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Research on Maize Leaf Counting Based on Computer Vision
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Summary

Food security is the top priority of all countries in the world, and as one of the world's three major food and agricultural products, the breeding and cultivation of maize is an important key link in ensuring food security. In recent years, with the advancement and development of science and technology, plant phenotype research has become a hot spot in the field of plant science.

To get rid of the time-consuming and labor-intensive characteristics of traditional phenotyping research, high-throughput plant phenotyping analysis technology has emerged. The analysis technology can quickly analyze plant pictures in a short time and obtain a large amount of phenotypic data with research value. It can play an important role in species and growth monitoring and has great application prospects.

The rapid development of computing hardware equipment, image processing technology, and deep learning technology has made the combination of computer vision and plant phenotyping technology. In this paper, high-throughput phenotyping technology based on computer vision was studied, and maize plants were designed in a laboratory environment. Data set, and through image processing and computer vision methods, the phenotype extraction of maize plant leaf number counting was realized. The computer vision-based research on maize leaf counting is carried out from three aspects: problem modeling, algorithm research, and experiment.

In this paper, the problem of counting the number of leaves of corn plants is firstly modeled, and the problem of counting corn leaves is defined as the target detection problem. Target detection algorithm for corn leaf tips, due to the large size of corn leaf photos in the laboratory environment, and corn leaf tips are very small, this paper uses the feature pyramid method to extract the photo features; considering the amount of data is large, fast training and inference work, algorithm reference

RetinaNet adopts a one-stage method, using a fully convolutional network as a regression and classification task head, plus Focal Loss

The framework of Loss realizes detection; because the one-stage target detector generally has an imbalance of positive and negative samples, it is designed a Focal Loss. For problems with obvious gaps, the algorithm uses an adaptive positive and negative sample division method to divide the positive and negative samples. Aiming at the problem that leaf tips may overlap, the algorithm uses a variety of feature fusion methods to fully combine context information to achieve accurate detection. Guidance of orientation for blade tip position prediction. Experiments have proved that this topic is aimed at the problems existing in the target detection. The proposed method has a very good effect on improving the evaluation index AP.

When labeling the dataset, target boxes of different sizes are used for labeling. The size of the target frame is mainly controlled at about 30x30 right. The area distribution of the target frame in the dataset after labeling is shown in Figure 2-1, where the abscissa represents the area of the bounding box. The statistics of the data set. The two pictures in the first row are marked when the leaves are occluded or overlapped. For this case, if there is no obvious leaf tip texture, it will not be marked, but if the shape of the leaf tip can be distinguished, it will be marked. The two pictures in the second row are marked for the overlapping of blades, for which it is impossible to distinguish

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Chapter 1 Introduction

1.1 The background of the subject and the purpose and significance of the research

Facing the challenges posed by resource scarcity, climate change and global population growth, crops will need to be increased sustainably in the co yield and quality. Genetic improvement through breeding is the best way to increase crop productivity. With the rapid development of functional genomics, crop genomes have been sequenced and dozens of genes affecting key agronomic traits have been identified. However, due to the absence of crop phenotyping data, current genome sequence information has not been fully exploited to understand polygenic complex features. Automated and accurate technologies and platforms capture phenotypic data that can be correlated with genomic information for manipulation at the plant level. Plant improvement is as important as genotyping. Therefore, high-throughput phenotyping has become a major bottleneck restricting crop breeding. Omics has been defined as the high-throughput, accurate capture and analysis of multidimensional phenotypes of crop growth stages. Crop phenotypic expression involves complex interactions between various factors, including climate, soil factors, abiotic/biotic factors and crop management practices. With new sensors, imaging techniques and analytical methods, crop phenotyping is becoming increasingly important in crop breeding and genetic improvement.

With the rapid development of methods, many basic platforms for phenotyping have been developed [1].

Computer vision, which extracts useful information from plant images and videos, is rapidly becoming an essential technique in plant phenology research. The phenology approach to plant science aims to determine the genetic basis of plant traits. The relationship between genetic diversity and phenotypic traits, these quantitative parameters reflect the traits and physiological state of plants through their growth and development. Recent advances in technology allow us to rapidly obtain population-scale maps of genomic variation. Using high-throughput analysis platforms for crop phenotyping, the combination of plant phenotype analysis is to use genetic map to map genotype to phenotype, and to explore complex quantitative traits in plant breeding. Genetic factors such as growth, environmental stress tolerance, disease resistance and yield provide opportunities. Genetic methods, including quantitative trait locus (QTL) analysis and genome-wide association studies (GWASs).

Furthermore, models of the relationships between genotype/phenotype maps of individuals in breeding populations can be used to calculate breeding values. Selecting the best parents for new crosses with genomic selection in animal breeding. Therefore, in the context of demographics and climate change, high-throughput phenotyping assisted by computer vision with the help of various sensors and image analysis algorithms will play a crucial role in crop breeding.

The so-called food is the most important thing for the people, and food security is the top priority of our country's national security. Therefore, among the major crops, corn, one of the crops, is of great research value. According to the announcement of the National Bureau of Statistics on grain production data in 2021, the amount accounts for 38.9% of my country's total grain output. At the same time, in addition to being used as food (food or feed), corn also has high economic value, corn is an important raw material for fuel, medicine, chemical industry and other industries, and can be processed at the same time,

Thousands of products such as alcohol are the products of corn reprocessing. In addition, corn is a typical gramineous plant, which belongs to the grass family. It has a wide range (wheat, rice, sorghum and other food crops are basically grasses), and the method of studying and observing the phenotype of maize can only be extended to the research on other Poaceae plants. Phenotyping maize can be used for precision breeding on the one hand and monitoring the growth of corn plants can be monitored. By comparing phenotypic data with known data, genotype can be compared with phenotypic Association analysis, so as to screen functional genes that are highly correlated with good traits, and then breed new varieties that meet specific needs. Obtain high-quality and high-yield crop varieties; through dynamic monitoring of crop phenotype changes, real-time and personalized planting management strategies, if there are pests and diseases, they can be predicted and discovered in time, making agricultural operations more precise and efficient.

1.2 Research status and analysis in this direction at home and abroad

1.2.1 Machine Learning and Deep Learning

Machine learning is a method of data analysis that automatically recognizes patterns within. Data can be tables, images, text, etc. according to. The process of machine learning involves building a model on an initial data set (called the training data set), and then using a separate (called the test set) to verify the performance of the model on data not used for training. Deep learning has a strong abstract expression ability. Deep neural networks belong to a class of general fitting methods, which means that no matter what function we want to learn, we can use deep learning fitting [2]. Deep learning models automatically perform feature extraction on input data without using any manual feature input.

Object detection, as one of the research fields of computer vision, can analyze the concept and position information of the object contained in the image. Likewise, the goal of object detection is to locate objects in a given image and determine which category each object belongs to. Traditional Object Detection The method first extracts feature descriptors, such as HOG and

SIFT. Then, based on the extracted feature descriptors, they trained tools such as Support Vector Machine (SVM) and

A classifier like AdaBoost to distinguish the target object from all other classes. Recently, deep learning-based Learned object detection methods. These methods, Single-Shot Detect in (SSD) [3],

You Only Look Once (YOLO) [4], and Faster-R-CNN [5] use the neural network to automatically extract the necessary image features

features, which greatly improve their accuracy compared to traditional object detection methods. However, these methods are also data-intensive and And it has the characteristics of large amount of calculation for training.

1.2.2 Plant phenotype research

In agriculture, there is no shortage of use cases when it comes to applying machine learning, image processing, and deep learning to object detection. The method of image processing is commonly known as image segmentation and has been applied in mango, apple, tomato and grape for performance detection and counting [6]. Despite the success of these methods, they usually require a large number of high-resolution images and require the image Small, cannot handle large differences in crop size, and only one crop can be identified per image.

Ok et al. used machine learning methods [7] to prove that random forest (RF) algorithm and maximum likelihood classification are indeed suitable for Examples include successfully sorting wheat, rice, corn, sugar beets, tomatoes and peppers in the field. In addition, Zawbaa et al. [8] designed a An experiment, the model automatically classifies images of apples, strawberries and oranges using RF and the k-nearest neighbor model [9]. Their Research further demonstrates the success of machine learning capabilities in agriculture. In addition, Guo et al. [10] applied quadratic SVM from UA Accurate detection and counting of sorghum heads in (drone) imagery. Although these examples show the usefulness of modern machine learning in especially in agriculture), but they are not without flaws, namely the limitations of traditional machine learning methods, which Machine learning methods do not generalize well to have different image resolutions, different image scaling (distance from camera to object) and objects with different object orientations (object angles).

Due to the ability of deep learning, the ability to recognize multiple objects in an image, and the lack of object-oriented requirements, recent studies on There is a large literature on the application of learning in the field of agriculture. In 2019, Ghosal et al. used their RetinaNet-based method method to detect and count sorghum heads from UAV images [11]. This deep learning approach significantly outperforms previous sorghum Detection and counting work. With the advent of transfer learning, it is possible to pre-train models on such datasets and In the case of long training time, the information of the model is transferred to detect similar objects [12].

1.2.3 Maize phenotype research

In recent years, there has also been a lot of research on image processing technology for maize phenotypes. Table of the corn plant as well as the corn Type features include seeds, leaves, ears and so on.

In phenotyping studies on maize seeds, single maize seed images are mainly used as input. Paulsen et al. [13] used the traditional graph The length, width and projected area of corn kernels are determined in the same way as processing. Ni et al.

[15] used deep learning methods to classify corn seeds. Khaki et al. [14] used convolutional neural network-based The method of sliding window realizes the counting study of corn kernels on the ear of corn, and the proposed method can successfully Corn kernels were detected and were also able to be detected on a batch of ears of corn positioned at different angles.

The positioning of corn ears is the key to solve the problem of automatic corn threshing. Kurtulmus et al. [19] used SVM to analyze the field image for corn ear positioning. Wang et al. [20] obtained different viewing angles by rotating the ear of corn at an appropriate angle in a greenhouse environment. For the image under the corner, use binocular stereo vision to calculate the point cloud of the corn ear surface, and perform 3D reconstruction of the Labeling at the pixel level locates ears of corn in the field and regresses the number of ears of corn at the same time.

There is a wide range of research on the properties of maize leaves, and there are different research emphases for different problems. For Plant Center In this paper, Ji et al. [16] used top-down RGB images to locate the plant center by detecting, tracking and expanding the main vein line of the leaf. A Rice leaf counting problem, Miao et al. [17] used the method of deep learning to solve the problem of leaf counting, and used simulated images to Auxiliary training of leaf counting method makes counting more accurate. In addition, the leaves are the key to distinguish whether the corn is dry or The important organs of the lesion, Ahmad et al. [18] used the RGB features and HIS features of corn leaves to describe the moisture content of corn and nitrogen, as well as color changes caused by normal physiological growth of plants, and based on the HIS characteristic

Extract classification features for recognition.

1.3 Main research content and main contributions of this paper

The main research content of this paper is the counting of corn leaf tips based on the target detection algorithm. Effect, the input of this algorithm is the RGB corn image in the laboratory environment, and the output is the target frame of the leaf tip. as the picture

The main contributions of this paper are as follows:

- 1) A certain scale of data was collected and manually screened to form a data set in a laboratory environment, and a practical and convenient It is convenient to realize the labeling scheme of the target detection algorithm, divide the data set, and form the corn leaf tip detection data for the te set.
- 2) Model the corn leaf detection problem as an object detection problem for the corn leaf tip. Also annotate high-resolution images The problem that the tip area is too small proposes a small target detection framework, which effectively improves the The effect of leaf tip detection.

1.4 Organizational structure of this article

The first chapter is the introduction, which firstly introduces the research background of this topic, and the research meaning in the two fields of agric righteous. Then it introduces the research status of related research contents, including computer vision and plant phenomics related to this topic. The development trend of maize, the research status of maize phenotype analysis, and the status of analysis methods for the trait of maize leaf tip. F The main contents and contributions of the topic are described.

The second chapter mainly introduces the object detection framework. Firstly, the data collection method is introduced, and then around the corn lee The problem formulates the labeling strategy, and shows the statistical results of the labeled data set. Afterwards the field of object detection is intro Related work, the field of target detection is mainly divided into anchor-based target detectors and anchor-free detectors. Among them, anchor-basec The detectors are divided into one-stage and two-stage detectors, and the detectors without anchor points are divided into two types: detectors base Then, this paper introduces the network structure used, including the skeleton network and the task head network, and then elaborates on the classifi Design of loss function and regression loss function. Finally, the evaluation metrics in the object detection task are briefly introduced.

The third chapter designs and selects the network structure and optimization method for the blade tip detection method. In order to solve the proble Use the adaptive positive and negative sample division method to divide the positive and negative samples on the anchor points on each layer of the problem, the algorithm adopts the method of pyramid pooling combined with context information to enrich the high-level semantic representation; When the detection frame deviates from the target frame, the centrality branch is introduced. At the end of this chapter, the experimental design is int analysis.

The conclusion part is a summary of the full text, and at the same time, the future research direction of this topic is expounded.

Chapter 2 Object Detection Framework

This chapter mainly describes the target detection framework. Firstly, the related work in the field of object detection is introduced.

The current method of target detection is mainly divided into two types: with anchor point and without anchor point. Among them, the anchor point m Anchor-free methods are further divided into center-based and key-point-based methods. To implement the object detection framework, it is necessa detection data set. Afterwards, the one-stage target detection framework used in this topic is introduced. The one-stage detector is functionally provi

There are two parts: extraction and leaf tip detection. The network structure includes the skeleton network used to extract features and the classifica Return to the network. at the end

The classification loss function and regression loss function used are introduced separately.

2.1 Target detection related work

2.1.1 Anchor point detection method

Two-Stage Approach: The emergence of FasterRCNN [5] established the dominance of the two-stage anchor-based approach. FasterR-CNN's The network structure includes a region of interest extraction network and a prediction network R-

CNN, first use the region of interest to filter out a large number of anchor points, and divide the positive and negative samples, and then use the task I kind. Since then, many works have been improved based on this framework, including modifying the network structure, application context and attent control, feature fusion and enhancement, etc. Recently, two-stage anchor-based methods still have leading results on common object detection stan

fruit.

Single-stage method: With the emergence of SSD[3], the one-stage anchor-based method has also attracted the attention of the industry, because compared with a complex and cumbersome network framework, the one-stage method has a lightweight and simple network framework, so there is a significant difference. Advantage. SSD introduces multi-scale network layers in a convolutional network, and lays anchor points on multi-scale network layers, directly for classification tasks and regression tasks. Since then, many SSD-based works have emerged, such as multi-scale feature context information fusion. Combined, the design uses a new loss function, the refinement and matching of anchor points, etc. Now the one-stage anchor-based method can achieve an inference speed that achieves a performance very close to that of the one-stage and two-stage anchor-based methods.

2.1.2 Anchor-free detection method

Keypoint-based method: The keypoints used in this method are obtained through predefined or pre-learned methods, and then generate predictions to detect objects. Corner Net [29] uses two key points on the upper left and lower right to detect

To measure the bounding box of an object, Center Net [30] expands the key point pairs of Corner Net into three-element points.

RepPoints[31] use a series of sample points to represent the object, learn how to use the sample points to surround the spatial content of the object; Semantically important local regions.

Center-based method: This anchor-free method regards the center point of the object as the foreground to define the positive sample, and then predicts the distance between the four boundaries of the target box. YOLO[4] divides the picture into $S \times S$ grids, and the grid containing the center point is responsible for the object. DenseBox [32] defines the filled circular area in the center of the object as a positive sample. FCOS[33] puts all objects inside the bounding box. The position of is regarded as a positive sample, and the four

Distance is used together with a new center point scoring method to detect objects.

2. 2 Maize leaf tip phenotype data set

The target detection method based on deep learning relies on the dataset labeled with the detection target, considering that there is currently no public data set of leaf tip, so this topic firstly makes the maize leaf tip phenotype data set. In this chapter, the data of the dataset are respectively described. The collection and leaf tip labeling work will be described.

2. 2. 1 Data collection

Using the maize image data under laboratory conditions provided by the official website of Huazhong Agricultural University [26], the RGB image dataset of Maize_ Jianbi ngYan&WanNengYang dataset. This dataset is a high-throughput plant phenotyping platform under laboratory conditions. The images of corn plants collected by the platform system. The data set labels the plants, and for a plant, the data set collects pictures of plants in each of the 16 stages of growth, including pictures of both small and large plants. Crawl the dataset to display all pictures, the uniform size of the picture is 1028x1226, and the larger the picture size, the higher the resolution. The total data obtained through crawling is 31232 (1952*16) pictures. Among all the 1952 plant data, some plants need to be selected for labeling. plant selection standards are as follows:

- 1) The pictures of the 16 growth cycles of the plant all have a complete plant body, that is, there will be no incompleteness of the corn plant as a whole
- 2) Choose plants with fewer weeds in the pots to avoid introducing unnecessary noise in the dataset.

Finally, a total of 400 images of 25 plants were selected for labeling, 15 of which were used as training sets and 10 were used as test sets. in test The result evaluation of the set is used as the model training result. Statistical data of data sets and labeling results

Specifically, as shown in Table 2-1, it can be seen from the figure that there are about 7 target frame labels in each picture on average

