Quantitative Calculation Method for Growth Status of Chinese Cabbage based on YOLOv5 Network with Multivariate Linear Fitting

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Abstract. Tracking the growth status of Chinese cabbage in real time is widely promising for exploring the effect of fertilization and increasing the yield of Chinese cabbage. In this paper, we constructed a quantitative computational model of Chinese cabbage growth status based on YOLOv5 network and multivariate linear fitting method using self-made Chinese cabbage growth stage dataset and leaf dataset. In order to accurately calculate the total fresh weight of Chinese cabbages, we used the YOLOv5 network to localize and identify the growth stages of individual cabbages, and to count the number of each of the four size types of leaves. Considering the leaf occlusion problem, here we use the leaf segmentation method based on HSV color space to calculate the image pixel ratio occupied by leaves. Together with the number of the four types of leaves as the independent variables, the equation for calculating the total fresh weight of Chinese cabbage was fitted by multivariate linear fitting. The fitting equation was tested by mAP and statistical manner, and the more accurate calculation effect was obtained.

Keywords: Chinese cabbage growth tracking · YOLOv5 network · Leaf segmentation · Multivariate linear fitting.

1 Introduction

Chinese cabbage, cruciferous vegetable crops, is one of the most widely distributed, cultivated and popular vegetables in China [1]. With the improvement of living standards, people's enthusiasm for a healthy diet is gradually rising, and the demand for Chinese cabbage is also increasing, so it is very necessary to cultivate high-yield, fast-growing Chinese cabbage [2]. Real-time and accurate growth tracking of Chinese cabbage is conducive to exploring the effects of plant fertilization and gene selection, providing a basis for predicting plant growth curves and enriching research on regulating the growth of Chinese cabbage.

Current research on plant growth tracking is mainly on camera or sensor acquisition and image recognition techniques, allowing real-time data acquisition and processing, and avoiding the impact that physical contact may have on the plant. Yan Pu et al. proposed a rice growth stage recognition method based on machine learning and fractal dimension, using the random forest method to screen the features. The recognition accuracy reaches 94.39%, which can achieve a better classification effect, but lacks the estimation of plant growth parameter values [3]. Jiahui Zhang builds a non-contact plant growth monitoring system based on the LoRa transmission technology of the Internet of Things and the method of constructing the mechanical structure of the monitoring mechanism. She proposed to realize the recognition of plant growth stages and the estimation of parameter values by segmenting the characteristic organs of the plant and measuring them, which provides a new way of thinking for plant growth monitoring [4].

The current research on plant growth state recognition mainly focuses on the recognition of growth stages, and lacks the estimation of plant growth parameter values. In addition, according to the growth characteristics of Chinese cabbage and the application requirements of the actual agricultural scenarios, the leaves in the photos taken by ordinary cameras will have different degrees of shade, making it difficult to be applied to the calculation of the value of the growth parameters of Chinese cabbage. In this paper, we take the complete growth cycle of Chinese cabbage plants as the research object, and propose a growth tracking model of Chinese cabbage based on digital image processing technology to recognize the growth stage and calculate the growth parameter values of multi-plant Chinese cabbage RGB images.

Following the introduction, Section 2 describes the proposed methodology and the construction of the associated dataset. Section 3 presents the analysis of the results. Finally, Section 4 wraps up the paper with conclusions.

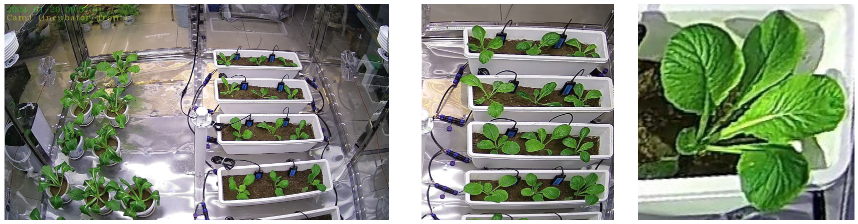
2 Material and methods

2.1 Constructing datasets

Due to the lack of cabbage growth process dataset, this paper produced its own cabbage growth stage dataset and leaf dataset.

The experiment used a camera with a resolution of 1920×1080 to record the process of the complete growth cycle of Chinese cabbage. The camera was fixed in the middle position above the incubator, one at the front and one at the back, and the lens was shot at a perpendicular distance of 1.2 m from the target leaves, skewed downward by 45°. The shooting interval is 4 h [5].

The image of cabbage growth process is shown in Fig. 1(a).Firstly, the top view was restored by perspective transformation, and the image was obtained as shown in Fig. 1(b), which was used to produce the growth stage dataset of Chinese cabbage, including three growth stages: germination, seedling, and vigorous growth stage.



(a) (b) (c)

Fig. 1: Cabbage dataset images. (a) is the original image captured by the camera, which was perspective transformed to get (b). Cropped (b) to get the single cabbage image (c).

Since a single image contains multiple Chinese cabbage plants, a single Chinese cabbage image needs to be cropped to produce a Chinese cabbage leaf dataset based on Fig. 1(b), as shown in Fig. 1(c), and the dataset consists of four leaf size types, namely, large, middle, little, and mini. The statistical profiles of datasets are shown in Table. 1 , and the pixel size of the images is uniformly compressed to 640×640 in order to improve the efficiency of the model training and ensure the accuracy of the training results.

Table 1: Datasets summary statistics

	Growth stage dataset(GS-CC)	Leaf type dataset(LT-CC)
Number of images	3780	4944
Number of labels	3	4
Resolution	640×640	640×640
Smallest class	960 images	618 images
Largest class	1758 images	1605 images

Due to the limited and uneven number of collected images of Chinese cabbage, as well as the single lighting and background, data augmentation processing is performed on the growth images of Chinese cabbage in order to improve model accuracy and robustness. We used a random mixture of the approaches such as brightness adjustment ($\pm 10\%$), flipping, angle rotation ($\pm 15°$), and image zoom (15%). The image after data enhancement is shown in Fig. 2. In addition, the YOLOv5 network model proposes Mosaic data enhancement, which splices four different input images into one large mosaic image [6]. This approach can effectively simulate the interrelationships and interactions between the backgrounds of cabbage planting in a real scene.

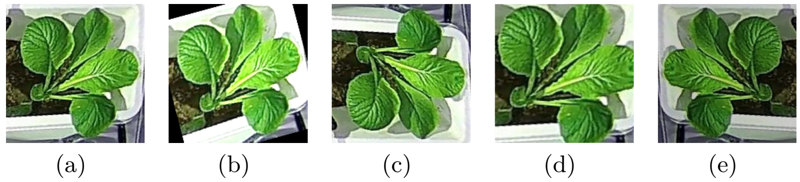


Fig. 2: Data Enhancement of Cabbage Pictures. (a) is the original image. (b) is the image after rotation and brightness enhancement. (c) is a vertical flip of the image. (d) is the enlarged image. And (e) is a mirror flip of the image with brightness reduction.

2.2 Proposed methodology

In this paper, a quantitative computational model for growth state of Chinese cabbage is proposed, as shown in Fig. 3. Since the captured image contains multiple cabbage plants, the first stage uses the YOLOv5 network to localize and identify the growth stages (germination, seedling, and vigorous growth) of a single cabbage plant, and the image of a single plant is cropped and segmented according to the localization results [7].

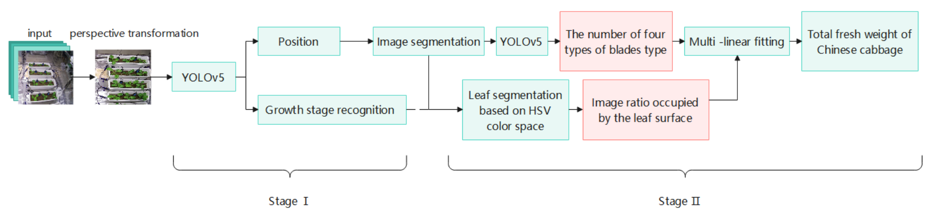


Fig. 3: Flowchart of the quantitative computational modeling of growth states.

The second stage is to calculate the values of growth parameters. The total fresh weight of plants is the weight immediately measured after the collection of fresh plants, directly reflecting the yield and quality of cabbage, so this paper selects the total weight of cabbage as the growth parameter value indicators for tracking [8].

Considering that the characteristics of Chinese cabbage in different growth stages are mainly reflected in the leaves, the leaf size and number were selected as reference indexes. The YOLOv5 network was used to recognize the leaf size categories (*large, middle, little, mini*) in the cropped single-plant images, and the number of leaves of each type was counted as the four independent variables in the equation for fitting the total fresh weight of Chinese cabbage [9]. Considering the problem of leaf occlusion, the image pixels ratio (*ratio*) occupied by the leaf surface was added to the independent variables. Among them, *large, middle, little* and *mini* represent the number of four leaf types respectively, which is an integer number with the unit of piece; *ratio* is a proportion, indicating the possibility of the existence of unknown leaves. Due to the early stages of cabbage growth images taken almost no leaf occlusion problem, *ratio* is calculated only when the cabbage growth stage recognition model predicts an Index3 stage, otherwise it is zero.

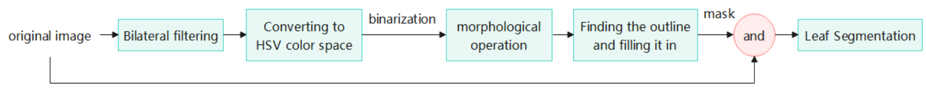


Fig. 4: Flow chart of leaf color segmentation based on HSV space.

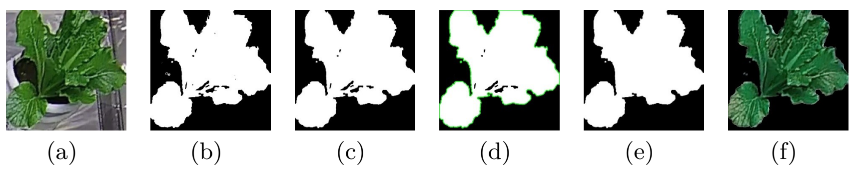


Fig. 5: Diagram of the leaf segmentation process. (a) is the original image. The binarized image is bilaterally filtered to obtain (b). (c) shows the image after morphological operations. (d) shows the contour drawing process. (e) shows the mask obtained after contour filling. (f) shows the segmentation result.

The *ratio* is calculated using the leaf segmentation method based on HSV color space, as shown in Fig. 4. Firstly, the cropped image is bilaterally filtered to smooth the image and reduce the effect of noise, thereby improving the quality of the color segmentation template [10]. Then the image is converted from RGB space to HSV space [11], and the binary image is segmented according to the green range, which is the mask. The green part is the white pixel, and the other colors are the black pixels. Next, the segmented binary image is first subjected to a closed operation to bridge the narrower discontinuities and fill the breaks in the contour lines which can make the contour smoother. And then the processed image is subjected to an open operation to eliminate the white noise and fine parts [12]. It can be seen that a more complete segmented image can be obtained at this time, but there are still some larger black point noise. Considering the morphological characteristics of cabbage with larger leaves and coarser rhizomes in the late stage of growth, here we look for the outline of the plant and fill it internally. Finally, the segmented mask and the original image are used to extract the leaves of a single cabbage plant by logic and operation. The leaf segmentation process image is shown in Figure. 5.

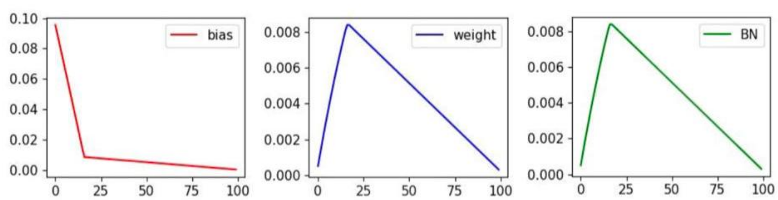
Let the width of the single Chinese cabbage image is w, height is h, leaf segmentation area region is C. If the growth stage of Chinese cabbage recognition results in x, the formula for the independent variable of the image pixel ratio occupied by the leaf surface is shown in Equation 1.

$$ratio = \begin{cases} 0, & x = \text{Index1,Index2} \\ \frac{\sum_{i=1,(i,j)\in C} i}{w \times h}, & x = \text{Index3} \end{cases} \tag{1}$$

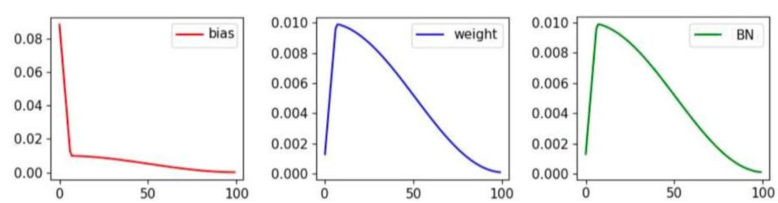
Finally, we obtained the equation for calculating the total fresh weight of single cabbage plants by multivariate linear fitting. Statistical tests such as residual test, analysis of variance (ANOVA), and independent variable covariance test were used to verify the fitting effect of this equation.

2.3 Training details

In this work, the YOLOv5 network model training is divided into two parts: growth stage recognition and leaf type recognition, and we set different hyperparameters and fine-tuning methods for different model training features, as shown in Table. 2. The learning rate is adjusted through LambdaLR, with the initial learning rate of the bias layer is 0.1 to ensure faster adjustment. The change strategy for the bias layer, weight layer, and BN layer is shown in Fig. 6(a). Here we use a warm-up learning strategy, where the learning rate increases linearly from a smaller value to the initial learning rate within the warm-up phase, and then decays linearly [13].



(a) Growth stage recognition



(b) Leaf type recognition

Fig. 6: Learning Rate Change Strategies for Training

When using LambdaLR to adjust the learning rate of the leaf type recognition model, we found that we could not achieve good results. Therefore, we add cosine annealing attenuation to LambdaLR, which is suitable for the more delicate recognition tasks such as distinguishing leaf types to achieve better results. The learning rate change strategy is shown in Fig. 6(b).

Table 2: Hyperparameter constant setting and fine-tuning hyperparameters

Hyperparameter	Growth stage identification	Leaf blade identification
Maximum Epochs	100	100
Batch Size	32	32
Optimizer	SGD	SGD
cos_lr	False	True
lr0	0.01	0.01
lrf	0.01	0.005

In this work, we used a working platform of Intel Xeon Platinum 8352V CPU, operating system Visual Studio Code, and Pytorch 1.11.0 to implement deep neural networks(see Table. 3).

Table 3: Experimental environment configuration for the YOLOv5 network model.

Experimental environment	Models and versions
Hardware Environment	Intel Xeon Platinum 8352V CPU @2.10GHz
Operating System	Visual Studio Code
Programming Languages	Python 3.8
Deep Learning Framework	Pytorch 1.11.0
GPU	CUDA 11.3

3 Results

3.1 Training process and analysis of YOLOv5 network

The training process of the cabbage growth stage recognition model and leaf recognition model is shown in Fig. 7. Considering that the main purpose of the blade recognition model is to recognize the type of blade, we believe that the model reaches the ideal training effect.

The training results of 100 rounds of training of the cabbage growth stage recognition model are shown in Table. 4, and we can see that the recognition accuracy of different growth stages of Chinese cabbage germination (Index1) > seedling (Index2) > growth stage (Index3). The overall F1 value of the model is 0.856.The average mAP reaches 0.925 when the intersection and concatenation ratio (IoU) is 0.5. When the IoU is taken in the range of [0.5:0.95], the average mAP of step size 0.05 is 0.756, which indicates that the model can maintain a good detection performance for different stages of Chinese cabbage. The training results of the leaf recognition model are shown in Table. 5, which shows that the model has the highest recognition accuracy for small leaves (little), followed by large leaves (large) and medium leaves (middle), and the lowest recognition ability for mini leaves. The overall F1 value of the model is 0.8 and when IoU=0.5, the average mAP reaches 0.837. The leaf recognition model provides preparations for the estimation of the values of the growth parameters of Chinese cabbage, and the detection performance can satisfy the subsequent computational needs [14–17].

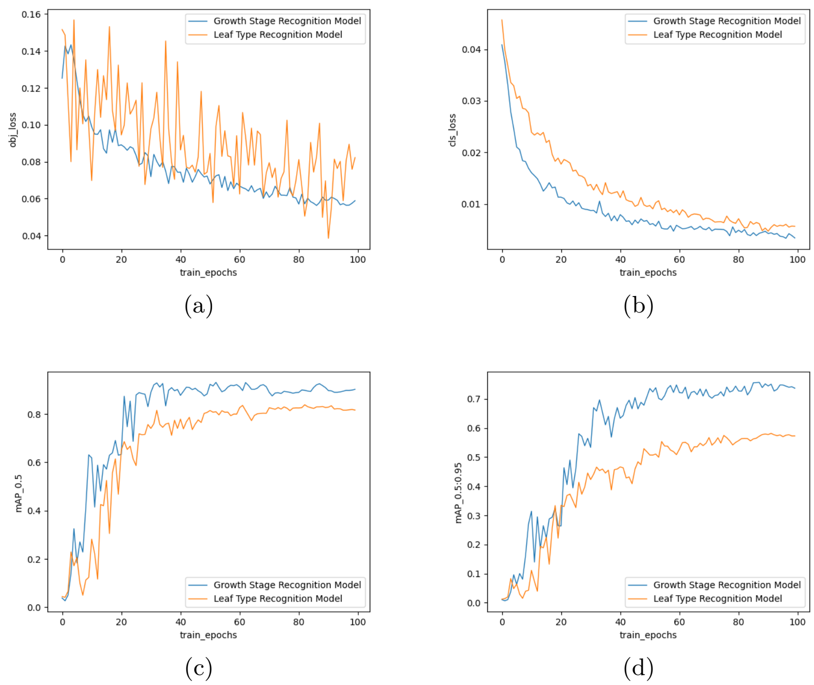


Fig. 7: Training Process. (a) shows the progression of objectness loss. (b) shows the progression of classification loss. (c) shows the change in mAP at thresholds greater than 0.5. (d) shows the change in mAP at thresholds between 0.5 and 0.95.

3.2 Results from fitting the total fresh weight equation

In this paper, we conducted fitting experiments for four variables (*mini, little, middle, large*) and five variables (*mini, little, middle, large, ratio*) respectively, and the fitting effect is shown in Table. 6. It can be seen that after increasing *ratio* as the independent variable, the adjusted R^2 rises to 0.930, indicating that the independent variable can explain 93% of the variation information of the total fresh weight, which meets the expected goal. DW-test showed 1.24, which

Table 4: Results of growth stage identification.

Categories	P	R	mAP 0.5	mAP 0.5:0.95	F1
all	0.82	0.909	0.925	0.756	0.856
Index1	0.988	0.991	0.995	0.857	0.989
Index2	0.587	0.853	0.818	0.647	0.695
Index3	0.886	0.885	0.961	0.765	0.885

Table 5: Results of growth stage identification.

Categories	P	R	mAP 0.5	mAP 0.5:0.95	F1
all	0.804	0.737	0.837	0.565	0.8
large	0.782	0.748	0.858	0.636	0.765
middle	0.876	0.746	0.852	0.519	0.806
little	0.884	0.787	0.905	0.621	0.833
mini	0.674	0.667	0.732	0.485	0.670

is between 1 and 3, so the independence of the fitted residuals can be considered to be met [18].

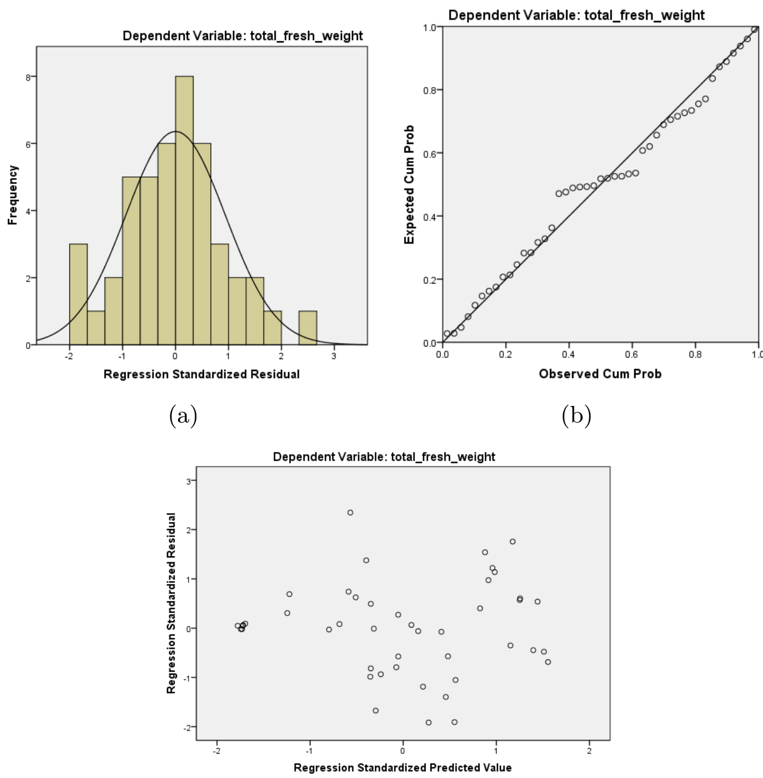
Table 6: Comparison of fitting effects.

Variables	R	R^2	adjusted R^2	Std. Error of the Estimate	Durbin-Watson
pre-additive	0.959	0.921	0.913	11.71169	1.331
post-additive	0.968	0.938	0.930	10.50210	1.245

Next we test the residuals, see Fig. 8. The mean of the standardized residuals is approximately 0, and the standard deviation is 0.941 close to 1. The residuals are overall normally distributed, and we can conclude that the normality condition for linearized regression reaches [19]. The normal probability plot (P-P plot) of the standardized residuals is shown in Fig. 8(b), which approximates a straight line and conforms to the normal distribution. In the standardized residual plot (see Fig. 8(c)) we can see the residual scatter distribution around the value of 0, basically maintaining the upper and lower symmetric distribution, and the characteristics do not change with the increase in the predicted value. It indicates that the residuals of the linear regression model meets the conditions of variance uniformity and independence.

The ANOVA results are shown in Table. 7. When F=117.379, P<0.001, it means that at least one independent variable will have an effect on the dependent variable, which makes the regression variance larger and the residual variance reduced, and the model passes the overall significance test [20].

Finally we calculated the regression coefficients and tested the significance and covariance of them, see Table. 8 [21]. It can be seen that the independent variables *large* (β=0.843, P=0.000) and *middle* (β=0.234, P=0.004) have a more significant effect on the total fresh weight of cabbage, followed by *ratio* (β=0.093) > *little* (β=0.037) > *mini* (β=0.09), which is in line with the actual expectations. The covariance statistics include two indicators, variance inflation factor (VIF) and tolerance. According to the table, it can be seen that the VIF of all variables is less than 10 (tolerance>0.1), indicating that the collinearity between independent variables is not severe, and this linear fitting equation is meaningful.



(a) (b) (c)

Fig. 8: Residual testing.(a) is a histogram of the standardized residuals. (b) is a normal probability plot of the standardized residuals showing the relationship between the cumulative frequency distribution and the theoretical distribution of the residuals. (c) is a scatter plot showing the characteristics of the residual distribution.

The equation for fitting the total fresh weight of Chinese cabbage is as follows:

Table 7: ANOVA

	Sum of squares	Degree of freedom	Mean square	F	Significance
Regression	64731.297	5	12946.259	117.379	.000b
Residuals	4301.469	39	110.294		
Total	69032.766	44			

Table 8: Results of regression analysis.

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	B	Std. Error	β			Tolerance	VIF
(Constant)	.290	7.991		.036	.971		
mini	.396	2.323	.009	.171	.865	.568	1.761
little	.892	1.274	.037	.700	.488	.557	1.795
middle	2.862	.928	.234	3.083	.004	.276	3.617
large	11.756	1.025	.843	11.473	.000	.296	3.382
ratio	15.161	14.787	.093	1.025	.312	.196	5.099

$$\begin{aligned} \text{total\_fresh\_weight} = {} & 0.29 + 0.396 \times mini + 0.892 \times little + 2.862 \times middle \\ & + 11.756 \times large + 15.161 \times ratio \end{aligned} \tag{2}$$

Among them, *large, middle, little, mini* respectively represent the number of four types of leaves. *ratio* is the possibility of unknown leaves, indicating the weight provided by them. The constant value includes the weight supplement of organs such as roots and stems of Chinese cabbage.

4 Conclusion

In this paper, we propose a model that can recognize and quantify the growth status of cabbage. We used the YOLOv5 network to recognize the localization, growth stage and leaf size categories of a single cabbage plant, all of which were obtained with high accuracy. The number of four types of leaves and the proportion of image pixels occupied by the leaf surface obtained by the HSV color space-based leaf segmentation method were selected as independent variables, and combined with its growth stage, an equation for calculating the total fresh weight of Chinese cabbage was fitted, which has good and efficient performance. Future work will be continued in the area of eliminating the effect of complex background of Chinese cabbage.

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