IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received 23 March 2024, accepted 2 April 2024, date of publication 4 April 2024, date of current version 12 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3385280

RESEARCH ARTICLE

Banana Individual Segmentation and Phenotypic Parameter Measurements Using Deep Learning and Terrestrial LiDAR

CHAO MA[1], JUAN WANG[1], TIWEI ZENG[1,2], QIFU LIANG[1], XINGUO LAN[1], SHAOMING LIN[1,2], WEI FU[1], AND LVSHENG LIANG[3]

[1]College of Mechanical and Electrical Engineering, Hainan University, Haikou 570228, China
[2]College of Information and Communication Engineering, Hainan University, Haikou 570228, China
[3]Hainan Zhongnong Hangfu Technology Company Ltd., Danzhou 571799, China

Corresponding author: Juan Wang (wj-jdxy@hainanu.edu.cn)

This work was supported in part by Hainan Province Science and Technology Special Fund under Grant ZDYF2022XDNY273, in part by the National Natural Science Foundation of China under Grant 32201670, in part by Hainan Province Science and Technology Special Fund under Grant ZDYF2020195, and in part by the National Natural Science Foundation of China under Grant 32160424.

ABSTRACT Banana phenotypic parameters are one of the important elements in the study of banana growth and development. Through the measurement of banana phenotypic parameters, we can obtain information about the growth status, nutritional status and quality indexes of banana plants, and pseudo-stem parameters are significant indicators in banana phenotypic parameters. This research proposes a two-stage approach combining morphological features and deep learning point cloud segmentation to extract banana pseudo-stem parameters. Specifically, in the first step, seed points are extracted using the DBSCAN clustering algorithm, and banana individual plant segmentation is accomplished using the region growing algorithm based on seed points. Its precision, recall and F1-score were 97.73%, 97.36% and 97.54%, respectively. This indicates that the DBSCAN clustering algorithm and the seed point based region growing algorithm can effectively realize the plant count of banana plants and initially realize the individual plant segmentation of banana. The second step is to use PointNet++, PointNet, and DGCNN for pseudo-stem and canopy segmentation of individual banana plants. All three models perform well in segmentation, with PointNet++ performing the best. Its precision, recall, F1-score, Matthews correlation coefficient and Dice coefficient reached 0.9956, 0.9709, 0.9831, 0.9670 and 0.9831. This shows that deep learning has a better applicability in segmenting banana plants. In the results of segmentation, we measure the banana pseudo-stem circumference and pseudo-stem height. The correlation between the extracted pseudo-stem height and pseudo-stem circumference compared to the measured values was 96.70% and 82.32%, respectively. The above two-stage method of extracting banana pseudo-stem parameters overcomes the difficulties of point cloud individual plant segmentation associated with intensive banana cultivation. It makes the management of individual banana plants possible and provides accurate phenotypic parameter information for banana plantation management. It lays the foundation for further assessment of banana growth and nutritional status.

INDEX TERMS Terrestrial LiDAR, individual segmentation, phenotypic parameter, deep learning.

I. INTRODUCTION

As one of the critical global cash crops, banana is widely planted and consumed worldwide. In 2018, China's banana production was 112.21 million tons, and sustainable development and efficient management of the banana industry has become a matter of close attention [1]. So, accurate measurement of external parameters of banana plants has been one of the challenges in agriculture. Traditional manual measurement methods suffer from issues such as being time-consuming, labor-intensive, subjective, and influenced by environmental conditions and the skills of the measurer [2].

The associate editor coordinating the review of this manuscript and approving it for publication was Prakasam Periasamy.

Therefore, an efficient and accurate measurement method is needed to extract the phenotypic parameters of banana plants. The height and circumference of pseudo-stems are essential indicators of banana plants' growth and health status [3]. By monitoring the changes in the height and circumference of pseudo-stems, growers can assess the growth rate, growth stage, and possible growth anomalies of the plant. It helps growers take timely and necessary measures, such as timely fertilization, irrigation, and pest control, to maximize the optimization of the banana plant's growing environment and improve yield and quality [4].

Currently, point clouds are widely used to measure plant phenotypic parameters [5], and the way to obtain the plant shape point cloud is mainly obtained by 3D reconstruction of UAV (Unmanned Aerial Vehicle) images and LiDAR (Light Detection and Ranging) scanning [6]. Song and Wang [7] generated a point cloud model of winter wheat plants based on UAV images to measure the canopy height of winter wheat, and the predicted RMSE and MAE reached 6.37cm and 5.07cm, respectively. Qi et al. [8] generated a point cloud model of orange tree based on UAV images and combined deep learning to segment the plant from the ground to calculate the volume of the orange tree, and the experimental results achieved R2 of 0.8215 and RMSE of 0.3186m3. Although obtaining point cloud data through UAV provides an efficient means to extract plant phenotypic parameters, the resulting ground-plant point cloud often fails to accurately capture ground-level vegetation's detailed shape due to camera resolution limitations. Additionally, foliage obstructs the aerial view, preventing the UAV camera from capturing certain information about tree trunks and the ground. Consequently, the acquired point cloud data may suffer from incompleteness or missing components [9].

Compared to UAV remote sensing image technology, LiDAR can not only obtain a large amount of point cloud data at a very high efficiency but also, the point cloud obtained from its scanning has a high data accuracy and density. Meanwhile, terrestrial LiDAR can also accurately collect the point cloud information under the plant's canopy, which can accurately reflect the phenological details and parameters of the plant [9], [10], [11]. LiDAR has an extensive scanning range and can scan a large farmland or plant population in a relatively short period. It allows LiDAR to efficiently acquire plant phenotypic parameters and improve data collection efficiency in large-scale agricultural production [12]. Ao et al. [13] obtained a point cloud model of maize plants based on terrestrial LiDAR and extracted five phenotypic parameters of maize plants by combining them with the PointCNN model, and the results had a low error. Yang et al. [14] terrestrial LiDAR reconstructed the forest stand in three dimensions, and the four canopy structure parameters obtained by virtual measurement estimation were highly consistent with the field measurement data. Miao et al. [15] collected a point cloud model of banana plants based on terrestrial LiDAR and realized the counting of banana plants and the measurement of morphological parameters. Fang et al. [16] obtained point cloud models of wheat plants based on terrestrial LiDAR and proposed a new algorithm, ALHC, for wheat tiller detection, which exploited point clouds' potential in extracting plant phenotypic parameters. LiDAR provides high-precision 3D point cloud data that can capture plants' spatial structure and morphological characteristics. By analyzing the geometry of the plant, parameters such as height, volume, and branch thickness can be obtained, which helps to understand the plant's growth status and structural characteristics [17].

With computer science's development and data accumulation, deep learning has been widely used in agriculture [18], [19]. Deep learning can automatically identify and classify plants by analyzing and processing farmland images [20] or farmland point clouds [21], which helps agricultural producers and researchers better monitor and manage farmland. Li et al. [22] acquired point cloud data of maize plants through the MVS-Pheno platform and introduced PointNet++ algorithm to achieve stem and leaf segmentation and organ instance segmentation of maize, and the accuracy of stem and leaf segmentation reached 0.91 and organ instance segmentation reached 0.94. Turgut et al. [23] compared the segmentation accuracies of six deep learning models for organ segmentation of roses based on 3D synthetic rose point cloud model, and the experimental results showed that PointNet++ had the highest segmentation accuracy. Deep learning in agricultural phenotyping provides new avenues and technical tools for agricultural production management, pest prevention and control, and agricultural research, which helps to improve crop yield and quality and promote sustainable agricultural development [24].

In this research, Individual plant segmentation and phenotypic parameter detection of banana plants are accomplished by collecting point cloud data of bananas by terrestrial LiDAR and combining it with deep learning technology. It provides an efficient and accurate management method for banana planting. We propose a method to extract seed points as the basis for Individual plant segmentation using the DBSCAN clustering algorithm [25], [26] and then complete Individual plant segmentation of banana plants using the region growing algorithm [27]. For Individual banana plant segmentation, PointNet++ [28], [29] deep learning was used to perform semantic segmentation to divide Individual banana segmentation into two parts, pseudo-stem, and canopy, and measure the circumference of the banana pseudo-stem and the height of the pseudo-stem, to provide accurate information about the phenotypic parameters for the management of banana planting. Finally, we assessed the accuracy of Individual plant segmentation at the level of number of plants and the accuracy of phenotypic parameter prediction at the level of number of point clouds.

The main aims of this paper are:

(1) We propose a new method to overcome the problem of Individual plant segmentation, which is difficult due to dense plant cultivation, and to achieve Individual banana segmen-

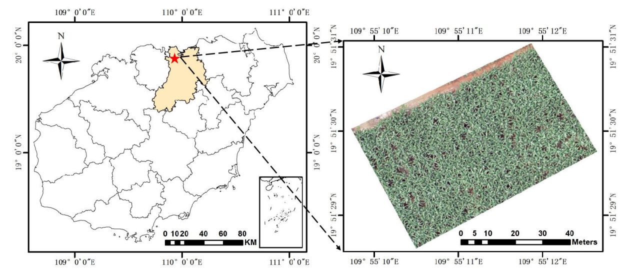

FIGURE 1. Experimental site location.

tation monitoring and management of the growth status of banana plants.

(2) Verify the segmentation effect of the method under different range thresholds and explore the factors affecting the Individual plant segmentation effect of banana plants.

(3) Based on the PointNet++ algorithm to achieve the segmentation of pseudo-stems and canopy of banana and extract the circumference and height of banana pseudo-stems according to the segmentation results by analyzing the size of banana pseudo-stems, it achieved the prediction and management of the nutritional status of banana growth.

II. MATERIAL AND METHODS

A. SITE DESCRIPTION

The experimental site of this research was located in a commercial banana plantation in Chengmai County, Hainan Province (Figure 1), with geographic coordinates of 109°55'11''E, 19°51'30''N, and an altitude of 88 m above sea level. The region has a tropical oceanic monsoon climate with abundant sunshine and rainfall, an average annual temperature of 23.8°C, and an average yearly rainfall of 1786.1 mm, making the climate and soil conditions suitable for banana plant growth. This research was conducted on 18 April 2023, when banana plants in the study area were mainly in the late nutritive growth period when the size of the pseudo-stems of the banana plants could reflect the health of banana growth.

B. DATA ACQUISITION

1) TERRESTRIAL LIDAR ACQUISITION OF POINT CLOUD DATA

The point cloud data was acquired on 18 April 2023 using terrestrial LiDAR (LiGrip H120, GreenValley, China), which has the performance parameters shown in Table 1. The weather on the day of the experiment was sunny, and the temperature was between 32°C and 35°C. The equipment used and the planned route are shown in Figure 2. Terrestrial LiDAR was held to walk and scan along the planned route (1) to (13) at a speed of 1m/s. The LiGrip H120 terrestrial LiDAR integrates a high-performance laser and a panoramic camera. The high-performance laser can quickly acquire high-precision point clouds, while the panoramic camera acquires the image information and renders the point clouds with colors. The LiGrip H120 LiDAR system can automatically measure the banana forest experimental area, which combines LiDAR and SLAM (Simultaneous localization and mapping). A high-density point cloud for the banana experimental area can be generated rapidly.

TABLE 1. Performance parameters of LiGrip H120.

Specifications	Parameters
Handheld Size	204×130×385 mm
Handhold weight	1.74 kg
Laser	XT-16
Laser class	Class 1 eye-safe
Lidar accuracy	±3 cm
Scan distance	120 m
Laser wavelength	930 nm
Scanning frequency	320,000 pts/s
Field of view	360°×280°
Data storage	USB, TD

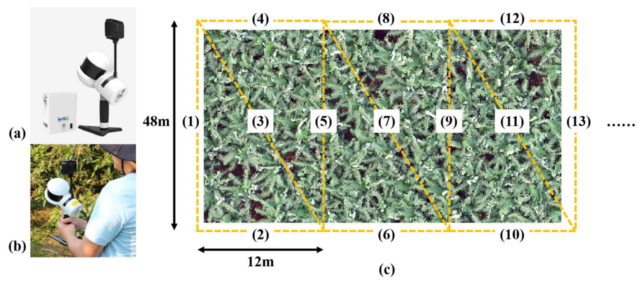

FIGURE 2. Terrestrial LiDAR planning scanning route. (a) and (b) show the LiGrip H120 terrestrial LiDAR and the use method; (c) represents the scanning planning route; only a part of the route is represented in the figure, and the route is scanned in the order of (1) to (13) until the planning area is scanned.

2) DATA PREPROCESSING

Data preprocessing includes the following steps: point cloud registration, point cloud denoising, ground point classification, and point cloud normalization. Point cloud registration was performed using LiFuser-BP software, which combines 2D panoramic images and 3D Lidar data for fast point cloud registration processing. The generated point cloud data produces noise point clouds due to environmental factors and jitter interference caused during data acquisition. Therefore, we use the radius outlier removal method to perform denoising operation on the point cloud data. Then, we implement ground point classification based on the Progressive TIN densification filtering algorithm [30]. In order to facilitate the subsequent point cloud processing, it is also necessary to normalize the point cloud data according to the DEM (Digital Elevation Model). We first matched the point cloud data with the DEM, and the elevation value of each point cloud data is subtracted from the corresponding DEM elevation value to achieve normalization.

3) GROUND DATA ACQUISITION

To ensure that the measurements are not affected by changes of the weather during the day, the collection of the point cloud data and the measurement of the ground-truth parameters occur on the same day. To verify the accuracy of individual plant segmentation, we manually counted the

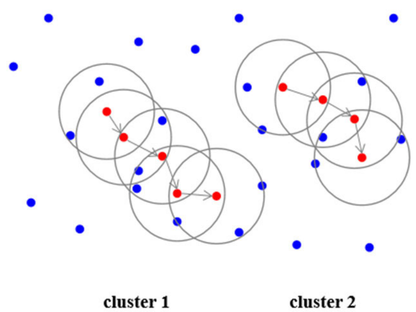

FIGURE 3. **Schematic diagram of the clustering process of the DBSCAN algorithm. The points in all circles connected by arrows on the left side form a point cloud cluster, the points in all circles connected by arrows on the right side form another point cloud cluster, and the rest of the points are the noise points.**

number of banana plants in the study area. We used a soft ruler to measure the banana pseudo-stem circumference data at a height of 1.5m from the ground. At the same time, we used a tower ruler to measure the height of the banana pseudo-stem. We measured 27 banana plants for pseudo-stem circumference and pseudo-stem height. We used a D-RTK 2 high-precision GNSS mobile station to accurately locate the measured 27 banana plants with a positioning accuracy of 0.01m.

C. INDIVIDUAL BANANA SEGMENTATION

1) EXTRACTION OF SEED POINTS

The region segmentation based on seed points starts by selecting multiple seed points, starting from these seed points, and gradually forming point clustering by adding the neighborhood points of seed points. The selection of the number and location of seed points usually affects the efficiency and quality of subsequent segmentation algorithms, and we propose a method to automatically extract seed points for subsequent Individual plant segmentation. Firstly, we cropped the normalized point cloud data with elevation values between 1m and 1.2m, and then the cropped point cloud data were segmented using the DBSCAN clustering algorithm. DBSCAN clustering [25], [26] algorithm is a clustering algorithm based on the density of the point cloud, such as Figure 3 represents the clustering process of the DBSCAN algorithm. A neighborhood with a number of MinPts within the radius of a neighborhood is considered a cluster. MinPts was set to 4, is the circle's radius in the figure, and the red points are core points. The set of all points in the neighborhood of core points forms a point cloud cluster [31]. After the point cloud clustering, the number of clustered point cloud clusters was calculated, and the coordinates of the central point cloud of each point cloud cluster were also calculated. The central point cloud was the average of the coordinates of all the point clouds in the point cloud cluster, and then the coordinates of the central point were the coordinates of the seed points.

2) INDIVIDUAL PLANT SEGMENTATION BASED ON REGION GROWING ALGORITHM

Point cloud region growing algorithm segments the point cloud based on the similarity of euclidean distances and normal vector angles between neighbouring points, it aggregates similar points into regions in the point cloud [27]. Specifically, the extracted seed points are used as the starting point of the segmentation, and for each seed point, the neighbouring points that are similar to its euclidean distance and normal vector angle are calculated, and the euclidean distance d from p_i to p_j is:

$$d = \left\| p_i - p_j \right\| \tag{1}$$

The normal vector angle θ from p_i to p_j is:

$$\theta = arccos \left| n_i^T n_j \right| \tag{2}$$

where n_i and n_j denote the normal vectors of p_i and p_j, respectively.

Since banana plants are grown in dense planting, dense planting leads to intersection of canopy leaves between banana plants. The result of segmentation by region growing algorithm will be over-segmented. Therefore, we add a new parameter called range threshold to the region growing algorithm. The range threshold represents the segmentation range of each banana plant point cloud, centered horizontally at the seed point, and point clouds beyond the range threshold will not be grouped together. Under the specified range threshold, for each newly added point, the points with similar Euclidean distances and normal vector angles to its neighboring points are computed and added to the set in which the point is located until all the points are assigned to a certain set. At this point, each point cloud set represents a segmented banana plant.

D. DEEP LEARNING BASED POINT CLOUD SEGMENTATION OF BANANA PLANTS

Point cloud semantic segmentation is to assign a semantic label to each point in the point cloud data, with the aim of distinguishing different objects or scenes in the point cloud data, so as to achieve semantic understanding and classification of the point cloud data. We use deep learning point cloud semantic segmentation to segment banana plant canopy and pseudo-stem. We selected the PointNet++ [28], [29] classical point cloud deep learning algorithm for testing, to verify the feasibility of point cloud deep learning for segmentation between banana plant canopy and pseudo-stem. The PointNet++ schematic is shown in Figure 4. Since PointNet++ fully considers the point cloud's local features through multi-level point cloud learning.

In this research, based on individual plant segmentation, the individual point cloud of a banana plant was used as a training sample, and the point cloud of each banana plant was labeled using manual labeling to divide it into canopy and pseudo-stem sections. In the preprocessing stage of the point cloud data, the dataset was augmented by randomly rotating the original samples by 0 to 180° in both vertical and horizontal directions, and randomly scaling them by a multiplicity of 0.8 to 1.2, to improve the robustness of the model. After data enhancement, the number of datasets was

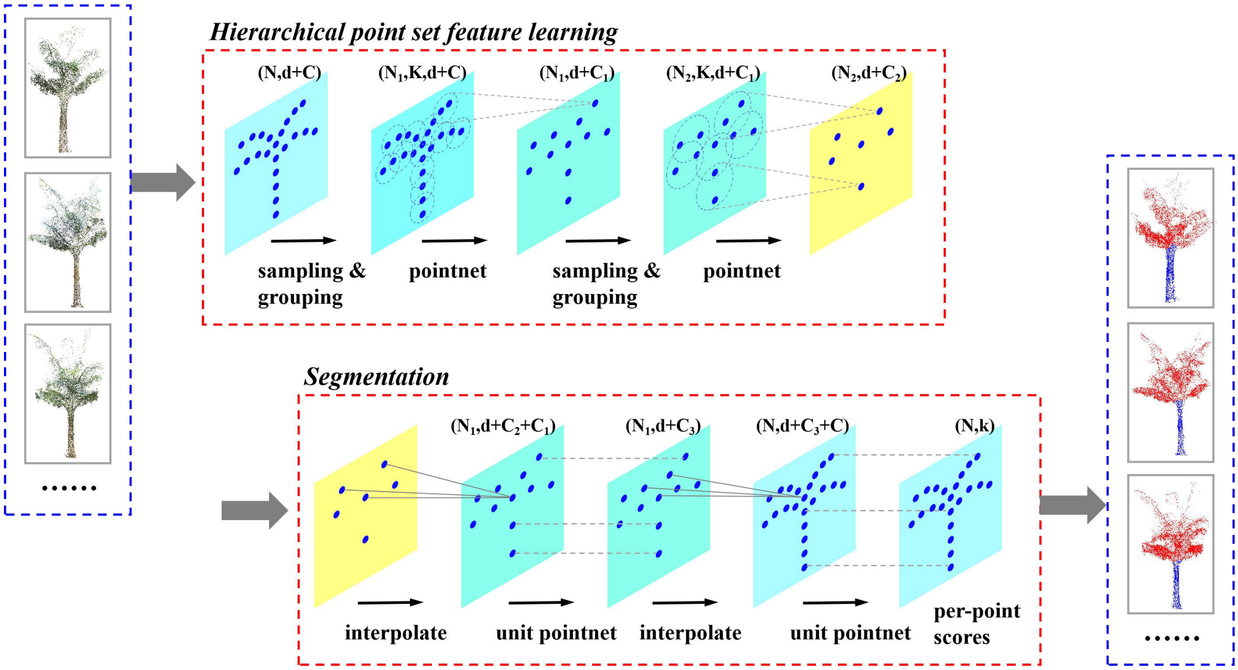

FIGURE 4. PointNet++ network architecture.

boosted to 960. Among them, 80% of the samples were randomly selected as the training set, 20% were randomly selected as the validation set, and 27 banana plants measured on the ground were selected as the testing set.

The experimental hardware configurations include an Intel i9-12900K CPU (3.20 GHz), a memory of 64 GB, and an RTX 3060 graphics card. In order to avoid overfitting, the initial learning rate was set to 0.00001, the learning rate decay was set to 0.5, the batch size was set to 4 according to the GPU memory size, and the Adam optimizer was used to minimize the loss function. To ensure the accuracy of the point cloud shape, 20480 point clouds were randomly selected for each sample data to train and test the model. 500 epochs of iterative training ensured the final convergence. Cross entropy loss function, which is commonly used in segmentation tasks, was used as the loss function in the training process. Figure 5 shows the framework for detecting phenotypic parameters of banana plants in this study.

E. ACCURACY EVALUATION METHOD

1) INDIVIDUAL PLANT SEGMENTATION ACCURACY EVALUATION

We assessed individual plant segmentation accuracy using precision, recall, and F1-score. For the Individual plant segmentation task, precision is the proportion of samples predicted by the algorithm to be positive that are actually positive, and it measures the accuracy and reliability of the algorithm in predicting positive cases. Recall is the proportion of samples that are actually positive cases that are correctly predicted by the algorithm as positive cases, which measures the algorithm's coverage of the positive case samples and the detection rate. F1-score is the reconciled average of precision and recall, which is used to comprehensively evaluate the accuracy and detection rate of the algorithm [32]. These three evaluation indexes are calculated as follows:

$$p = \frac{TP}{TP + FP} \tag{3}$$

$$r = \frac{TP}{TP + FN} \tag{4}$$

$$F = \frac{2 \times p \times r}{p + r} \tag{5}$$

where p denotes precision, r denotes recall, F denotes F1-score, TP denotes the number of banana plants correctly segmented by the algorithm, FP denotes the number of banana plants incorrectly segmented by the algorithm, and FN denotes the number of banana plants not segmented by the algorithm.

2) ACCURACY EVALUATION OF DEEP LEARNING ALGORITHMS

We evaluate the partial segmentation results of PointNet++, PointNet and DGCNN on the basis of the number of point clouds. Segmentation results are evaluated by precision, recall, F1-score, Matthews correlation coefficient (Mcc) and Dice coefficient.

Mcc is a metric used to evaluate the performance of binary classification models, which is especially suitable for dealing with imbalanced datasets. The Mcc is calculated as follows.

$$Mcc = \frac{TP \times TN - FP \times FN}{\sqrt{(TP + FP) \times (TP + FN) \times (TN + FP) \times (TN + FN)}} \tag{6}$$

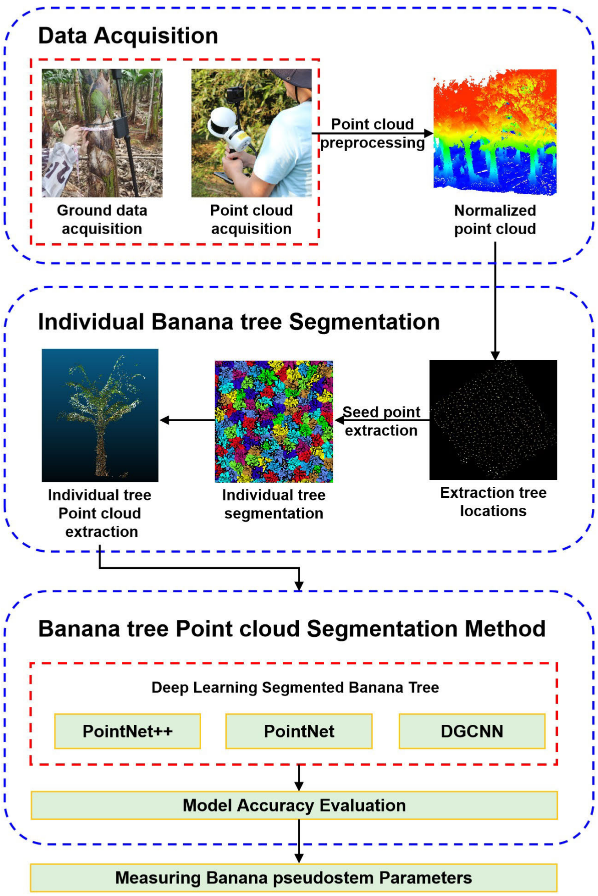

FIGURE 5. Framework for detection of phenotypic parameters in banana plants based on terrestrial LiDAR.

The dice coefficient is a set similarity measure that is commonly used to calculate the similarity of two samples. The dice coefficient is calculated as follows.

$$Dice = \frac{2 \times TP}{2 \times TP + FN + FP} \tag{7}$$

The formulas for calculating Precision, recall and F1-score refer to (3), (4) and (5). The meanings represented by TP, FP, TN and FN in the above four indicators are different from those in the individual plant segmentation. For the point cloud segmentation task, we define it at the level of the number of point clouds. TP denotes the number of point clouds correctly predicted by the algorithm as positive instances. TN denotes the number of point clouds correctly predicted by the algorithm as negative instances. FP denotes the number of point clouds incorrectly predicted by the algorithm as positive instances. FN denotes the number of point clouds incorrectly predicted by the algorithm as negative instances.

3) ACCURACY EVALUATION OF BANANA PHENOTYPIC PARAMETERS

As shown in Figure 6, we automatically measured the height of the segmented resultant pseudo-stems, and intercepted the point cloud data with elevation values between 1.45m and 1.55m, and fitted the banana pseudo-stem circumference

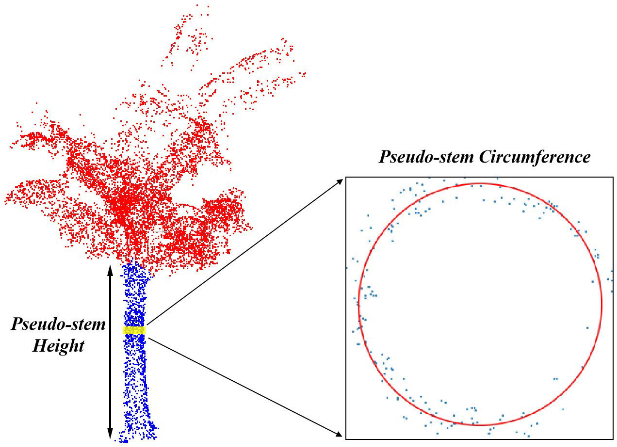

FIGURE 6. Schematic diagram of the extraction method for the phenotypic parameters of banana plants.

using the least squares method to obtain the banana pseudo-stem circumference. RMSE and R2 were used to evaluate the accuracy of phenotypic parameter extraction. These two evaluation indexes were calculated as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \tag{8}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \bar{y}_i)^2} \tag{9}$$

where n denotes the number of samples to be compared; y_i denotes the value of the ground-truth measurement; $\hat{y}_i$ denotes the value of the phenotypic parameter extracted from the segmentation result by the algorithm; and $\bar{y}$ denotes the average value of the ground-truth measurement.

III. RESULTS

A. ACCURACY OF INDIVIDUAL PLANT SEGMENTATION

The range threshold in the region growing algorithm is the main factor affecting the effect of single plant segmentation, and the different range threshold is related to the efficiency and effect of clustering. Setting a range threshold that is too large or too small will affect the number of banana plants that are eventually correctly divided, as well as the efficiency of the segmentation. Four range threshold parameters were selected for study and comparison, namely 1m, 2m, 3m and 4m. The segmentation accuracy of single plant with different range thresholds is shown in Table 2.

When the range threshold is greater than 2m, the segmentation accuracy index decreases rapidly. When the range threshold is 4m, Precision, Recall and F1-score are only 81.32%, 65.16% and 72.35%. This range threshold is manifested in the actual segmentation as banana plants planted close to each other are classified into one category. When the range threshold is between 1 and 2, the algorithm maintains a high segmentation accuracy. When the range threshold is 2m, Precision, Recall and F1-score reach the highest values, which are 97.73%, 97.36% and 97.54%, respectively. This

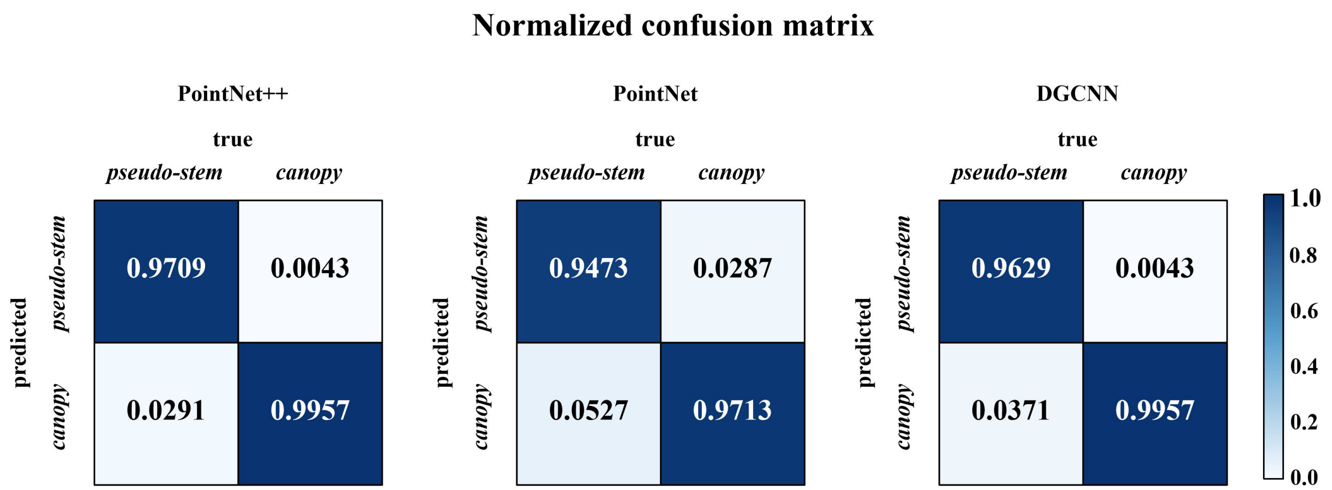

FIGURE 7. Normalized confusion matrix diagrams of the three deep learning algorithms.

TABLE 2. Individual plant segmentation accuracy of banana segmentation under 4 range thresholds. RT stands for the range threshold.

RT (m)	precision	recall	F1-score
1	97.72%	96.98%	97.35%
2	97.73%	97.36%	97.54%
3	91.34%	87.55%	89.40%
4	81.32%	65.16%	72.35%

TABLE 3. Segmentation accuracy of three deep learning algorithms.

	precision	recall	F1-score	Mcc	Dice
PointNet++	0.9956	0.9709	0.9831	0.9670	0.9831
PointNet	0.9713	0.9473	0.9591	0.9186	0.9591
DGCNN	0.9749	0.9629	0.9688	0.9636	0.9688

means that when the range threshold is 2m, the number of correctly divided banana plants is more, and the possibility of misjudgment is less. Under this range threshold, the whole banana field can be covered more completely, which is more suitable to reflect the overall situation. Through comprehensive comparison of various evaluation indicators, the range threshold was set to 2m for single plant segmentation, so as to count the number of plants.

B. SEGMENTATION ACCURACY FOR DEEP LEARNING

We evaluated the accuracy of the point cloud of banana plants in the testing set by five quantitative indexes: precision, recall, F1-score, Mcc and Dice. As shown in Table 3, the semantic segmentation accuracy results of the three deep learning algorithms are presented. PointNet++ has the highest performance in the five indicators, and its precision, recall, F1-score, Mcc and Dice are 0.9956, 0.9709, 0.9831, 0.9670, 0.9831 respectively. Figure 7 illustrates the ability of three semantic segmentation models PointNet++, PointNet and DGCNN to accurately label and segment the point cloud model of banana plants. All three models can identify the pseudo-stem point cloud well. Among them, PointNet++ has better segmentation effect on banana pseudo-stem, and its normalized TP reaches 0.9709. Figure 8 illustrates the segmentation results for four random banana plant point cloud sets in the testing set. By visualizing the images, the PointNet++ segmentation came out highly consistent with the manually annotated labeled samples, with no extensive false or missed segmentation.

C. ACCURACY OF BANANA PHENOTYPIC PARAMETERS

Figure 9 demonstrates the correlation between the phenotypic parameters extracted based on PointNet++ point cloud segmentation and the comparison of the ground-truth values. In the comparison results of pseudo-stem height, R2, and RMSE were 0.9670 and 0.079, respectively. In the comparison results of pseudo-stem circumference, R2, and RMSE were 0.8232 and 0.0296, respectively. Among these two phenotypic parameters, the extracted pseudo-stem height has a higher correlation with ground truth, while the extracted pseudo-stem circumference has a slightly lower correlation with ground truth. However, their accuracy satisfies banana plants' growth monitoring and nutritional management.

IV. DISCUSSION

A. ACCURACY OF POINT CLOUD SEGMENTATION

In this research, Individual plant segmentation is mainly implemented by the region growing algorithm based on seed points. When extracting seed points, intercepting point cloud data with different elevation values will affect the generated seed points differently. As shown in Figure 10(a), if the point cloud with too low elevation value (0.6m-0.8m) is intercepted, this will result in the intercepted point cloud containing some redundant point clouds, such as weeds and residual shadows. In the DBSCAN clustering algorithm, the

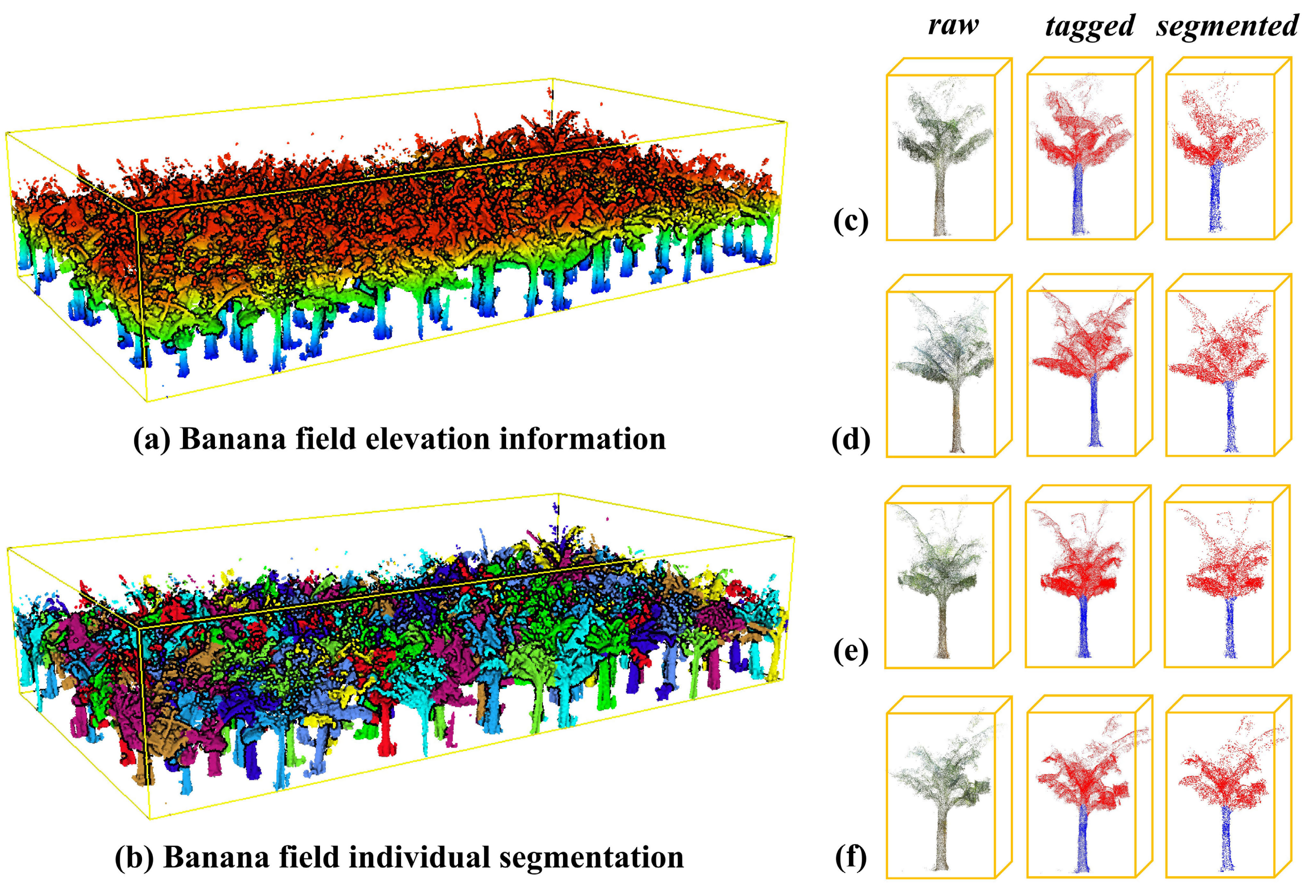

FIGURE 8. Algorithm segmentation results. (a) represents the elevation information of the banana field. (b) indicates Individual plant segmentation results of the banana field. (c) to (f) denote the comparison graphs of four random groups of segmentation results in the testing set, and each comparison graph from left to right is thus: the original banana plant point cloud samples, the manually labeled banana plant point cloud samples, and the banana plant point cloud samples segmented by the PointNet++ algorithm.

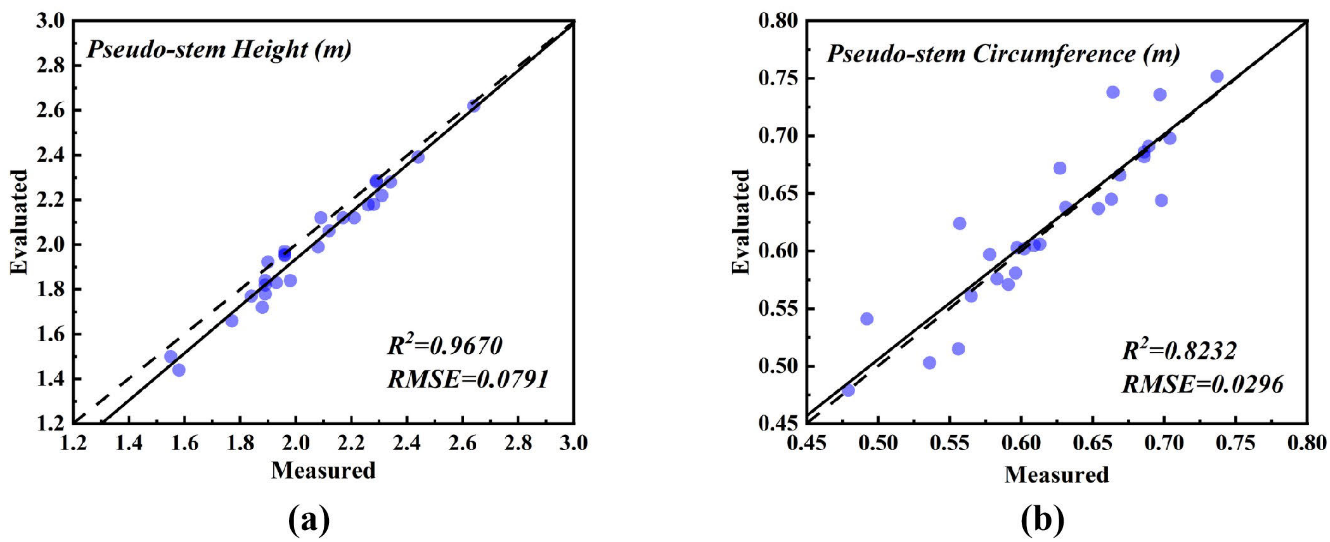

FIGURE 9. Correlation of phenotypic parameters extracted based on PointNet++ point cloud segmentation with ground-truth values. (a) Pseudo-stem height correlation. (b) Pseudo-stem circumference correlation.

partially redundant point clouds may be segmented into a separate class, which results in a higher number of seed points generated. When intercepting the point cloud with too high elevation value (1.4m-1.6m), as shown in Figure 10(c), sagging leaf point cloud could be segmented and recognized as part of pseudo-stem point cloud. It affects the extraction of seed points and causes the generated seed points to deviate from the pseudo-stem center position. Finally, we cropped the point cloud data with elevation values between 1m and 1.2m for seed points extraction, as shown in Figure 10(b). It avoided as much as possible the weed noise points that were too low and the sagging leaf point cloud that was too high while ensuring that the density of the point cloud clusters was suitable for clustering.

Better seed points extraction led to Individual plant segmentation with higher accuracy. In Individual plant segmentation based on the number of plants level, the range threshold reached its highest F1-score at 2 m, with a value of 97.54%. Although the method accurately detected the number of plants, the plants were poorly segmented in the canopy region. It is because locally grown bananas are habitually planted densely, and the leaves of mature banana plants usually cross and overlap each other. As a result, some of the segmented plants have broken leaves. At the same time, because the banana canopy leaves are too dense, terrestrial LiDAR can only scan the pseudo-stems and features in the middle and lower layers of the canopy when scanning the banana field, and there is a small portion of the point cloud acquisition in the upper part of the canopy is missing. In the following research step, the growth characteristics of banana leaves can be combined with the banana plant skeleton to subdivide the canopy segmentation further. In addition, airborne LiDAR can also be introduced to try to obtain higher quality point cloud data with air-ground cooperation mode by matching and fusing the point cloud data collected on the ground and in the air.

In the comparison results for pseudo-stem height, the R2 and RMSE are 0.9670 and 0.0791, respectively. The segmentation results maintain a high degree of fit and low error. However, the overall position of the fitted straight line is slightly lower than the standard line, which means that the overall pseudo-stem height predicted by PointNet++ is slightly smaller than the ground-truth measurement. This situation is because there is a transition region where the pseudo-stem meets the canopy, and this transition region consists mainly of the petiole and pseudo-stem. As the pseudo-stem gets smaller towards the top until it merges with the petiole, the algorithm does not segment the petiole and pseudo-stem well, resulting in a slightly smaller predicted pseudo-stem height than the ground-truth measurement. This can be corrected by expanding the dataset to obtain higher accuracy or by using empirical formulas.

However, in the comparison results of pseudo-stem circumference, its R2 and RMSE are 0.8232 and 0.0296, respectively. Compared with pseudo-stem height, the fit of pseudo-stem circumference is slightly worse. However, its final fitted straight line was very close to the standard line, and its error was kept within 10cm. The performance of its prediction results meets the efficient prediction management model of the banana industry, which is of guiding significance in understanding the growth and development of banana plants, assessing the growth potential and physiological status

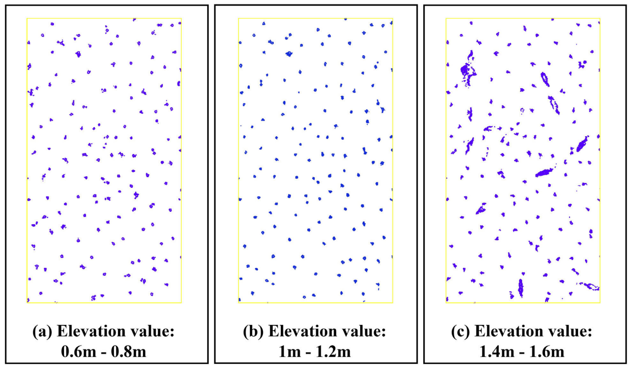

FIGURE 10. Point clouds in different elevation value ranges. (a) represents the point cloud with elevation values ranging from 0.6m to 0.8m. (b) illustrates the point cloud with elevation values ranging from 1m to 1.2m. (c) illustrates the point cloud with elevation values ranging from 1.4m to 1.6m.

of plants, and determining the growth stage and maturity of bananas.

B. ADVANTAGES EVALUATION

Terrestrial LiDAR acquired the raw point cloud data for this research. The advantage of using terrestrial LiDAR is its high throughput characteristics, which enables it to acquire a large amount of point cloud data in a short period of time. In this research, it took 15 minutes to complete the initial acquisition of data under the planned route. Terrestrial LiDAR enables the acquisition of phenotypic parameters over a larger area and at a faster rate than manual measurements.

Currently, the accuracy of most studies using LiDAR for Individual plant segmentation is usually affected by understory shrubs and herbaceous plants [33]. We extracted the seed points of each plant based on the morphological structure of banana plants, effectively avoiding the shrub and weed point clouds with low elevation values. The precision reached 97.73% in the final result, and the method has high feasibility in the number of plants detection, which provides new possibilities for Individual plant segmentation directions.

In a related research, Miao et al. [15] accomplished the plant counting of banana plants with k-means clustering algorithm, and the precision reaches 97.32% at the highest. In this research, we not only realize the plant count of banana plants, on the basis of which, we also preliminarily realize the individual plant segmentation of banana plants. In this case, the precision of plant counting reached up to 97.73%. In addition, we found that PointNet++ model has better effect on organ segmentation of banana plants, and the final segmentation result has an R2 of 0.9670, RMSE of 0.0791. The method in this research has a high degree of fit and a small error in the measurement of pseudo-stem height.

Although the method proposed in this research can effectively realize banana individual plant segmentation, it is still difficult to accurately segment the banana canopy region. On the one hand, because the point clouds of the banana canopy region have large-scale overlap or complete overlap, and on the other hand, the point clouds are acquired in the field environment, and it is inevitable that there will be the influence of wind disturbance and other weather causes during the acquisition process, which will result in errors in the acquisition of the point clouds. Therefore, future work will focus on acquiring higher precision point cloud data, while involving algorithm improvement and the combination of new technologies to improve segmentation accuracy and computational efficiency. In addition, the fusion of multi-source data is also very valuable for plant segmentation and phenotypic parameter extraction, for example, the combination of high-precision remote sensing imagery, multi-spectral remote sensing imagery and airborne LIDAR will result in more accurate plant modeling data. This will be more conducive to the development and progress of precision agriculture technology.

V. CONCLUSION

We propose a two-stage approach to extract the parameters of banana pseudo-stems: the first stage is the individual plant segmentation stage, and the second stage is the segmentation of pseudo-stems and canopies. In the first stage, the DBSCAN clustering algorithm is used to extract seed points as the basis for individual plant segmentation, and then the region growing algorithm based on seed points is used to segment banana plants individually. In the second stage, three semantic segmentation models are compared to segment the pseudo-stem and canopy. The results show that both individual plant segmentation and pseudo-stem parameter measurement have high accuracy. This study provides an efficient, accurate and non-contact method for growth monitoring and agricultural management of banana plants. Future studies could further optimize the ground-based lidar technology in combination with other biological parameters to gain a more complete understanding of the dynamics and physiological characteristics of banana growth and development.

REFERENCES

[1] L. Fu, J. Duan, X. Zou, G. Lin, S. Song, B. Ji, and Z. Yang, "Banana detection based on color and texture features in the natural environment," *Comput. Electron. Agricult.*, vol. 167, Dec. 2019, Art. no. 105057, doi: 10.1016/j.compag.2019.105057.

[2] Y. Huang, Z. Ren, D. Li, and X. Liu, "Phenotypic techniques and applications in fruit trees: A review," *Plant Methods*, vol. 16, no. 1, pp. 1–107, Dec. 2020, doi: 10.1186/s13007-020-00649-7.

[3] G. Cedeño, Á. Guzmán, H. Zambrano, L. Vera, C. Valdivieso, and G. López, "Effect of planting density and complementary irrigation on the morpho-phenology, yield, profitability, and efficiency of banana fertilization," *Scientia Agropecuaria*, vol. 11, no. 4, pp. 483–492, Nov. 2020, doi: 10.17268/sci.agropecu.2020.04.03.

[4] R. Ploetz, "Banana diseases in the subtropics: A review of their importance, distribution and management," *Acta Horticulturae*, no. 490, pp. 263–276, Sep. 1998.

[5] M. Moriondo, L. Leolini, N. Staglianò, G. Argenti, G. Trombi, L. Brilli, C. Dibari, C. Leolini, and M. Bindi, "Use of digital images to disclose canopy architecture in olive tree," *Scientia Horticulturae*, vol. 209, pp. 1–13, Sep. 2016, doi: 10.1016/j.scienta.2016.05.021.

[6] A. Ozdarici-Ok and A. O. Ok, "Using remote sensing to identify individual tree species in orchards: A review," *Scientia Horticulturae*, vol. 321, Nov. 2023, Art. no. 112333, doi: 10.1016/j.scienta.2023.112333.

[7] Y. Song and J. Wang, "Winter wheat canopy height extraction from UAV-based point cloud data with a moving cuboid filter," *Remote Sens.*, vol. 11, no. 10, p. 1239, May 2019, doi: 10.3390/rs11101239.

[8] Y. Qi, X. Dong, P. Chen, K.-H. Lee, Y. Lan, X. Lu, R. Jia, J. Deng, and Y. Zhang, "Canopy volume extraction of *Citrusreticulate* blanco cv. Shatangju trees using UAV image-based point cloud deep learning," *Remote Sens.*, vol. 13, no. 17, p. 3437, Aug. 2021, doi: 10.3390/rs13173437.

[9] S. Madec, F. Baret, B. de Solan, S. Thomas, D. Dutartre, S. Jezequel, M. Hemmerlé, G. Colombeau, and A. Comar, "High-throughput phenotyping of plant height: Comparing unmanned aerial vehicles and ground LiDAR estimates," *Frontiers Plant Sci.*, vol. 8, p. 2002, Nov. 2017, doi: 10.3389/fpls.2017.02002.

[10] S. Jin, X. Sun, F. Wu, Y. Su, Y. Li, S. Song, K. Xu, Q. Ma, F. Baret, D. Jiang, Y. Ding, and Q. Guo, "LiDAR sheds new light on plant phenomics for plant breeding and management: Recent advances and future prospects," *ISPRS J. Photogramm. Remote Sens.*, vol. 171, pp. 202–223, Jan. 2021, doi: 10.1016/j.isprsjprs.2020.11.006.

[11] Y. Lin, "LiDAR: An important tool for next-generation phenotyping technology of high potential for plant phenomics?" *Comput. Electron. Agricult.*, vol. 119, pp. 61–73, Nov. 2015.

[12] Q. Guo, Y. Su, T. Hu, H. Guan, S. Jin, J. Zhang, X. Zhao, K. Xu, D. Wei, M. Kelly, and N. C. Coops, "LiDAR boosts 3D ecological observations and modelings: A review and perspective," *IEEE Geosci. Remote Sens. Mag.*, vol. 9, no. 1, pp. 232–257, Mar. 2021, doi: 10.1109/MGRS.2020.3032713.

[13] Z. Ao, F. Wu, S. Hu, Y. Sun, Y. Su, Q. Guo, and Q. Xin, "Automatic segmentation of stem and leaf components and individual maize plants in field terrestrial LiDAR data using convolutional neural networks," *Crop J.*, vol. 10, no. 5, pp. 1239–1250, Oct. 2022, doi: 10.1016/j.cj.2021.10.010.

[14] X. Yang, A. H. Strahler, C. B. Schaaf, D. L. B. Jupp, T. Yao, F. Zhao, Z. Wang, D. S. Culvenor, G. J. Newnham, J. L. Lovell, R. O. Dubayah, C. E. Woodcock, and W. Ni-Meister, "Three-dimensional forest reconstruction and structural parameter retrievals using a terrestrial full-waveform LiDAR instrument (Echidna®)," *Remote Sens. Environ.*, vol. 135, pp. 36–51, Aug. 2013, doi: 10.1016/j.rse.2013.03.020.

[15] Y. Miao, L. Wang, C. Peng, H. Li, X. Li, and M. Zhang, "Banana plant counting and morphological parameters measurement based on terrestrial laser scanning," *Plant Methods*, vol. 18, no. 1, p. 66, Dec. 2022, doi: 10.1186/s13007-022-00894-y.

[16] Y. Fang, X. Qiu, T. Guo, Y. Wang, T. Cheng, Y. Zhu, Q. Chen, W. Cao, X. Yao, Q. Niu, Y. Hu, and L. Gui, "An automatic method for counting wheat tiller number in the field with terrestrial LiDAR," *Plant Methods*, vol. 16, no. 1, p. 132, Dec. 2020, doi: 10.1186/s13007-020-00672-8.

[17] A. Ali and M. Imran, "Remotely sensed real-time quantification of biophysical and biochemical traits of citrus *(Citrus sinensis L.)* fruit orchards—A review," *Scientia Horticulturae*, vol. 282, May 2021, Art. no. 110024.

[18] L. Santos, F. N. Santos, P. M. Oliveira, and P. Shinde, "Deep learning applications in agriculture: A short review," in *Proc. 4th Iberian Robot. Conf.*, 2019, pp. 139–151, doi: 10.1007/978-3-030-35990-4_12.

[19] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Comput. Electron. Agricult.*, vol. 147, pp. 70–90, Apr. 2018, doi: 10.1016/j.compag.2018.02.016.

[20] D. Wang, W. Cao, F. Zhang, Z. Li, S. Xu, and X. Wu, "A review of deep learning in multiscale agricultural sensing," *Remote Sens.*, vol. 14, no. 3, p. 559, Jan. 2022, doi: 10.3390/rs14030559.

[21] Y. Chen, Y. Xiong, B. Zhang, J. Zhou, and Q. Zhang, "3D point cloud semantic segmentation toward large-scale unstructured agricultural scene classification," *Comput. Electron. Agricult.*, vol. 190, Nov. 2021, Art. no. 106445, doi: 10.1016/j.compag.2021.106445.

[22] Y. Li, W. Wen, T. Miao, S. Wu, Z. Yu, X. Wang, X. Guo, and C. Zhao, "Automatic organ-level point cloud segmentation of maize shoots by integrating high-throughput data acquisition and deep learning," *Comput. Electron. Agricult.*, vol. 193, Feb. 2022, Art. no. 106702, doi: 10.1016/j.compag.2022.106702.

[23] K. Turgut, H. Dutagaci, G. Galopin, and D. Rousseau, "Segmentation of structural parts of rosebush plants with 3D point-based deep learning methods," *Plant Methods*, vol. 18, no. 1, p. 20, Dec. 2022, doi: 10.1186/s13007-022-00857-3.

[24] A. K. Singh, B. Ganapathysubramanian, S. Sarkar, and A. Singh, "Deep learning for plant stress phenotyping: Trends and future perspectives," *Trends Plant Sci.*, vol. 23, no. 10, pp. 883–898, Oct. 2018, doi: 10.1016/j.tplants.2018.07.004.

[25] C. Paris, D. Kelbe, J. van Aardt, and L. Bruzzone, "A novel automatic method for the fusion of ALS and TLS LiDAR data for robust assessment of tree crown structure," *IEEE Trans. Geosci. Remote Sens.*, vol. 55, no. 7, pp. 3679–3693, Jul. 2017, doi: 10.1109/TGRS.2017.2675963.

[26] L. Comesaña-Cebral, J. Martínez-Sánchez, H. Lorenzo, and P. Arias, "Individual tree segmentation method based on mobile backpack LiDAR point clouds," *Sensors*, vol. 21, no. 18, p. 6007, Sep. 2021, doi: 10.3390/s21186007.

[27] W. Li, Q. Guo, M. K. Jakubowski, and M. Kelly, "A new method for segmenting individual trees from the LiDAR point cloud," *Photogrammetric Eng. Remote Sens.*, vol. 78, no. 1, pp. 75–84, Jan. 2012, doi: 10.14358/pers.78.1.75.

[28] C. R. Qi, H. Su, K. Mo, and L. J. Guibas, "PointNet: Deep learning on point sets for 3D classification and segmentation," 2016, *arXiv:1612.00593*.

[29] C. R. Qi, L. Yi, H. Su, and L. J. Guibas, "PointNet++: Deep hierarchical feature learning on point sets in a metric space," 2017, *arXiv:1706.02413*.

[30] P. E. Axelsson, "DEM generation from laser scanner data using adaptive TIN models," *Int. Arch. Photogramm. Remote Sens.*, vol. 33, no. 4, pp. 110–117, 2000.

[31] H. Fu, H. Li, Y. Dong, F. Xu, and F. Chen, "Segmenting individual tree from TLS point clouds using improved DBSCAN," *Forests*, vol. 13, no. 4, p. 566, Apr. 2022, doi: 10.3390/f13040566.

[32] C. Goutte and E. Gaussier, "A probabilistic interpretation of precision, recall and F-score, with implication for evaluation," in *Proc. Adv. Inf. Retr.*, 2005, pp. 345–359, doi: 10.1007/978-3-540-31865-1_25.

[33] D. Xu, H. Wang, W. Xu, Z. Luan, and X. Xu, "LiDAR applications to estimate forest biomass at individual tree scale: Opportunities, challenges and future perspectives," *Forests*, vol. 12, no. 5, p. 550, Apr. 2021, doi: 10.3390/f12050550.

CHAO MA received the B.S. degree in mechatronic engineering from the College of Mechanical and Electrical Engineering, Hainan University, Haikou, China, in 2022, where he is currently pursuing the M.S. degree in control engineering.

His current research interests include plant phenotype and plant protection drone applications.

JUAN WANG received the Ph.D. degree in agricultural mechanization engineering from South China Agricultural University, Guangzhou, China, in 2020.

She is mainly engaged in the teaching of mechanical design and mechanics of materials. Her current research interests include plant protection drone application and plant disease control.

TIWEI ZENG received the B.S. and M.S. degrees from East China Jiaotong University, in 2015 and 2019, respectively. He is currently pursuing the Ph.D. degree in information and communication engineering with Hainan University.

His current research interests include UAV remote sensing image application and plant disease control.

QIFU LIANG received the B.S. degree in mechatronic engineering from the College of Mechanical and Electrical Engineering, Hainan University, Haikou, China, in 2021, where he is currently pursuing the M.S. degree in mechanical engineering.

His current research interests include plant phenotype and plant protection drone applications.

XINGUO LAN received the B.S. degree in mechanical engineering and automation from the College of Mechanical and Electrical Engineering, Hainan University, Haikou, China, in 2022, where he is currently pursuing the M.S. degree in control engineering.

His current research interests include CFD and plant protection drone applications.

SHAOMING LIN received the B.S. and M.S. degrees from South China Agricultural University, Guangzhou, China. He is currently pursuing the Ph.D. degree in information and communication engineering with Hainan University.

His current research interests include UAV remote sensing image applications and plant protection drone applications.

WEI FU received the Ph.D. degree from South China Agricultural University, Guangzhou, China.

He is mainly engaged in the teaching of robotics and agricultural robotics. His current research interests include intelligent pruning of fruit trees, robot picking of fruit, and intelligent monitoring and control of pests and diseases.

LVSHENG LIANG is currently the Executive Director of Hainan Zhongnong Aviation Clothing Technology Company Ltd. His current research interests include UAV agricultural plant protection and UAV aerial photography.