Development and application of machine vision technology in agricultural production

Abstract: As a country with a large population and agriculture, China plays an important role in the international agricultural arena, and grain output affects the development of people's livelihoods all the time. The emergence of smart agriculture has improved the cognitive ability of the nature of agricultural animal and plant life, as well as the regulation and control of complex agricultural systems and the ability to deal with agricultural emergencies. At present, agriculture mainly focuses on how to rationally use agricultural resources, reduce agricultural production costs, improve agricultural ecological conditions and other problems. Compared with the traditional agricultural management inefficiency, large input, machine vision technology with its efficient, non-destructive characteristics has gradually integrated into agricultural production management, and in the quality classification of agricultural products, automatic picking of agricultural products, plant growth process monitoring and crop pest detection and other aspects of successful application, for food security escort. Based on the research of machine vision technology, this topic deeply studies the principle composition, software and hardware composition and related technologies of machine vision technology, so as to explore the development and application of machine vision technology in agricultural production.

Keywords: smart agriculture; machine vision; disease detection; food security

I. Introduction of machine vision technology

Machine vision technology is an interdisciplinary subject involving artificial intelligence, image processing and other fields. Computers are mainly used to simulate human visual functions, extract information from images of objective things and process them, and finally use them in actual detection, measurement and control.

II. Literature review of recent machine vision technology research

Machine vision technology is used as a carrier, using optical devices and non-contact sensors to obtain the feature information required for recognition from the imaging of objective objects, and then collect, process, analyze and judge, and finally apply to measurement, detection and control.

With the continuous exploration and innovation of research scholars on machine vision technology and deep learning methods, this technology is gradually applicable to the agricultural field. Mainly used in health monitoring, disease identification, automatic picking and quality inspection. Among them, Vassallo-Barco [1] and Li Qi [2] used machine vision technology to detect the health status of coffee leaves and kiwi fruit by using machine vision cameras combined with image processing software. Machine vision technology is also applicable to plant disease diagnosis. Wang [3] and Zhang [4] used deep learning algorithms to detect cucumber disease images collected by mobile phones and binocular cameras, extracted key information about disease characteristics, and then used analysis software to analyze them. Analyzed to obtain the severity of the disease. In recent years, the application of machine vision technology in automatic picking of agricultural products has become a hot spot. Chen Jun [5] preprocessed the collected strawberry images, and finally developed an automatic strawberry-picking system based on the actual growth environment of strawberries and mechanical devices. Quality inspection is the last key step in the flow of agricultural products to the market. Traditional inspection methods are inefficient and destructive, but machine vision technology can effectively avoid these problems. For example, Peng Wan [6] used machine vision to extract the color and shape features of tomatoes to detect tomato maturity; Zhang Chen[7] combined image processing methods with machine vision methods to design a set with machine vision. The conveyor belt of the visual camera realizes the detection of apple surface defects, and then classifies the quality grades of apples.

III. Working principle of machine vision technology

1. Introduction to the principle of machine vision technology

The machine vision system converts the optical signal into an image signal through the image acquisition hardware (camera, lens, light source, etc.), and transmits it to the image processing software. The image processing software extracts the features of the target and makes corresponding judgments based on information such as pixel brightness and color distribution and controls the field equipment according to the result output to realize the detection function. Vision processing system includes both hardware and software. According to different hardware, machine vision systems are divided into smart cameras and PC-based vision systems. The core part of a PC-based machine vision system consists of four parts: light source, lens, camera, and vision processing system. The main function of the lens is to image the measured target to the photosensitive chip of the camera. The main function of the camera is to collect images, convert optical signals into electrical signals, and output images to the computer. The core technology of the software is the image processing and analysis algorithm, which includes image enhancement, image segmentation, feature extraction, image recognition and analysis, etc. Through image processing and analysis, the product quality is judged, the size is measured, and the result signal is transmitted to the corresponding hardware for display or execution.

2. Common hardware equipment

Currently, commonly used machine vision hardware devices include monocular cameras, binocular cameras, hyperspectral cameras, and mobile phones. Monocular cameras can identify information such as geometric features and colors of objects. The technology is mature, and the cost is low, but it is greatly affected by the environment. The binocular camera can detect and perceive three-dimensional space and does not require prior knowledge for the identification and ranging of obstacles. It has low cost and low power consumption but is easily affected by light. Hyperspectral cameras can extract spectral bands of shooting targets and further analyze band characteristics, but their high cost and poor environmental applicability lead to low popularity.

In addition, in the field of machine vision, in addition to common camera equipment, its built-in sensors also have a greater impact on measurement results. Currently, common machine vision sensors include two-dimensional vision sensors, three-dimensional vision sensors, infrared vision sensors, and high-resolution RBG sensors. They are all key components to realize photoelectric conversion in various photoelectric detection systems, and are devices that convert optical signals (infrared, visible and ultraviolet radiation) into electrical signals. In agriculture, it can be used to detect the specific size, shape, color, etc. of crops. The following picture shows several common machine vision equipment and data acquisition process images.

Picture 1 Monocular camera, binocular camera, and hyperspectral camera

Picture 2 Hyperspectral camera data acquisition

3. Software system workflow

The workflow of the machine vision system can be roughly divided into the following parts: 1. Place the target to be collected in the center of the camera screen. 2. Image acquisition: image or video capture by using cameras, mobile phones or other shooting equipment to treat research targets. 3. Image processing: After the image or video acquisition is completed, the dataset is preprocessed, such as noise reduction, image enhancement and other operations, so that the model can better extract valuable information. 4. Feature extraction: When identifying or detecting objects, key features need to be extracted from images or videos, including the shape, size, color, texture and other characteristics of the object. 5. Feature matching: match the extracted feature information with the known features of the labeled object. 6. Target detection: Once the feature matching is successful, the target detection operation can be performed on the object to be measured, and this step will involve a series of algorithms, such as YOLO series and DeepLab series algorithms.

IV. The methodology introduction - take cucumber disease segmentation as an example

1. Data

(1). Collection

Based on machine vision and deep learning methods, cucumber disease segmentation uses mobile phones as image acquisition equipment, which is easier to obtain data, less affected by environmental factors, and simple and convenient shooting. In order to meet the influence of different lighting on the shooting effect in the real application, different time periods were selected for image acquisition, and the collection time was in the morning (8:00-10:00), noon (12:00-14:00), afternoon (12:00-16:00) in February. The types of image data collected in Picture 3 include healthy leaves of cucumbers, anthracnose of cucumbers, and downy mildew of cucumbers, collected in a facility greenhouse.

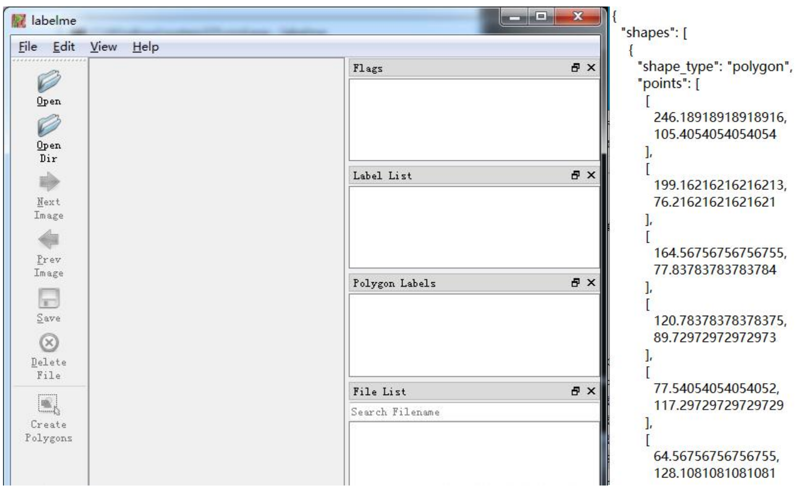
healthy leaves | Leaves with anthracnose | Leaves with downy mildew

Picture 3 Raw cucumber data acquisition image

(2) Processing

(a) Image callouts

In order to make the deep learning model operate normally, under the premise of trying to avoid affecting the accuracy of model segmentation, the collected image data is resized to 512×512 pixels, and the image annotation is carried out using Labelme software to generate the corresponding Mask diagram, and the manually labeled image is used as the standard to measure the segmentation accuracy, Figure 4 is the Labelme software interface and annotation information schematic diagram, Figure 5 is the annotated image.

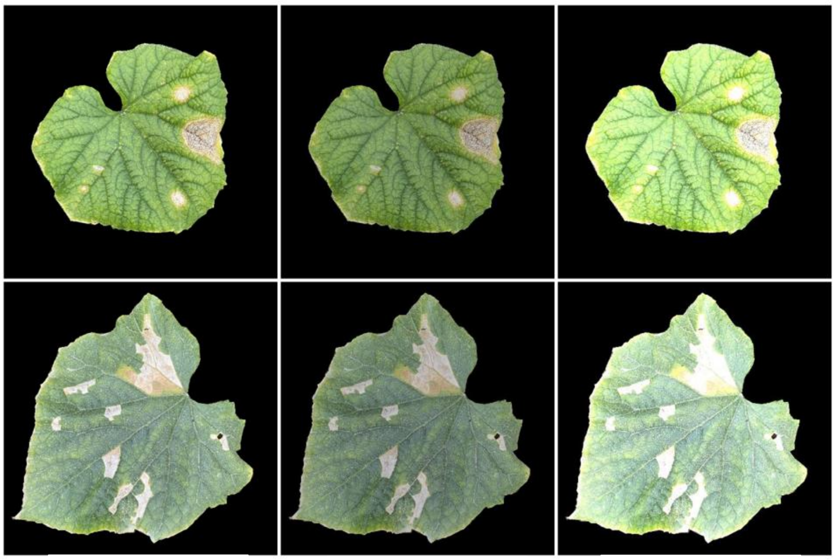


Picture 4 Labelme software interface and annotation information

Picture5 Image annotation

(b) Image enhancement

Deep learning requires sufficient data sets to complete training, and too few datasets often lead to underfitting, which ultimately leads to poor model training and testing. Therefore, in order to improve the segmentation accuracy of the model, the original cucumber downy mildew and anthracnose datasets were image enhanced, that is, the values of 0.5-1.5 multiples were randomly selected to enhance the brightness of the original image. This can not only meet the requirements of the dataset for model training, but also simulate the impact of different light intensities on training. The diversity of training samples is increased, and the robustness and pan-Chinese ability of the model are improved. The dataset image enhancement is shown in Picture 6.



Picture 6 Image enhancement

2. Analysis

3. Based on machine vision and deep learning methods, cucumber disease segmentation uses mobile phones as image acquisition equipment, which is easier to obtain data, less affected by environmental factors, and simple and convenient shooting. And deep learning often requires enough data sets to complete training, the hardware equipment used to train the dataset is a crucial factor affecting the accuracy of the model, so the processor selected for this application is configured as Intel(R) Core(TM) i7-10700K CPU @ 3.80GHz, 128G memory, and the graphics card is NVIDIA GeForce RTX 3080 10G video memory.

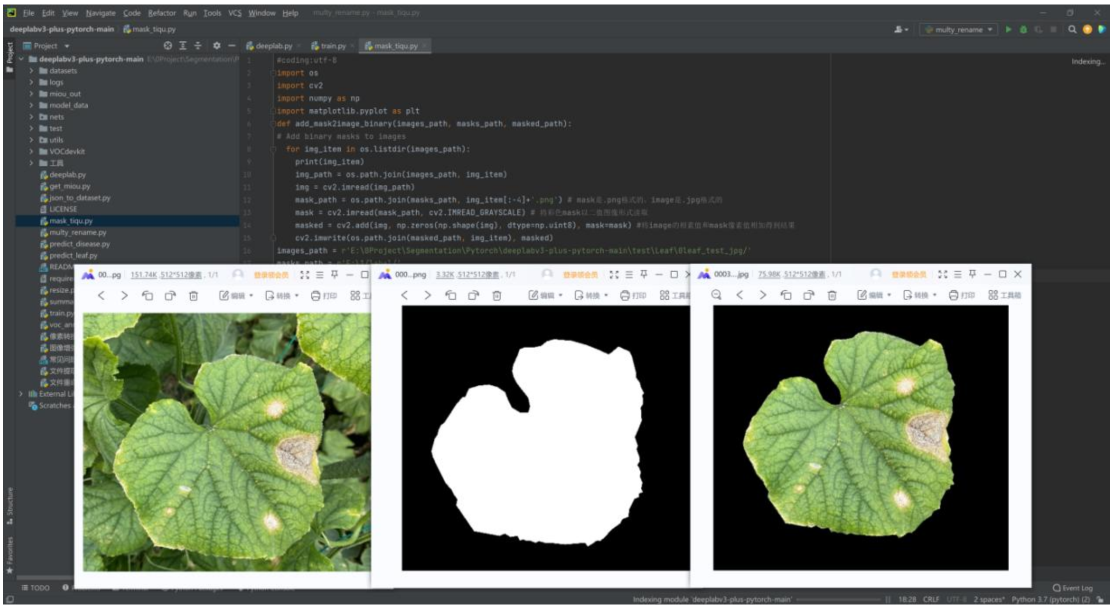
In this application, the segmentation algorithm fused with DeepLabV3+ and U-Net is used to calculate the leaf area and disease spot area separately to achieve the purpose of dividing the disease grade. Because the leaves grow in the natural environment, the background is more complex when shooting, and directly segmenting the disease spots will often divide some similar features in the background, which will have a certain impact on the accuracy of the final disease grade division, so it is first necessary to segment and extract the leaves in the complex background to obtain the leaves in the simple background, and then further segment the disease spot area of the target leaves.

DeepLabV3+ uses Xception[8] as the main feature extraction network, and uses deep separable convolution to convolute the space of each channel separately, which has the advantage of greatly reducing the amount of computation while ensuring that the performance remains unchanged. Moreover, by leading branches in the DCNN module for decoding and up-sampling operations, compared with other semantic segmentation networks, the edge information segmentation effect of the segmentation target is more accurate.

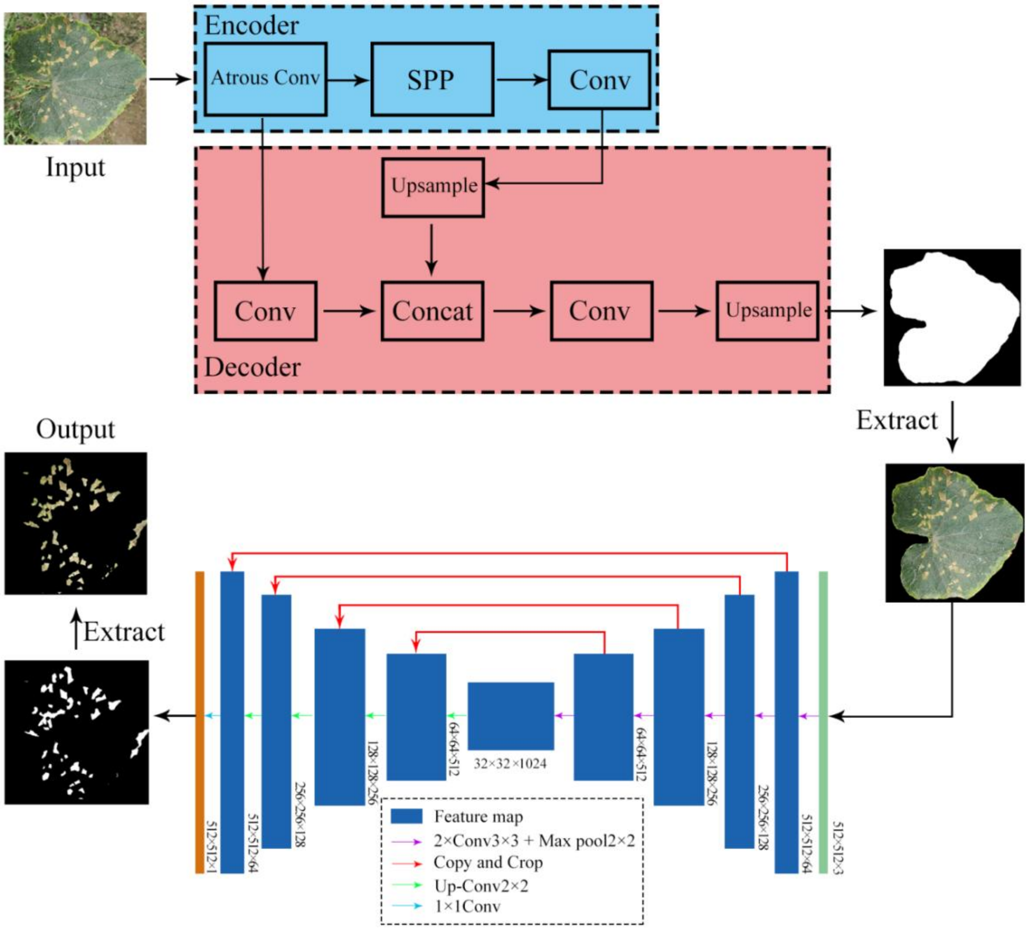
In the first stage, because the cucumber image contains more background interference information, such as soil and other leaves similar to the color of the leaf to be segmented, it is difficult to achieve the expected segmentation effect by extracting color features alone, but the use of DeepLabV3+ can effectively mine the shallow and deep feature information of cucumber leaves in different complex backgrounds, and accurately control the output feature resolution by changing the expansion rate in the

ASPP module, effectively improving the segmentation accuracy. The back layer of the network can capture the edge of the object by gradually recovering the spatial information, and the segmentation of the blade edge is more delicate than that of other semantic segmentation networks.

In the second stage, due to the different shapes of the disease spots and the small number of training samples, U-Net is selected as the model at this stage, and the feature maps of different sizes are sampled and down sampled and fused in U-Net through concatenate operation, and the upper layer of the network has more detailed map features due to the large size of the input image, the small down sampling multiple, the feature map has more detailed map features, the underlying down sampling multiple is large, the information is condensed a lot, and the space loss is large, but it is helpful to judge the target area. As a result, details in the image, such as spot shape, color, etc., are preserved. The following pictures are the experimental image processing process diagram and the model structure diagram, respectively.



Picture 7 Experimental image processing



Picture 8 Structural diagram of cucumber disease segmentation model

V. Discussion on Machine vision technology feasibility and limitation analysis

1. Feasibility analysis

China is a big agricultural country, and the development of smart agriculture is the path to rural revitalization is an inevitable requirement to promote agricultural modernization. To achieve agricultural modernization, mechanization and automation, the development of intelligent devices is urgent. The use of advanced agricultural technologies such as machine vision technology, agricultural big data, artificial intelligence and the Internet of Things to control agricultural production can effectively improve agricultural production efficiency and agricultural product quality. Machine vision technology can realize real-time monitoring from the whole growth period of crops and quality inspection and product traceability in the later stage, in addition, if the crop is infected with diseases, machine vision technology can identify the type of disease, provide corresponding solutions for planting managers, and guide the infected plants with precise dosage, avoiding the occurrence of drug abuse problems caused by subjective experience. At the time of crop harvest, machine vision technology can calculate the contour information of the fruit and calculate the approximate mass and volume of the fruit through logistic regression equations, to achieve the purpose of yield prediction. In recent years, in agriculture, many medium and large enterprises have also been involved in the research of smart agriculture, such as Binocular cameras and hyperspectral cameras of companies such as Double Profit Spectrum, Elson and Intel, and hyperspectral cameras have had many applications in agricultural machine vision.

2. Limitation analysis

The application research of machine vision technology in the field of agriculture has accelerated the speed of agricultural development, greatly improved production efficiency, and upgraded and optimized the performance of agricultural machinery and equipment. However, there are still several issues that need to be solved urgently:

(1). The amount of data is large and agricultural production requires high-speed and accurate completion of the specified tasks, so the image data is processed in a short time, which also leads to the cost of the overall system software and hardware increase, the volume becomes larger, and it is not suitable for conventional field operations.

(2). The environment is complex, the meteorological environment of field operation is uncontrollable, the background information is complicated, and the camera needs to be kept clean and stable as much as possible, so the algorithm designed for a single environment cannot adaptively handle all conditions in the field.

(3). The degree of automation is relatively low because machine vision technology is still in the early stage of development, manual processing is often required in data processing, which directly leads to the problem of excessive investment in research manpower and material resources.

VI. Conclusion

The rapid development of computer and vision sensor technology has promoted the wide application of machine vision in the field of agricultural engineering, and all links in traditional agricultural production (such as seeding, fertilization, harvesting, etc.) are gradually realizing automation and intelligence, and mechanized operations will further liberate productivity, improve production efficiency, and increase product added value. In addition, non-destructive testing and quality grading based on machine vision will become an important part of modern agriculture, and machine vision also has great application prospects in the subsequent processing, transportation, packaging and other links of agricultural products. Image processing algorithms also with the high-quality development of agricultural production put forward higher requirements, in the face of complex, huge amounts of image information, how to quickly and accurately extract feature information is the direction of subsequent algorithm optimization, threshold segmentation as the most used, the most widely used image segmentation algorithm, combined with denoising, corrosion, expansion and other processing methods, and strive to improve the applicability and accuracy of the algorithm without changing the segmentation effect. It can be seen that machine vision technology continues to develop in agriculture and plays a vital role in the future improvement of vegetable or grain production in China and even the world. Popularizing machine vision technology in agricultural production management is an important goal for a country to achieve agricultural modernization. In view of the current problems in the development of machine vision technology, the future development should focus on several aspects. Firstly, improve the hardware configuration, accelerate the processing capacity of data, reduce hardware costs, improve the commonality of machine vision technology and equipment in agriculture, optimize algorithms, improve existing algorithms or research new methods, further streamline computing steps, reduce the demand for processing data to improve the real-time and portability of algorithms; Secondly, enhance the ability of equipment to adapt to the environment, implement standardized planting, unify background information to ensure the stability of algorithm processing results, monitor factors affecting the operating environment, and study dynamic adjustment of algorithms based on environmental changes to broaden practicality; After that, the overall automation level is improved, and the manual links in machine vision are gradually replaced with machine operations by a gradual method, so as to achieve the goal of improving agricultural modernization, automation and intelligence. Finally, multi-technology integration is carried out, the latest technologies such as system insulation and heat dissipation are studied to reduce the power consumption of system operation, and the latest materials are used as components or actuators to improve system capabilities.

In summary, the pace of modern agricultural development is accelerating, and the integration of machine vision technology into agricultural production is imminent, which provides more support for improving agricultural production technology and sustainable development and creates a solid foundation for the improvement of China's grain production while ensuring the efficiency and reliability of agricultural production.

VII. References

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