GERMPLASM SELECTION BASED ON THE DEPTH LEARNING NETWORK MOBILENET

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ABSTRACT

With the agricultural Internet of Things technology, real-time images of tomato plants can be obtained and processed through the remote video surveillance system. The image processing technology and the conventional neural network (CNN) based on visual algorithms will be used to process the collected images so as to accomplish the acquisition, processing and analysis of physiological indexes of tomato plants, which can identify the growth status of plants by breeading good traits and obtaining high-quality germplasm resources, improve agricultural production effciency and mitigate the loss caused by pest, insufficient of nutrition of soil and so forth.

KEYWORDS

Internet of Things；Image processing technology；MobileNet Deep Convolutional Neural Network；Germplasm selection

1. INTRODUCTION

There has been remarkable increasing with the application of the Internet of Things (IOT) technology in smart agriculture in recent years. However, there has been little research on the real-time monitoring of plants' growth status and disease analysis. Therefore, mode recognition and solution of issues of growth status of plants are critical to the existing agriculture. In recent years, deep learning has been rapidly developed due to the update of hardware devices and the large increase in the amount of data, and has shown great advantages in image processing and pattern recognition. The deep learning network does not require artificial selection features, it uses a large number of samples to allow the computer to automatically extract features, and the recognition accuracy is very high, with unique advantages that other pattern recognition does not have.

The conventional plant cultivation still features the low level of mechanization and automation of farm production, which leads to low productivity. More and more attention has been paid to the quantity and quality of agricultural plant products. In this paper, a scheme for tomato germplasm selection through the image processing and the conventional neural network technology[1] has been proposed and verified. .It can select high-quality and high-quantity tomato plants, realizing the smart germplasm selection and the management efficiency of agriculture and optimizing tomato plants so as to obtain excellent germplasm resources

2. TECHNICAL METHOD

Compared with the traditional germplasm selection method, the image processing and the CNN-based technology can select high-quality plants, realize automation of selecting high-quality germplasm, and breed plants with high yields, thus increasing their output. The technique of the tomato germplasm selection proposed in this paper can optimize the cultivation of tomato plants without people on the scene, and obtain excellent germplasm resources .This scheme is based on tomato growth characteristics in order to promote the scientific, intelligent, networked and intensive management of the production, which helps to develop the IoT smart monitoring and management platform.

This platform consists of three parts. The first part is the user-controlled front end, including the sense monitoring and the subsystem acquisition. The second and last part are the wireless transmission network and the back-end image analysis cloud management service terminal respectively. The platform adopts advanced technologies such as the wireless multi-sensor stereo perception, the wireless sensor network (WSN), the heterogeneous network aggregation and the data modeling and data mining algorithms, processes the collected tomato production status and other multi-information through visualized monitoring subsystems, compresses all data, and uses detection algorithms and the massive data analysis and processing[2].

Then, the processed data, is transmitted to the cloud management service terminal by the wireless sensor network, which realizes the monitoring of up to 20 kinds of dynamic tomato growth states, the analysis of the collected data and the acquisition of valuable data. Therefore, tomato plants with good trait are preferably bred. The plarform has characteristics of advanced technology, strong functionality, good compatibility, uniformity, openness, manageability, scalability, ease of use and low operating cost, which better meets the intelligent production management of modern crops.

3. TECHNICAL PROCESS

Firstly, the image data of the plants is collected by using its online analysis imaging device and system. The system supports real-time monitoring of plants' basic morphological characteristics that can be set as scheduled and automatically uploads the compressed data to the analysis platform[3].

According to different growth stages of plants, their characteristics such as leaf length, leaf color, leaf shape, fruit length, fruit color, fruit shape, plant height and others can be intelligently analyzed, classified, uploaded and stored so as to assist in data statistics.

Secondly, the communication module used for data transmission satisfies multi-network management and multi-protocol. The data interface meets the requirements of standard external platform communication protocol, and supports VPN access, data exchange, data sharing, data access and data analysis. After the data arrives at the data processing center, Opencv is used to preprocess the collected images (scaling, shifting, denoising, etc)[4], which lays a foundation for the subsequent training of the MobileNet Deep Convolutional Neural Network (hereinafter referred to as MobileNet); in order to expand the data volume, the data enhancement method is adopted, which consists of rotating, panning and other operations to generate new images, so as to expand the limited sample size, improve the generalization of the model, and avoid over-fitting. Finally, the trained MobileNet that meets the requirements can be applied to judge the growth status of tomato plants by accessing the platform interface[5].

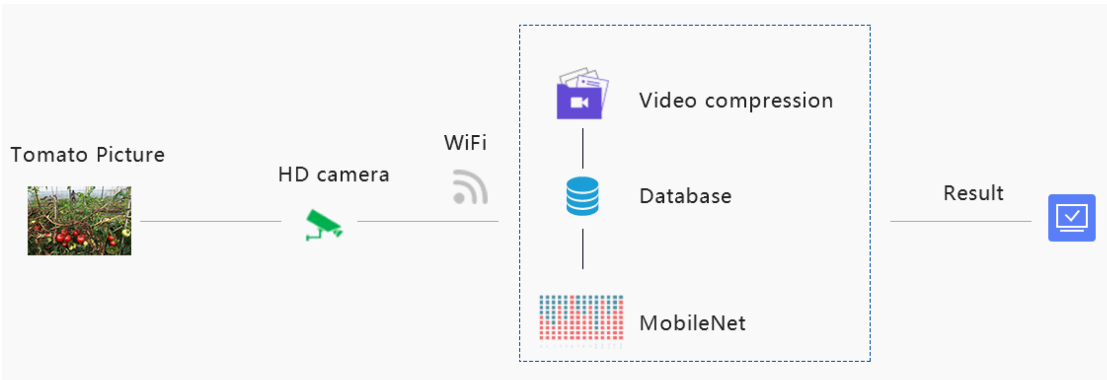

Figure 1. System architecture diagram

4. Convolutional Neural Network

The CNN is a neural network composed of a volume base layer, a pooled layer and a fully connected layer. Its advantages lie in feature extraction and pattern recognition. Since the great success of AlexNet in the large-scale image recognition contest ILSVRC in 2012, deep CNN has become more and more popular, because it can eliminate the complicated process of artificially selecting features of SVM classifiers or Adaboost classifiers, and directly use big data to drive CNN to automatically learn the characteristic information in images, which has great advantages and potential[6].

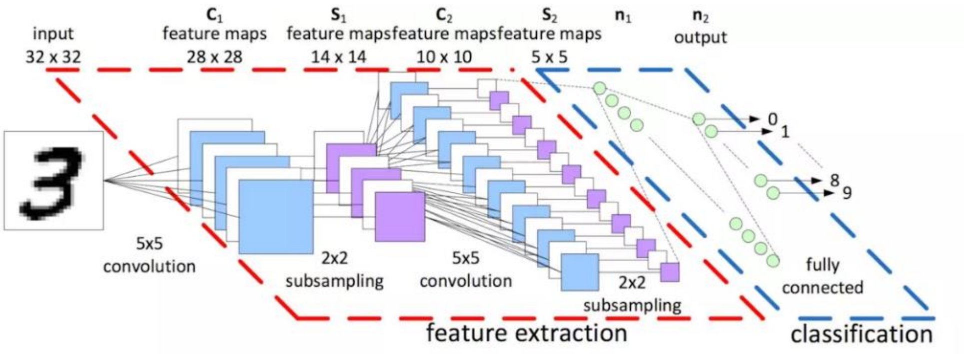

Figure 2. fkow of CNN

The CNN operation formula:

$$g(i, j) = \sum_{m=-1,n=-1}^{m=1,n=1} f(i+m, j+n)h(m,n)$$

$$g = f * h$$

Where (i, j) is the central pixel coordinate, i = 1, 2, ..., h, j = 1, 2, ..., w, where h is the height of image, w is the width of image, and the convolution needs to traverse the entire image. f is the original image, g is the new image, h is the convolution kernel, and * is the convolution operator.

5. MOBLIENET-SSD NETWORK:

Mobilenet is mainly a lightweight deep network model proposed for mobile. The deep separable convolution mainly uses a standard convolution kernel into a deep convolution kernel and a 1x1 point convolution kernel, reducing the amount of computation.

The calculated ratio of the depth separable convolution to the standard convolution kernel is:

$$\frac{D_k * D_k * D_f * D_f * M + D_f * D_f * M * N}{D_k * D_k * M * N * D_f * D_f} = \frac{1}{N} + \frac{1}{D_k^{\ 2}}$$

Where Dk*Dk is the convolution kernel size, Df*Df is the size of the input feature map, M is the number of input channels, and N is the number of output channels.
The mobilenet has a total of 28 layers (deep convolution and point convolution separately), and each layer is followed by a batchnorm layer and a relu layer[7].

Table.1.MoblieNet-SSD Network Structure

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
$5\times$ Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

6. ALGORITHM DESCRIPTION

For parameters of the plant growth potential, the flowering period, the initial harvest period, the harvest period, and the final harvest period, it is necessary to conduct discriminant analysis from various aspects and provide sample data characteristics by MoblieNet. If sample data feature dimension is unbalanced after obtaining data, data needs to be normalized. 80% of data is used as training set, while 20% is used as test set. The training set is used for training the built MobileNet model so as to determine the weight, deviation and other parameters of the network,and test set is used for testing the model[8]. In the program, the discriminant data of the size and color of the tomato plants is taken as the parameter, and the parameter value is used as the output. If the accuracy is lower than the threshold, the parameter of the model need to be optimized. Thus, the accuracy of the model on the test set can meet the requirements. The model is made into an interface for use in the program. Compared with other algorithms, MoblieNet is more convenient and faster in analyzing multi-factor models. It runs fast when the amount of data is large, and can be understood and interpreted each variable in MoblieNet as long as the data is appropriate, which can achieve high accuracy.

Compared with other algorithms, the proposed linear regression is more convenient and high efficient in analyzing multi-factor models. It understands and interprets each variable in linear regression. Proper data can achieve high accuracy.

For trivia type, leaf color, leaf shape, fruit shape, fruit color and fruit neak, all these parameters can be directly identified by images that provided by the MobileNet (for instance, how to identify green leaves? The answer is to provide a series of green leaf images with different angle directions and other features of the images are apporiate in avoid of interference).

Then the collected image data needs to be,preprocessed (including illumination pretreatment, image cropping and layer pyramid). And some of the data will be used as the training set, others will be used as the test set. Then, the convolution neural network can be used for feature extraction and modeling from the training set. Two convolutional layers and two pooling layers are preliminarily defined in the neural network, and several more layers can be added as the case may be.

The dropout connection is adopted between layers to reduce the fitting degree of model to the training set and enhance the generalization of the model. The Relu has been applied as activation function, which is fast in calculation and not easy to disappear the gradient[9]. After the model has been established, the test set is applied for testing. If recognition accuracy reaches the threshold, the model is made into an interface and passed into program image to be recognized will be passed as parameter, result of parameters identified is output as a result.

If the data is lower than the threshold, model parameters need to be tuned until recognition accuracy reaches the threshold, the interface is substituted into the program. Compared with other CNN algorithms, the proposed MobileNet is efficient for high-dimensional data processing as convolution kernels shared. In avoid of manually selection of features, have spatial invariance, which automatically extract features and have better feature classification effects. In terms of image processing, the input image of the MobileNet and the topology of the network can be well matched, and the feature extraction can be performed at the same time[10].

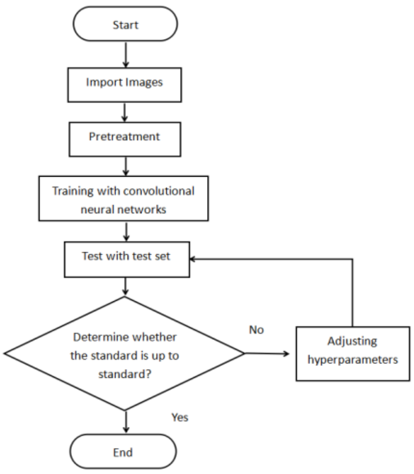

Figure 3. Algorithm flowchart

7. System Configuration

In this paper, images of tomato growth have been collected in real time through the wireless remote video network monitoring system. The collected images will be high-ratio compressed and transmitted to the back-end platform for identifying tomatoes with apporiorate growth conditions.

Table.2 system configuration

Database	Sqlserver	Storing video data
platform	Studio 2008	Data processing
Image Processing	Opencv3.4.3	open source computer vision library
Visualization tool module	Matplotlib 2.2.2	Display various parameter indicators in real time
Machine learning framework	Tensorflow 1.3.0	Building a (CNN) to train data

8. SIMULATION

Fig.4. Good growth tomato

Fig.5. Bad growth tomato

It can be seen that tomatoes in good growth condition tend to have large leaves, regular shapes, the dark green color and a large full fruit. On the contrary, tomatoes in poor growth condition may have small leaves which color is dry and yellow, small or rotten fruit, and irregular shapes.

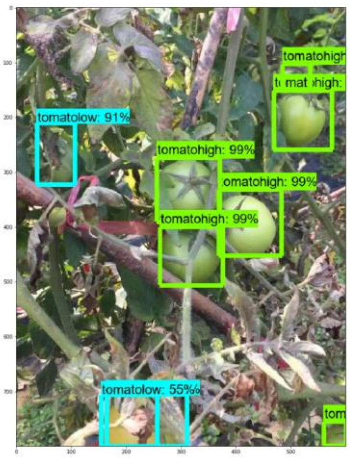

Figure 6. Simulation Result 1

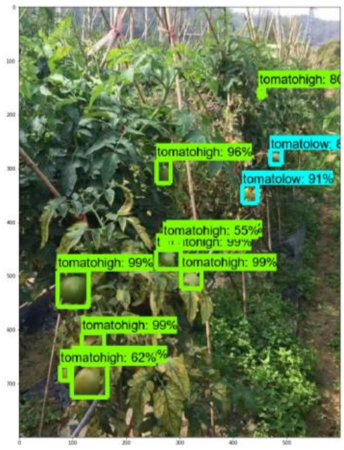

Figure 7. Simulation Result 2

In the simulation, tomatoes with high height are used to indicate a good growth condition, tomatoes with low height is used to indicate a poor growth condition. 400 pictures are used as the training set, 100 pictures are used as the test set, and training is carried out by mini-batch to improve the generalization of the model, update the gradient with the Adam algorithm and speed up the training time. Also, the Dropout method is to prevent over-fitting. It can be seen from the results, MobileNet has a good recognition effect for the target and meets the expected requirements.

9. CONCLUSIONS

The IoT-based technology is used to obtain image information of tomato plants through the sensing layer and transmit the collected information to the network center. Then the MobileNet algorithm, deep learning and other technical means are adopted to analyze and distinguish tomato plants with excellent traits for better cultivation and selection. Repeating the above process can ensure that the selected tomato plants have excellent growth productivity so as to achieve the goal of increasing plant production.

In the future research, adjust the MobileNet layer structure, extract more features to improve the recognition accuracy and optimize the IoT modules to improve the system operation speed and achieve more efficient and accurate detection.

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