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# A Review of Deep Learning in The Field of Plant Root Segmentation

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**Abstract:** Plant root segmentation is an important research task, which is of great significance for understanding plant growth and development process. Deep learning has become a research direction worthy of attention in this field. This paper mainly introduces plant root segmentation methods based on deep learning, and reviews the application of various methods in different fields. The problems of data quality, model fitting ability and real-time performance, and the significance of transfer learning, multi-task learning and reinforcement learning in application are put forward. Finally, it is pointed out that future research should focus on how to better cope with the challenges of root morphology and scale change, and pay more attention to the robustness and scalability of the algorithm. In conclusion, deep learning has had an important impact on image segmentation of plant roots.

**Keywords:** Plant root segmentation, Deep learning, Root morphology, Image segmentation.

## 1. Introduction

In the new era of socialism, where science and technology are advancing rapidly, studying plant roots is crucial for discovering the beneficial shape of crops, breeding new varieties, predicting climate change, and optimizing cultivation methods. Our research methods on root systems have also changed, from destructive to non-destructive research methods, from traditional manual root in situ segmentation methods to automatic segmentation methods, and more efficient technology provides a shortcut for the analysis of root phenotypic characteristics. However, due to the similar color of plant roots and soil, it is difficult to extract root characteristics, there are few image data of plant roots, and the soil background is complex, usually containing impurities such as soil particles and small stones, so it is extremely challenging to apply deep learning to plant root segmentation.

## 2. Research on Roots of Traditional Plants

The roots of plants have been studied since the 18th century [1]. Early studies on root configuration can be traced back to the early 20th century, when Cannon's research revealed the variability of taproots and lateral roots of desert plant roots [2], laying the foundation for later studies on plant roots.

### 2.1. Collection of plant root data

In the early stage, researchers usually used destructive research methods such as excavation method, single block method, drilling method and section wall method to study roots [3], which made it difficult to realize in-situ sampling and accurate measurement of roots. Due to the lack of effective non-destructive testing methods to obtain the actual state of roots in soil, the in-depth study of root behavior and characteristics is hindered.

After the 1950s and 1960s, due to the development of optical and microelectronics technology, plant root research was further strengthened, and non-destructive or minimally invasive methods were adopted, such as glass wall method, endoscopy tube method (microroot canal), container method, etc., to minimize root damage. Among them, microroot canal technology is a method of root observation and research, which uses a transparent test tube inserted into the soil to create a small observation window, and uses a multi-tube observation lens or a miniature digital camera to take pictures inside the tube, record and observe the growth dynamics of new roots inside and outside the tube [4]. The image data collected in the field were applied to the indoor special computer software to calculate the root parameters. The advantage of this method is that the root system can be observed and studied without loss, and the dynamic growth process of the same root system can be tracked and recorded in real time. However, its limitation lies in the high cost of equipment and the limited application range [5]. In addition, there are non-invasive methods sensor method. The sensor method can be used for non-invasive detection of root phenotypes, does not interfere with root growth, does not affect soil structure, and can be continued throughout the breeding period without changing the soil environment. The sensor performs 4D root imaging, relying on detectors placed around or inside the culture unit to obtain information through methods such as MRI and X-ray tomography. The image obtained from a single scan needs to be filtered, analyzed, corrected, fitted and reconstructed in three dimensions to obtain the final result. However, complex soil composition and water restrictions can interfere with the results, as can the depth of penetration of the rays. Therefore, most of the traditional methods for obtaining root phenotype information are difficult to achieve non-destructive, dynamic, accurate and quantitative description of plant root configuration, which cannot meet the actual needs of current in-situ root research.

### 2.2. Plant root imaging

In situ root detection is the imaging detection of roots under the condition of avoiding root damage. With the continuous development and progress of high and new technologies, currently commonly used root in-situ detection methods include X-ray tomography (XCT) [6], Magnetic Resonance Imaging (MRI) [7] and digital device imaging [8].

XCT of roots scans the in-situ root soil with X-rays to obtain attenuation coefficients of cross-sectional faults of different objects, and then realizes three-dimensional visualization of plant root configuration through image fault reconstruction algorithm [9][10][11]. In the 1990s, Wantanabe et al. [12] first applied XCT technology to the analysis and study of plant roots, but due to the limitations of technical conditions, the complete form of plant roots could not be clearly observed. With the advancement of technology, Han et al. [13] discussed the common diseases of potato in soil on the basis of XCT imaging technology, and proved the potential of XCT observation method in plant pathology research. Subsequently, Zhou Xuecheng et al. [14] conducted qualitative tomography scanning of root images by X-ray, and used gray histogram analysis to find the overall characteristics of gray distribution of in situ CT images of plant roots, so as to quickly and accurately detect root characteristics. In recent years, Zhao Xu et al. [15] constructed a three-dimensional lossless geometric model of maize in-situ root system by combining XCT in-situ scanning technology and filtered back projection reconstruction method. In addition, Chen Jun [16] used CT imaging technology to obtain CT images of corn roots, and used image processing technology to conduct non-destructive testing of samples. XCT technology has played a great role in promoting the research of in situ root imaging of plants. However, XCT technology only relies on the difference of a single attenuation coefficient between substances to determine the imaging features. When confronted with complex soil environment and root distribution, the contrast will deteriorate and root noise will appear in the imaging results, which brings difficulties to root image segmentation research and leads to errors in the subsequent statistical data of plant root phenotype [17].

Magnetic resonance imaging uses radio frequency electromagnetic waves to obtain image information, codes signals sent out by detecting different positions of magnetic field cores, and presents the internal structure and organizational morphology of scanned objects on the image, thus using computer image reconstruction to generate images [18]. This observation technology has been applied in many fields of plant root research. For example, super-resolution images of plant roots were obtained by three-dimensional reconstruction of plant roots [19], dynamic distribution of water and sugar in wheat filling period [20], and underground pathological symptoms of sugar beet [21]. Although the technology will not cause noise due to the similar density of soil and roots, the detection of trace elements such as iron will interfere with the NMR signal, resulting in greater noise in the root image, making it difficult to image.

In recent years, digital technology has become more and more powerful, and the research of plant roots also tends to use digital equipment imaging method. Digital device imaging refers to non-invasive image acquisition of roots through the use of digital devices such as smart cameras, scanners and smartphones. Progress has been made in root segmentation of many plants. Firstly, high-resolution root growth imaging device based on digital equipment was used to obtain in situ root image of cotton [17], and the image of plant in situ root with 1920*1080 pixels was collected by digital equipment [22], or the morphological changes of in situ root of potted castor bean were dynamically observed by scanner [23]. At the same time, scanning devices such as handheld scanners and flatbed scanners were used to detect walnut roots, so as to extract the organizational characteristics of the huge tree roots [24]. Digital imaging of plant roots is a non-invasive root analysis method based on computer vision technology. Compared with traditional manual operation or root dyeing methods, it has many advantages. First, the method can image the whole root system with high resolution and large area without manual reconstruction or cutting, which improves the efficiency of sample processing. Secondly, because there is no need to use special reagents such as fluorescent labeling or pigment dyeing, the effects of these reagents on plant growth and morphology can be avoided. Finally, especially with the rapid development of artificial intelligence, combined with digital image processing [25] and deep learning [26] algorithms, this method can more accurately and quickly analyze and measure the structure and physiological indicators of each part of the root system, which is of great significance for accurately obtaining the complete configuration of the in-situ root system, exploring its development law and defining its functional mechanism.

These plant root imaging methods can obtain high-resolution plant root images by adjusting and combining different imaging parameters, but the data acquisition process is time-consuming and has a large amount of data, and corresponding software tools are required to segment and analyze the data to obtain relevant results.

## 2.3. Plant root segmentation

Plant root segmentation refers to the process of separating plant roots from other backgrounds through image processing technology. At present, in the study of plant root phenotype, although it is possible to obtain high-resolution root images from complex soil environments by using in situ root nondestructive observation technology, the automatic segmentation of root morphology is usually faced with great challenges due to the opacity of soil particles.

Traditional root segmentation methods mainly include manual segmentation, morphological image processing and machine learning based image segmentation. Among them, manual segmentation can be further divided into manual characterization and semi-automatic interactive segmentation. In the manual mapping method, researchers need to manually identify each root system in a complex soil background and describe it. Due to the low efficiency of this method, the need for huge workload, and the problem of visual fatigue, the segmentation results are easy to be affected by high errors, and are not suitable for practical engineering applications. The semi-automatic interactive segmentation method requires the combination of human-computer interaction, and the researchers use auxiliary software to label and segment it. For example, MATALABR2016a image processing software was used to segment plant root images [27], WinRHIZO Tron MF was used for image analysis [28], and GT-Roots was used for root segmentation in the specified segmentation region selection method [29].

The morphology-based image processing method is to continuously filter the image to distinguish the root system from the background. It can be divided into the following types: Firstly, morphological operation [30], which is divided into expansion, corrosion, open operation, close operation and other specific methods, can improve image quality, remove noise, and enhance object contours to a certain extent; The second method is Region Growing [31], which selects a point or a region as a seed and grows along the adjacent pixels until some stopping criteria are reached. The third method is Thresholding [32], which can divide the image into several parts according to the threshold value so as to separate the background from the foreground. Common threshold selection strategies include Otsu method [33] and adaptive threshold method [34]. There is also a method based on wavelet transform [35], which can realize multi-scale analysis and local processing, and can deal with noise better.

Root image segmentation methods based on traditional machine learning are divided into the following common methods. The first is based on support vector machines, (SVM) [36] is a binary classification machine learning method that classifies data by finding hyperplanes with the greatest spacing. It is widely used in root image segmentation, and can train a good classification model to distinguish roots and backgrounds in images. The second is the method based on decision tree [37], which is a classification algorithm that can classify data sets into different categories according to feature attributes. By selecting suitable features and constructing decision tree model, it can be used to segment root image. There are also methods based on clustering [38] analysis, which is a method of dividing data sets into multiple categories. By clustering the pixels in the root image, objects of different colors and textures can be separated, and then the clustering results are used for root segmentation.

In addition, more and more researchers are focusing on the development of automated tools for the processing of high-throughput root phenotypes, such as root scanners. Although these systems can obtain relatively high precision root phenotypic parameter values, they still rely on subjective factors to locate the initial root position, and the imaging equipment used is expensive, which belongs to the semi-automatic root image segmentation method. With the rapid development of deep learning technology, the cross-fusion technology based on deep learning and computer vision technology has opened up a new field, providing a more accurate, fast, cheap and automated solution for plant root image segmentation.

# 3. Research on Plant Roots Based on Deep Learning

With the continuous development of computer vision and deep learning technology, deep learning-based plant root segmentation has become a research hotspot. Traditional root analysis methods require a lot of manual processing work and are prone to subjective errors, while deep learning technology can effectively realize automated analysis, and use multi-layer neural networks to learn and extract complex image information accurately.

## 3.1. Deep learning plant root segmentation method

At present, a large number of studies have explored the application of deep learning in plant root image segmentation. Two kinds of methods are mainly used in deep learning-based plant root segmentation: object detection and semantic segmentation. The object detection method can find the region of interest first, and then further segment and extract the region, so it has high speed and robustness. However, the semantic segmentation method pays more attention to details and precision, and can accurately segment each part of plant root system. Root segmentation methods include Convolutional Neural Network (CNN) [39], Full Convolutional Neural Network (CNN), FCNN) [40] and Deep Convolutional Neural Network (DCNN) [41]. Among them, convolutional neural network is the most widely used architecture in deep learning, which has a good performance in the root image segmentation task. By constructing appropriate network structure and training sample data set, high precision root segmentation results can be obtained. Therefore, in recent years, many scholars have conducted research on it. For example, Tao et al. [42] adopted the convolutional neural network architecture and segroot network to directly learn morphological features with different abstraction levels from root images for pixel-level classification, so as to achieve high-throughput segmentation of root images. In addition, the idea of pixelsuffle algorithm is used to enhance the fusion features before the decoder output, so as to achieve high-throughput in-situ root image segmentation [28]. Tao and Shen et al. achieved segmentation on two-dimensional root images, which can be used to analyze the growth of plants on the plane, but the internal morphological structure of the root system is not well analyzed and studied. Subsequently, Zhao et al. [43] utilized a convolutional neural network composed of an encoder and a decoder, and the encoder was composed of three convolutional modules to achieve three-dimensional super-resolution image segmentation of plant root MRI. Thus, the morphological characteristics inside the root system can be further analyzed, and the changes of nutrients absorbed by plants can be obtained by using the root structure. Some scholars also designed the root segmentation network in order to realize the research of a certain growth parameter of plant roots. Just as Seidenthal et al. [44] obtained a high-quality two-dimensional root segmentation model by using the iterative neural network architecture to accurately segment the thin and highly branched roots. Based on DeepLabv3+ semantic segmentation model, Kang et al. [45] introduced subpixel convolution and added attention mechanism structure. More weight is given to fine root pixels and root hairs, and a more accurate semantic segmentation model of cotton root in situ image is obtained. On this basis, the network model is improved to obtain a more accurate and effective root extraction network. Alle et al. [46] used the combination of deep convolutional neural network and weakly supervised learning paradigm to detect finer root structures, thereby improving the accuracy of root extraction. Shen Chen [17] uses SP-DeepLavb3+ model based on sub-pixel convolution [47] to segment cotton root images in situ and improve the segmentation accuracy of small branch contours. Huang et al. [48] added a global attention mechanism (GAM) [49] to the OCRNet network to increase the focus on root targets and improve the accuracy of automatic root segmentation. On the premise of certain accuracy, the root morphological structure was studied. Wulan et al. [50] based on the improved DeepLabv3+[51] network to segment potato root image and calculate potato root length and other features, they can have a more comprehensive understanding of plant growth under different environmental conditions, which is helpful to explore plant physiological ecology and optimize plant planting management. Robail et al. [52] used a multi-task convolutional neural network to extract image features from the encoder, and then used the seeds, primary and secondary root tips located by the network to drive the search algorithm to find the best path and extract root structure to achieve automated root structure navigation, thereby quantification and recording of various plant growth parameters (such as taproot length or total area, etc.). Allowing for more detailed structural analysis. Although the current research has achieved good results in the accurate acquisition of roots, the requirements for equipment are becoming higher and higher, resulting in increasing costs. Yu et al. [53] used DeepLabV3+ semantic segmentation model to design a time-saving fast prediction strategy to achieve low-cost and portable root image acquisition and segmentation. Although the time and cost were reduced, the extraction accuracy would also be reduced. However, in general, as one of the current research hotspots in this field, many scholars have carried out a lot of work on plant root segmentation based on deep learning in this direction, and gradually achieved good results. Among them, the most common deep learning model is convolutional neural network, such as U-Net[54], FCN, DeepLab[55], etc. For different plant root image characteristics, the researchers also combined the deep learning model with other methods, including preprocessing, image enhancement, feature fusion, etc., to improve the performance of the algorithm. At the same time, more and more scholars have begun to apply this technology in actual agricultural production to solve practical problems and promote sustainable development of agriculture and ecology.

### 3.2. Application Areas

With the development and progress of science and technology, deep learning-based plant root segmentation technology can be widely used in plant science, ecology and agronomy. In the field of plant science, deep learning-based techniques can be used to study root development and structure. By segmentation of root images, the morphological parameters of each root system, such as length, diameter and volume, can be extracted, so as to study the adaptability and growth of plant roots in different environments. In the field of ecology, combined deep learning techniques can be used to study the structure and function of plant communities. By segmentation of a large number of plant root images, various types of root information can be obtained, such as root density, depth, distribution area, etc., so as to better grasp the root composition and functional characteristics of plant communities. In agronomy, deep learning techniques can be used to study the impact of plant roots on agricultural production. Through the segmentation of plant root images in farmland, the information of root morphology and structure is used to predict climate change, and the growth of agricultural products under different climate and environment changes is understood, so as to provide manufacturing tools for digital agriculture.

## 4. Conclusion

In summary, compared with traditional methods, deep learning models can automatically segment plant roots and produce more accurate root segmentation results. But its shortcomings are also obvious. Since there are few image data of plant roots, it is difficult to obtain large-scale labeled data sets, which makes it difficult to train deep learning models. In addition, due to the complex and varied soil background, inconsistent lighting conditions and many small roots, the model has limited generalization performance in the new scenario. Therefore, deep learning-based methods often lack explainability, and there are certain limitations to the morphological analysis and physiological characteristics of roots.

## 5. Current Challenges and Future Trends

With the acceleration of the new round of scientific and technological revolution and industrial change, many key subject issues and core technologies have appeared the precursor of revolutionary change. In this context, new subject areas and growth points continue to emerge, and the deep integration of interdisciplinary has become an irresistible trend. Plant root segmentation based on deep learning plays an important role in promoting interdisciplinary integration. However, there are still some challenges and problems in this field. Firstly, the quality of plant root data directly affects the performance of the segmentation model. Since roots grow in soil, obtaining clear, high-quality images of roots is a challenging task. In the image, there may be noise interference such as soil particles and weed cover, and the root structure is complex and diverse, and its shape will change with the change of environment and growth conditions. These factors may lead to the instability of data quality, which in turn affects the accuracy and generalization ability of the model. Secondly, the fitting ability of root segmentation model is limited by traditional segmentation methods. Previous studies have used rule-based, threshold-based, or feature-based methods to extract root profiles, but these methods tend to be less effective for complex root structures. Deep learning models perform significantly better than traditional methods in root segmentation, but there are still difficulties in some cases. For example, in cases where roots are crossed or obscured, the model may not accurately segment the roots or have difficulty distinguishing between roots and background.

In order to overcome these challenges, we can concentrate on collecting more high-quality root image data, establish a larger dataset of plant root image, and optimize and improve the segmentation model for different types of root structure to improve the accuracy and robustness of root segmentation. Secondly, multi-source data can be used for joint analysis. At present, plant root segmentation based on deep learning can use different types of data such as RGB image, infrared image and X-ray image to obtain more comprehensive root characteristic information. Further, future studies can explore how to organically combine data from these different sources, and transfer the model training from large-scale image data sets to plant root images by means of transfer learning, so as to make the model more generalization ability, so as to achieve more accurate and comprehensive plant root segmentation. Plant root segmentation can also be combined with animal or human medical image segmentation to conduct cross-species comparative studies to discover common algorithms and techniques. In addition, the introduction of advanced technical means and framework. At present, deep learning is the mainstream method to deal with the problem of plant root segmentation, and other advanced technical means and frameworks can be considered in the future. For example, some new image processing algorithms, 3D vision reconstruction from two-dimensional image training, natural language processing technology and biological computing methods also have a wide range of application prospects in the analysis and identification of plant roots. All in all, for plant root segmentation based on deep learning algorithm, further relevant research needs to be carried out in the future to inject new ideas to achieve more accurate, faster and higher level plant root segmentation.

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