ONLINE DETECTION SYSTEM FOR CRUSHED RATE AND IMPURITY RATE OF MECHANIZED SOYBEAN BASED ON DEEPLABV3+
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基于 DeepLabV3+的大豆机械化收获破碎率和含杂率在线检测系统

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ABSTRACT
In this study, an online detection system of soybean crushed rate and impurity rate based on DeepLabV3+model was constructed. Three feature extraction networks, namely the MobileNetV2, Xception-65, and ResNet-50 models, were adopted to obtain the best DeepLabV3+model through test analysis. Two well-established semantic segmentation networks, the improved U-Net and PSPNet, are used for mechanically harvested soybean image recognition and segmentation, and their performances are compared with the DeepLabV3+ model's performance. The results show that, of all the models, the improved U-Net has the best segmentation performance, achieving a mean intersection over union (F_{MIOU}) value of 0.8326. The segmentation performance of the DeepLabV3+ model using the MobileNetV2 is similar to that of the U-Net, achieving F_{MIOU} of 0.8180. The DeepLabV3+ model using the MobileNetV2 has a fast segmentation speed of 168.6 ms per image. Taking manual detection results as a benchmark, the maximum absolute and relative errors of the impurity rate of the detection system based on the DeepLabV3+ model with the MobileNetV2 of mechanized soybean harvesting operation are 0.06% and 8.11%, respectively. The maximum absolute and relative errors of the crushed rate of the same system are 0.34% and 9.53%, respectively.

摘要
为了实现大豆机械化收获破碎率和含杂在线检测，本研究构建了基于 DeepLabV3+的在线检测系统，并采用三种特征提取网络（MobileNetV2、Xcepton-65 和 ResNet-50 模型）测试分析获得最佳的 DeepLabV3+模型。引入改进的 U-Net 和 PSPNet 模型，评估 DeepLabV3+模型的性能。结果表明，在所有模型中，改进的 U-Net 具有最佳的分割性能，平均交并比值达到 0.8326。基于 MobileNetV2 的 DeepLabV3+模型的分割性能与改进的 U-Net 相似，平均交并比值为 0.8180。基于 MobileNetV2 的 DeepLabV3+模型分割大豆图像速度为 168.6ms。以人工检测结果为基准，基于 MobileNetV2 的 DeepLabV3+模型检测大豆含杂率的最大绝对误差和相对误差分别为 0.06%和 8.11%，破碎率的最大绝对误差和相对误差分别为 0.34%和 9.53%。

INTRODUCTION
Soybean is one of the main crops grown in China and occupies an important position in food crops. At present, soybean harvesting in China is mainly conducted by a harvester for mechanized harvesting at the early stage of plant maturity. A mechanized soybean harvesting method is to use a rice–wheat combine harvester, configure a flexible header, and adjust the parameters of the threshing drum to harvest soybeans *(Chen et al., 2020)*. Different from cereal crops, soybean has agronomic characteristics of low pod setting and easy breakage. In the process of mechanized harvesting, using inappropriate harvesting machinery and selecting the harvesting period improperly can result in high impurity and crushed rates. At present, the intelligence level of soybean combine harvesters is low, and there is a lack of an online quality detection system for mechanized soybean harvesting.

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Soybean harvester drivers cannot accurately determine the operation quality of a harvester, which can easily lead to high impurity rate and crushed rate of soybean mechanization, affecting the quality of harvested soybeans and reducing the economic benefits of soybean planting *(Kang et al., 2022)*. Therefore, an online inspection of the operation quality of mechanized soybean harvesting is urgently needed, which can provide a harvester driver with real-time information on harvesting quality crushed rate and impurity rate, helping the driver to determine the working status of the harvester in real time. This can effectively improve the quality of mechanized soybean harvesting.

Mechanically harvested soybeans typically contain crushed grains (e.g., skin-damaged grain and cotyledon split grain) due to mechanical damage and impurities (e.g., pods, plant stems, and leaves) in addition to intact grains. Mixed impurities differ obviously in color and in shape compared to intact grain. Namely, crushed grain does not change much in color but can vary in texture. Differences in color and texture between intact grains, crushed grains, and impurities enable the application of machine vision and image processing to the component classification of mechanically harvested soybean samples.

An online quality inspection system for mechanized soybean harvesting operation needs to segment intact grains, crushed grains, and impurities in soybean samples accurately. As a powerful technology in the field of artificial intelligence, deep learning has become a research hotspot in the field of agriculture *(Bhupendra et al., 2022)*. This technology has been applied in the fields of wheat variety classification and grain disease identification *(Laabassi et al., 2021)*, rice seed identification *(Zhang et al., 2021)*, and soybean plant leaf identification *(Wang et al., 2022)*.

Compared with traditional machine vision, deep learning is more robust and can learn more characteristics of soybean samples, such as the color and texture of impurities and crushed grains *(Jin et al., 2022)*. The DeepLabV3+ model is a semantic segmentation network, which has been proven to be effective and accurate in many studies *(Shoushtari et al., 2022)*.

In the field of agricultural production research, this technology has been applied to the classification of cucumber leaf disease severity *(Wang et al., 2021)*, wheat scab and lodging recognition *(Dai et al., 2021)*, lettuce abnormal leaf segmentation *(Wu et al., 2021)*, grape cultivation area recognition *(Sun et al., 2022)*, and rice lodging recognition *(Mu et al., 2022)*. The previous studies have demonstrated the promising application potential of the DeepLabV3+ model in semantic segmentation. The aforementioned studies have shown that semantic segmentation can be an effective method for grain recognition segmentation. Therefore, the application of semantic segmentation networks to identifying and segmenting mechanically harvested soybeans' intact grains, crushed grains, and impurities is promising.

On the basis of identifying and segmenting grain image components effectively using a reasonable scientific quantitative model, the online detection of grain mechanized harvesting quality can be realized. Chen et al. used an improved watershed algorithm to segment soybean images effectively and constructed an online detection system for mechanized soybean harvesting quality. The test results have shown that the designed system can accurately calculate the crushed and impurity rates and can also provide the visual monitoring and warning alarm of mechanized soybean harvesting quality *(Chen et al., 2020)*. Chen et al. segmented the images of rice grains harvested by a combine harvester using the U-Net model based on machine vision. The experimental results showed that the comprehensive evaluation index values of the rice grain segmentation, branch and stem segmentation, and stem segmentation were 99.42%, 88.56%, and 86.84%, respectively *(Chen et al., 2020)*. According to the results of recent related studies, an online inspection of mechanized soybean harvesting quality can be achieved by combining machine vision and deep learning technology.

This study aims to segment soybean sample composition (i.e., intact grain, crushed grain, and impurity) at the pixel level using the DeepLabV3+ model. In this study, the collected machine-harvested soybean sample images are labeled as "background," "intact grain," "crushed grain," and "impurity." Aiming to identify and segment image components of soybean samples accurately, this paper proposes a calculation model of the crushed and impurity rates of mechanized soybean harvesting operations based on the soybean image data. Three backbones, namely the MobileNetV2, ResNet-50, and Xception-65 models, are used to determine an optimal backbone for the DeepLabV3+ model. The improved U-Net model (*Jin et al., 2022*) and the PSPNet model (*Li et al., 2022*) are introduced to verify the performance of the DeepLabV3+ model. The field experiments are conducted to verify the performance of the proposed online quality inspection system for mechanized soybean harvesting based on the DeepLabV3+ model.

MATERIALS AND METHODS

Online quality inspection of mechanized soybean harvesting

This study developed an online detection device for the crushed and impurity rates of machine-harvested soybean quality and the corresponding test bench, as shown in Fig. 1.

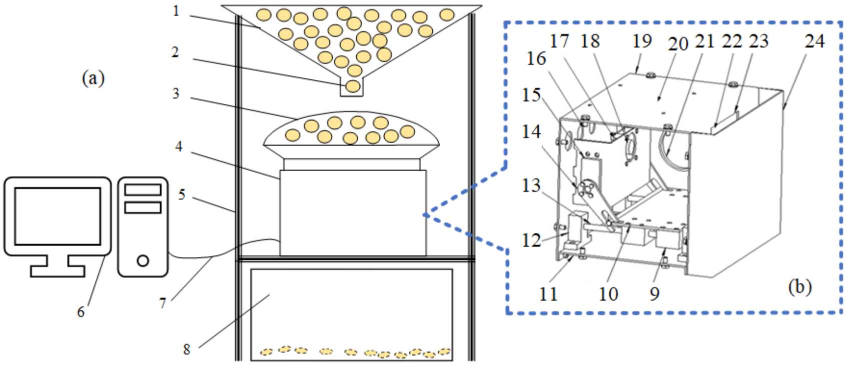


Fig. 1 – The online inspection system of the soybean harvesting machine operation quality.
(a) The block diagram of the test bench for online detection of the soybean harvesting machine quality;
(b) the structure of the online detection device of broken impurity content

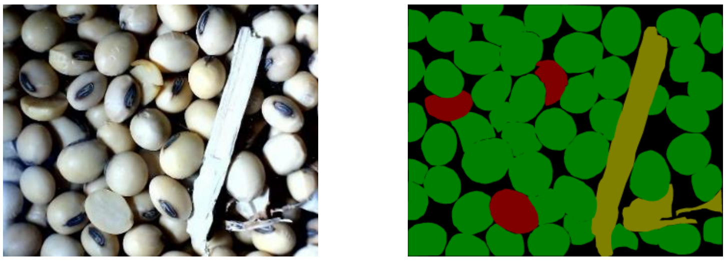
1. storage bin for samples to be tested; 2. soybeans; 3. sampling funnel; 4. online detection device of crushed impurity content; 5. brackets, 6. image processing equipment; 7. data bus; 8. tested sample collection bin; 9. sliders; 10. telescopic plates; 11. bases; 12. guide rail seats; 13. guide rails; 14. levers; 15. direct-current steering gears; 16. data bus connectors; 17. industrial cameras; 18. industrial camera fixing bracket; 19. shell; 20. embedded data processing module; 21. light emitting diode visual light source; 22. transparent plexiglass; 23. photo window; 24. sampling chamber

The proposed online detection device for the crushed and impurity rates of machine-harvested soybean quality is composed of an image recognition part and a dynamic sample collection part. The image recognition part is used to collect and classify soybean samples in a photographing window, as well as to realize online recognition and segmentation of intact grains, crushed grains, and impurities in soybean samples. Meanwhile, the dynamic collection part is used to update soybean samples in a sampling bin dynamically. The online inspection system of the soybean harvesting machine operation quality controls the DC steering gear to rotate by 65° forward to drive the retractable plate to retract and release soybeans in the sampling bin. By reversing the DC steering gear by 65°, the system makes the telescopic plate extend, thus preventing the soybeans in the sampling bin from being discharged and achieving the goal of grain collection. The system realizes the dynamic update of soybean samples in the sampling bin by periodically controlling the forward and reverse rotation of the DC steering gear.

The image recognition part includes an industrial camera (LRCP10230, Huarui Vision Technology, Guangzhou, China), with a lens having a focal length of 12 mm and being 105 mm away from the transparent plexiglass, which is facing the photo window of the sampling bin. Under a LED visual light source, an RGB (red, green, blue) image captured by the industrial camera has a resolution of 1,280 × 1,024 pixels, and it is saved in the JPEG format. The image recognition part also includes an image processing device, which is mainly used for the recognition and classification of components of a soybean sample image. The image processing device is an Ubuntu18.04 host, which is Tsinghua Tongfang T45PRO laptop, with an Intel® Core® i7-6500U processor, 16-GB, 3,200-MHz DDR4 memory, and 6-GB Nvidia GeForce RTX3060 graphics card.

Data annotation and augmentation

A total of 300 images of machine-harvested soybean samples with a resolution of 1,280 × 1,024 were collected and saved as the original dataset. Generally, 50-70 soybeans were included in one image. The original image size was too large, which could cause the GPU memory to be exhausted, so the original images were downsampled. Image downscaling not only can save computational costs but can also serve as a basis for low-pixel-resolution vision sensor research. Therefore, each image was scaled to 512 × 512 pixels by bilinear interpolation. LabelMe 3.16.7, which is an Image Labeling Toolbox developed by the MIT Computer Science and Artificial Intelligence Laboratory, was used to label the images. The intact grains, crushed grains, and impurities of soybeans were marked by polygons first and then were given labels of “0” for background, “1” for crushed grains, “2” for intact grains, and “3” for impurities. Some of the RGB images and the corresponding label images are shown in Figs. 2(a) and 2(b), respectively. To avoid unbalanced performance evaluation on the test set, the data were randomly divided into a training set (240 images) and a test set (60 images) according to the division ratio of 4:1.



a) Original image *b) Labeled image*

Fig. 2 – An example of collected RGB images

Data augmentation plays a vital role in deep learning model training. A small number of training samples can cause overfitting or non-convergence of a deep learning-based model *(Deng et al., 2021)*. Data augmentation was performed on each image in the training set and the corresponding ground truth image *(Cotrim et al., 2020)*. The data augmentation methods used in this study included random image rotation (30–150°, 210–330°), random image scaling (0.5–0.8 times, 1.5–2.0 times), random image shearing (−30–30°), and horizontal mirroring; six augmented samples were generated for each training sample. Thereafter, the training set size was increased to 1,680 images by the above six methods. The training set images were randomly divided into a training set and a validation set according to the ratio of 9:1, so 1,512 images were used as a training set, and the remaining 168 images were used as a validation set. Based on the training set and validation set, the online identification and verification tests of different models for evaluating the soybean machine-based harvesting quality were conducted.

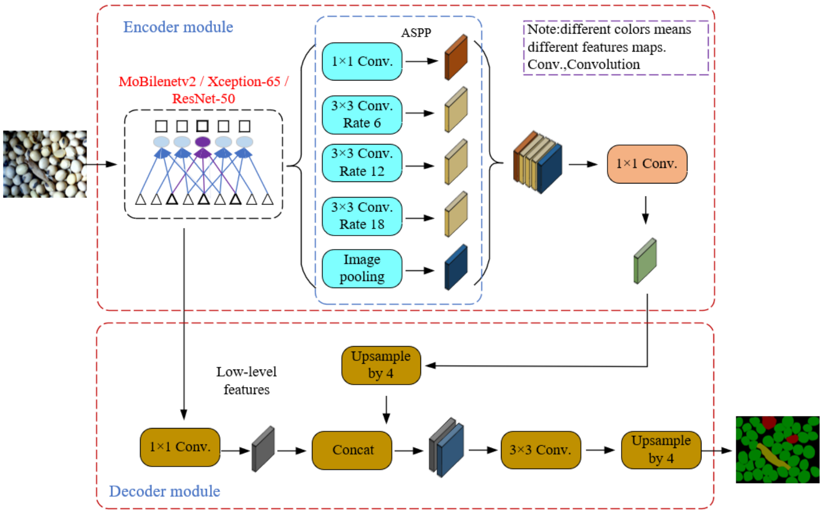


Fig. 3 – Block diagram of the DeepLabV3+ processing a machine-harvested soybean image

Deeplabv3+ architecture

The DeepLabV3+ model is a semantic segmentation network, which is based on the DeepLabV3 structure, where a simple and effective decoder has been added to refine segmentation results, especially the segmentation results along the boundary of a target object. The DeepLabV3+ uses a spatial pyramid pooling module or a two-in-one encoding-decoding structure for segmentation. As shown in Fig. 3, the DeepLabV3+ network consists of two main parts, encoder and decoder modules. It uses the Atrous Spatial Pyramid Pooling (ASPP) mechanism to detect convolutional features at multiple scales by applying atrous convolutions with different image-level feature rates. In the encoder module, the training set is input into the backbone to obtain the feature map, which is then input into the ASPP that consists of a 1 × 1 convolution, three 3 × 3 atrous convolutions (with the atrous rates of 6, 12, and 18), and an image pooling layer. The convolution layers extract features locally, while the image pooling layer extracts features globally, thus obtaining multi-scale features. All feature maps obtained by the ASPP are concatenated into combined feature maps. Then, a 1 × 1 convolutional layer is used to fuse the information in the combined feature map and reduce the number of channels of the feature map. The last feature map after the 1 × 1 convolution is used as an encoder output module. The encoder features are first bilinearly upsampled four times and then concatenated with the corresponding low-level features from the backbone with the same spatial resolution. Another 1 × 1 convolution is applied to the low-level features to reduce the number of channels. After concatenation, 3 × 3 convolutions are used to refine the features, followed by four simple bilinear upsampling.

Network training

The U-Net, PSPNet, and DeepLabV3+ models were trained and tested using Ubuntu20.04 host (Dell Precision 7920 Tower graphics workstation) with a GPU (Nvidia Quadro RTX5000 16 GB GPU), a 26-core CPU (Dual Intel® Xeon® Gold 6230R), 4.00 GHz), and a 128-GB, 3200-MHz DDR4 memory. The models were deployed using Python 3.6, torch 1.2.0, torchvision 0.4.0, scipy 1.2.1, numpy 1.17.0, matplotlib 3.1.2, opencv_python 4.1.2.30, tqdm 4.60.0, Pillow 8.2.0, and h5py 2.10.0 training environment, and the GPU and CPU dual devices were employed to train and test different networks. To train DeepLabV3+, improved U-Net and PSPNet models for soybean dataset in this study, weights of a pretrained model were used for initialization, which were fine-tuned with further training. These initial weights were obtained from pretrained model of the PASCAL VOC 2007 dataset *(Yin et al., 2021)*.

Field test design

The experimental site was the experimental soybean field in Houliu Village, Rencheng District, Jining City, Shandong Province. The soybean variety was also Qihuang 34; the moisture content was 12.1%; the thousand-kernel weight was 246.5 g. The test was conducted on October 18, 2021. The experimental harvesting machine was a 4LZ-6 intelligent soybean combine harvester. The field test was repeated test three times, with a single trip length of 200 m and an operating speed of 6 km/h. The test site is shown in Fig. 4.

Fig. 4 – Field validation experimental environment

The soybean sampling device was installed under the outlet of the grain conveying device of the 4LZ-6 intelligent soybean combine harvester, and the combine harvester was connected to the onboard power supply to debug the equipment. The combine harvester started harvesting, and the soybean crushed and impurity content detection device automatically and dynamically detected the operation effect online. After completing one field test, the machine was stopped, three samples were selected randomly from the grain tank, and the crushed rate and impurity rate were manually checked according to the NY/T738-2020 "Operation Quality of Soybean Combine Harvester" standard, which were used to verify the accuracy of the proposed system's detection results. After the sampling was completed, the machine was started to perform the harvesting test; the field test was repeated two times; and the experimental data were used to verify the performance of the online detection system for monitoring soybean crushed rate and impurity rate.

Performance evaluation

In this study, precision rate P, recall rate R, comprehensive evaluation index F_1, intersection ratio F_{IOU}, average intersection ratio F_{MIOU}, and average processing speed I_{v} of a machine-harvested soybean sample image were used as evaluation indicators of the image recognition and classification results of different models, and they were respectively calculated as follows:

$$P = \frac{T_P}{(T_P+F_P)} \times 100\% \ \ [\%] \tag{1}$$

$$R = \frac{T_P}{(T_P+F_N)} \times 100\% \ \ [\%] \tag{2}$$

$$F_1 = \frac{2 \times P \times R}{P+R} \times 100\% \ \ [\%] \tag{3}$$

$$F_{IOU} = \frac{T_P}{T_P+F_P+F_N} \tag{4}$$

$$F_{MIOU} = \sum_{i=1}^{n} \frac{F_{IOUi}}{n} \tag{5}$$

where: T_P is the number of correctly classified pixels predicted to be correctly classified;

F_P is the number of wrong classified pixels predicted to be correctly classified;

F_N is the number of correctly classified pixels predicted to be misclassified;

n is the number of categories of classification;

I_v is the average processing speed of a soybean sample image, [ms].

In the existing methods for quality detection of a soybean combine harvester, the impurity rate represents the percentage of the mass of grains and impurities in a sample; the crushed rate is the percentage of the mass of crushed and intact grains in a sample. According to the existing measurement methods, the pixel-based crushed and impurity rates were calculated as follows:

$$P_z = \frac{T_z}{(T_z+\partial T_w+\partial T_s)} \times 100\% \quad [\%] \tag{6}$$

$$P_s = \frac{T_s}{(T_w+T_s)} \times 100\% \quad [\%] \tag{7}$$

where: P_z is the impurity rate of soybean, [%];

P_s is the crushed rate of soybean, [%];

T_w is the number of pixels of intact grains in a predicted image;

T_s is the number of pixels of crushed grains in the predicted image;

T_z is the number of impurities pixels in the predicted image;

∂ is the ratio of the average mass of grains to the average mass of impurities for 1,000 pixel points. In laboratory conditions, ∂ was set to 8.66 by manual calibration.

The absolute and relative errors of the average value of the proposed system's detection results and manual detection results were used to evaluate the performance of the online DeepLabV3+-based monitoring system of soybean machine-based harvesting quality. The calculation formulae were as follows:

$$R_{az} = |\overline{P_{Sz}} - \overline{P_{Mz}}| \quad [\%] \tag{8}$$

$$R_{rz} = \frac{|\overline{P_{Sz}} - \overline{P_{Mz}}|}{\overline{P_{Mz}}} \times 100\% \quad [\%] \tag{9}$$

$$R_{as} = |\overline{P_{Ss}} - \overline{P_{Ms}}| \quad [\%] \tag{10}$$

$$R_{rs} = \frac{|\overline{P_{Ss}} - \overline{P_{Ms}}|}{\overline{P_{Ms}}} \times 100\% \quad [\%] \tag{11}$$

where: $\overline{P_{Sz}}$ is the average impurity rate of samples detected by the proposed system, [%];

$\overline{P_{Mz}}$ represents the average impurity rate of manually detected samples, [%];

R_{az} represents the absolute error of the impurity rate, [%];

R_{rz} represents the relative error of the impurity rate, [%];

$\overline{P_{Ss}}$ represents the average crushed rate of samples detected by the proposed system, [%];

$\overline{P_{Ms}}$ represents the average crushed rate of manually detected samples, [%];

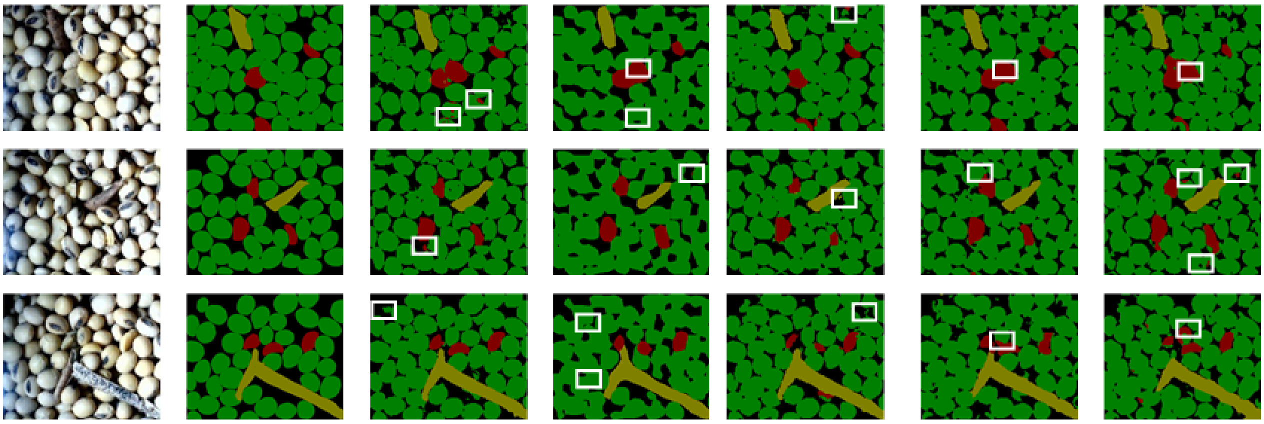
R_{as} represents the absolute error of the crushed rate, [%];

R_{rs} represents the relative error of the crushed rate, [%].

RESULTS

Training performance

The recognition and classification performances of the improved U-Net, PSPNet, and DeepLabV3+ models for different backbone networks on the test set images are shown in Fig. 5. As shown in Fig. 5, compared to the other models, the improved U-Net achieved sample component profiles with better connectivity and smoother channel shapes.



a) Original image b) Labeled image c) Improved U-Net d) PSPNet e) MobileNetV2 f) Xcepton-65 g) ResNet-50

Fig. 5– Classification results of different networks on the machine-harvested soybean images

The statistical results of different evaluation indicators of the recognition and classification effects of the improved U-Net, PSPNet, and DeepLabV3+ for different backbone networks on the test set are given in Table 1. This study focused on three metrics, namely F_1, F_{MIOU}, and I_v. Metric F_1 denotes the harmonic mean of precision and recall. The maximum F_1 indicates that a model has an optimal balance of recall and precision. Further, F_{MIOU} is a standard semantic segmentation metric, and it denotes the average value of the ratios of intersections and unions of all categories. The maximum F_{MIOU} indicates that a model achieves the optimal overall image recognition and segmentation performance. The proposed online detection method of machine-based soybean harvesting operation quality was applied to the mechanized soybean harvesting process to realize the online detection of a soybean harvester's operation quality. It should be noted that the processing time of a network directly defines the system's image recognition performance. A higher I_v indicates a faster image recognition speed of a model and demonstrates the actual needs of production are met better.

Table 1

Recognition and classification performances of different models on machine-harvested soybean images

Detection object	Parameter	Improved U-Net	PSPNet	DeepLabV3+		
		Vgg-16	MobileNetV2	MobileNetV2	Xception-65	ResNet-50
Intact grains	Precision rate [%]	89.04	86.19	87.63	88.54	85.45
	Recall rate [%]	95.07	90.66	95.61	93.62	94.43
	Comprehensive evaluation index [%]	91.75	88.18	91.25	90.90	89.51
	Intersection ratio [%]	0.8483	0.7891	0.8406	0.8346	0.8109
Crushed grains	Precision rate [%]	86.16	74.59	89.16	73.97	70.04
	Recall rate [%]	88.70	78.65	80.78	92.15	86.57
	Comprehensive evaluation index [%]	87.23	75.47	84.23	80.92	76.98
	Intersection ratio [%]	0.8043	0.618	0.7364	0.6916	0.6419
Impurities	Precision rate [%]	93.23	91.53	91.74	86.10	80.81
	Recall rate [%]	97.10	85.43	95.40	95.86	94.62
	Comprehensive evaluation index [%]	95.09	88.10	93.39	90.23	86.95
	Intersection ratio [%]	0.9068	0.7894	0.877	0.825	0.7702
Average intersection ratio [%]		0.8531	0.7322	0.8180	0.7837	0.741
Average processing speed of a soybean sample image [ms]		266.4	166.3	168.6	213.1	190.3

In terms of F_1, the improved U-Net model performed the best among all models, having the recognition accuracies of 91.75%, 87.23%, and 95.09% for the intact grains, crushed grains, and impurities, achieving improvements of 3.57%, 11.76%, and 6.99% compared with the PSPNet model, respectively. The recognition performance of the DeepLabV3+ model was similar to that of the improved U-Net. Among the DeepLabV3+ models, the DeepLabV3+ model based on MobileNetV2 had the best performance, with F_1 values of 91.25%, 84.23%, and 93.39% for the intact grains, crushed grains, and impurities, respectively. The F_{MIOU} value of the improved U-Net model was the highest among all models, reaching 0.8531. The PSPNet model had the lowest F_{MIOU} value, of only 0.7322. The F_{MIOU} value of the DeepLabV3+ was slightly lower than that of the improved U-Net model; particularly, the F_{MIOU} values of the DeepLabV3+ based on MobileNetV2, Xception-65, and ResNet-50 were 0.8180%, 0.7837%, and 0.741%, respectively. In terms of average image processing time, the U-Net model had the worst performance among all models, with an average image processing time of 266.4 ms. The image processing times of the DeepLabV3+ and PSPNet models based on the MobileNetV2 were the shortest, having values of 168.6 ms and 166.3 ms, respectively. Considering the image processing time and accuracy jointly, the DeepLabV3+ model based on the MobileNetV2 achieved best recognition and segmentation results with low time consumption among all models. According to the result, the DeepLabV3+ model based on MobileNetV2 was more suitable for online quality inspection of machine-based soybean harvesting than the other models.

Field test results analysis

During the test, the MobileNetV2-based DeepLabV3+ online quality inspection system for machine-harvested soybeans worked normally, realizing dynamic online detection of machine-harvested soybean samples. Table 2 provides statistical data of the bench and field experiments.

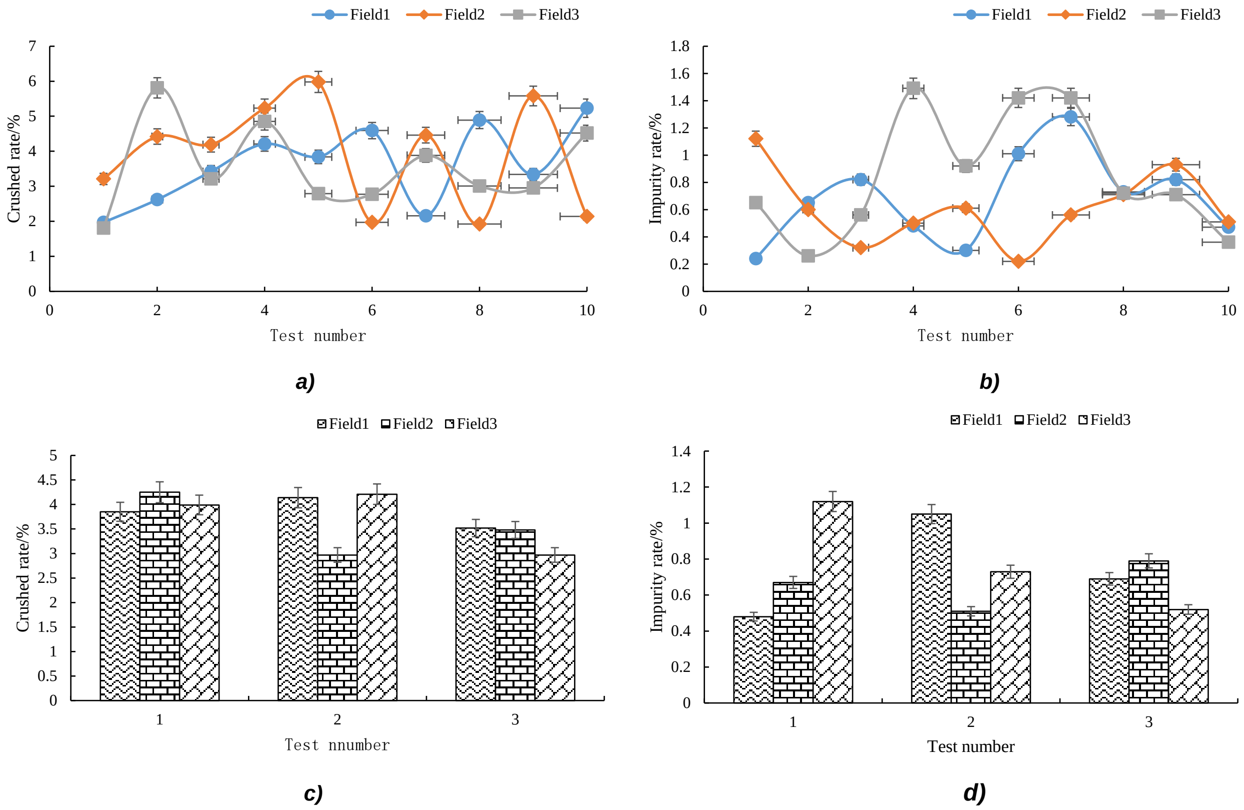


Fig. 6 – Field test results. System detection results of (a) crushed rate and (b) impurity rate. Manual detection results of (c) crushed rate and (d) impurity rate

The test results are shown in Fig. 6 and Table 2. In the online three-stroke mechanized soybean harvesting operation quality inspection test, the average impurity rates detected by the system and manual detection were 0.71% and 0.73%, respectively. Taking the manual detection results as a benchmark, the maximum absolute and relative errors of the system's impurity rate detection results were 0.06% and 8.11%, respectively. The average crushed rates detected by the system and manual detection were 3.70% and 3.71%, respectively. Taking the manual detection results as the standard values of impurity rate and crushed rate of soybean samples to be tested, the maximum absolute and relative errors of the system's crushed rate detection results were 0.34% and 9.53%, respectively. Therefore, there was a certain difference between the system's numerical results and the manual detection results. However, all detection results indicated that during the actual operation, the impurity rate of the soybean combine harvester was less than 3%, while the crushed rate was less than 5%. According to the NY/T738-2020 "Operation Quality of Soybean Combine Harvester" standard, the soybean harvester shall ensure that the impurity rate is less than 3% and the crushed rate is less than 5% during the soybean harvesting operation. It can be seen that both detection methods showed that the operational performance of the soybean combine harvester conformed to the national standard.

Table 2

Statistical results of the bench and field tests

Field test number	System monitoring results		Manual inspection results		Statistics			
	Average impurity rate of samples [%]	Average crushed rate of samples [%]	Average impurity rate of samples [%]	Average crushed rate of samples [%]	Absolute error of the impurity rate [%]	Relative error of the impurity rate [%]	Absolute error of the crushed rate [%]	Relative error of the crushed rate [%]
1	0.68	3.63	0.74	3.84	0.06	8.11	0.21	5.47
2	0.61	3.91	0.66	3.57	0.05	7.61	0.34	9.53
3	0.85	3.56	0.79	3.72	0.06	7.59	0.16	4.30

CONCLUSIONS

To realize online quality inspection of machine-harvested soybeans and ensure their quality, this paper proposes an online inspection system for machine-harvested soybeans based on deep learning. A machine-harvested soybean component detection model is constructed using three different backbones in the DeepLabV3+ model. The improved U-Net and PSPNet models are introduced to analyze the detection performance of the constructed detection models. Considering the real-time performance and accuracy jointly, an optimal detection model is determined, and the crushed and impurity rates of machine-harvested soybeans are calculated by the quantitative model. The results show that the improved U-Net model achieves the F_{MIOU} value of 0.8531 on intact grains, crushed grains, and impurities identification segmentation. The DeepLabV3+ model based on the MobileNetV2 has the F_{MIOU} value of 0.8180, while its F_1 values reach 91.25%, 84.23%, and 93.39% for the three soybean categories. In terms of speed, the MobileNetV2-based DeepLabV3+ model needs 168.6 ms to segment an image with a resolution of 512 × 512 pixels using an Nvidia Quadro RTX5000 16 GB GPU, while the improved U-Net model takes 266.4 ms for the same task. Based on the manual inspection results, in the field test, the maximum absolute and relative errors of the impurity rate of the DeepLabV3+ model using the MobileNetV2 are 0.06% and 8.11%, respectively, and those of the crushed rate are 0.34% and 9.53%, respectively. The quality detection results of the crushed and impurity rates obtained by the proposed system in the soybean machine-based harvesting test can meet the needs of actual production. In the future, we will continue to conduct relevant field trials to verify the reliability of the mechanized harvesting soybean quality inspection system, and promote the industrial application of the system.

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