

Measurement of the Angle between stems and leaves of rice based on key point detection

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Abstract: Stem-leaf angle is an important phenotypic parameter of rice, which is crucial for the growth and development of rice plants and scientific breeding. However, the traditional method is inefficient and subjective. In order to quickly and accurately calculate the stem-leaf pinch angle of rice, this paper proposes a key point-based stem-leaf pinch angle detection method. Experimentally, four periods of rice (Jointing stage, Booting stage, Heading stage and Mature stage) are selected as research objects, image data are collected, key points are extracted by YOLOv7-pose network model, and a lightweight convolution method GSConv is introduced, which is able to reduce the complexity of the model and improve the accuracy of the key point detection, the average accuracy of key point detection was improved from 93.7% to 98.7%, an improvement of 5%. Finally, the angular size of the pinch angle was determined based on the coordinates of the key points located by the model, and the R2 of the pinch angle calculation results to the actual manual measurements was the highest of 0.84, the errors for the four periods were 1.543°, 1.716°, 1.213°, and 0.998°. So the method ensures the accuracy of identification while the model size is reduced, and can effectively measure the angle of rice stem and leaf pinch, and the investigated method can better help farmers to understand the growth and development of plants and provide support for the selection of excellent crop traits.

Keywords: Rice; Stem-leaf angle; Deep learning; Key points; Phenotypic characteristics.

1. Introduction

Rice is an important food crop, and its phenotypic characteristics include morphology, physiology, quantity and so on. The canopy structure of rice crops directly affects the interception of solar energy [1], and determines the important factors of radiation transmission in the canopy. As the main component of the crop canopy, the leaf direction distribution, the stem-leaf angle distribution and the leaf shape all play a vital role in the interception and transmission of light in the crop cluster [2]. Among them, the stem-leaf angle is the main trait that affects the plant configuration and then affects the photosynthesis efficiency of the plant. It can be used to describe the individual and population structure of crops [3]. The tangent of the rice leaf curve is consistent with the base of the leaf pillow, therefore, the angle between the main stem and the base of the leaf axis (the lowest part of the leaf) is the angle between the stem and the leaf of the rice leaf. The angle between the stem and the leaf determines the ability of the leaf to receive sunlight and affects the photosynthesis efficiency and the transmission of light energy in the plant [4]. In the rice population, the top leaves of the plant pass down the light at the heading stage, and the bottom leaves with larger leaf angles help to accept the upper light energy and reduce energy loss, thereby increasing the seed setting rate [5]. In addition, the angle between stem and leaf will not only affect the lodging resistance of rice, but also affect the distribution and utilization efficiency of nutrients. Therefore, through the research and regulation of rice stem-leaf angle, breeders can select suitable parents and optimize the genetic expression of stem-leaf angle, and then cultivate rice varieties with high yield and stronger adaptability to adversity.

In the domestic research on crop geometric shape parameter measurement, there are few reports on the

measurement of the angle between stems and leaves. Most of the measurement methods are still carried out manually, which requires a large amount of labor and low efficiency, making it impossible to measure the growth of a large number of plant samples. Meanwhile, the data quality is greatly affected by subjective factors, and it is easy to touch and damage crop organs during manual measurement, The normal growth of crops is affected. The development of modern technology makes the study of phenotypic parameters of rice population more efficient, which has important value for rice breeding.

In recent years, the measurement of the angle between stems and leaves has gradually entered the image level. Yang et al [6] used skeleton extraction algorithm to describe the main stem, but the efficiency of the algorithm was low, and the extraction results of curved, full or bifurcated rice panicles were poor. Lu et al [7] used cameras to obtain the base image of rice blade leaf, and obtained the angle of rice blade leaf through image preprocessing, linear detection, K-means clustering and vector methods, the test results showed that compared with the results measured by manual protractor, the average absolute error of this system was 1.34°, and the relative error was 2.7%. The correlation coefficient between the measured value and the true value is 0.997, which can effectively measure the sword leaf angle. Zhuang et al [8] proposed a flag leaf node search algorithm based on machine vision to solve the problem that the main stem in the rice sample image is occluded, and the existing algorithm is difficult to identify the flag leaf node and the main axis of the scattered rice panicle. The center of rice panicle and flag leaf is generated by custom clustering, and the axis of scattered rice panicle is identified and determined, and finally the angle between panicle and leaf is obtained. Among them, the proposed sword leaf node search algorithm quantifies the

fuzzy positioning of the sword leaf node. After experimental verification, it has good robustness and accuracy. Kenchanmane Raju [9] used Leaf angle Xtractor (LAX), an image processing framework, which includes color conversion of image, binary conversion, bridging of unconnected components, skeletonization and pruning of branches to determine the leaf angle. For extracting and quantifying leaf angles from images of corn and sorghum plants under drought conditions.

Detection of key points have important applications in many fields, which can provide important information and characteristics of objects. With the development of deep learning, researchers have made corresponding progress by combining deep learning and key point detection technology [10]. This method is not only applied to attitude estimation, but also can be used to detect and track targets. By identifying the key points of objects, it is helpful for object recognition and classification. Chen et al [11] proposed a method of skeleton extraction and phenotypic parameter acquisition based on the combination of target detection and key point detection model. The Cascaded pyramid network (CPN) of human pose estimation was used to extract the plant skeleton. Convolutional block attention module (CBAM) is introduced to improve the process. The CBAM-CPN model improved the prediction accuracy by 9.68, 8.83 and 0.5 percentage points to 94.75% compared to HN, SHN and CPN, respectively. Wu et al [12] used the target detection algorithm to identify grape clusters, and applied the key point detection model to locate the fruit stem. Different target detection algorithms and key point detection models were used in sequence for verification. The test results showed that HRNet's YOLOv5m was used as the detection algorithm to achieve the best result, and the stalk recognition accuracy was 90.2%. As can be seen from the above literature, the combination of deep learning and key point technology can be applied in many aspects, showing a good application prospect and achieving remarkable results, which verifies the feasibility of this method. However, it is not widely used in the extraction of rice phenotypic parameters, which needs further study.

In summary, this study proposes a method for measuring the angle between stems and leaves, this method can quickly and accurately detect the angle between the stem and leaf of rice, and provide theoretical support for farmers to choose better crop traits.

2. Materials and methods

The experiment was carried out in the paddy field of Tianjin High Quality Agricultural Products Development Demonstration Center, from September to October 2022 and July to September 2023. The rice varieties with high yield, high quality and multi-resistance were selected as the research object, and the normal cultivation management was carried out during the experiment.

In this paper, the key point detection technology combined with YOLOv7 model is used to realize the identification of rice stem leaf angle. This method needs to go through four stages: (1) Data acquisition and data set production; (2) Key point detection; (3) Calculation of the angle between stem and leaf; (4) Results and analysis.

2.1. Data acquisition

In order to increase the model robustness and establish a multi-period universal recognition model, this study was conducted by acquiring rice images from four periods of rice,

and the acquisition equipment included mobile phones, high-definition cameras, tripods, and laptop computers. To reduce the effect of background interference on recognition accuracy, a whiteboard was used to place behind the rice during the acquisition process, and the rice serial number was marked in the lower left corner. To ensure data quality and reliability, a tripod was used to fix the camera and keep the appropriate distance and vertical angle for shooting, while a protractor was used to measure the angle between the stems and leaves and record the measurement results on the computer. During the whole collection process, a total of 3063 image data were collected, and 2096 image data that met the requirements were obtained by manually screening and removing blurred and non-standard photos. Table 1 summarizes the data set used in this experiment.

Table 1. Statistics of the data set

Periods	Capture Image	Filter	Total
Jointing stage	643	469	469
Booting stage	754	480	480
Heading stage	497	438	438
Mature stage	1169	709	709
Total	3063	2096	2096

Then the dataset was manually labelled using the labelling software Labelme (Fig. 2), and the labelled file was saved in the original folder in json format. After the labelling was completed, the dataset was divided according to the ratio of 8:2 to obtain the training set and validation set.

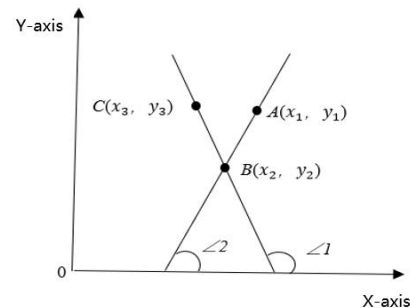


Figure 1. Stem leaf angle position diagram

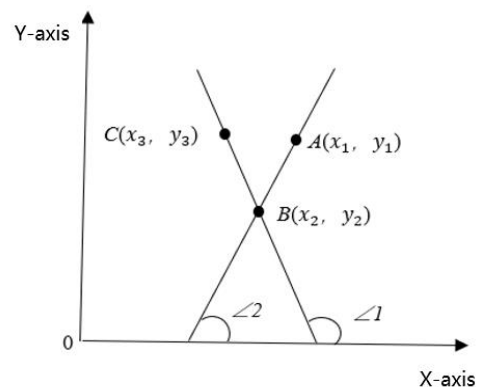


Figure 2. Data annotation

In the image, the key points are usually points that can characterize some features. For rice, the key points can refer to the important parts of rice traits. To identify the angle between the stems and leaves of rice, three key points can be selected: one key point is above the stem (Point A in Fig. 1), one key point is above the leaf (Point C in Fig. 1), and the last

key point is at the junction of the stem and leaf (Point B in Fig. 1). These three key points can determine the angle of the stem and leaf. Each rice plant may have more than one angle, so in order to locate the position of the angle between each stem and leaf, the rectangular box is marked first, then the key points are marked in the rectangular box, and three key points are marked on the stem and leaf of each angle. The text data

of the annotation results is shown in Table 2, where the first column represents the category of the target, which is the rectangle, the second column to the fifth column. The four data represent the coordinates of the rectangular box, and the last three columns represent the coordinate values of the three key points.

Table 2. Marking of key points

Class	x	y	w	h	Key point 1	Key point 2	Key point 3
0	0.49	0.555	0.114	0.087	0.467,0.536	0.486,0.582	0.49,0.537
0	0.517	0.68	0.11	0.085	0.487,0.661	0.491,0.705	0.526,0.661
0	0.496	0.806	0.11	0.085	0.456,0.799	0.49,0.832	0.494,0.789

2.2. Method introduction

2.2.1. Measuring method of Angle between stems and leaves based on key points

YOLO-Pose [13-14] is a model without heat map and capable of end-to-end training. It optimizes the target key point similarity (OKS) metric itself. Compared with the top-down method, the model can directly process the original input and eventually generate output without multiple stages of processing. In this study, the key point detection model of human pose estimation was applied to the key point location of plants. With YOLOv7 as the baseline, the key points of stems and leaves of rice were located in combination with the key point detection method, and then the angle was calculated according to the key point information located. As shown in Fig. 1, calculate the size of $\angle 1$ according to the key points B and C, and then calculate the size of $\angle 2$ according to the key points A and B; Finally, according to the difference between $\angle 1$ and $\angle 2$, the angle between stems and leaves is obtained, and the specific calculation formula is shown in formula 1. x represents the horizontal position of the key point coordinates, and y represents the vertical position of the key point coordinates.

The formula for calculating the angle is:

$$Angle = \angle 1 - \angle 2 = \tan^{-1} \frac{y_3 - y_2}{x_3 - x_2} - \tan^{-1} \frac{y_1 - y_2}{x_1 - x_2} \quad (1)$$

2.2.2. Key point detection algorithm based on YOLOv7-pose

The basic principle of key point detection is to find some feature points in the image that are significant and not easy to be affected by image transformation. These feature points can be corner points, edge points, spots and so on. In the detection process, some specific algorithms are usually used to find these feature points. In recent years, the research of key point detection based on deep convolutional neural network is particularly hot, and a series of key point detection algorithms have been developed.

One is based on convolutional neural networks (CNN). CNN is a deep learning model suitable for image processing and computer vision tasks, such as Hourglass [15] networks, ResNet etc. CNN-based key point detection methods usually use CNN to extract image features, and then map the features to the coordinates of key points through the full connection layer and the output layer; The trained model can be used to predict the location of key points in the image [16]. The other is the key point detection method combined with the target detector. First, the target detector (such as Faster R- CNN, YOLO et al) is used to identify and locate the location of the

target object from the image, and then the key point prediction is carried out on the interior or boundary of the located target object [17]. This method combines the two tasks of target detection and key point detection to achieve more accurate key point location. There is also a Heatmap based method [18]. Its principle is based on the heatmap generated by the deep learning model. The core idea is to use convolution of the output feature layers to obtain the confidence of each key point, that is, each channel represents the confidence of each position of a certain key point on the input image. Then take the maximum confidence and the corresponding position on each channel. In addition, there are also networks based on pose estimation, such as OpenPose, which can detect key points of the human body (the head, limb joints et al), and networks based on multi-scale and multi-level feature fusion, such as pyramid structure or cascade structure, to improve the accuracy and robustness of key point detection [19].

YOLOv7 [20] is the latest YOLO structure in the YOLO family, which is extremely fast and can operate in the range of 5 frames per second to 160 frames per second, while maintaining high accuracy. The YOLOv7 offers significant advantages over other known target detectors in terms of both speed and accuracy. When running in a GPU V100 environment, YOLOv7 can achieve the highest accuracy in real-time running at more than 30 frames per second. In order to adapt to different operating environments, YOLOv7 offers three basic models, namely YOLOv7-Tiny, YOLOv7 and YOLOv7-W6. With the advancement of research, key point algorithms based on target detection have entered everyone's field of vision, such as KAPAO based on YOLOv7 [10] and YOLOv7-pose based on YOLOv7. This kind of method does not use Heatmap but a regression-like method for key point detection, so it can achieve better speed accuracy [19]. YOLOv7-pose adopts a network structure similar to YOLOv7. Its network mainly consists of four parts: Input, Backbone, Neck and Head. Its structure diagram is shown in Fig. 3 [21-22].

First of all, the image enters the input layer, set the image input size to 640×640 , and after a series of pretreatment operations such as data enhancement of the input part, it is sent to the backbone network. The backbone part extracts features from the processed images, including a large number of CBS modules and SPPCSPC modules. Among them, CBS module is mainly composed of Conv+BN+SiLU activation function, SPPCSPC module adopts the idea of space pyramid pool, used to enhance the expression ability of features; Then, the extracted features are fused by the Neck module to get the features of large, medium and small sizes. Finally, the fused features are sent to the detection head, and the result is output after detection. Finally, the Head network will classify, locate

and estimate the pose of the feature map output by the Neck network to output the final detection result and pose information. In this study, the selected model still includes Backbone and Neck modules of YOLOv7, but the Head part is modified for key point detection.

GSCnv is a new convolution layer, which is constructed by combining SC, DSC and shuffle mixed convolution. This convolution layer can improve the detection speed while maintaining accuracy, thus meeting the need for precision and speed. In the lightweight model, the original convolution layer can be directly replaced with the GSCnv layer, and significant accuracy gain can be achieved without additional

operations [23]. The structure diagram of GSCnv is shown in Fig. 4. The advantage of GSCnv structure is that it can make the output of convolutional calculation as close as possible to SC, reduce the calculation amount, and has a slender neck of standard backbone. Whether it is in the first stage or the second stage, its central basis is the CNN fundamental structure. Therefore, the GSCnv structure can improve the performance of the network and reduce the computation. Therefore, this paper introduces GSCnv module to replace the original convolution layer, reduce the number of parameters, and ensure the training accuracy to the maximum extent.

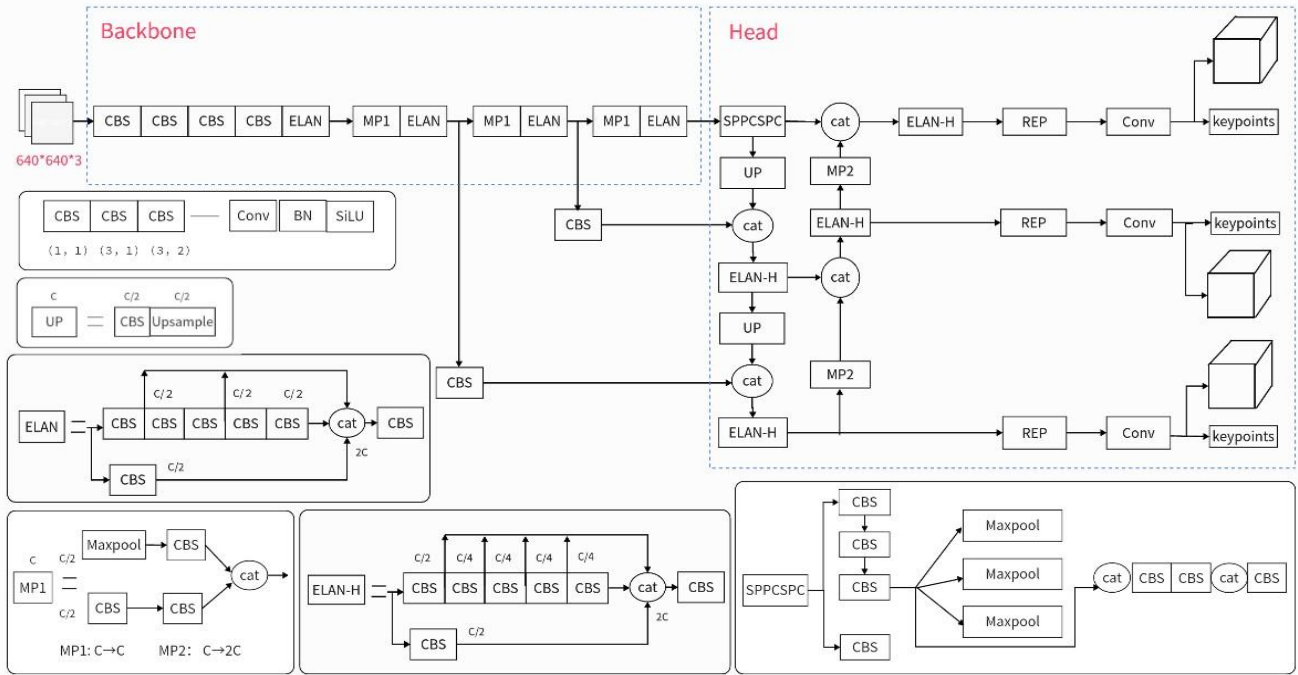


Figure 3. YOLOv7-pose structure diagram

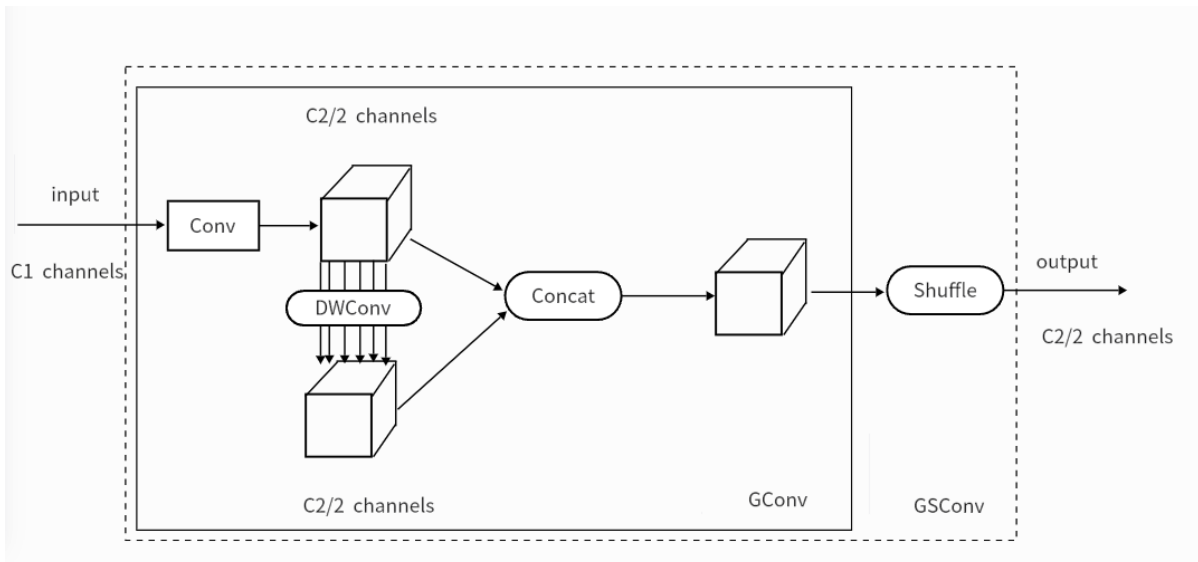


Figure 4. GSCnv structure diagram

2.3. Experimental environment and evaluating indicator

2.3.1. Experimental environment

In this project, the Head module of YOLOv7 model is replaced by key point detection, so that it can quickly locate key points, so as to intelligently identify the angle between

stems and leaves of rice. According to the server memory, the batch size is set to 16, the number of experimental training is 300 rounds, and the optimal results are obtained by repeated verification. The GPU is NVIDIA RTX A5000, the experimental environment is Window 11 (64-bit) operating system, the development language is Python, and the deep learning framework is configured as Pytorch 1.13 + cu116.

The specific experimental environment initialization configuration is shown in Table 3.

Table 3. Experimental environment configuration

Name	Configuration
System	Window 11 professional version
CPU	Intel(R) Xeon(R) CPU E5-2690 v4 @ 2.60GHz
GPU	NVIDIA RTX A5000
Python	Python 3.8
PyCharm	PyCharm 2022.2
Pytorch	1.13
CUDA	11.6
Memory	128G

2.3.2. Evaluating indicator

In order to compare and evaluate the performance of the model, several common network model evaluation indicators are used, including F1、Precision、Recall and mAP, The specific calculation is as follows:

Precision represents the proportion of the actual positive examples in the positive examples, and the calculation formula is shown in formula 2.

$$P = \frac{TP}{TP + FP} \quad (2)$$

Recall represents the coverage of positive samples with correct prediction. The larger the Recall is, the less the missed detection is, and the smaller the Recall is, the more the missed detection is. The calculation formula is formula 3.

$$R = \frac{TP}{TP + FN} \quad (3)$$

F1-score is a measure of the classification problem. Some machine learning competitions for multi-classification problems often use F1-score as the final evaluation method. The calculation formula is formula 4.

$$F1 - score = \frac{2 * precision * recall}{precision + recall} \quad (4)$$

mAP (mean Average Precision), the mean value of the average precision, where C represents the total number of categories, and AP_i represents the AP value of category i . The calculation formula is formula 5.

$$mAP = \frac{\sum_{i=1}^C AP_i}{C} \quad (5)$$

3. Results and discussion

3.1. Use methods analysis

The commonly used method to compute the rice pinch angle is based on image vision. Firstly, rice image data are acquired; then a series of pre-processing is carried out on the acquired image data, including gray-scale treatment, smoothing denoising, image binarization [24] and other steps; after the pre-processing is completed, further skeleton extraction is carried out on the image, followed by detecting the straight lines in the skeleton image by using the Hough transform, and calculating the absolute pinch angle difference of these straight lines, so as to obtain the stem-leaf pinch angle of rice.

The specific experimental processing process is shown in Fig. 5. Fig. 5a is the original drawing. Fig. 5b is the original image processing. FIGURE 5c is the skeleton extraction of the image. The figure shows the result of straight line

detection after skeleton extraction (Fig. 5d), and Fig. 5e is the final result. Although this method can calculate the angle, the calculated results have errors, and this method is not suitable for a large number of calculations.

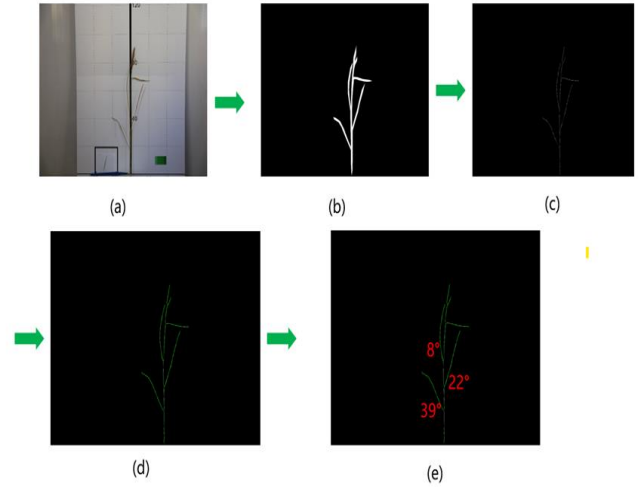


Figure 5. Flow of calculating the angle between stems and leaves

HRNet [25-26] is a classical key point detection network. The performance comparison of YOLOv7 with YOLOv7 and HRNet shows that YOLOv7 model has better training effect (Table 4). The accuracy rate of YOLOv7-pose reached 93.7%, higher than that of HRNet and YOLOv5-pose models. The results show that the YOLOv7-pose model is more suitable for the extraction of key points of rice stem-leaf angle, which provides more accurate data for the subsequent calculation of stem-leaf angle and provides certain technical support for agricultural personnel.

Table 4. Evaluation of model results based on key point detection algorithm

Model	mAP	Weight(M)
Yolov5s-pose	0.743	150
Yolov7-pose	0.937	160.3
HRNet	0.74	211

The position of the key points of the stems and leaves is predicted by YOLOv7-pose. By extracting the coordinate information to calculate the angle, the text information is rendered to the picture by using putTxt of opencv. The prediction results are shown in Fig. 6.

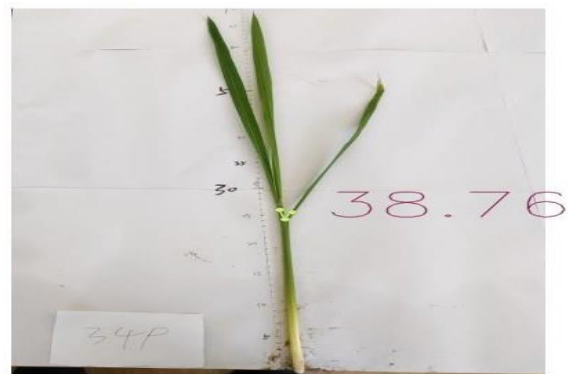


Figure 6. Forecast results

3.2. Performance comparison of improved models

Considering the influence of model size on processing speed, the model is lightweight optimized. Specifically, we

use ShufflenetV2, MobilenetV3 [27] and Ghostnet [28-29] to replace the original Backbone network to extract the features

of the input images. These lightweight network structures

Table 5. Evaluation of model results based on key point detection algorithm

Model	F1-score	Precision	Recall	mAP
YOLOv7-pose	0.86	0.881	0.96	0.937
YOLOv7-pose+shufflenetv3	0.81	0.817	0.802	0.841
YOLOv7-pose+mobilenetv3	0.84	0.868	0.805	0.889
YOLOv7-pose+ghostnet	0.89	0.891	0.896	0.951
YOLOv7-pose+GSCnv	0.98	0.977	0.988	0.987

have low computational complexity and memory requirements, and are suitable for applications in resource-constrained environments. The extracted feature map is input into the Neck and Head parts of YOLOv7-pose for key point detection. Finally, the validity of the model is verified by experiments on the original data set, and the influence of different hyperparameters on the performance of the model is also discussed to determine the best model configuration. The loss function is an important concept in machine learning and deep learning. It is used to measure the difference or error between the model prediction result and the real value. It is a numerical evaluation index. Usually, we think that the smaller loss value indicates that the model prediction is more accurate, and the larger loss indicates that the model prediction has a larger error. The specific loss and mAP value curve of the model used is shown in Fig. 7. Fig. 7a shows the loss change curve for the validation set. With the increase of the number of iterations, the curve of the model gradually converges, and gradually stabilizes after 150 iterations. While the loss changes, the mAP value also gradually changes, the curve gradually tends to be smooth, and the overall mAP is slightly higher than the original YOLOv7 model (Fig. 7b). The accuracy, recall rate, F1 value and average accuracy of the key point detection algorithm before and after improvement are shown in Table 5. From the table, the accuracy of the method with GSCnv module is the highest which is better than other methods. Therefore, the method used in this paper can effectively confirm the position coordinates of the key points of rice, and then calculate the angle between the stem and leaf of rice.

The experimental results are shown in Fig. 8, which are the analysis of the fitting results of the four periods. The evaluation indexes are mean square error (MSE), root mean square error (MAE) and coefficient of determination (R2). It can be seen from the Fig. 8 that R2 is 0.82, 0.84, 0.78, 0.80 respectively. The fit between the calculated results and the actual manual measurements is better.

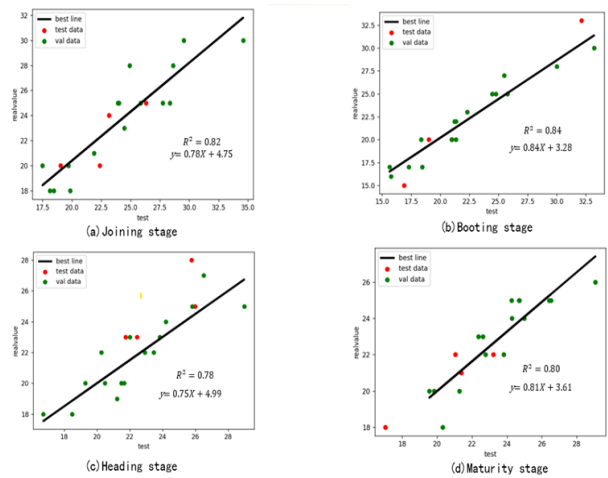


Figure 8. Analysis of measurement results

The angle data calculated by the skeleton extraction method were sorted out. Similarly, 20 samples were selected for testing in the four growth periods of rice, and the relative error was calculated. The results of the comparison with the method in this paper are shown in Fig. 9. It can be seen from the histogram of Fig. 9 that the average value of the sample obtained by the method in this paper is obviously higher than the average value of the sample obtained by the skeleton extraction method. From the error analysis, the representative error of the short error bar is small, which indicates that the angle calculated by the YOLOv7-pose+GSCnv method is more accurate. In addition, in order to evaluate the performance of the two methods more accurately, the mean square error (MSE), root mean square error (MAE) and coefficient of determination (R2) are calculated. The stem and leaf angles of the four periods obtained by the skeleton extraction method are analyzed with the real values. The R2 obtained by the analysis is 0.7, 0.84, 0.70, 0.79, and the R2 obtained by the method in this paper is 0.82, 0.84, 0.78, 0.80. In comparison, the R2 obtained by the method in this paper is larger and better. In summary, the method used in this paper is suitable for the measurement of the angle between the stems and leaves of rice, and has certain accuracy.

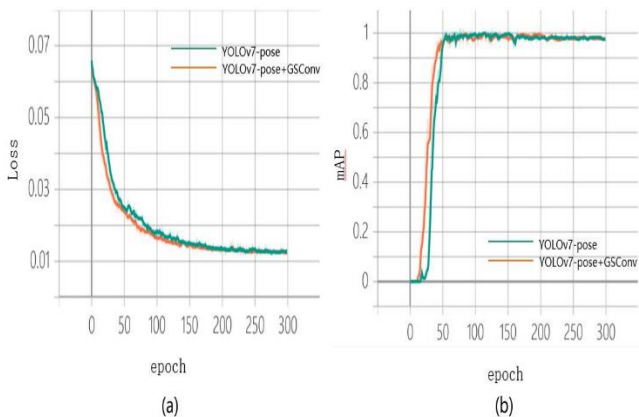


Figure 7. Loss curve and mAP change curve of the model

3.3. Experimental verification and analysis

In order to verify the accuracy of the algorithm, the method in this paper was used to calculate the angle between stems and leaves of the samples. At different growth stages of rice growth, 20 samples were randomly selected for testing. Each plant was manually measured and the results were recorded.

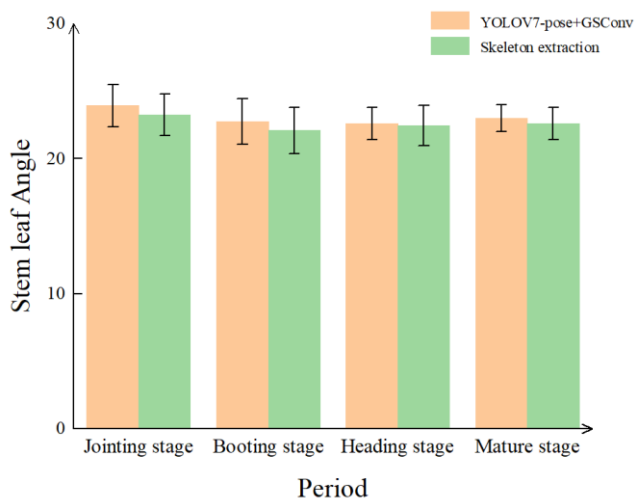


Figure 9. Error Analysis Chart

4. Conclusion

In this paper, an intelligent identification method of rice stem and leaf pinch angle based on key points is proposed, which is able to intelligently identify the stem and leaf pinch angle of rice in a large number and accurately. The YOLOV7-pose model is used in this paper which cleverly integrated with the key point detection module. In order to further enhance the performance of the model, the GSCConv module is introduced to replace the original standard convolution, and the average accuracy of the key point detection reaches 98.7%, F1 value is 98%, which is capable of quickly detecting the information of the key points of the rice stems and leaves. Then we can calculate the angle of the stems and leaves based on the information of the key point coordinates. The investigated method can reduce the labor cost and enable agriculturalists to get the information of stem and leaf angle quickly and accurately.

Stem and leaf pinch angle algorithms for rice may be affected by a variety of factors, such as background interference, stem and leaf folding, and shadowing, resulting in poor recognition accuracy. In order to improve the robustness and versatility of the algorithms, future research will be devoted to developing more accurate and versatile clip angle recognition algorithms, as well as exploring the fusion of multi-scale and modal information such as multispectral images and point cloud data to more accurately differentiate the different tissues and organs of rice. In this paper, we used the method of placing a whiteboard behind the rice and shooting vertically to effectively remove the interference of complex backgrounds on image acquisition and reduce the geometric aberrations of stem and leaf pinch angle images, thus ensuring that the measurement results can meet the needs of general research. In the future, the research will focus on more conveniently obtaining geometric parameters of rice plants, which will provide powerful support for rice growth monitoring, plant type characterization and digital rice research, and thus promote the further development of rice research and application fields.

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