Computers and Electronics in Agriculture 211 (2023) 108014

Contents lists available at ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Improved 3D point cloud segmentation for accurate phenotypic analysis of cabbage plants using deep learning and clustering algorithms

Ruichao Guo [a,1], Jilong Xie [a,1], Jiaxi Zhu [a], Ruifeng Cheng [b], Yi Zhang [b], Xihai Zhang [a,*], Xinjing Gong [a], Ruwen Zhang [a], Hao Wang [a], Fanfeng Meng [a,*]

[a] College of Electrical and Information, Northeast Agricultural University, Harbin 150030, China
[b] Institute of Environment and Sustainable Development in Agriculture, Chinese Academy of Agricultural Sciences, Beijing 100080, China

ARTICLE INFO

Keywords:
Plant phenotype
Point cloud
ASAP-PointNet
DBSCAN
Semantic segmentation

ABSTRACT

Plant phenotyping is essential for understanding and managing plant growth and development. 3D point clouds provide a better understanding of plant 3D structures. Point cloud segmentation is the basis for studying the 3D structure of plants through 3D point clouds, and accurate point cloud segmentation is crucial for extracting relevant phenotypic parameters. In this study, cabbage was used as an example, and a plant point cloud segmentation method combining deep learning algorithms and clustering algorithms was proposed. Specifically, a cabbage point cloud dataset was constructed using a 3D scanning platform. The ASAP attention module was incorporated into the PointNet++ model, resulting in the improved ASAP-PointNet model. Superior semantic segmentation performance on the cabbage point cloud dataset was demonstrated by this model. The workflow of the DBSCAN algorithm was also optimized, which exhibited enhanced performance in organ-level plant point cloud segmentation experiments. Subsequently, five phenotypic features were extracted. The experimental results revealed that an accuracy of 0.95 and an intersection over union (IoU) of 0.86 for semantic segmentation were achieved by the ASAP-PointNet model. The correlation coefficients between the four phenotype parameters (plant height, leaf length, leaf width, and leaf area) and their corresponding measured values were 0.96, 0.91, 0.95, and 0.94, respectively. An automated data analysis, from plant 3D point clouds to phenotypic parameters, is enabled by the proposed method, which serves as a valuable reference for plant phenotype research.

1. Introduction

Plant phenotype, determined by the interaction between plants and their environment, is considered an indispensable source of information for studying and managing plant growth and development(Gallinat et al., 2021; Guo & Zhao, 2022). Nevertheless, conventional phenotypic analysis methods exhibit constraints including limited scale, low efficiency, high error rates, and restricted applicability. These limitations impede the progress of scientific breeding and the optimization of plant growth management processes (X. Jin, Yang, Doonan, & Atzberger, 2022). In recent years, significant progress has been made in high-throughput plant phenotyping techniques leveraging computer vision. These advancements have successfully addressed the aforementioned challenges by offering precise and automated approaches to extract plant phenotypic parameters encompassing plant morphology, structure, color, texture, as well as disease status(C. Hu, Li, & Pan, 2018; Song, Wang, Guo, Yang, & Zhao, 2021). These techniques offer promising opportunities to significantly enhance plant research and agriculture through their ability to facilitate high-throughput and high-quality phenotyping data acquisition and analysis (L. Gong et al., 2021; Rawat et al., 2022).

In recent years, significant advances in sensing technology and computational performance have enabled researchers to rapidly acquire and analyze 3D plant data (S. Zhang, 2018), providing valuable data support for plant phenotypes (Tardieu, Cabrera-Bosquet, Pridmore, & Bennett, 2017). Various tools and techniques, such as LiDAR (Ao et al., 2022), structured light (S. Zhang, 2018), and stereo imaging (Bernotas et al., 2019), have been employed to collect 3D plant data and extract phenotypic parameters (L. Gong et al., 2021), like plant height and leaf area, enhancing our understanding of plant growth and development (X. Gong et al., 2022). However, research on analyzing 3D plant data has mainly focused on segmenting plant populations into individual plants

* Corresponding authors.
E-mail addresses: xhzhang@neau.edu.cn (X. Zhang), 191899205@qq.com (F. Meng).
[1] These authors contributed equally to this work and should be considered co-first authors.

https://doi.org/10.1016/j.compag.2023.108014
Received 7 April 2023; Received in revised form 16 June 2023; Accepted 20 June 2023
Available online 5 July 2023

(Chen, Jiang, Zhu, Wang, & Yun, 2021), leaving bottlenecks in conducting 3D plant phenotyping studies at the organ or individual plant level. For instance, accurately segmenting plant organs in complex 3D datasets, such as separating leaves from stems, remains a challenging task due to computational demands and high-throughput data processing requirements (Elnashef, Filin, & Lati, 2019). To address these challenges, researchers have developed various methods, including machine learning methods based on thresholds and normal vectors (Ge et al., 2022), to improve plant organ segmentation and 3D phenotyping accuracy (X. Jin et al., 2022). In practice, however, these methods exhibit limited efficiency and predominantly depend on manual intervention by experts, rendering them unsuitable for meeting the processing demands of larger point cloud databases (S. Jin et al., 2018). Therefore, a new method is needed for organ segmentation in single-plant 3D data that can accommodate large-scale, high-throughput dataset processing (B. Liu, Huang, Tian, & Ren, 2022). Currently, combining deep learning techniques with traditional clustering algorithms for processing 3D plant data and extracting phenotypic parameters has opened new avenues for comprehensive 3D plant phenotyping studies (Ao et al., 2022). This approach not only improves the efficiency of automatic segmentation of plant organs, but also enhances accuracy of the segmentation process. Consequently, it aids in obtaining high-precision plant phenotypes through the analysis of 3D plant data more effectively(Ninomiya, 2022).

The segmentation of plant point clouds and the extraction of phenotypic parameters using deep learning techniques remain challenging tasks (Saeed & Li, 2021). Training deep learning models using point cloud data presents difficulties due to the rotation invariance and unordered nature of point clouds (Yin, Huang, Cohen-Or, & Zhang, 2018). These characteristics make it difficult for deep learning models to extract both local and global features of point clouds. The PointNet algorithm proposes an efficient point cloud segmentation model (Charles R Qi, Su, Mo, & Guibas, 2017), and PointNet++ achieves better results in the extraction of local features using multi-scale grouping methods (Charles Ruizhongtai Qi, Yi, Su, & Guibas, 2017). In the field of plant point cloud segmentation, Li et al. employed PointNet to perform semantic segmentation of maize organs, demonstrating the enormous potential of this deep learning method for plant point cloud segmentation and phenotypic parameter extraction(Y. Li et al., 2022). The loss of the relationship between local features and local point clouds is a significant factor that affects the performance of deep learning models. To overcome this problem, Cui et al. designed the DGCNN neural network (Cui et al., 2021). With the development of attention module, researchers have started to use them to enhance model performance (Niu, Zhong, & Yu, 2021).

Another challenge faced in this field is the lack of open-source plant point cloud datasets for training and evaluating plant point cloud segmentation methods(S. Jin et al., 2019). Obtaining plant-related datasets is difficult as it requires suitable sensors and acquisition methods, and the complex structures of plants entail significant manual annotation efforts(Ma et al., 2019). The availability of large, diverse, and well-annotated datasets is critical for training deep learning models and evaluating their performance(C. Hu et al., 2018). To overcome this challenge, Dutagaci et al. provided a rose plant point cloud dataset with complete 3D annotations, but the dataset only consists of 11 samples, which is a small-scale dataset that may still affect the model's training (Turgut, Dutagaci, Galopin, & Rousseau, 2022). High-quality point cloud datasets often lead to better segmentation performance in deep models, making the construction of high-quality datasets a key focus in plant point cloud segmentation research (J. Zhang, Zhao, Chen, & Lu, 2019).

Aiming to overcome the challenges faced in extracting plant phenotypes based on 3D point clouds, such as acquiring plant point clouds, creating high-quality datasets, and segmenting plant point clouds, an efficient method for plant phenotype extraction is proposed in this study. Firstly, multiple views of cabbage were obtained on a 3D scanning platform to generate high-quality single plant point clouds. Then, preprocessing algorithms were used for denoising and data augmentation. The open-source software CloudCompare was used for cabbage point cloud annotation and training dataset construction. A model named ASAP-PointNet, based on PointNet++ with improvements, was proposed for cabbage point cloud segmentation to achieve better semantic segmentation results. Additionally, the DBSCAN algorithm was improved for better cabbage instance segmentation. Finally, phenotype parameters were extracted from segmented cabbage point clouds. As an example, high-throughput plant phenotype parameter extraction is realized for cabbage. This high-throughput, automated phenotype extraction method has the potential to serve as a reference for many plant phenotype studies.

2. Materials and methods

2.1. Overview

The proposed method in this study comprises four main stages: acquisition of materials and data, generation of plant point clouds, segmentation of plant point clouds, and extraction of plant phenotypic parameters. Fig. 1 illustrates the research content presented in this paper and the specific process involved in extracting plant phenotypic parameters through 3D point clouds.

2.2. Plant and image acquisition

To obtain cabbage in similar growth stages, experiments were conducted in the smart plant factory at Northeast Agricultural University (45.7427° N, 126.6236° E) in Harbin, Heilongjiang Province. A cabbage variety with a growth period of approximately 40 days was selected and transplanted after 25 days of seedling cultivation (Fig. 2). During this period, the cabbage belonged to the growth stage, and the detection of phenotype parameters at this stage can serve as a reference for breeding (Gratani, 2014). If problems such as poor growth and development occur, scientific guidance for cultivation can be provided through phenotype parameters (Zhu et al., 2020).

In order to collect high-throughput data in this study, a different approach was employed compared to traditional crop photography at fixed angles. Multiple view images of the plants were captured to ensure complete acquisition of the plant's structural information (D. Li et al., 2021). To achieve this goal, a 3D scanning platform was designed (Fig. 3), consisting of a PC, a motorized turntable, cameras, and two sets of lighting. The cameras and PC were utilized to collect images, while the turntable controlled the shooting angle. Lighting played a crucial role in the experiment due to the limited sensitivity of the camera's photosensitive element. Overlapping and dark areas of the plant were often challenging to capture, increasing the probability of 3D reconstruction failure (Nikolov & Madsen, 2016). In order to ensure that the point cloud dataset of cabbage contains sufficient structural information, high-throughput data from 30 cabbage plants were collected in this study. The cabbage was grown using hydroponics on a cultivation frame, so transfer and shooting did not cause structural damage to the plant. The cabbage was placed on the turntable, and the rotation angle was controlled by a motor control unit, while the camera angle was adjusted manually to obtain multiple views of the cabbage. Approximately 150 images were taken for each cabbage for 3D reconstruction and high-throughput data collection. As the plant had to remain relatively still during the shooting process, the turntable had to pause rhythmically rather than continuously moving. The cabbage images were collected in a laboratory environment, free from external interferences such as lighting conditions and wind effects. The shooting time for a single cabbage was 5–8 min, and shortening the shooting time also helped avoid significant changes in the plant's morphology. After shooting, the plant's phenotype parameters, including leaf number, plant height, leaf length, leaf width, and leaf area, were measured for validation of the

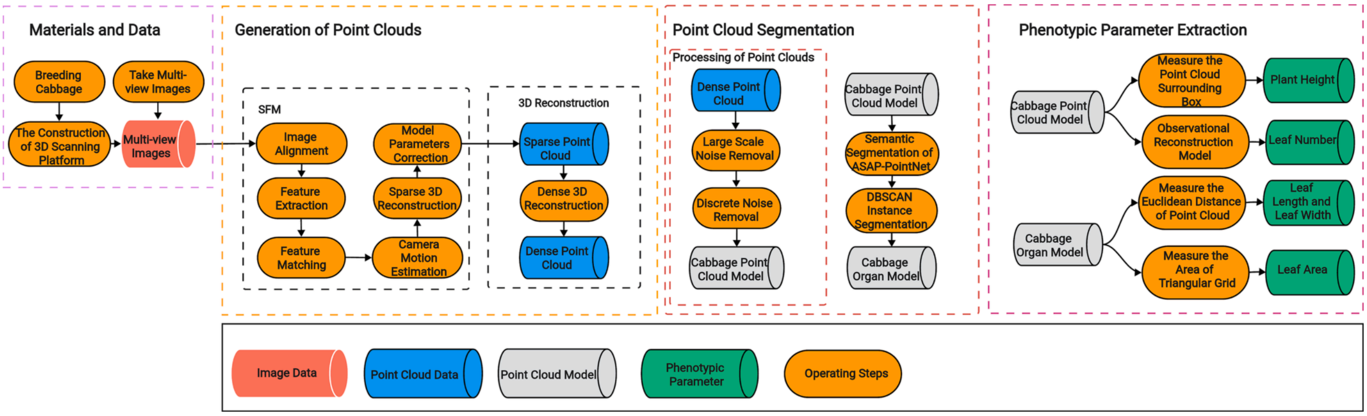

Fig. 1. Methodology flow chart.

Fig. 2. Cabbage in plant factory.

Fig. 3. 3D point cloud scanning platform.

proposed method in this study.

2.3. Generation of point clouds

The 3D reconstruction of cabbage was accomplished using multi-view images and the Structure from Motion (SfM) method, which produced raw point clouds of the cabbage (Sweeney, Fragoso, Höllerer, & Turk, 2016). SfM is an low-cost 3D reconstruction technique that accurately reconstructs an object's 3D structure by obtaining continuous multi-view images (Xue, Zhang, Zhou, & Zhu, 2021). This method involves highly redundant iterative calculations for program adjustment, following a sequence of image alignment, feature extraction, feature matching, sparse point cloud generation, model parameter adjustment, dense point cloud generation, and 3D reconstruction completion (Westoby, Brasington, Glasser, Hambrey, & Reynolds, 2012). RealityCapture is a professional 3D reconstruction software that employs various techniques, such as structured light, laser, and photogrammetry, to obtain 3D models. The software uses the SfM algorithm as its core method, enabling comprehensive workflow processes, including photo alignment, feature extraction, feature matching, camera viewpoint calculation, and 3D point cloud reconstruction (Hellmuth, Wehner, & Giannakidis, 2020).

In this study, RealityCapture was used to generate the required cabbage point cloud data. The software's reconstruction speed is rapid, with each object taking approximately 20 min to reconstruct, although this time may vary depending on the number of photos involved in the process. During the reconstruction process, continuous multi-view images of the cabbage were imported and aligned using the software. Next, the software extracted and matched features to create 3D point cloud data for calculating the target cabbage dimensions (Fig. 4). The 3D point

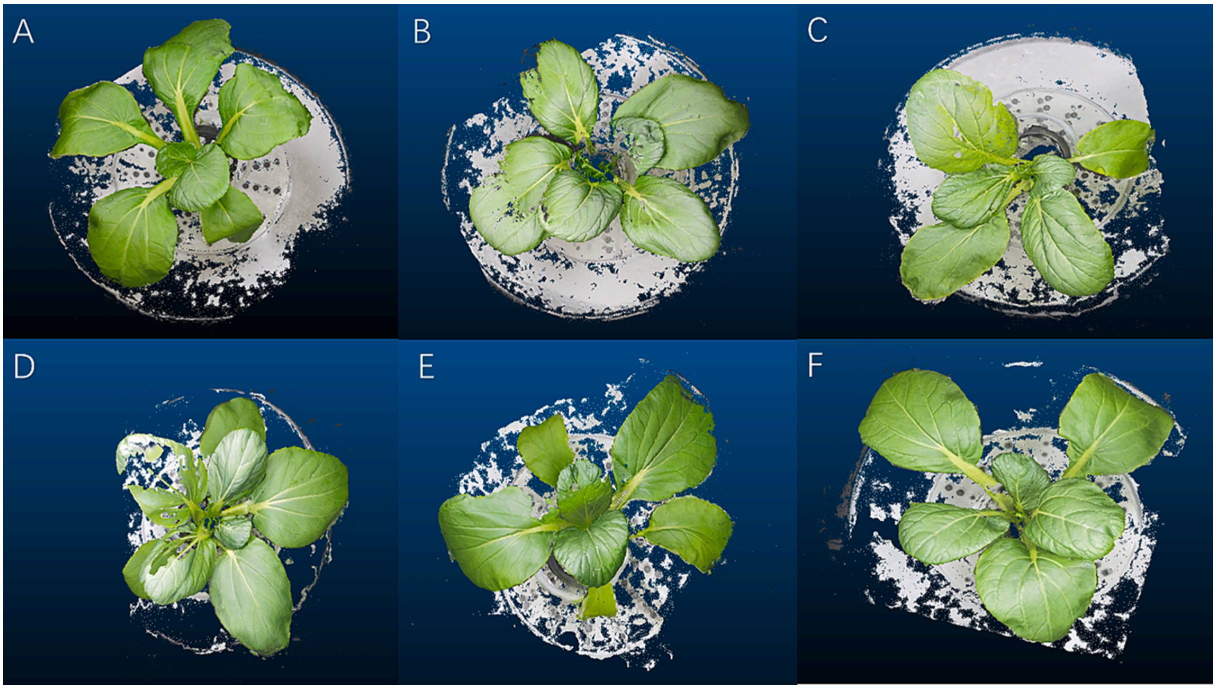

Fig. 4. Reconstructed cabbage point cloud model.

cloud data were exported as an M × 6 array (where M represents the number of points, and the six columns represent the dimensions of the X, Y, and Z axes, along with the Red (R), Green (G), and Blue (B) color channels), and saved as PLY files (J. Zhou et al., 2019).

2.4. Point cloud segmentation

2.4.1. Point cloud preprocessing

The point cloud model of the cabbage generated by RealityCapture is dense, containing approximately 80,000 to 100,000 points within each cabbage's 3D model. At this stage, the 3D model includes the cabbage, tray, calibration film on the turntable, and a significant amount of point cloud noise. Firstly, a large number of outliers in the cabbage 3D model must be manually removed, followed by the utilization of point cloud radius filtering and statistical filtering to eliminate noise (Fig. 5). The majority of outliers is difficult to be manually removed. The utilization of filters enables effective filtration of these point cloud noises. Regarding the preservation of shapes and edges, the radius filter demonstrates superior performance and exhibits fast processing speed, rendering it effective in handling large volumes of noise. Conversely, the statistical filter places greater emphasis on global statistical characteristics and achieves better noise removal results for small noise volumes.

In this study, uniform and random downsampling were employed as the primary data augmentation techniques (Fig. 6). Point cloud downsampling serves to reduce the point cloud data volume and enhance computational efficiency (Yan, Zheng, Li, Wang, & Cui, 2020). Random downsampling can decrease data density while maintaining data distribution (J.-P. Liu, Wu, & Tsang, 2020), and uniform downsampling can preserve data distribution and essential feature information (Marin et al., 2019). Theoretically, this data augmentation method can improve the model's robustness and generalization ability, thereby enhancing the model's performance (J. S. Hu & Waslander, 2021).

Point cloud annotation is labor-intensive work, and current research predominantly relies on open-source 3D point cloud annotation tools (E. Li et al., 2020). CloudCompare is an open-source point cloud processing software that offers a series of plugins for point cloud processing, segmentation, registration, measurement, and other operations(Girardeau-Montaut & ParisTech, 2016). In this study, CloudCompare was employed for point cloud-assisted segmentation and annotation to generate the cabbage point cloud dataset. The format of the cabbage point cloud dataset resembles that of the open-source dataset S3DIS (Thabet, Alwassel, & Ghanem, 2020), consisting of the point cloud itself and the corresponding annotation files, which include the category of each point. The cabbage point cloud dataset constructed in this study

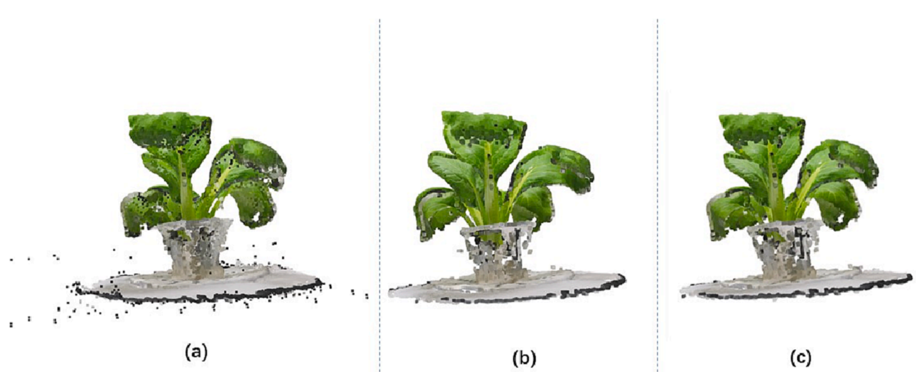

Fig. 5. a: the original model of the point cloud. b: the point cloud model after radius filtering. c: the point cloud model after statistical filtering.

Fig. 6. a: The denoised point cloud model. b: Point cloud model after uniform downsampling. c: Point cloud model after random downsampling.

comprises 60 complete cabbage point clouds and 892 corresponding point cloud annotation files.

2.4.2. Training by ASAP-PointNet

PointNet++ is an enhanced version of the PointNet model, specifically designed for 3D point cloud segmentation and classification tasks. Utilizing Set Abstraction (SA) and Feature Propagation (FP) layers, PointNet++ effectively captures both global and local features within point cloud data. However, certain limitations persist in PointNet++'s feature extraction capabilities. The model may struggle to capture long-range dependencies and intricate structures within point cloud data, and the downsampling of point cloud data during forward propagation could lead to a loss of point cloud features, thereby affecting the model's feature capturing ability (Qian et al., 2022). To address these limitations, ASAP-Net was proposed by Cao et al., which incorporates an attention mechanism module to enhance the model's capacity to compute spatial local features (Cao et al., 2020).

To better capture point cloud features and achieve semantic segmentation of cabbage point clouds, this study optimized the PointNet++ architecture and proposed the ASAP-PointNet model. The research was inspired by the ASAP-Net solution proposed by Cao et al. In the PointNet++ model, an Adaptive Self-Attention for Point Cloud Processing (ASAP) module was introduced. ASAP module is a self-attention mechanism that enhances the ability of the model to capture point cloud features by utilizing local and global features of input point cloud data and extracting features through a series of convolutional layers, normalization layers, and activation functions. This module comprises three linear transformation layers, which transform the input features into query (Q), key (K), and value (V) matrices, respectively. Subsequently, the attention matrix is obtained by calculating the dot product of Q and K, and the attention weight is derived by applying the SoftMax function to the matrix. The weighted sum of V is computed using these weights. The ASAP attention mechanism divides the input features into multiple subspaces, applying the self-attention module separately to each subspace. This approach enables the model to learn more diverse point cloud features. The output of the multi-head attention is then concatenated and transformed back to the original feature space through a linear transformation layer. Lastly, the input features are added to the output of the module, enhancing the training stability of the model. This module is integrated into the PointNet++ architecture to improve the semantic segmentation accuracy and intersection over union (IoU) of the cabbage dataset. The input tensor of the ASAP attention module, denoted as X, has a size of $B \times C \times N$, where B represents the batch size, C corresponds to the number of input features, and N signifies the number of points in the point cloud. The module calculates three matrices: query matrix (Q), key matrix (K), and value matrix (V) through a 1D convolutional layer.

$$Q = query\_conv(X) \in \mathbb{R}(B \times C' \times N) \tag{1}$$

$$K = key\_conv(X) \in \mathbb{R}(B \times C' \times N) \tag{2}$$

$$V = value\_conv(X) \in \mathbb{R}(B \times C' \times N) \tag{3}$$

C' represents the number of output channels for the query, key, and value matrices. Next, the attention weights are computed using the dot product between the query and key matrices:

$$A = softmax(QKT) \in \mathbb{R}(B \times N \times N) \tag{4}$$

The attention weights matrix (A) is subsequently used to compute the attention output (O) by multiplying the weights with the value matrix:

$$O = AV \in \mathbb{R}(B \times N \times C') \tag{5}$$

The attention output is then scaled by a learnable parameter γ and added to the input tensor X to obtain the final output tensor Y:

$$Y = X + \gamma O \in \mathbb{R}(B \times C \times N) \tag{6}$$

The integration of the ASAP attention module into the PointNet++ architecture entails its insertion into the SA layers with 128, 256, and 512 dimensional channels. By incorporating the ASAP self-attention module into these SA layers, the point cloud's feature capture ability is effectively enhanced during the downsampling stage, enabling the model to better capture both local and global contextual information within the point cloud data. To further optimize the model's performance, the optimizer in ASAP-PointNet was replaced with AdamW, an improved version of the Adam optimizer that provides better performance in weight decay (Loshchilov & Hutter, 2017). AdamW has been proven to achieve enhanced convergence performance and generalization effects when training deep models (Guan, 2023).

During semantic segmentation of the cabbage point cloud dataset, the ASAP-PointNet model was set to classify the clouds into three categories: leaf, stem, and bottom. The segmented point cloud was assigned specific colors, with green representing leaves, blue representing stems, and red representing bottoms. The training and testing data ratio in the cabbage point cloud dataset was 5:1.

It should be noted that all cabbage point cloud files needed to be converted to NPY format to meet the requirements of ASAP-PointNet. The NPY file included the cabbage point cloud data and labels, where the point cloud data was an array of n × 1024 × 6, with n representing the total number of blocks in the segmented input network, 1024 representing the number of point clouds in each block, and 6 representing the dimensions of spatial location information (x, y, z) and color information (R, G, B). The labels were used to identify specific attributes and features within the objects in the classification. The architecture of the PointNet++, ASAP-PointNet network and the structure of the ASAP module were depicted in Figs. 7-9.

2.4.3. Accuracy assessment

The evaluation metrics utilized in this experiment encompassed ac-

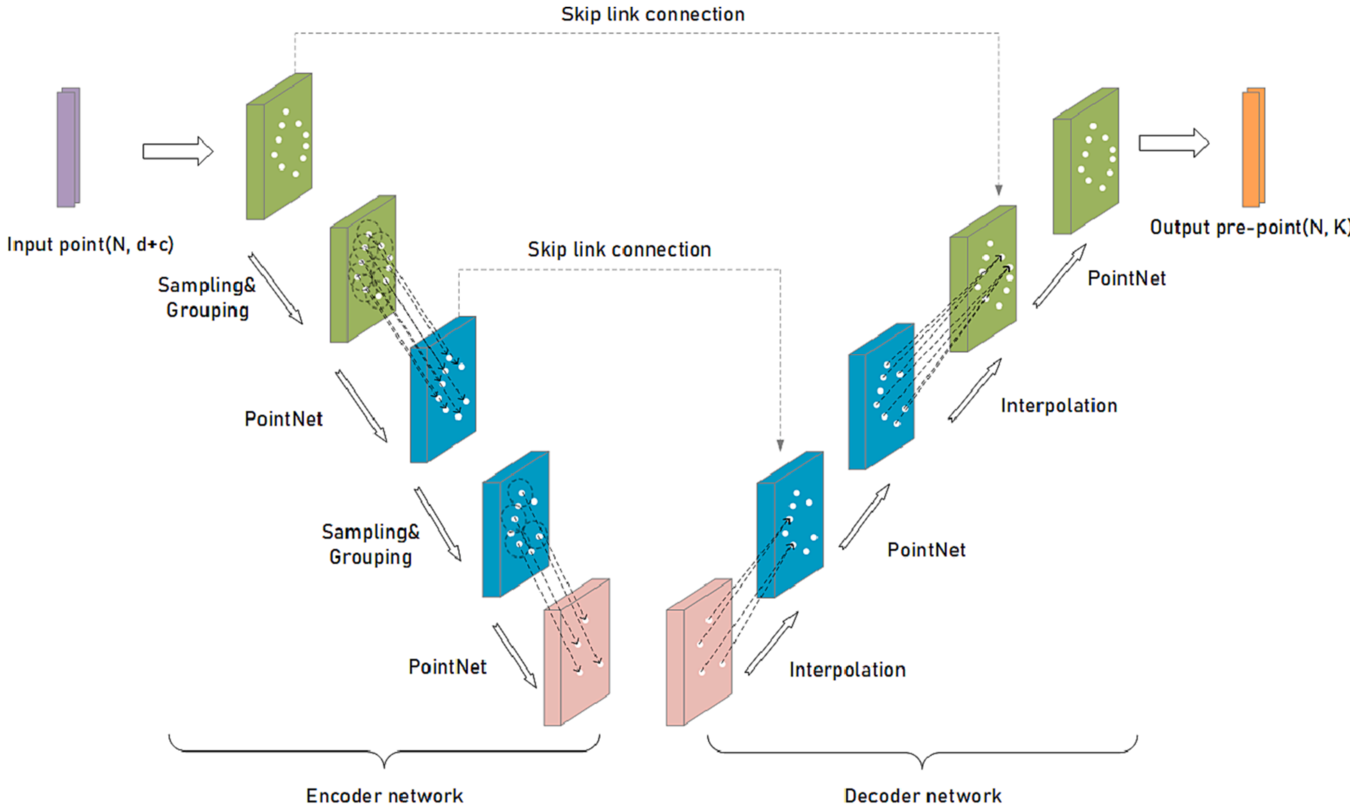

Fig. 7. The figure shows the architecture of PointNet++, which is composed of Sampling&Grouping and PointNet to form a Set Abstraction (SA) layer. interpolation and PointNet form the Feature Propagation (FP) layer.

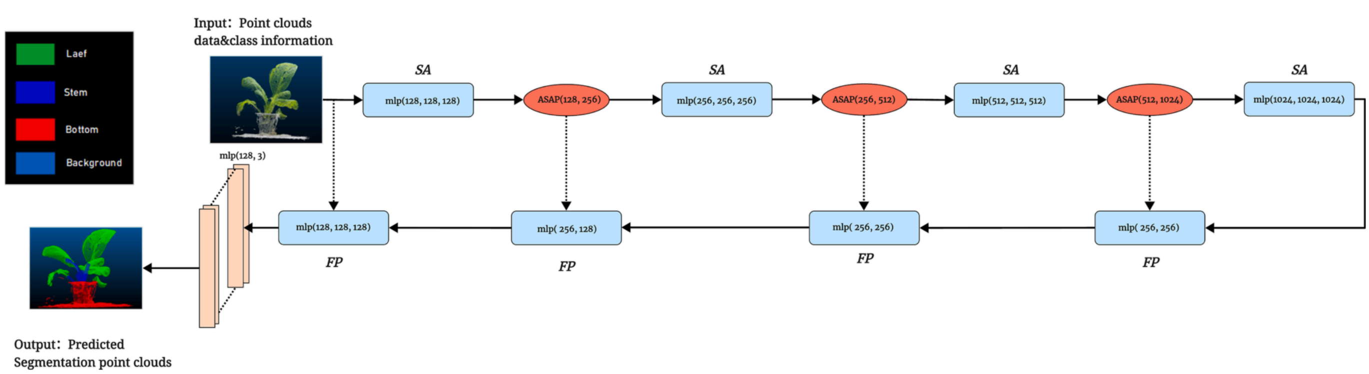

Fig. 8. The network architecture of ASAP-PointNet.

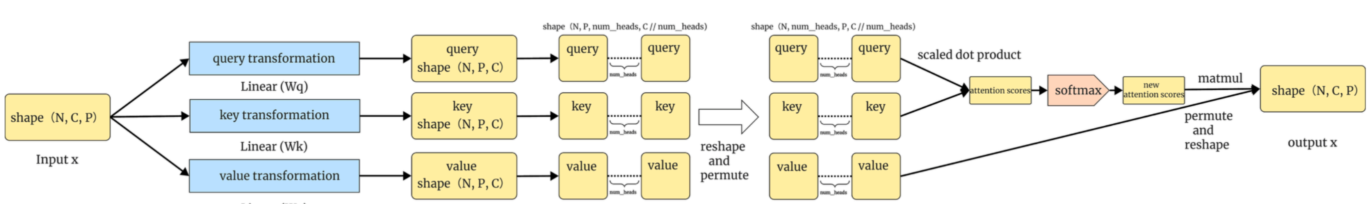

Fig. 9. The composition of ASAP module.

curacy, intersection over union (*IoU*), and cross-entropy loss function. In calculating accuracy, the predicted values (p_i) generated by the ASAP-PointNet model were compared with the actual labels (y_i) of the point clouds to assess the degree of agreement between them. The *IoU* metric evaluated the overlap between the predicted and actual label sets, while the cross-entropy loss function quantified the discrepancy between the predicted and actual values(D. Zhou et al., 2019). To address class imbalance, a weighted cross-entropy loss function was employed, assigning each class a weight (w_i) based on the number of point clouds in that class. This weighting mechanism aimed to prioritize classes with fewer point clouds, ensuring fair evaluation of the model's performance across all classes (Ho & Wookey, 2019). Furthermore, the performance of the ASAP-PointNet model could be analyzed in greater detail by computing the number of true positive (*TP*), false positive (*FP*), and false negative (*FN*) samples. The calculation methods for accuracy, intersection over union (*IoU*), cross-entropy loss, and class weights are outlined in the following formulas.

$$Acc = \frac{1}{m}\sum_{i=1}^{m} f_i, f_i = \begin{cases} 1 & y_i = p_i, \\ 0 & y_i \neq p_i \end{cases} \quad (7)$$

$$\mathrm{IoU} = \frac{\text{Area of overlap}}{\text{Area of union}} = \frac{\text{Area (prediction} \cap \text{target)}}{\text{Area (prediction} \cup \text{target)}} = \frac{\mathrm{TP}}{\mathrm{TP}+\mathrm{FP}+\mathrm{FN}} \quad (8)$$

$$Loss = \sum_{i=1}^{m}(y_i log(p_i) + (1-y_i)log(1-p_i)) \quad (9)$$

$$w(p,y) = \sum_{i=1}^{C} w_i p_i \log(y_i) \quad (10)$$

2.4.4. Instance segmentation of point clouds

Utilizing clustering algorithms for organ-level point cloud segmentation in plant phenotyping research is a prevalent method within the domain of three-dimensional point clouds (Ferrara et al., 2018). Elnashef et al. achieved instance segmentation of stems and leaves for dicotyledonous plants using the DBSCAN algorithm (Elnashef et al., 2019). Mirande et al. integrated deep learning techniques with clustering algorithms to perform organ-level point cloud segmentation for tomatoes and spinach (Mirande et al., 2022). Clustering algorithms can compute object features, such as normal vectors and color information, to group point clouds with distinct features into clusters. However, clustering algorithms still exhibit two limitations when processing plant point clouds. Firstly, the color of leafy vegetables predominantly appears green, and using color features as clustering conditions is subject to various constraints. Secondly, point cloud overlap of leaves in leafy vegetables is inevitable, posing challenges to the performance of clustering algorithms in point cloud segmentation (Schunck et al., 2021).

This study optimized the DBSCAN algorithm (Schubert, Sander, Ester, Kriegel, & Xu, 2017) workflow to better address organ-level point cloud segmentation in plants. In the prior experiment, the cabbage point cloud was classified into three categories and assigned different colors. However, in this study, the primary target for determination at the organ level is the leaf, necessitating the segmentation of stems and leaves as the initial step in instance segmentation. First, the point cloud data after semantic segmentation is filtered by color, and the DBSCAN algorithm processes only the green point cloud, which is why deep learning techniques are required to complete point cloud semantic segmentation. Next, the separation of individual leaves must be considered. After color filtering, most of the leaf point clouds are already separated, and the DBSCAN algorithm can easily cluster these leaf parts without expert-level parameter adjustment. Nevertheless, some leaves exhibit varying degrees of adhesion, necessitating additional steps to complete leaf segmentation. To address this issue, this study incorporated two steps to resolve the adhesion between leaf point clouds: (1) adding a point cloud edge filter to achieve an effect similar to erosion in 2D images (Han et al., 2017), which works effectively on slightly overlapping leaves, and (2) for leaves with high overlap, point cloud edge filtering and DBSCAN clustering are iteratively applied within the overlapping leaf point cloud cluster(Fig. 10). The utilization of these two steps in the DBSCAN algorithm reduces the reliance on parameter adjustment, thereby enhancing the method's applicability and significantly improving the success rate of segmenting adhesive leaf point cloud instances. Thus, the optimization of the DBSCAN algorithm facilitates improved point cloud segmentation at the organ level.

2.5. Plant phenotype parameter extraction

In this study, the cabbage point cloud model and the segmented leaf point cloud were employed to extract five phenotypic parameters, including plant height, leaf number, leaf length, leaf width, and leaf area. The determination of plant height was obtained by measuring the height of the bounding box encompassing the cabbage point cloud. The plant height (Fig. 11a) was determined by subtracting the minimum z-coordinate value of the point cloud from the maximum z-coordinate value of the point cloud, as illustrated in Equation (11). In equation (11), S_h represents the plant height, z_{max} represents the maximum value of the Z-axis in the point cloud, and z_{min} represents the minimum value of the point cloud. The number of leaves was determined by examining the reconstructed cabbage point cloud model. Although the number of segmented point cloud leaves can also be calculated, it is more crucial to focus on the quality of point cloud reconstruction and the completeness of leaf acquisition. Leaf length and width (Fig. 11b) were measured by calculating the Euclidean distance between the farthest points on the segmented leaves along the × and y axes(Xiangyang, Yang, Yunfei, & Mapping, 2017). The formula for calculating the Euclidean distance between the farthest points, $p_i(x_i, y_i)$, and $p_j(x_j, y_j)$, on the x-axis and y-axis is shown in Equation (12). The leaf area(Fig. 11c) was estimated using the Delaunay triangulation method (Luo, Mi, & Tao, 2021), which generates multiple triangles on the point cloud surface and calculates the sum of the areas of these triangles to approximate the leaf area. In

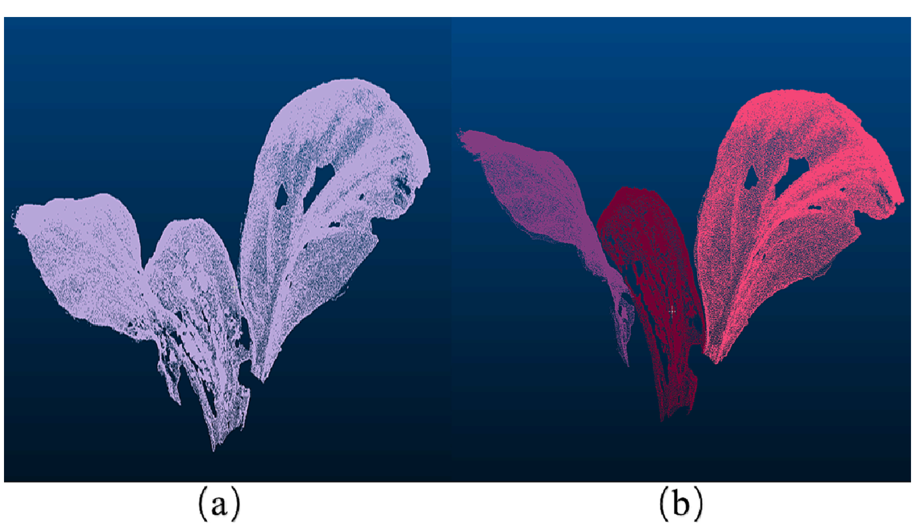

Fig. 10. Comparison of Leaf Point Cloud Segmentation Results: Original(a) vs. Optimized(b) DBSCAN Algorithm.

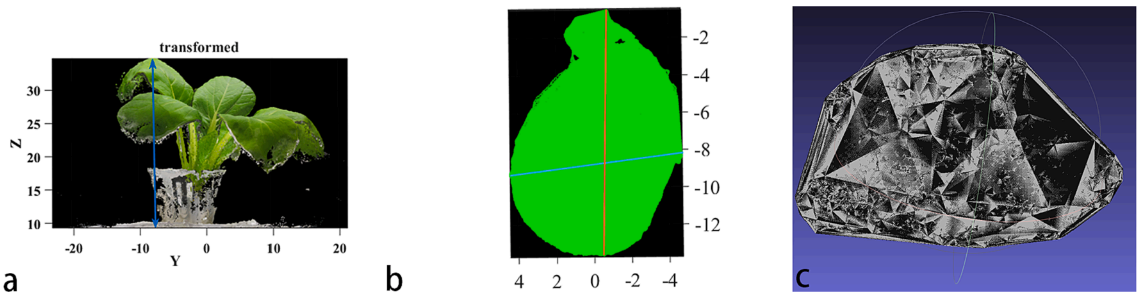

Fig. 11. The figure shows the method of phenotypic parameter extraction (a) measurement of plant height (b) measurement of leaf length and leaf width (c) measurement of leaf area.

Equation (13), the variables a, b, and c represent the three sides of a triangle, where P_i, P_j, and P_k are the vertices of the triangle. In Equation (14), the variable s represents the semiperimeter of each triangle. In Equation (15), S represents the area of an individual triangle. In Equation (16), S_i represents the area of the i triangle, S_{sum} represents the cumulative sum of triangle areas, which also represents the leaf area. Lastly, the measurement values were converted into phenotypic parameters using the reference object coordinate transformation method (Zhou et al., 2017). As shown in Equation (17), where r represents the ratio between the actual value and the reconstructed value, h_{real} is the actual height of the reference object, and $h_{\mathrm{reconstructed}}$ is the reconstructed height of the reference object.

$$S_h = z_{max} - z_{min} \tag{11}$$

$$Euclideandistance = \sqrt{\left((x_i - x_j)^2 + (y_i - y_j)^2\right)} \tag{12}$$

$$a = \|P_i - P_j\|, b = \|P_j - P_k\|, c = \|P_k - P_i\| \tag{13}$$

$$s = \frac{a+b+c}{2} \tag{14}$$

$$S = \sqrt{s \bullet (s-a) \bullet (s-b) \bullet (s-c)} \tag{15}$$

$$S_{\mathrm{sum}} = \sum_{i=1}^{n} S_i \tag{16}$$

$$r = \frac{h_{\mathrm{real}}}{h_{\mathrm{reconstructed}}} \tag{17}$$

3. Results

3.1. Result of semantic segmentation of ASAP-PointNet network

In this study, all network model-related experiments were conducted on a computer equipped with an Intel(R) Core (TM) i9-10850 k CPU @3.60 GHz, NVIDIA RTX 3080Ti GPU, and 64 GB RAM. The system environment utilized was Ubuntu 20.04, and the network models were built using Pytorch.

ASAP-PointNet was trained for 100 epochs in this study, with each epoch comprising 870 batches and a batch size of 8. The initial learning rate was set to 0.001. During the initial 80 epochs, the training loss experienced a rapid decrease, followed by a gradual stabilization of the reduction rate, as depicted in the Fig. 12. Ultimately, ASAP-PointNet achieved an IOU of 0.86 and an accuracy of 0.95 on the cabbage point cloud testing set. As ASAP-PointNet is an optimized model based on PointNet++, four different models, including PointNet, PointNet++, PointNet++_MSG, and ASAP-PointNet, were evaluated under identical experimental conditions in this study, as presented in Table 1. The ablation experiment results indicated that ASAP-PointNet enhanced the accuracy and stability of the network, particularly regarding the IOU metric. Furthermore, it demonstrated that the ASAP-PointNet model effectively performed semantic segmentation on the cabbage point cloud. The visualization results of ground truth, PointNet, PointNet++, PointNet++_MSG, and ASAP-PointNet for semantic segmentation of the

Table 1
Comparison results of ablation experiments of network models.

Networks	Accuracy	IoU	Epochs
PointNet	0.86	0.60	100
PointNet++	0.91	0.68	100
PointNet++_MSG	0.94	0.78	100
ASAP-PointNet	0.95	0.86	100

Fig. 12. Accuracy and Loss Analysis of ASAP-PointNet Network Training.

cabbage point cloud are shown in Fig. 13.

3.2. Result of instance segmentation of DBSCAN

The DBSCAN algorithm was improved to enhance the instance segmentation of cabbage point clouds, effectively addressing the utilization of color features and the issue of adhered leaf point clouds. Experimental results demonstrated that the optimized DBSCAN algorithm effectively performs instance segmentation of cabbage point clouds at the organ level. The visualization segmentation results of the original cabbage point cloud, the segmented point cloud following semantic segmentation, and the instance segmentation employing the optimized DBSCAN algorithm are illustrated in Fig. 14.

3.3. Results of phenotypic parameter extraction

The accuracy of the proposed method for extracting cabbage phenotypic parameters was assessed by comparing results from point cloud segmentation to those from manual measurements. The validation of leaf number is presented in Fig. 4 and Table 2. Plant height validation results are displayed in Fig. 15a, yielding R^2 and RMSE values of 0.96 and 0.48 cm, respectively. Leaf length and width validation results are depicted in Fig. 15b and Fig. 15c, with R^2 values of 0.91 and 0.95 and RMSE values of 0.68 cm and 0.39 cm, respectively. Leaf area validation results are illustrated in Fig. 15d, with R^2 and RMSE values of 0.94 and 6.24 cm^2, respectively. The validation outcomes reveal a higher correlation between plant height and leaf width, and a moderate correlation between leaf area and leaf length. These results demonstrate that the proposed method fulfills the requirements for automated and high-precision extraction of phenotypic parameters.

4. Discussion

4.1. Acquisition of multi-view images and point cloud generation

The generation of high-quality point clouds has been shown to improve the performance of neural networks, alleviate challenges in point cloud segmentation, and enhance the accuracy of phenotype extraction results (Rose, Paulus, & Kuhlmann, 2015). A method for generating high-throughput point clouds by calculating multi-view images was proposed in this study, which facilitated the construction of high-quality point cloud datasets. Utilizing 3D scanning platforms to capture multi-view images in laboratory environments effectively circumvented interference from environmental factors, such as wind-induced changes in plant morphology and angle limitations encountered in plant factories or field environments. Additionally, the multi-view images captured in the laboratory contained minimal background information, resulting in significantly reduced background noise in the generated point cloud models when compared to outdoor scenes. The stable lighting conditions in the laboratory environment also contributed to the enhanced quality of the generated point clouds. The point clouds produced by the Structure from Motion (SfM) algorithm were characterized by high density and quality, effectively avoiding uneven point cloud density caused by distance variations (Rossi et al., 2022). Moreover, these point clouds retained the original color information of the plants, offering the possibility of extracting more phenotype features through the plant point cloud model (Yang et al., 2020).

However, the method proposed in this study for point cloud generation also presented some limitations. During the acquisition of multi-view images on the 3D scanning platform, the rotation of the turntable, albeit slow and paused, still exerted an impact on plant morphology to a certain extent. Consequently, the experiment employed slower turntable rotation speeds and longer pauses to minimize alterations in plant morphology.

4.2. Point cloud segmentation and plant phenotypic extraction

In the testing results of semantic segmentation, it was found that dense point clouds had lower robustness in semantic segmentation (Kamann & Rother, 2020). To address this issue, a down-sampling point cloud processing method was used to effectively improve the quality of the dataset by reducing input data during network training. This improved the processing speed of the network and preserved the original morphological features of plant point clouds without affecting the performance of network training during feature fusion (Najafi & Lilja, 2018). For organ-level point cloud segmentation in plants, an optimized DBSCAN algorithm was utilized, which effectively segmented the leaves. However, even with algorithm optimization, the segmentation of large overlapping leaves remains a common problem in current research on the extraction of plant phenotypic parameters through 3D point clouds (Miao et al., 2021). It was found that artificial measurement of phenotypic parameters can cause changes in the morphological characteristics of plants, which is why the correlation between leaf length and leaf area is lower than other phenotypic parameters. Therefore, for plants such as cabbage that are prone to morphological changes, extracting their phenotypic features using 3D point clouds is also challenging (Z. Li et al., 2020).

4.3. Analysis of experiment results

This study presents the acquisition of multi-view images of cabbage and the generation of cabbage point clouds. It details the point cloud processing and the construction of the cabbage point cloud dataset. A novel method combining ASAP-PointNet and an optimized DBSCAN algorithm was proposed for segmenting cabbage point clouds at the organ level. The ASAP-PointNet model improved the performance of cabbage point cloud semantic segmentation, while the optimized DBSCAN algorithm addressed challenges such as overlapping leaves and color limitations.

In order to achieve more efficient point cloud segmentation at the organ level, Elnashef et al. employed a computational approach to separate stems and leaves of plants and used the DBSCAN algorithm for segmenting individual leaves (Elnashef et al., 2019). This approach may reduce computational costs but necessitates expert-level adjustment of the algorithm's parameters, and it did not address the handling of overlapping leaf point clouds. Lai et al. integrated deep learning techniques with clustering algorithms for organ-level point cloud segmentation in plants (Lai et al., 2022). This method effectively segmented leaves and offered solutions for managing overlapping leaf point clouds.

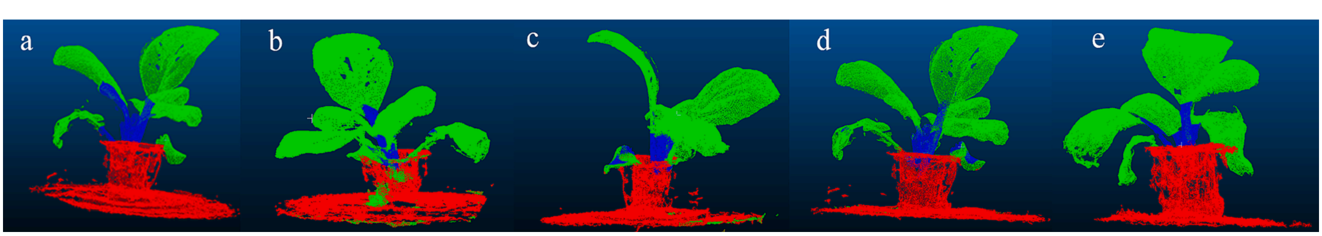

Fig. 13. Comparison of Semantic Segmentation Results for Cabbage Point Cloud Models: Ground Truth vs. PointNet-based Approaches.

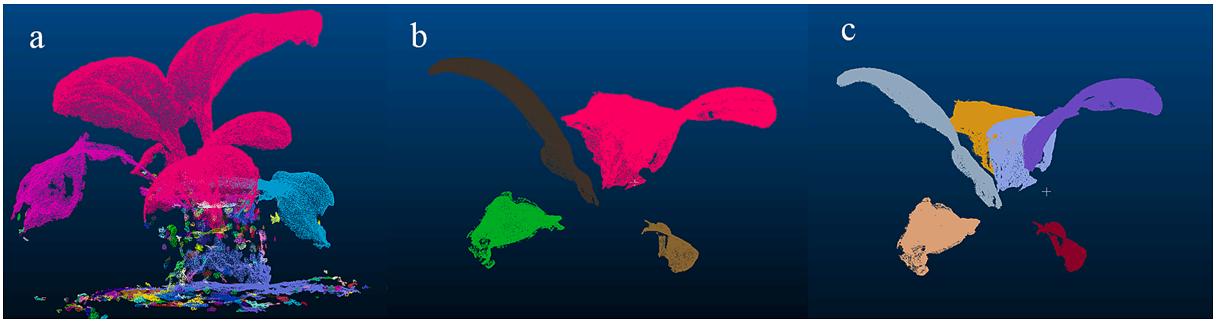

Fig. 14. Comparing Leaf Segmentation Results for Cabbage Point Cloud Models using DBSCAN: Original(b) vs. Optimized Algorithms(c) with and without Semantic Segmentation(a).

Table 2
Comparison of Reconstructed Leaves: Successful vs. Failed Reconstructions.

	Cabbage					
	A	B	C	D	E	F
No. of total leaves	7	7	6	9	7	7
No. of leaves that failed	0	1	0	0	0	0
Successful rate (%)	100	85.71	100	100	100	100

However, the original PointNet series networks still possess room for improvement in semantic segmentation of plant point cloud datasets.

The proposed ASAP-PointNet achieved an IOU of 0.86 and an accuracy of 0.95 on the cabbage point cloud testing set, demonstrating excellent performance in the ablation experiment. The experimental results also highlighted the effectiveness of the optimized DBSCAN algorithm in instance segmentation at the organ level. The accuracy of the proposed method for extracting cabbage phenotypic parameters was validated by comparing the results obtained through point cloud segmentation with those obtained through manual measurements. The validation results revealed a high correlation between plant height and leaf width, and a moderate correlation between leaf area and leaf length. This indicates that the proposed method can fulfill the requirements for automated and high-precision extraction of phenotypic parameters, making it a valuable contribution to the field and a promising basis for further research.

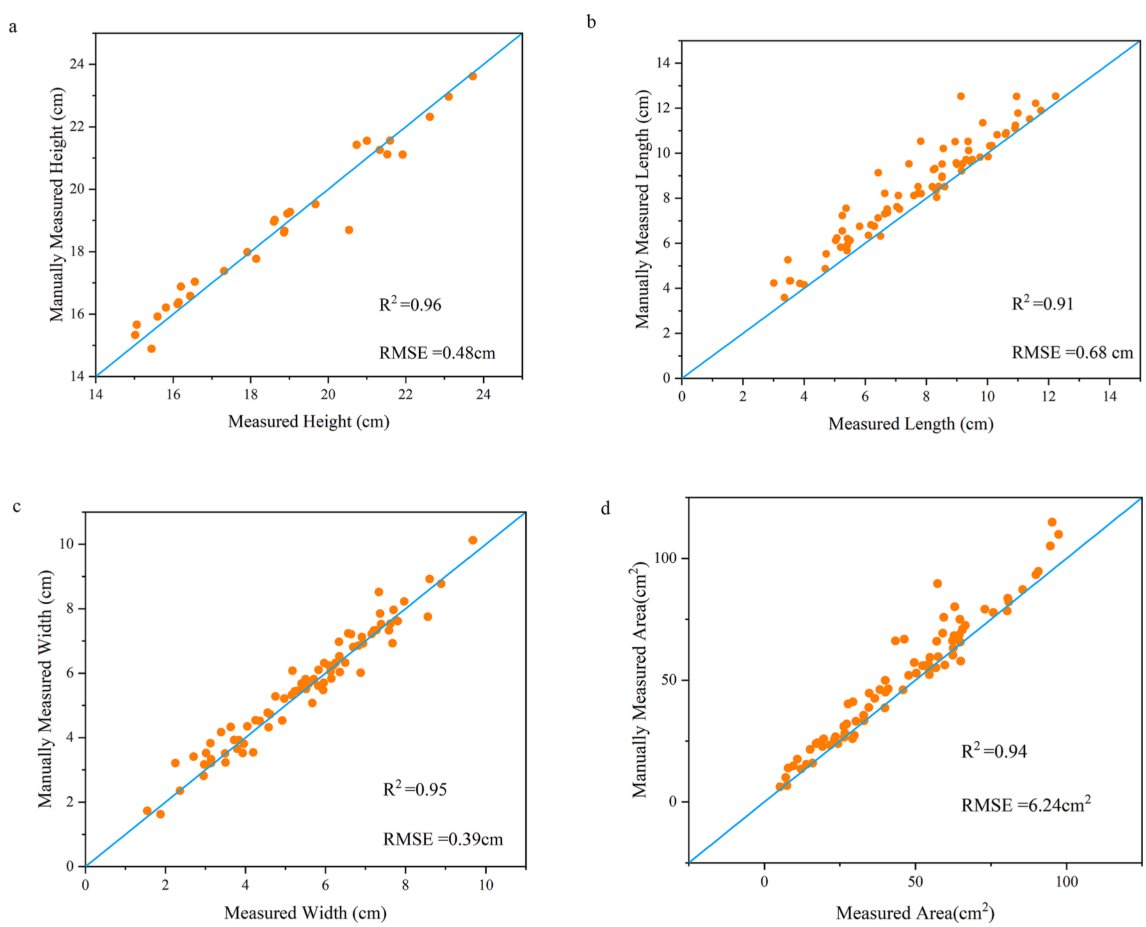

Fig. 15. Comparison of phenotypic parameters extracted based on cabbage point cloud segmentation and measured values. (a) plant height, (b) leaf length, (c) leaf width, and (d) leaf area.

4.4. Future work

Although the optimized DBSCAN algorithm can address some challenges in overlapping leaf point cloud segmentation, it still struggles with efficiently segmenting large-scale overlapping or completely overlapping leaves. Thus, future work will involve algorithm improvements and the incorporation of novel techniques to enhance segmentation accuracy and computational efficiency. Additionally, it is valuable to consider the phenotypic parameters of plant organs other than leaves. Hence, the integration of multiple imaging techniques, including hyperspectral and thermal imaging, will allow researchers to develop more sophisticated and accurate models, expanding the exploration of plant phenotypes. Thus, promoting the advancement of precision agriculture technology.

5. Conclusion

In conclusion, this study presented a novel method for cabbage point cloud segmentation and phenotypic parameter extraction at the organ level by combining ASAP-PointNet and an optimized DBSCAN algorithm. The ASAP-PointNet model achieved an IOU of 0.86 and an accuracy of 0.95, significantly improving the performance of semantic segmentation. Meanwhile, the optimized DBSCAN algorithm effectively addressed the challenges of instance segmentation, including overlapping leaves and color limitations. The experimental results and validation demonstrated that the proposed method provides high accuracy in extracting phenotypic parameters such as plant height, leaf length, leaf width, and leaf area, meeting the requirements for automated and high-precision extraction. This research contributes to the field of plant phenotyping and provides valuable insights for future work in precision agriculture technology.

CRediT authorship contribution statement

Ruichao Guo: Conceptualization, Methodology, Resources, Software, Data curation, Writing – original draft. **Jilong Xie:** Methodology, Resources, Supervision, Writing – review & editing. **Jiaxi Zhu:** Software. **Ruifeng Cheng:** Software. **Yi Zhang:** . **Xihai Zhang:** Methodology, Resources, Software, Supervision, Writing – review & editing. **Xinjing Gong:** Resources, Methodology. **Ruwen Zhang:** Resources, Methodology. **Hao Wang:** Methodology, Software. **Fanfeng Meng:** Methodology, Resources, Software, Supervision, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The data that has been used is confidential.

Acknowledgments

Central Public-interest Scientific Institution Basal Research Fund (No. Y2023PT22), The Agricultural Science and Technology Innovation Program (ASTIP)

References

Ao, Z., Wu, F., Hu, S., Sun, Y., Su, Y., Guo, Q., Xin, Q., 2022. Automatic segmentation of stem and leaf components and individual maize plants in field terrestrial LiDAR data using convolutional neural networks. Crop J. 10 (5), 1239–1250. https://doi.org/10.1016/j.cj.2021.10.010.

Bernotas, G., Scorza, L.C.T., Hansen, M.F., Hales, I.J., Halliday, K.J., Smith, L.N., Smith, M.L., McCormick, A.J., 2019. A photometric stereo-based 3D imaging system using computer vision and deep learning for tracking plant growth. GigaScience 8 (5). https://doi.org/10.1093/gigascience/giz056.

Cao, H., Lu, Y., Lu, C., Pang, B., Liu, G., & Yuille, A. 2020. Asap-net: Attention and structure aware point cloud sequence segmentation. arXiv preprint arXiv: 2008.05149.

Chen, X., Jiang, K., Zhu, Y., Wang, X., Yun, T., 2021. Individual tree crown segmentation directly from UAV-borne LiDAR data using the PointNet of deep learning. Forests 12 (2). https://doi.org/10.3390/f12020131.

Cui, Y., Liu, X., Liu, H., Zhang, J., Zare, A., & Fan, B. J. N. 2021. Geometric attentional dynamic graph convolutional neural networks for point cloud analysis. 432, 300-310.

Elnashef, B., Filin, S., Lati, R.N., 2019. Tensor-based classification and segmentation of three-dimensional point clouds for organ-level plant phenotyping and growth analysis. Comput. Electron. Agric. 156, 51–61. https://doi.org/10.1016/j.compag.2018.10.036.

Ferrara, R., Virdis, S. G., Ventura, A., Ghisu, T., Duce, P., Pellizzaro, G. J. A., & meteorology, f. 2018. An automated approach for wood-leaf separation from terrestrial LIDAR point clouds using the density based clustering algorithm DBSCAN. 262, 434-444.

Gallinat, A. S., Ellwood, E. R., Heberling, J. M., Miller-Rushing, A. J., Pearse, W. D., & Primack, R. B. J. A. J. o. B. 2021. Macrophenology: insights into the broad-scale patterns, drivers, and consequences of phenology. 108(11), 2112-2126.

Ge, L., Zou, K., Zhou, H., Yu, X., Tan, Y., Zhang, C., Li, W., 2022. Three dimensional apple tree organs classification and yield estimation algorithm based on multi-features fusion and support vector machine. Inform. Process. Agric. 9 (3), 431–442. https://doi.org/10.1016/j.inpa.2021.04.011.

Girardeau-Montaut, D. J. F. E. R., & ParisTech, D. T. 2016. CloudCompare. 11.

Gong, L., Du, X., Zhu, K., Lin, K., Lou, Q., Yuan, Z., . . . Liu, C. 2021. Panicle-3D: Efficient Phenotyping Tool for Precise Semantic Segmentation of Rice Panicle Point Cloud. Plant Phenomics, 2021, 9838929. 10.34133/2021/9838929.

Gong, X., Zhang, X., Zhang, R., Wu, Q., Wang, H., Guo, R., . . . Agriculture, E. i. 2022. U3-YOLOXs: An improved YOLOXs for Uncommon Unregular Unbalance detection of the rape subhealth regions. 203, 107461.

Gratani, L. J. A. i. b. 2014. Plant phenotypic plasticity in response to environmental factors. 2014.

Guan, L. J. a. p. a. 2023. Weight Prediction Boosts the Convergence of AdamW.

Guo, W., & Zhao, J. J. P. O. A. i. B. D. B. 2022. Plant Phenomics. 67-78.

Han, X.-F., Jin, J. S., Wang, M.-J., Jiang, W., Gao, L., & Xiao, L. J. S. P. I. C. 2017. A review of algorithms for filtering the 3D point cloud. 57, 103-112.

Hellmuth, R., Wehner, F., & Giannakidis, A. J. D. i. B. 2020. Datasets of captured images of three different devices for photogrammetry calculation comparison and integration into a laserscan point cloud of a built environment. 33, 106321.

Ho, Y., & Wookey, S. J. I. a. 2019. The real-world-weight cross-entropy loss function: Modeling the costs of mislabeling. 8, 4806-4813.

Hu, J. S., & Waslander, S. L. (2021). *Pattern-aware data augmentation for lidar 3d object detection.* Paper presented at the 2021 IEEE International Intelligent Transportation Systems Conference (ITSC).

Hu, C., Li, P., Pan, Z., 2018. Phenotyping of poplar seedling leaves based on a 3D visualization method. Int. J. Agric. Biol. Eng. 11 (6), 145–151. https://doi.org/10.25165/j.ijabe.20181106.4110.

Jin, S., Su, Y., Wu, F., Pang, S., Gao, S., Hu, T., . . . Sensing, R. 2018. Stem–leaf segmentation and phenotypic trait extraction of individual maize using terrestrial LiDAR data. 57(3), 1336-1346.

Jin, S., Su, Y., Gao, S., Wu, F., Ma, Q., Xu, K., . . . Guan, H. 2019. Separating the structural components of maize for field phenotyping using terrestrial LiDAR data and deep convolutional neural networks. IEEE Transactions on Geoscience and Remote Sensing, 58(4), 2644-2658 %@ 0196-2892.

Jin, X., Yang, W., Doonan, J. H., & Atzberger, C. J. C. J. 2022. Crop phenotyping studies with application to crop monitoring. 10(5), 1221-1223.

Kamann, C., & Rother, C. (2020). *Benchmarking the robustness of semantic segmentation models.* Paper presented at the Proceedings of the IEEE/CVF conference on computer vision and pattern recognition.

Lai, Y., Lu, S., Qian, T., Chen, M., Zhen, S., & Guo, L. 2022. Segmentation of Plant Point Cloud based on Deep Learning Method.

Li, E., Wang, S., Li, C., Li, D., Wu, X., & Hao, Q. (2020). *Sustech points: A portable 3d point cloud interactive annotation platform system.* Paper presented at the 2020 IEEE Intelligent Vehicles Symposium (IV).

Li, Z., Guo, R., Li, M., Chen, Y., Li, G. J. C., & Agriculture, E. i. 2020. A review of computer vision technologies for plant phenotyping. 176, 105672.

Li, D., Quan, C., Song, Z., Li, X., Yu, G., Li, C., . . . Biotechnology. 2021. High-throughput plant phenotyping platform (HT3P) as a novel tool for estimating agronomic traits from the lab to the field. 8, 623705.

Li, Y., Wen, W., Miao, T., Wu, S., Yu, Z., Wang, X., Guo, X., Zhao, C., 2022. Automatic organ-level point cloud segmentation of maize shoots by integrating high-throughput data acquisition and deep learning. Comput. Electron. Agric. 193, 106702. https://doi.org/10.1016/j.compag.2022.106702.

Liu, J.-P., Wu, M.-H., & Tsang, P. W. J. O. E. 2020. 3D display by binary computer-generated holograms with localized random down-sampling and adaptive intensity accumulation. 28(17), 24526-24537.

Liu, B., Huang, H., Tian, X., & Ren, M. (2022). *Individual Tree Species Classification Using the Pointwise MLP-Based Point Cloud Deep Learning Method.* Paper presented at the Iecf 2022.

Loshchilov, I., & Hutter, F. J. a. p. a. 2017. Decoupled weight decay regularization.

Luo, Y., Mi, Z., & Tao, W. (2021). *DeepDT: Learning geometry from Delaunay triangulation for surface reconstruction.* Paper presented at the Proceedings of the AAAI Conference on Artificial Intelligence.
Ma, X., Zhu, K., Guan, H., Feng, J., Yu, S., Liu, G., 2019. High-throughput phenotyping analysis of potted soybean plants using colorized depth images based on a proximal platform. Remote Sens. (Basel) 11 (9), 1085.
Marin, D., He, Z., Vajda, P., Chatterjee, P., Tsai, S., Yang, F., & Boykov, Y. (2019). *Efficient segmentation: Learning downsampling near semantic boundaries.* Paper presented at the Proceedings of the IEEE/CVF International Conference on Computer Vision.
Miao, T., Zhu, C., Xu, T., Yang, T., Li, N., Zhou, Y., . . . Agriculture, E. i. 2021. Automatic stem-leaf segmentation of maize shoots using three-dimensional point cloud. 187, 106310.
Mirande, K., Godin, C., Tisserand, M., Charlaix, J., Besnard, F., Hetroy-Wheeler, F., 2022. A graph-based approach for simultaneous semantic and instance segmentation of plant 3D point clouds. Front. Plant Sci. 13, 1012669. https://doi.org/10.3389/fpls.2022.1012669.
Najafi, M. H., & Lilja, D. J. J. I. T. o. E. T. i. C. 2018. High quality down-sampling for deterministic approaches to stochastic computing. 9(1), 7-14.
Nikolov, I., & Madsen, C. (2016). *Benchmarking close-range structure from motion 3D reconstruction software under varying capturing conditions.* Paper presented at the Digital Heritage. Progress in Cultural Heritage: Documentation, Preservation, and Protection: 6th International Conference, EuroMed 2016, Nicosia, Cyprus, October 31–November 5, 2016, Proceedings, Part I 6.
Ninomiya, S. J. B. S. 2022. High-throughput field crop phenotyping: current status and challenges. 72(1), 3-18.
Niu, Z., Zhong, G., & Yu, H. J. N. 2021. A review on the attention mechanism of deep learning. 452, 48-62.
Qi, C. R., Su, H., Mo, K., & Guibas, L. J. (2017). *Pointnet: Deep learning on point sets for 3d classification and segmentation.* Paper presented at the Proceedings of the IEEE conference on computer vision and pattern recognition.
Qi, C. R., Yi, L., Su, H., & Guibas, L. J. J. A. i. n. i. p. s. 2017. Pointnet++: Deep hierarchical feature learning on point sets in a metric space. 30.
Qian, G., Li, Y., Peng, H., Mai, J., Hammoud, H., Elhoseiny, M., & Ghanem, B. J. A. i. N. I. P. S. 2022. Pointnext: Revisiting pointnet++ with improved training and scaling strategies. 35, 23192-23204.
Rawat, S., Chandra, A. L., Desai, S. V., Balasubramanian, V. N., Ninomiya, S., & Guo, W. 2022. How Useful Is Image-Based Active Learning for Plant Organ Segmentation? Plant Phenomics, 2022, 9795275. 10.34133/2022/9795275.
Rose, J. C., Paulus, S., & Kuhlmann, H. J. S. 2015. Accuracy analysis of a multi-view stereo approach for phenotyping of tomato plants at the organ level. 15(5), 9651-9665.
Rossi, R., Costafreda-Aumedes, S., Leolini, L., Leolini, C., Bindi, M., Moriondo, M. J. C., & Agriculture, E. i. 2022. Implementation of an algorithm for automated phenotyping through plant 3D-modeling: A practical application on the early detection of water stress. 197, 106937.
Saeed, F., & Li, C. (2021). *Plant organ segmentation from point clouds using Point-Voxel CNN.* Paper presented at the 2021 ASABE Annual International Virtual Meeting.
Schubert, E., Sander, J., Ester, M., Kriegel, H.P., Xu, X., 2017. DBSCAN revisited, revisited: Why and how you should (Still) use DBSCAN. ACM Trans. Database Syst. 42 (3), 1–21.
Schunck, D., Magistri, F., Rosu, R. A., Cornelißen, A., Chebrolu, N., Paulus, S., . . . Kuhlmann, H. J. P. o. 2021. Pheno4D: A spatio-temporal dataset of maize and tomato plant point clouds for phenotyping and advanced plant analysis. 16(8), e0256340.
Song, P., Wang, J., Guo, X., Yang, W., & Zhao, C. J. T. C. J. 2021. High-throughput phenotyping: Breaking through the bottleneck in future crop breeding. 9(3), 633-645.
Sweeney, C., Fragoso, V., Höllerer, T., & Turk, M. (2016). *Large scale sfm with the distributed camera model.* Paper presented at the 2016 Fourth International Conference on 3D Vision (3DV).
Tardieu, F., Cabrera-Bosquet, L., Pridmore, T., Bennett, M., 2017. Plant phenomics, from sensors to knowledge. Curr. Biol. 27 (15), R770–R783. https://doi.org/10.1016/j.cub.2017.05.055.
Thabet, A., Alwassel, H., & Ghanem, B. (2020). *Self-supervised learning of local features in 3d point clouds.* Paper presented at the Proceedings of the IEEE/CVF conference on computer vision and pattern recognition workshops.
Turgut, K., Dutagaci, H., Galopin, G., Rousseau, D., 2022. Segmentation of structural parts of rosebush plants with 3D point-based deep learning methods. Plant Methods 18 (1), 20.
Westoby, M. J., Brasington, J., Glasser, N. F., Hambrey, M. J., & Reynolds, J. M. J. G. 2012. 'Structure-from-Motion'photogrammetry: A low-cost, effective tool for geoscience applications. 179, 300-314.
Xiangyang, C., Yang, Y., Yunfei, X. J. B. o. S., & Mapping. 2017. Measurement of point cloud data segmentation based on Euclidean clustering algorithm. (11), 27.
Xue, Y., Zhang, S., Zhou, M., & Zhu, H. J. U. S. 2021. Novel SfM-DLT method for metro tunnel 3D reconstruction and Visualization. 6(2), 134-141.
Yan, X., Zheng, C., Li, Z., Wang, S., & Cui, S. (2020). *Pointasnl: Robust point clouds processing using nonlocal neural networks with adaptive sampling.* Paper presented at the Proceedings of the IEEE/CVF conference on computer vision and pattern recognition.
Yang, S., Zheng, L., Gao, W., Wang, B., Hao, X., Mi, J., & Wang, M. J. R. S. 2020. An efficient processing approach for colored point cloud-based high-throughput seedling phenotyping. 12(10), 1540.
Yin, K., Huang, H., Cohen-Or, D., & Zhang, H. 2018. P2P-NET: bidirectional point displacement net for shape transform. 37(4 %J ACM Trans. Graph.), Article 152. 10.1145/3197517.3201288.
Zhang, S., 2018. High-speed 3D shape measurement with structured light methods: A review. Opt. Lasers Eng. 106, 119–131. https://doi.org/10.1016/j.optlaseng.2018.02.017.
Zhang, J., Zhao, X., Chen, Z., & Lu, Z. J. I. A. 2019. A review of deep learning-based semantic segmentation for point cloud. 7, 179118-179133.
Zhou, J., Reynolds, D., Cornu, T. L., Websdale, D., Orford, S., Lister, C., . . . Stitt, T. J. B. 2017. CropQuant: an automated and scalable field phenotyping platform for crop monitoring and trait measurements to facilitate breeding and digital agriculture. 161547.
Zhou, D., Fang, J., Song, X., Guan, C., Yin, J., Dai, Y., & Yang, R. (2019). *Iou loss for 2d/3d object detection.* Paper presented at the 2019 International Conference on 3D Vision (3DV).
Zhou, J., Fu, X., Zhou, S., Zhou, J., Ye, H., Nguyen, H.T., 2019. Automated segmentation of soybean plants from 3D point cloud using machine learning. Comput. Electron. Agric. 162, 143–153. https://doi.org/10.1016/j.compag.2019.04.014.
Zhu, R., Sun, K., Yan, Z., Yan, X., Yu, J., Shi, J., . . . Zhang, Z. J. S. R. 2020. Analysing the phenotype development of soybean plants using low-cost 3D reconstruction. 10(1), 1-17.