation rates. Second, a specially designed Simple Inverted Residual (SIR) module is used to extract features from the lower layers of the network. This module has only a small receptive field of 3×3 and adopts an inverted bottleneck structure to expand the number of channels, ensuring stronger feature extraction capability. Finally, based on the combination of the DWR module and the SIR module, the network DWRSeg was constructed. In this network, the decoder adopts a simple structure similar to FNC. The decoder uses strong semantic information from the last two stages to directly upsample the feature maps and then concatenate them with feature maps from earlier stages for the final prediction.

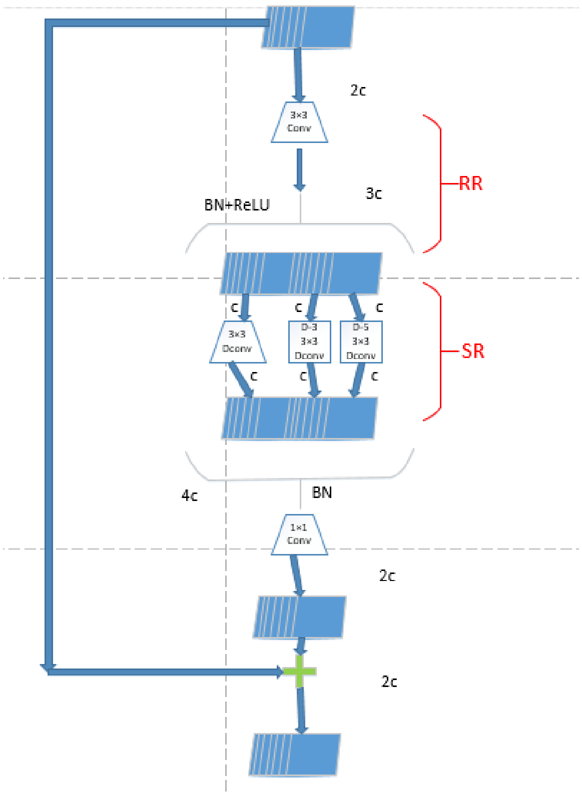


Fig. 4 - Diagram of the DWR Module

In summary, the introduction of the DWR (Dilation-wise Residual) module in the YOLO algorithm plays a crucial role in improving the accuracy of object detection. Its efficiency lies in the following key aspects:(1) Powerful receptive field expansion capability: The DWR module leverages the characteristics of dilated convolution to expand the receptive field of the convolution operation on the input image. This helps the network capture more extensive spatial information in the image. By expanding the receptive field, the model can better understand object features such as position, size, and shape, thereby improving the accuracy of object detection. (2) Multi-scale feature fusion: The DWR module introduces a residual connection mechanism to fuse feature information at different scales, enabling the network to comprehensively utilize feature representations from multiple levels. Through residual connections, the model can better learn semantic information across different scales, enhancing its ability to detect objects in complex scenes and small targets. (3) Enhanced network representation capability and learning efficiency: By incorporating residual connections and dilated convolution, the DWR module improves the network's representation capacity and learning efficiency. Residual connections help mitigate the vanishing gradient problem, accelerate the network's convergence process, and improve the model's learning efficiency.

Meanwhile, dilated convolution enhances the network's ability to learn contextual information from the image, enabling it to better understand global information in the image, thereby improving object detection accuracy. The introduction of this module allows the YOLO algorithm to achieve better performance in object detection tasks and demonstrates greater potential for practical applications.

TripletAttention Model

The Triplet Attention mechanism (Triplet Attention) refers to a mechanism in the field of deep learning that enables models to focus on multiple specific regions. It is a specialized attention mechanism designed for processing sequential data, extending the traditional bidirectional attention mechanism. It allows the model to simultaneously consider the past, present, and future information when calculating attention weights.

The YOLOv8-ALTE bridge crack detection algorithm proposed by *Yang et al. (2024)* incorporates the Triplet Attention mechanism into the shallow layers of the backbone feature extraction module. In the traditional bidirectional attention mechanism, the model generates attention weights based on the current input and achieves a more specific and detailed understanding of the context by comprehensively considering a series of historical and future information. The Triplet Attention mechanism introduces the representation of future information, enabling the model to balance the importance of past, current, and future information when calculating attention weights. Specifically, the Triplet Attention mechanism consists of three independent attention weight vectors, which represent the importance of past, present, and future information, respectively. These three attention weights are then combined to produce the final attention weight.

This mechanism is often applied to tasks such as image segmentation and object detection to help models better focus on important regions of the image, thereby improving model performance and accuracy.

In the field of deep learning, attention mechanisms are typically used to help models focus on important parts of the input when processing sequential data or images. By weighting and integrating information from different parts, attention mechanisms enhance the model's ability to process input effectively. Multi-head attention, on the other hand, learns multiple sets of different attention weights in various subspaces, allowing for a more comprehensive capture of the complex features of the input data. Triplet Attention combines these two mechanisms to help the model focus on three important regions in an image.

By learning three sets of different weight parameters, the model can independently focus on these three regions and better integrate their information to understand the image. This mechanism improves the model's ability to locate and recognize objects, thereby enhancing the performance of tasks such as object detection. The Triplet Attention mechanism offers several advantages, including a comprehensive understanding of context, reduced risk of information leakage and overfitting, and improved predictive performance. Therefore, this study primarily improves the YOLOv8n algorithm based on the Triplet Attention mechanism.

Improvement Method in This Study

The shape of wheat grains is inherently small, and factors such as adhesion further increase the difficulty of wheat grain detection. To enhance the model's ability to extract features of small objects, this study incorporates a Dilation-wise Residual (DWR) module into the C2F module of the YOLOv8n backbone network. In C2F module, the feature aggregation functionality is mainly implemented by the Bottleneck module. Therefore, in the process of algorithm improvement in this paper, the Bottleneck module is replaced with the DWR module to achieve a shift in the feature aggregation direction. This modification shifts the detection focus toward the feature extraction of small objects, strengthening the network's ability to extract features of wheat grains and improving the network's capability to learn image details and contextual information. This ultimately enhances the accuracy and robustness of the detection results. Additionally, the Triplet Attention mechanism is integrated into the YOLOv8n model after the 9th-layer SPPF module. This enables the network to focus more on multiple specific regions and capture the minute features of wheat grains, thereby enhancing the network's effectiveness in handling complex target scenes.

This makes the model's feature extraction and recognition capabilities more precise and reliable. The improved network is named YOLO-wheat (as shown in Figure 5). The YOLO-wheat model comprehensively understands the context, reduces the risks of information leakage and overfitting, and improves prediction performance, ultimately enhancing the recognition results.

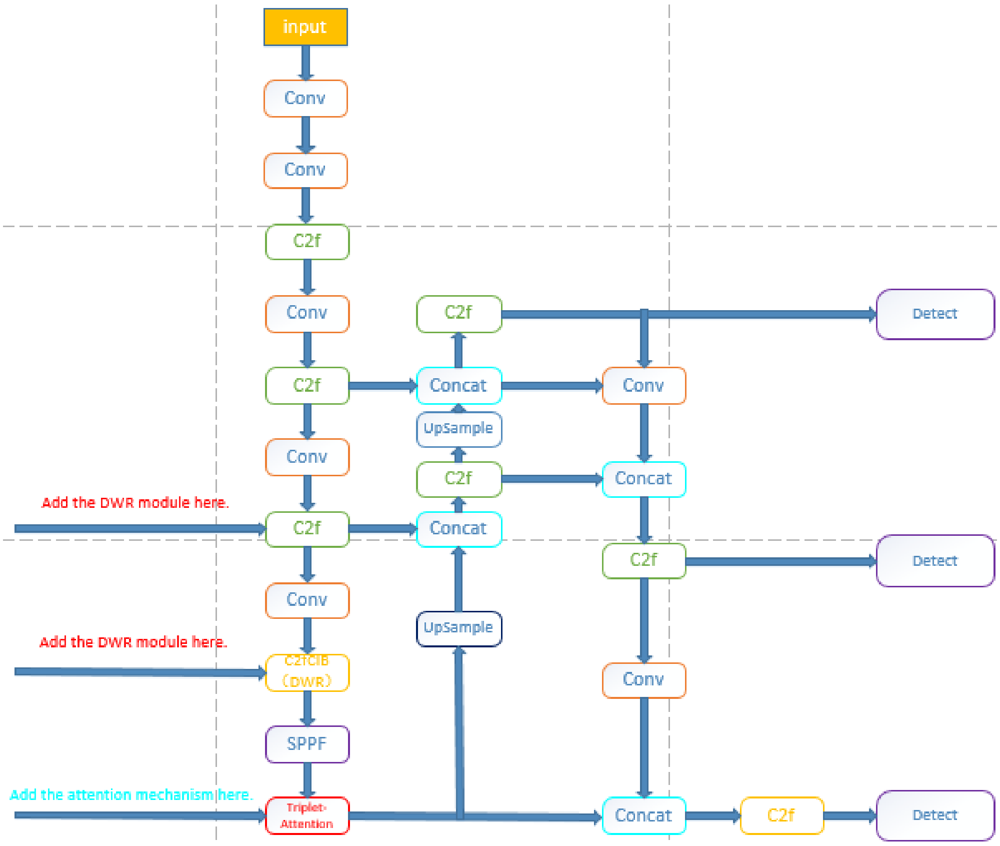


Fig. 5 - Flowchart of the Improved Algorithm Network

Model Evaluation Metrics

To quantitatively evaluate the performance of the proposed method and other comparative methods, three metrics were adopted as the evaluation criteria for object detection: Precision, Recall, and Mean Average Precision (mAP). These metrics can be calculated using Equations (1) to (4).

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

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

$$AP = \sum_n (R_n - R_{n-1})P_n \tag{3}$$

$$mAP = \frac{1}{|C|}\sum_{i=1}^{|C|} AP_i \tag{4}$$

Here, TP and FP represent the number of true positives and false positives, respectively. FN indicates the number of all actual instances that the network model failed to detect. n is the index of data points sorted in ascending order based on recall, P_n (Precision) denotes the precision of the data point at index n, R_n (Recall) denotes the recall of the data point at index n, $|C|$ represents the number of categories, and AP_i denotes the average precision for category i.

RESULTS

The operating system used for the experiment was Windows 10. The GPU model was NVIDIA GeForce RTX 3080. The CPU model was 12th Gen Intel(R) Core(TM) i7-12700H 2.30 GHz. The system memory was 16GB, and the solid-state drive capacity 1TB. The GPU acceleration libraries used were CUDA 12.3 and cuDNN 8.7. The Python version used was Python 3.11.7, and the deep learning framework PyTorch 2.3.1. The image size for deep learning training was 640×640 pixels, with 200 training epochs.

Comparison of Detection Results for YOLO Models

In this study, YOLOv5, YOLOv8, and YOLOv10 models for wheat grain quality detection were developed, and the experimental results are shown in Table 2.

As observed in Table 2, the YOLOv8n model achieved the highest mAP value of 87%, demonstrating the best detection performance.

From the above analysis, it is evident that the core parameters of YOLOv8n are superior, resulting in better detection outcomes. Therefore, this study adopts YOLOv8n as the baseline model and optimizes it further to achieve efficient detection of wheat grain quality.

Table 2

Comparison of Experimental Parameters for Different YOLO Models

Model	P	R	mAP	mAP0.5:0.95	GFLOPs
YOLOv10n	72.7	76.2	81	65.5	6.5
YOLOv8n	79.7	79.7	87	66.3	7.6
YOLOv5n	73.7	82.7	85.5	65.9	7.1

Detection Results of the Improved Algorithm

To evaluate the effectiveness of the improved algorithm, experiments were conducted on the wheat grain dataset using the improved YOLO-wheat model and the baseline YOLOv8 model. The results are shown in Table 3. In the table, “w” represents the "intact" category, “p” represents the "damaged" category, “f” represents the "moldy" category, and “g” represents the "shriveled" category. As seen in the table, after applying the improved algorithm, the mAP value for the "intact" category increased from 93.3% to 95.6%, with an improvement of 2.3%. For the "damaged" category, the mAP value increased from 89.9% to 93.4%, with an improvement of 3.5%. For the "moldy" category, the mAP value increased from 84.2% to 87.5%, with an improvement of 3.3%. For the "shriveled" category, the mAP value increased from 80.2% to 88.9%, with an improvement of 8.7%. Overall, the mAP value for all categories improved from 87% to 91.3%, showing an increase of 4.3%. The mAP@0.5:0.95 metric improved from 66.3% to 75.8%. These results demonstrate that the proposed YOLO-wheat model achieves better detection performance for different categories of wheat grains.

Table 3

Detection results with YOLO-wheat and YOLOv8n

Model	Category	P	R	mAP	mAP0.5:0.95
YOLOv8n	w	85.9	87.1	93.9	74.4
	p	81.7	84.1	89.9	68.6
	f	77.4	75.1	84.2	61.2
	g	73.8	72.7	80.2	60.9
	all	79.7	79.7	87	66.3
YOLO-wheat	w	88.8	90	95.6	81.5
	p	90.3	87.3	93.4	77.5
	f	81.4	78.6	87.5	71.4
	g	84	74.7	88.9	72.9
	all	86.1	82.7	91.3	75.8

Ablation Experiment

As shown in Table 4 of the ablation experiment results, the baseline YOLOv8n algorithm achieves an mAP of 87%. After adding the DWR module to YOLOv8n, the mAP increases to 90%. When only the Triplet Attention is added, without the DWR module, the mAP reaches 89.1%. Finally, when both DWR and Triplet Attention are incorporated together, the model achieves the best recognition performance: Precision increases to a maximum of 86.1%, Recall rises to a maximum of 82.7%, and mAP reaches a peak of 91.3%.

The experimental results demonstrate that adding either DWR or Triplet Attention individually enhances the network's feature extraction capability, but the performance is optimal when both are incorporated into the network.

Table 4

The results of the ablation experiment

Baseline	DWR	Triplet Attention	P	R	mAP
√	×	×	79.7	79.7	87
√	√	×	84.6	81.8	90
√	×	√	82.3	82.7	89.1
√	√	√	86.1	82.7	91.3

Overall, YOLO-wheat has the following advantages over the original YOLOv8 model: With the addition of the Triplet Attention mechanism, the model can better and more accurately capture important information in images, improving the precision and performance of object detection, particularly for detecting the appearance and types of wheat grains. It also enhances the handling of both global and local information. The DWR module allows the algorithm to provide better feature extraction for complex and small objects by expanding the receptive field. In other words, the Triplet Attention mechanism helps balance the attention given to global and local information, making the model more effective at handling targets of different scales. The DWR module, on the other hand, offers better adaptability to complex backgrounds and higher precision for small targets.

Experimental results with different backgrounds

In real-world application scenarios, different backgrounds may be encountered. Therefore, during the data collection phase, wheat grains were collected with both white and black backgrounds to explore the impact of background color on the algorithm's accuracy. The detection results of wheat grains with different backgrounds using the YOLO-wheat algorithm established in this paper are shown in Table 5. From Table 5, it can be observed that compared to the white background, the Precision of wheat grains with the black background increased by 14.4%, and the mAP improved by 7.8%. Specifically, the mAP for intact grains increased by 3.1%, the mAP for damaged grains increased by 5.2%, the mAP for moldy grains increased by 12.7%, and the mAP for shriveled grains increased by 10.2%. This suggests that background color has a certain impact on wheat grain detection, with a more significant improvement in target detection when using a black background. In practical applications, setting the background to black would yield the best detection results.

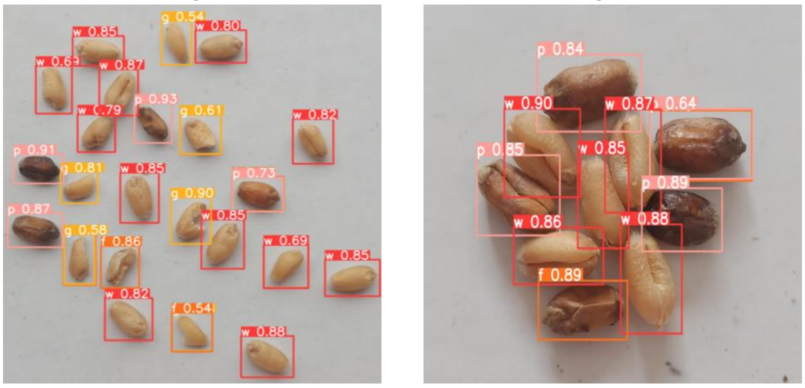
Table 5

Detection results under different backgrounds

Background	Category	P	R	mAP	mAP0.5:0.95
White background	w	84.3	94.4	92.1	71.8
	p	75.1	89.1	91.9	68.8
	f	75.9	73.9	82.2	59.2
	g	70.7	77.8	83.6	64.1
	all	76.5	83.3	87.5	66
Black background	w	96.9	83.3	95.2	65.9
	p	92.9	89.9	97.1	61.9
	f	88.5	88.6	94.9	61.7
	g	85.6	86.8	93.8	65.3
	all	90.9	87.2	95.3	63.7

Visualization of detection results

The trained YOLO-wheat model was used to validate the wheat grain dataset, and the detection results are shown in Figure 6. It can be observed that the improved algorithm in this study performs well in detecting both dispersed and clustered wheat grains under black and white backgrounds.



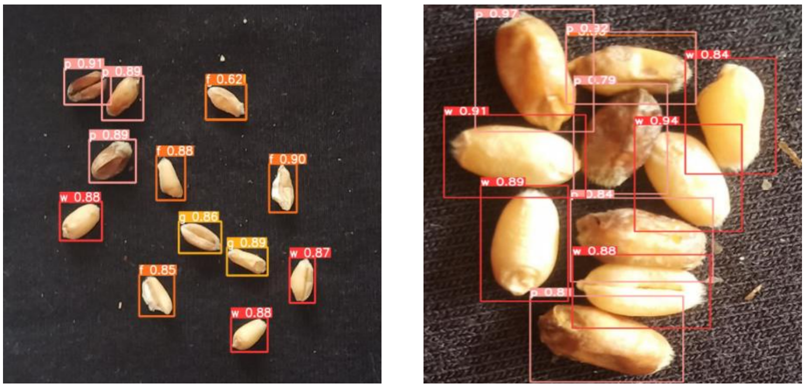


Fig. 6 - Visualization of detection results

CONCLUSIONS

With the development of machine learning and deep learning technologies, machine vision has become increasingly widespread in the agricultural sector. This study successfully developed an improved object detection model based on YOLOv8n, named YOLO-wheat, which aims to precisely locate the position and recognize the appearance quality of wheat grains. It provides technical support for intelligent wheat harvesting and recognition, as well as data collection for wheat yield analysis, making it suitable for related production environments.

(1) The dataset used in this study was constructed with black and white backgrounds as templates, incorporating image processing techniques such as random rotation, noise addition, and brightness adjustment. The goal was to simulate real-world environmental conditions and provide optimal templates for real detection environments. For example, detection should ideally be performed in a black background setting.

(2) This study employed the DWR module and the Triplet Attention module to enhance the recognition performance. YOLOv8n was used as the base model, with the DWR module placed in the C2F (Cross Feature Fusion) layer, and the Triplet Attention mechanism added after the SPPF (Spatial Pyramid Pooling Fast) layer to further improve the accuracy of the YOLOv8n model. The improved model achieved a mean Average Precision (mAP) of 91.3% for wheat grain quality detection, a 4.3% improvement over the original YOLOv8n model. This demonstrates that the proposed improvement enhances accuracy for small object detection.

This study focused on the appearance quality detection of a single type of wheat grain. However, the quality detection of multiple wheat varieties remains limited, highlighting the need for a more comprehensive dataset to increase sample diversity and improve the model's generalization capability. Finally, as this experiment is still in the algorithm research phase, further research and design of lightweight models or optimized algorithms for high-real-time scenarios may be needed before applying this in actual automated classification tasks.

ACKNOWLEDGEMENT

This research, titled “Wheat Grain Appearance Quality Detection Based on Improved YOLOv8n ”, was funded by The College Students Innovation Training Program of Shanxi Agricultural University (202410113026) and the Basic Research Program of Shanxi Province (202303021212115).

REFERENCES

[1] Dhanya V.; Subeesh A.; Kushwaha N.; Vishwakarma D.; Nagesh K.; Ritika G.; Singh A. (2022). Deep learning based computer vision approaches for smart agricultural applications. *Artificial Intelligence in Agriculture*, 6, 211-229.

[2] Jiang P.; Ergu D.; Liu F.; Cai Y.; Ma B. (2022). A Review of Yolo algorithm developments. *Procedia computer science* 199: 1066-1073.

[3] Li B.; Li Z. (2024). UAV Aerial Small Target Detection Algorithm Based on Improved YOLOv8n [J]. *Intelligent Computer and Applications*, 1-9.

[4] Liu Y.; Yu Q.; Geng S. (2024). Real-time and lightweight detection of grape diseases based on Fusion Transformer YOLO. *Frontiers in Plant Science*, 15, 1269423.

[5] Ma N.; Li Z.; Kong Q. (2024). Wheat grains automatic counting based on lightweight YOLOv8. *INMATEH-Agricultural Engineering*, 73(2).

[6] Qin X.; Li A.; Wang C. (2024). Fault Diagnosis of X-DR Cable Switch Based on Lightweight SGG-YOLOv8n [J]. *Journal of Changsha University of Science and Technology (Natural Science Edition)*, 1-1.

[7] Ren R.; Sun H.; Zhang S.; Zhao H; Wang L.; Su M.; Sun T. (2024). FPG-YOLO: A detection method for pollenable stamen in 'Yuluxiang' pear under non-structural environments. *Scientia Horticulturae,* 328, 112941.

[8] Sangaiah A.; Yu F.; Lin Y.; Shen W.; Sharma A. (2024). UAV T-YOLO-rice: An enhanced tiny YOLO networks for rice leaves diseases detection in paddy agronomy. *IEEE Transactions on Network Science and Engineering*, 11(6), 5201-5216.

[9] Shewry P. (2023). Wheat grain proteins: Past, present, and future. *Cereal chemistry*, 100(1), 9-22.

[10] Soori M.; Arezoo B.; Dastres R. (2023). Artificial intelligence, machine learning and deep learning in advanced robotics, a review. *Cognitive Robotics*, 3, 54-70.

[11] Terven J.; Esparza C.; González R. (2023). A comprehensive review of yolo architectures in computer vision: From yolov1 to yolov8 and yolo-nas. *Machine Learning and Knowledge Extraction.* 5.4: 1680-1716.

[12] Wang L.; Zhang Q.; Feng T.; Wang Y.; Li Y.; Chen D. (2023). Research on Wheat Grain Counting Method Based on YOLO v7-ST Model [J]. *Transactions of the Chinese Society of Agricultural Machinery*, 54(10): 188-197.

[13] Wang Q. (2021). Research on Wheat Fusarium Head Blight Grain Recognition Method and Online Detection System Based on Deep Learning [D]. *Nanjing Agricultural University.*

[14] Yang R.; Zhang H.; Cheng Y. (2024). Lightweight Remote Sensing Image Military Aircraft Detection Algorithm Based on Improved YOLOv8n [J]. *Electronic Measurement Technology*, 1-12.

[15] Yang W.; Fang H.; Tang X. (2024). Lightweight YOLOv8-ALTE Algorithm for Bridge Crack Disease Detection [J]. *Journal of Traffic and Transportation Engineering*, 1-17.

[16] Yu Z. (2024). Construction of Genetic Algorithm Optimizer and Its Application in Soybean Grain Recognition Based on YOLO Algorithm [D]. *Wuhan University of Light Industry.*

[17] Yue G.; Liu Y.; Niu T.; Liu L.; An L.; Wang Z.; Duan M. (2024). Glu-yolov8: An improved pest and disease target detection algorithm based on yolov8. *Forests*, 15(9), 1486.

[18] Zahra N.; Hafeez M.; Wahid A.; Al M.; Ullah A.; Siddique K.; Farooq M. (2023). Impact of climate change on wheat grain composition and quality. *Journal of the Science of Food and Agriculture*, 103(6), 2745-2751.

[19] Yang Z.; Fan Y.; Zheng Q. (2020). Study on the time-varying characteristics of appearance quality of stored wheat. *Journal of Henan University of Technology (Natural Science Edition)* 41.5: 116-120.

[20] Tomáš Z.; Roman B.; Jean D.; Miroslav S.; Martin F.; František Š.; Petr B. (2025). Advancing precision agriculture with computer vision: A comparative study of YOLO models for weed and crop recognition. *Crop Protection* 107076-107076.