EGG QUALITY DETECTION BASED ON LIGHTWEIHT HCES-YOLO
/
基于轻量化的 HCES-YOLO 的鸡蛋品质检测算法

Zhimin TONG*), Shengzhang LI, Chuanmiao SHI, Tianzhe XU, Yu ZHOU, Changhao LI
1) College of Electrical and Mechanical Engineering, Qingdao Agricultural University, Qingdao/ China
Tel: +8615845982569; E-mail: leicahit@qau.edu.cn
Corresponding author: Zhimin Tong
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ABSTRACT
The quality detection of eggs based on deep learning faced many problems, such as similar feature colors and low computational efficiency, which resulted in an increased probability of false detection or missed detection. To effectively solve these problems, this paper proposed an egg quality detection method based on YOLOv8n, which integrated the ContextGuideFusionModule, EfficientHead, and SIOU loss functions by improving the backbone network. The recognition rate from the field test was 88.4%, indicating that the algorithm could meet the real-time monitoring requirements, effectively identify the quality status of eggs, and provide support for intelligent poultry house management.

摘要
基于深度学习的鸡蛋的品质检测面临特征颜色相近，计算效率低等诸多问题，导致误检或漏检的概率增加。为有效解决这些问题，本文提出了一种基于 YOLOv8n，通过改进骨干网络，集成 ContextGuideFusionModule、EfficientHead 和 SIOU 损失函数的鸡蛋品质检测方法。现场试验识别率为 88.4%，表明该算法能满足实时监测，有效的识别鸡蛋的品质状态，为智能化禽舍管理提供支持。

INTRODUCTION
Eggs, as one of the main foods for humans, are rich in protein, fat, and other important nutrients. With the improvement of food safety awareness, the quality of eggs is getting more and more attention. The appearance of eggs is one of the important indexes to evaluate their quality, which is usually negatively correlated with egg age (*Eddin et al., 2019*; *Hisasaga et al., 2020*; *Malfatti et al., 2021*). Traditional methods for assessing egg appearance utilized the Haugh unit (HU) to evaluate quality by measuring the weight and protein height of the eggs. However, this approach was often destructive and applicable only to sampling, failing to meet the demands of modern agriculture for large-scale production. Such losses were unacceptable to hatcheries, the food processing industry, and consumers (*Guanjun et al., 2019*). Currently, non-destructive testing of egg defects primarily relied on transmission techniques, which typically required observing the eggs under a light source. For instance, Omid et al. extracted features of crack regions through spatial transformations of the HSV color space of images, constructing a corresponding discriminant system with an accuracy rate of 94.5% (*Omid et al., 2013*). Cruz-Tirado et al. combined near-infrared spectroscopy with a PLS-DA model to identify fresh and unfresh eggs, achieving an accuracy of 87% (*Cruz-Tirado et al., 2021*). Dong et al. developed a method based on VIS-NIR spectroscopy that established a quantitative model for the freshness of different egg varieties through global updates, direct standardization, and slope/deviation correction (*Dong et al., 2020*). However, this method proved inefficient in practical applications, with poor sanitation conditions and a propensity for errors. Therefore, there was an urgent need for a rapid and non-invasive technique to evaluate egg quality.

Research indicated that abnormal eggs exhibited noticeable color differences compared to normal eggs, which can be identified by taking multiple sets of egg surface images to extract abnormal features. For example, Yao et al. employed hyperspectral imaging (HSI) technology to assess both the internal and external quality of eggs, achieving an overall accuracy rate of 93.33% (*Yao et al., 2022*). Luo et al. constructed an egg collection system to obtain images of severely damaged eggs and applied an improved YOLOv5 algorithm for their identification, ultimately achieving an accuracy of 92.4% (*Luo et al., 2023*).

Narushin et al., (2023), and *Sehirli et al., (2022),* conducted a comparative analysis of various non-destructive detection methods based on existing studies. In recent years, with the continuous improvement of computing power, many researchers have begun to use deep learning technology to quickly and accurately judge the quality and grade of agricultural products, thereby improving their added value and market competitiveness (*Okinda et al., 2020*; *Turkoglu et al., 2021*; *Zhao et al., 2023*). *Du et al., (2024)*, realized the effective identification of young apples by improving the YoLOV5 algorithm, with an average accuracy of 82.2%. *Liang et al. (2024*), realized the effective identification of maize pests and diseases by improving the YoLOV8 n algorithm, and the average accuracy reached 94.8 %. Compared to other YOLO models, YOLOv8 demonstrated higher detection precision and efficiency in object detection tasks, showcasing remarkable overall performance (*Gevorgyan et al., 2022*; *Xu et al., 2024*; *Yang et al., 2023)*. Consequently, some scholars applied the YOLOv8 algorithm to target detection in the livestock industry to enhance production efficiency and product quality (*Wang et al., 2024*; *Yang et al., 2023*). However, previous studies mainly focused on the assessment of single quality parameters, while research on the multi-quality detection of eggs remained relatively scarce. Therefore, this paper designs a lightweight model method to accurately identify the quality of eggs. This project optimizes the YOLOv8n algorithm, uses the HGNetv2 (*Zhao et al., 2024*) network to replace the original backbone network, and introduces the pyramid network ContextGuideFusionModule (*Hu et al., 2018*). The lightweight grouping convolution detection head EfficientHead (*Zhang et al., 2019*) is used and the CIOU loss function is replaced with the SIoU (*Gevorgyan et al., 2022*) loss function, named HCES-YOLOv8 algorithm. The algorithm aims to replace the traditional detection methods to achieve effective detection of objects in many fields such as animal husbandry production lines, thereby improving the detection effect.

The purpose of this study is to use the improved YOLOv8 network to perform multiple quality assessments of egg quality, focusing on:

(1) The morphological characteristics of egg appearance were extracted to identify different quality problems, such as color, breakage and contaminants, etc.;

(2) Create a multiple egg quality assessment data set to fill the existing non-destructive quality test data and facilitate a more comprehensive assessment of egg quality;

(3) The original network of YOLOv8n was improved to establish a model suitable for egg quality detection.

MATERIALS AND METHODS

Image acquisition system

An egg image acquisition platform is built in the laboratory, as shown in Fig. 1. The main hardware of the system consists of four parts: camera, 15w LED light source, computer and conveyor belt. The industrial camera used in this study is a CMOS type, which can capture a 1920×1080 pixel RGB image using a 90° distortionless fixed-focus lens. In this study, the LED light source was placed directly above the egg slope to illuminate the characteristics of the egg surface and facilitate the observation of the upper surface of the egg. This method is easy to install and can meet the image acquisition requirements of light source installation.

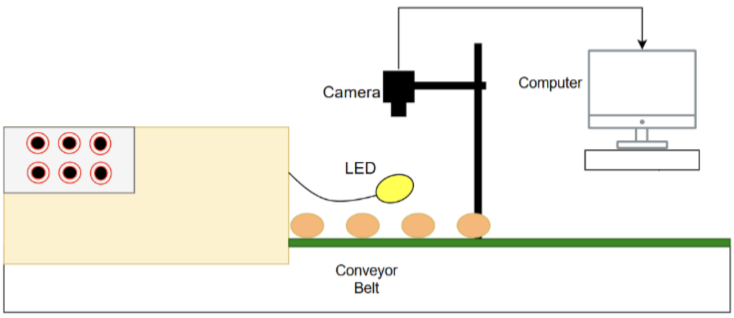


Fig. 1 – Egg image acquisition system

Image acquisition

In this study, eggs were used as experimental subjects, and the selected egg samples were obtained from Kaimeng Farm in Wudi County. In order to improve the experimental results, the obtained images will be manually classified. According to the eggshell characteristics, the eggs were divided into white spotted eggs, brown spotted eggs, pink skin eggs, white skin eggs, blood-stained eggs, broken shell eggs, dirty eggs and normal eggs. A total of 1100 images were taken, and Fig. 2 is the egg category map. The bounding boxes and categories of all objects in each image are labelled, and the corresponding annotation files are generated.

In order to simulate different conditions and enhance the robustness of the model, data enhancement methods such as mirroring, rotation, cropping, and brightness transformation are randomly used, and brightness transformation coefficients are randomly generated in the interval to double the number of images. After selection, 3300 enhanced egg images constitute an egg quality detection data set, numbered in order. Finally, the data set was divided into training set, validation set and test set according to the ratio of 7: 2: 1, including 2310, 660 and 330 egg images, respectively.

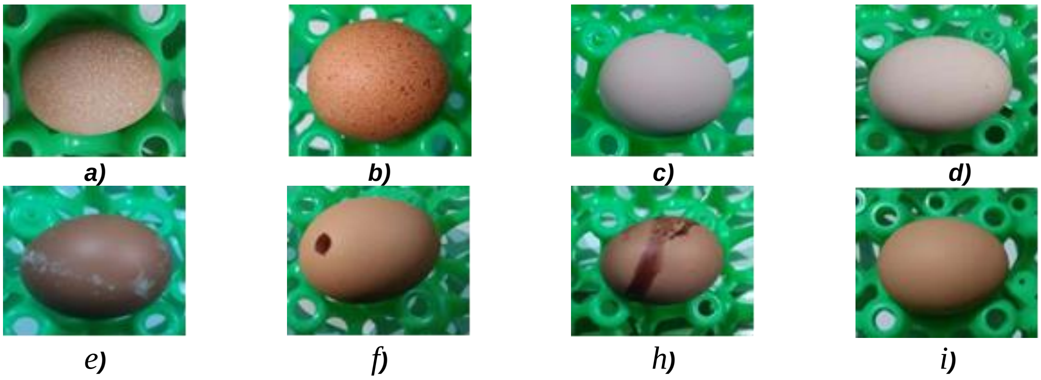


Fig. 2 – Egg category distinction diagram

a) White spotted egg; b). Brown spotted egg; c) Pink skin egg; d) White skin eggs; e) Bloody eggs; f) Broken egg; h) Dirty egg; i) Normal egg

YOLOv8n model

YOLO model is a single-stage target detection algorithm. Its core idea is to divide the image into regions and predict them, which has the characteristics of fast and efficient training. The backbone feature extraction network of YOLOv8 consists of CBS module, C2f module and SPPF module. The C2f module combines the design of the C3 module and the efficient lightweight attention network, which enhances the feature fusion ability and speeds up the inference speed. Based on the concept of spatial pyramid pooling, the SPPF module has lower parameters and calculation amount, which effectively expands the receptive field of the model and improves the recognition accuracy. Compared with YOLOv5, the head part of YOLOv8 has been greatly changed. The decoupling head structure is used to separate the classification and detection head, and it is changed from Anchor-Based to Anchor-Free, which significantly improves the target detection accuracy and alleviates the problem of inaccurate positioning and classification errors in complex scenes.

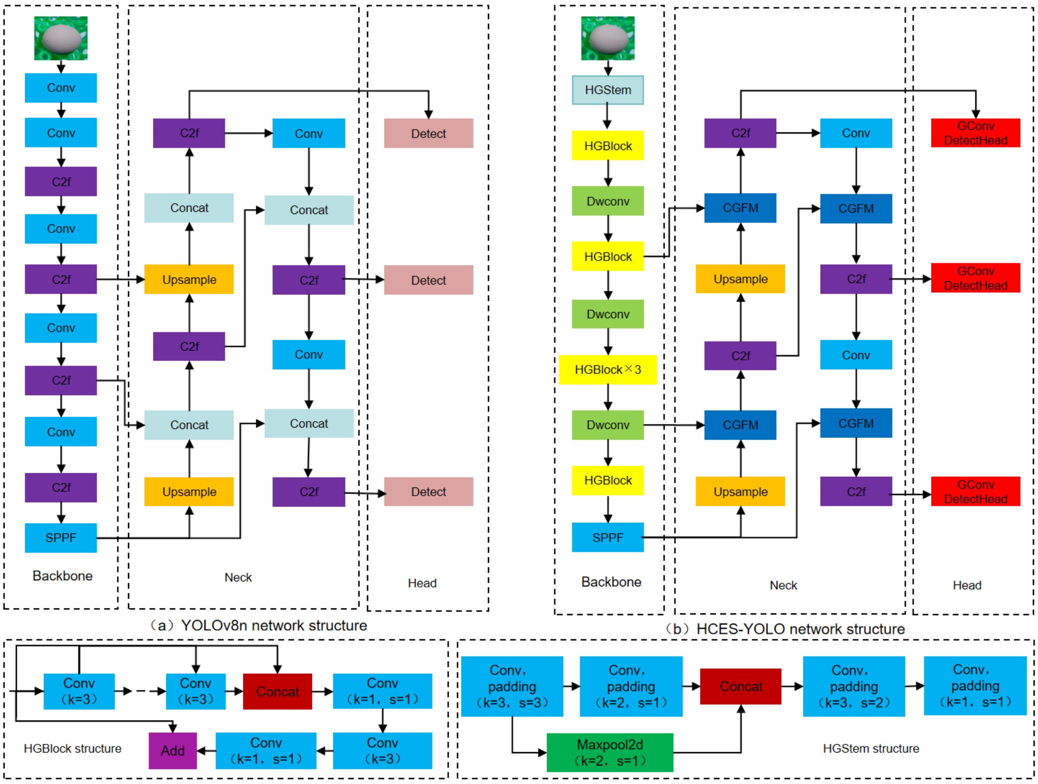


Fig. 3 –YOLOv8n and HCES-YOLO network structure

HCES-YOLO model

In this study, the Backbone and Neck parts of YOLOv8 were improved. The lightweight backbone network HGNetv2 is used to replace the original YOLOv8 backbone to reduce the computational load and model size, and the calculation speed is improved by the optimized Transformer structure. On this basis, the ContextGuideFusionModule is introduced, and the channel attention mechanism is used to weight the feature map, so as to improve the feature expression ability. The detection head of the original YOLOv8 is also optimized and the standard convolution is replaced with grouping convolution to reduce the amount of parameters and calculation, and the calculation efficiency is improved. In this study, the SIOU loss function is used in the model to comprehensively consider the shape similarity and spatial relationship of the target, so as to improve the accuracy of target location. The YOLOv8n model and the improved lightweight HCES-YOLO model are shown in Fig. 3.

Lightweight backbone network HGNetv2

The latest version of YOLOv8n has improved in accuracy and speed, but its backbone network still has limitations, especially in terms of computational complexity. This limits the application of YOLOv8n on resource-constrained devices. At the same time, as the depth and width of the network increase, the size of the model also increases, resulting in increased storage and transmission costs, which is a significant problem for applications that need to be deployed on edge devices. In addition, although YOLOv8n has improved in multi-scale feature fusion, it still has room for improvement in dealing with fine-grained features and global information.

Therefore, HGNetv2 is used to significantly optimize the original DETR network structure, which has many advantages. First, it uses a lightweight basic network, which significantly reduces the computational load and model size, and is suitable for running on resource-constrained devices. Secondly, through the optimized Transformer structure, HGNetv2 improves the calculation speed while maintaining high precision, which is especially suitable for real-time target detection tasks. In addition, HGNetv2 abandons the traditional NMS processing, so that the network can be optimized together during the training process, thereby improving the generalization ability and performance of the model.

The network structure of HGNetv2 includes pretreatment Stem layer, HG block, learnable LDS layer and GAP layer. The Stem layer is responsible for the initial processing of the input data for subsequent feature extraction. The HG block enhances the detection ability of targets of different scales by hierarchically processing data. The LDS layer performs downsampling to reduce the computational load and increase the receptive field. The GAP layer converts the feature map into a vector, which can improve the robustness to spatial transformation. The final classification layer includes a convolutional layer and a fully connected layer to complete the classification task. The HGNetv2 structure is shown in Fig.4.

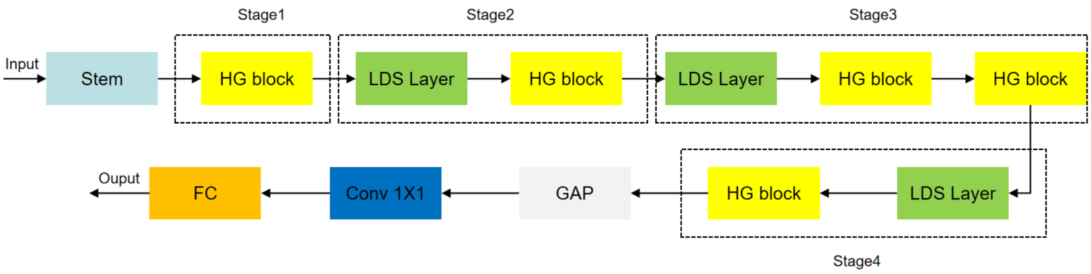


Fig. 4 – HGNetv2 structure

Pyramid Network ContextGuideFusionModule

The Concat module of YOLOv8 is widely used in computer vision tasks, which fuses different levels of features by stitching feature maps on channel dimensions. Although this method is efficient and has low computational cost, its simple splicing fails to consider the correlation between levels, resulting in insufficient information fusion. In addition, simple stitching cannot distinguish the importance of each feature map, and all features are treated equally. This may lead to the loss of egg image details, resulting in false detection and missed detection, and may also be detrimental to the final performance of the egg quality detection model. In contrast, ContextGuideFusionModule provides a more advanced and detailed feature fusion method to overcome the limitations of simple stitching. Through careful design, CGFM not only simply stitches feature maps, but also achieves more effective feature integration through weight adjustment and attention mechanism.

The core of ContextGuideFusionModule is Squeeze-and-Excitation Attention (SEAttention). This mechanism emphasizes important features and suppresses unimportant channels by weighting the importance of each channel. Specifically, SEAttention first uses the global average pooling to compress the spatial dimension of each channel into a scalar, representing the global feature of the channel. Then, these scalars are nonlinearly transformed through the fully connected layer to generate the weight of each channel. Finally, the weighted feature map is obtained by multiplying the original feature map by elements. After completing the feature adjustment, ContextGuideFusionModule realizes feature fusion by weighted addition, and the structure is shown in Fig. 5. The specific step is to multiply the two input feature maps by their corresponding weights, and then add them to form a fused feature map. This method not only retains the important information in the input feature map, but also enhances the information complementarity between different feature maps through weight adjustment, thereby improving the feature expression ability and model performance.

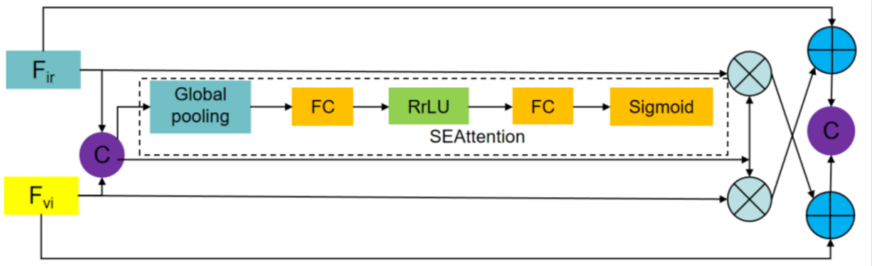


Fig. 5 – ContextGuideFusionModule structure

Lightweight detection head EfficientHead based on grouping convolution

Head of YOLOv8n uses independent classification and localization branches. Since the sample allocation strategy is task-independent, there is a lack of information interaction between classification and localization tasks. This will lead to inaccurate prediction positions with high scores and inaccurate prediction scores with accurate positions. At the same time, the classification and positioning are separated, and the model calculations are independent of each other, which will cause the Head part to be complicated and the calculation amount to be huge. Based on the above shortcomings, this paper designs a new detection head EfficientHead with reference to the idea of grouping convolution.

As a lightweight convolution operation, group convolution divides the input data and convolution kernel into multiple groups, and each group performs convolution operation independently, which greatly reduces the amount of parameters and calculations, as shown in Fig. 6. Grouping convolution effectively reduces the amount of parameters and calculations by grouping the input feature maps, and improves the computational efficiency of the model, which is especially suitable for the training of deep networks and large-scale data sets. In order to further reduce the model complexity and computational complexity without affecting the detection accuracy, this paper improves the detection head part of YOLOv8.

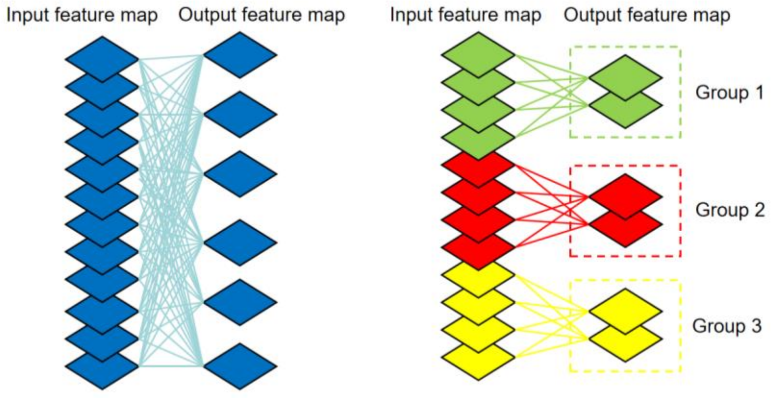


Fig. 6 –Comparison of the implementation process of conventional convolution and group convolution
a）conventional convolution; b）group convolution

YOLOv8 adopts a decoupling head structure, and two parallel branches extract location features and category features respectively. Each layer uses a *1 × 1* convolution to complete the classification and positioning tasks. Based on the original YOLOv8 head structure, this paper replaces the standard convolution with group convolution, as shown in Fig. 7.

This improved method combines the advantages of group convolution, which can effectively reduce the complexity and computational complexity of the model. At the same time, the detection accuracy is maintained, so that the model can also perform well in a limited computing resource environment.

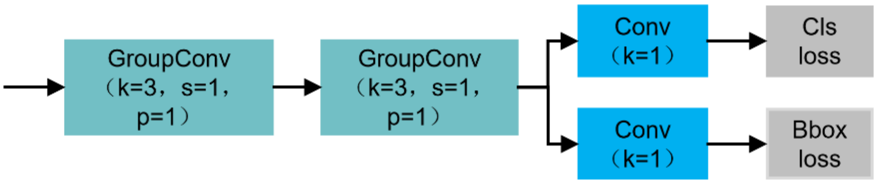


Fig. 7 – Lightweight detection head EfficientHead structure diagram

SIoU loss function

The loss function is the key to evaluate the performance of the model, especially in deep learning target detection. The CIoU loss function adopted by the YOLOv8n network focuses on the position and size of the bounding box, but does not consider the directional mismatch between the label box and the prediction box. In contrast, the SIoU loss function introduces four parts: angle, distance, shape, and IoU to comprehensively evaluate the position, size, and direction of the object. By redefining the distance loss and combining the angle loss, SIoU considers the distance and angle between the center of the object and the center of the predicted bounding box, enhances the robustness to shape changes, and helps to cope with deformation in the image. In addition, SIoU is suitable for multi-class target detection, without additional complexity, ensuring the convergence speed of the algorithm, and is insensitive to target size changes to avoid excessive errors. Its differentiability enables the model to optimize parameters through back propagation, thereby improving the accuracy of small target detection in egg images.

RESULTS

Experimental environment

The computer configuration used for training and testing in this article is CPU model: Intel (R) Core97-12900H, GPU model: NvidiaGeForceRTX3060. The program compilation environment is: Window11 system, Pytorch1.1.0, python3.8, CUDA11.0, OpenCV library, and other parameters use YOLOv8 default parameters.

Performance evaluation index

In order to effectively evaluate the performance of the HCES-YOLOv8n model, five indicators—accuracy, recall rate, mAP, GFLOPs, and parameter quantity—were used to assess the performance of the model, as shown in Equations (1) - (4).

$$P = \frac{T_p}{T_p + F_p} \tag{1}$$

$$P = \frac{T_p}{T_p + F_n} \tag{2}$$

$$AP = \int_1^0 P(R)dR \tag{3}$$

$$mAP = \frac{\sum_1^n AP}{n} \tag{4}$$

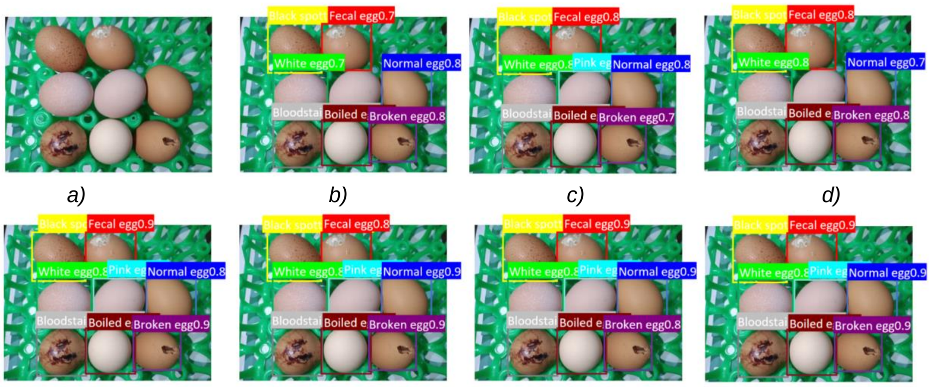
In the formula, T_p was the number of correctly predicted targets, F_p was the number of incorrectly predicted targets, and F_n was the number of omitted targets to be predicted. P was the accuracy rate, defined as the proportion of samples correctly predicted as the target to the samples predicted as the target. R was the recall rate, defined as the proportion of samples correctly predicted as the target to all target samples. AP was the average accuracy, and *n* was the number of detected categories.

Ablation experiment

The purpose of this study was to improve the YOLOv8n network and develop a lightweight egg quality detection algorithm. To evaluate the impact of various improvements, ablation experiments were conducted under the same training environment and hyperparameters, testing a total of 8 schemes. Models 2, 3, and 4 added the HGNetv2 module and ContextGuideFusionModule to the original model, respectively, and replaced the original structure with EfficientHead, all of which were single module changes. Models 5, 6, and 7 added ContextGuideFusionModule and EfficientHead one by one based on HGNetv2, and replaced the original loss function of YOLOv8 with SIoU. All models detected the same image, and the effect was shown in Fig. 8.

From the perspective of detection effect, the improved model reduced missed detections and false detections, successfully identifying eggs with small features. The evaluation indexes of the seven models were sorted out, as shown in Table 1.

Table 1 showed that under the same experimental conditions, after replacing the original backbone with HGNetv2, the accuracy, recall, and average accuracy of the model increased by 1.8%, 3%, and 3%, respectively, while the floating-point operations and parameter scale were reduced by 1.2G and 0.66M, respectively. Using the ContextGuideFusionModule structure, the accuracy, recall, and average accuracy increased by 1.8%, 3.1%, and 2.7%, respectively. Using the DetectEfficient structure, the model's performance improved while the floating-point operations and parameter scale were reduced by 3.3G and 1.41M, respectively. Combined with HGNetv2 and ContextGuideFusionModule, the accuracy, recall, and average accuracy increased by 2.9%, 3.7%, and 3.4%, respectively, and the floating-point operations and parameter scale decreased by 1.1G and 0.5M, respectively. After improving DetectEfficient based on Model 5, the floating-point operations and parameter scale were reduced by 2.4G and 0.58M, respectively, while the accuracy and recall rate remained almost unchanged. Finally, after replacing CIOU with SIOU in model 6, the accuracy and recall rate increased by 0.3% and 1.0%, respectively. In summary, these four improved strategies effectively enhanced the performance of the model while maintaining high detection accuracy.



a) b) c) d)

e) f) h) i)

Fig. 8 – Ablation experiment detection effect diagram

Table 1

Performance comparison of ablation experiments

Network model	HGNetv2	ContextGuide FusionModule	Efficient Head	SIOU	P/%	R/%	mAP@0.5%	FLOPs/G	Parameter size / MB
Model 1	—	—	—	—	80.2	78.6	85.4	8.1	3.01
Model 2	√	—	—	—	82.0	81.6	88.4	6.9	2.35
Model 3	—	√	—	—	82.0	81.7	88.1	8.3	3.16
Model 4	—	—	√	—	80.5	80.8	86.9	4.8	1.60
Model 5	√	√	—	—	83.1	82.3	88.8	7.0	2.51
Model 6	√	√	√	—	83.7	82.5	88.7	4.6	1.93
Model 7	√	√	√	√	84.0	83.5	88.6	4.6	1.93

A is the original image, b is the detection result of the YOLOv8n model, and c ~ j is the detection result of models 3 ~ 7.

Comparative experiments of different lightweight backbone networks

In the previous section, several improvements were implemented to YOLOv8n and verified their effectiveness. To further prove the effectiveness of the introduced lightweight HGNetv2 backbone network, comparative experiments were conducted with other lightweight backbone networks.

The GhostHGNetv2, RepHGNetV2, and EfficientViT networks were used in this experiment. These networks served as replacements for the backbone network of the benchmark model and were compared with the HGNetv2 proposed in this paper. Table 2 listed the comparative experimental results of different lightweight backbone networks. It could be seen from the experimental results in Table 2 that both GhostHGNetv2 and RepHGNetv2 showed improvements in accuracy, but the recall rate and average accuracy hardly changed. In contrast, StarNet's recall rate and average accuracy improved, but its accuracy declined.

The HGNetv2 proposed in this paper not only successfully reduced the floating-point operations by 14.8% and the number of parameters by 21.9%, but also achieved significant improvements in accuracy, recall, and average accuracy. This result demonstrated that HGNetv2 could effectively improve the overall performance of the model while maintaining high efficiency.

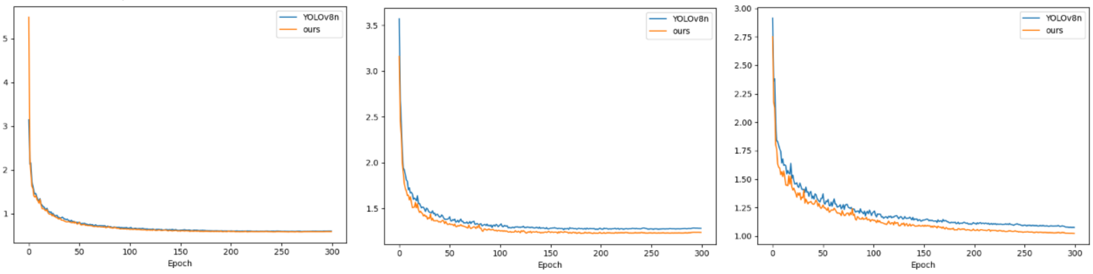
Table 2

Comparative experiments of different lightweight trunks

Network model	P/%	R/%	mAP@0.5%	FLOPs/G	Parameter size / MB
YOLOv8n（Baseline）	80.2	78.6	85.4	8.1	3.01
GhostHGNetv2	83.8	78.5	85.8	6.8	2.31
RepHGNetV2	82.3	78.8	85.9	6.9	2.37
StarNet	79.5	81.1	86.2	7.1	2.40
HGNetv2	82.0	81.6	88.4	6.9	2.35
YOLOv8n（Baseline）	80.2	78.6	85.4	8.1	3.01
GhostHGNetv2	83.8	78.5	85.8	6.8	2.31

Model performance

To verify the performance of HCES-YOLO in the training process, the training effect was evaluated by observing the change trend of the SIOU loss function value compared to the original loss function. The model comparison curve was shown in Fig. 9. In Fig. 9 (a), as training deepened, the loss value of the bounding box gradually decreased, indicating that the model continued to improve the positioning accuracy of the bounding box. In Fig. 9 (b), the decreasing trend of classification loss showed that the model was gradually enhanced in its ability for category discrimination. Fig. 9 (c) illustrated that the model also had high recognition ability for a few categories of samples. The stationary state curve in Fig. 9 indicated that there was no overfitting or underfitting phenomenon during the model training process. Throughout the training process, the model learned effective feature representation, demonstrating that it had good stability and generalization ability when completing the recognition task. From the above, it could be concluded that the loss value of the improved HCES-YOLO model converged faster compared to the original YOLOv8n loss function, and the loss value was smaller than that of YOLOv8n. This indicated that the improved method in this paper effectively enhanced the convergence ability of the model.



a） b） c）

Fig. 9 - Loss function comparison curve

a）Box Loss; b）CLS Loss; c）DFL Loss

Comparative experiment of different models

In this paper, a series of improvements were made to the YOLOv8n model to enhance the accuracy and efficiency of target detection, and the performance was compared with other mainstream models through experiments. Following the principle of control variables, the data training and evaluation in Table 3 were carried out in a unified hardware and software environment. The experimental results showed that Faster R-CNN, as a two-stage object detection algorithm, generated a large number of redundant boxes due to the need to produce candidate boxes, which increased the computational burden, and the recall rate was not satisfactory. The recall rate and average accuracy of the SSD algorithm on the egg quality dataset were 70.4% and 71.4%, respectively. Although multi-scale feature fusion was used, the response was insufficient when dealing with small targets, which affected accuracy, leaving a gap compared to other algorithms.

Single-stage object detection algorithms such as Tood and YOLOv7 had similar accuracy, recall, and average accuracy to YOLOv8n, but their floating-point operations and parameter scale were much larger than those of YOLOv8n. Although the floating-point operations and parameter scale of YOLOv5n were lower than those of YOLOv8n, its performance index was not as good as that of YOLOv8n. In summary, YOLOv8n significantly reduced computing resources and memory usage while achieving better detection results, thereby improving the interpretability of the model. Therefore, this paper chose YOLOv8n as the original model. Compared with YOLOv8n, HCES-YOLOv8 improved accuracy by 3.8%, recall rate by 4.9%, and average accuracy by 3.2% on key indicators, respectively. At the same time, the floating-point operations and parameter scale were greatly reduced, making the model lighter and especially suitable for resource-constrained devices. The comparative experimental results clearly showed that the HCES-YOLOv8 algorithm exhibited superior performance in the field of egg quality target detection.

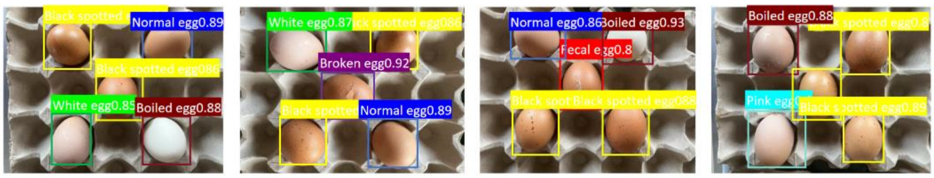
Table 3

Performance comparison of different models

Network model	P/%	R/%	mAP@0.5%	FLOPs/G	Parameter size / MB
Faster R-CNN	—	76.6	79.2	182.3	41.37
SSD	—	70.4	71.4	33.6	25.6
Tood	—	80.1	86.6	172	32.03
YOLOv5n	75.4	84.4	83.3	7.2	2.51
YOLOv7	77.7	80.1	86.6	103.2	34.79
YOLOv8n	80.2	78.6	85.4	8.1	3.01
PSCW-YOLOv8n	84.0	83.5	88.6	4.6	1.93

Test result

To verify the practicality of the improved model, real-time detection of egg quality in the egg image acquisition system was carried out. According to the research, the egg-feeding capacity of a single processing line was 10,000 to 20,000 eggs per hour, and the required egg-feeding speed was 3 to 5 meters per minute. Therefore, it was planned to conduct experiments on the laboratory test platform to evaluate the performance of the improved YOLOv8n model in practical applications. 300 eggs were obtained from the farm and all categories of samples were uniformly mixed. Before the start of the experiment, all the sample eggs were manually placed on the tray on the conveyor belt, with the surface eggs in the area with obvious features facing upward, and there was no obstruction between the eggs.



a) b) c) d)

Fig. 10 - Model real-time detection effect diagram

After starting the drive motor, all the eggs were transported at a set speed. The egg image was collected by the camera, and the trained improved YOLOv8n model was introduced to detect the egg quality, with the detection result being output at the end. The eggs detected each time were counted and their accuracy was assessed. The accuracy of egg quality was 88.4%. Fig. 10 showed a random screenshot from the detection process. It could be seen from Fig. 10 that the detection model proposed accurately detected the quality of the eggs appearing in the visual window and met the real-time detection requirements of the egg assembly line collection work on the farm.

CONCLUSIONS

In this study, an egg quality detection model was established based on an improved YOLOv8n network, which can effectively recognize small targets. The test results on the same dataset show that the improved model achieves an accuracy of 84.0%, a recall of 83.5%, and an average accuracy of 88.6% in egg quality detection, outperforming the original YOLOv8n network and other detection models. Its computational cost was also reduced and its accuracy in identifying minor damages and pollution was improved. On-site experiments were conducted on the testing platform built in the laboratory, and the improved YOLOv8n model can effectively detect leaking eggs during movement at a conveying speed range of 3 to 5 m/min. The comprehensive detection performance reached 88.4%, providing a new solution for rapid non-destructive testing of eggs.

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