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Machine Learning Algorithm in Agricultural Machine Vision System

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Abstract: The agricultural machine vision system is intelligent and automatic in spraying pesticides and fertilizing, harvesting, weeding, and pest detection. Compared with other technologies, machine vision system has high efficiency and low cost, so it has been popularized and applied. In order to solve the shortcomings of the existing agricultural machine vision system research, this paper discusses the composition, key technologies and machine learning algorithms of agricultural machine vision system, and briefly discusses the system hardware selection and software development environment for the application of agricultural machine vision system. And the overall results of agricultural machine vision monitoring system are designed and discussed. The convolutional neural network (RCNN) and K-means algorithm in machine learning are used to study the identification and classification of seedlings in images. Finally, through the experimental analysis of selected samples, it is known that the accuracy of RCNN and K-means algorithm in image recognition detection in agricultural machine vision monitoring system is up to 94.25%. Therefore, it is verified that machine learning algorithm has high practical value in agricultural machine vision system.

1. Introduction

With the rapid development of computer technology in China and the continuous progress of human thought, agricultural robots began to emerge. Among them, agricultural machine vision system means that it can work automatically without human intervention. It can judge and solve problems independently according to the changes of farming. Make agricultural machinery work more intelligent and modern.

Nowadays, more and more scholars have done a lot of research in agricultural machine vision system through various technologies and system tools, and have also made certain research achievements through practical research. Mahdavian A considers the segmentation of seedlings and residues based on machine vision system, and establishes a simple dichroic reflection model in RGB color space, which indicates that seedlings can be identified by their color characteristics. The

R, G, B component values of seedlings and residues were obtained in Photoshop software, and statistical analysis was carried out to obtain the relationship between them. The Ex G index, which can obtain the best threshold, is combined with the Otsu method (Ex G+Otsu method) to better distinguish seedlings and residues. The RGB method and the previous Ex G+Otsu method are used to visually compare their performance. The segmentation quality factor and time consumption are used to evaluate their comprehensive performance. The results show that the latter segmentation is more effective, more stable and time-saving [1]. Husain T has developed four machine vision systems as non-destructive measurements to monitor crop factors at different stages of crop growth. First, in the early stage of fruit development, a yield prediction system for a specific location was developed using a new depth data conversion method, which can identify the three-dimensional fruit surface structure. Second, two machine vision systems have been developed to detect the drop of early ripening fruits from pre harvest to harvest to measure the severity of fruit tree diseases (such as HLB). Finally, a citrus disease and defect detection system is developed by using transfer learning technology and real-time video processing algorithm with graphics processing unit (GPU) for the post-harvest stage. The final accuracy of each system is 89.2%, 88.1%, 89.6% and 94.9% [2]. Bill studied an automatic monitoring system for rice light trap pests based on machine vision. The system designed a light trap to detect, capture and kill insects, and sent the collected images of the detected insects to the cloud server. Through the pest identification model designed in the server. The model can automatically identify and detect the number of target pests in the image. The vibrating plate and moving rotary transmission belt are used to avoid the accumulation of light trapping insects. Among the methods to detect the number of insects, automatic and manual identification methods have a certain correlation [3]. Although the existing research on agricultural machine vision system is very rich, there are still some limitations in the application of machine learning algorithms.

This paper first discusses the composition and key technologies of agricultural machine vision system, including active vision technology, image processing technology and visual information processing technology. The linear regression and deep learning in machine learning algorithm are analyzed. Secondly, the machine and tools used in the experiment are selected, mainly including lens, camera and controller. The system software development environment is analyzed. Then RCNN and K-means algorithm are used to design and discuss the process of seedling recognition and image classification. Finally, the three experimental algorithms are compared and analyzed, the results show that the agricultural machine vision monitoring system based on machine learning algorithm achieves the expected experimental results, and better meets the actual needs.

2. Design and Application of Machine Learning Algorithm in Agricultural Machine Vision System

2.1. Agricultural Machine Vision System

(1) Composition of agricultural machine vision system

1) Image acquisition module: the original image (analog signal) acquired by the visual sensor (CCD camera, digital camera, etc.) is converted into digital signal through the acquisition module, and then stored in the memory [4]. The quality of the collected image is directly related to the performance of the visual sensor and has a direct impact on the subsequent image processing [5].

2) Image processing module: mainly includes image preprocessing (enhancement restoration, smoothing, sharpening, etc.), image segmentation, feature extraction, understanding, decision-making, etc. [6].

3) The final purpose of information output image processing: to understand and judge according to the processing results of the previous module, and output in the specified form (information or

pictures) [7].

(2) Key technologies of agricultural machine vision system

1) Active vision technology: active vision navigation methods include monocular vision, binocular vision and hybrid vision [8]. Compared with the other two active vision systems, the monocular vision system has a relatively simple processing algorithm and less computation, which ensures the real-time performance of the system [9].

2) Image processing technology: preprocessing, image segmentation, feature extraction, etc. Get the required feature image; Then classify according to the structure or feature information contained in the image, namely pattern recognition; Describe and explain the image itself and the things it represents, so as to make decisions on the next action [10].

3) Visual information processing technology: visual information processing technology is one of the key technologies of agricultural robots, which can mainly compress and store visual effective information, explore walking roads, identify objects or obstacles, etc. [11].

2.2. Machine Learning Algorithm

(1) Linear regression

In many agricultural machine vision system image researches, when the image information is missing, it will often produce large deviation. Linear regression has been used more and more because of its stability and timeliness [12].

Suppose there is a series of coordinate points (u_x, v_y), and the fitted straight line of these coordinate points is H, then the equation of H is:

$$k = fu + c \tag{1}$$

Where c is the slant distance and f is the slope, the distance a from point (u_x, v_y) to the straight line is:

$$a = \frac{|fu + c - k|}{\sqrt{1 + f^2}} \tag{2}$$

The sum of squares A of the distances from all points to the straight line is:

$$A = \sum_{x=1}^{M} \left[\frac{k_x - (c + fu_x)}{\sqrt{1 + f^2}} \right]^2 \tag{3}$$

Where M is the number of seedlings in the image. If point (u_x, v_y) is on a straight line, then a is 0, but it is impossible for all image feature points to fall on the straight line [13]. The square sum A of the distance from the feature point to the straight line is the minimum, and the straight line H calculated from this can make the feature points basically distributed near both sides of the distance from the straight line H [14].

(2) Neural network

Deep learning (DL) is introduced into machine learning to make it closer to the original goal - artificial intelligence. Three types of methods are mainly popularized:

1) The neural network system based on convolution arithmetic is called convolutional neural network (CNN).

2) Self coding neural networks based on multilayer neurons include self-coding and sparse coding.

3) The method of multi-layer self-coding neural network is used for pre training, and then the

depth confidence network (DBN) of neural network weights is further optimized by combining the discriminant information [15].

3. Investigation and Application of Machine Learning Algorithm in Agricultural Machine Vision System

3.1. Hardware Selection of Agricultural Machine Vision System

(1) Lens selection

In order to use the industrial camera selected above, this paper also selects the HT-0612 lens from Shenzhen Midi Micro Vision Co., Ltd. Parameters of camera and lens are shown in Table 1 [16].

Table 1. Parameters of camera and lens

MD-UB300 camera parameters	HT-0612 lens parameters
Name and Value	Name and Value
Effective pixels:2048*1536(30 万	The focal length(mm):6-12
Size of the camera(mm):38*38*53	Interface:C
Exposure time(ms):0.1~1237	Horizontal field of view Angle:539 °-28 °
Data interface:USB2.0TypeB	Size(mm):32*50
The frame buffer:32MBytes	C

(2) Controller selection

The PLC controller in this paper adopts KSC-10 programmable controller. The input interface mainly includes: analog signal acquisition interface, switch signal acquisition interface and frequency signal acquisition interface. Output interfaces mainly include: analog signal output interface, switch signal output interface and frequency signal output interface [17].

3.2. Development Environment of Agricultural Machine Vision System Software

The CCS integrated development environment provides basic code generation tools, including the following simple components: concept/design, code/compilation, debugging, analysis, and extension of basic code generation tools. CCS supports all phases of the software development cycle as shown in Figure 1 [18].

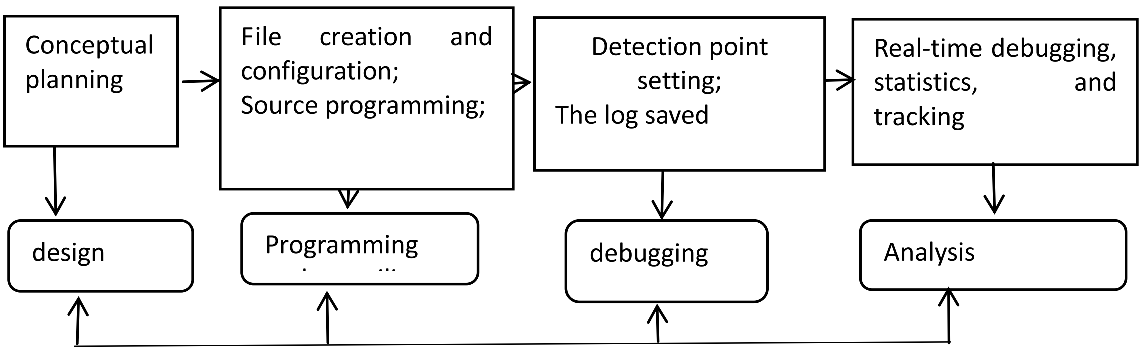

Figure 1. CCS development cycle phases

4. Analysis and Application of Machine Learning Algorithm in Agricultural Machine Vision Monitoring System

4.1. Machine Learning Algorithm for Detection and Recognition of Seedling Status in Machine Vision Monitoring System

The agricultural machine vision monitoring system consists of three systems, namely, information acquisition system, remote communication system and remote monitoring system. The information collection system first collects the pictures of seedlings in the paddy field and records the working condition information. The remote communication system collects the picture information and then transmits it to the remote monitoring system, which is responsible for identifying and detecting the seedlings in the pictures. The whole system is attached with an alarm device, which will give an alarm if abnormal seedlings occur or the transplanter runs out of range. This paper focuses on the realization of machine learning algorithm for the detection and recognition of seedling state.

(1) Classification of Seedling Images Using K-means Algorithm

The specific steps of K-means algorithm for seedling image classification are as follows:

1) Select the initial division of G seedling image into a clusters, and calculate the mean $n_1, n_2, \ldots n_a$ and Y_c of each cluster.

2) Select a candidate seedling image k, and set k in γ_x.

3) If $G_x = 1$, turn to (2), otherwise continue.

4) calculation:

$$f_y = \begin{cases} \frac{G_y}{G_y + 1} \left\| k - n_y \right\|^2, y \neq x \\ \frac{G_y}{G_x + 1} \left\| k - n_x \right\|^2, y = x \end{cases} \tag{4}$$

5) For all y, if $f_u \leq f_y$, move k from γ_x to γ_u.

6) Recalculate the n_u value of and n_x, and modify Y_c.

7) If Y_c does not change for successive iterations G, then stop; otherwise, go to (2).

(2) RCNN was used to identify seedling status in the image

Based on the calculation process steps and principles of convolutional neural network (RCNN) algorithm, combined with the need to automatically identify the image features of missing and drifting seedlings in this paper, an image recognition model of missing and drifting seedlings based on RCNN algorithm is proposed. The algorithm process of drifting seedlings recognition is shown in FIG. 2:

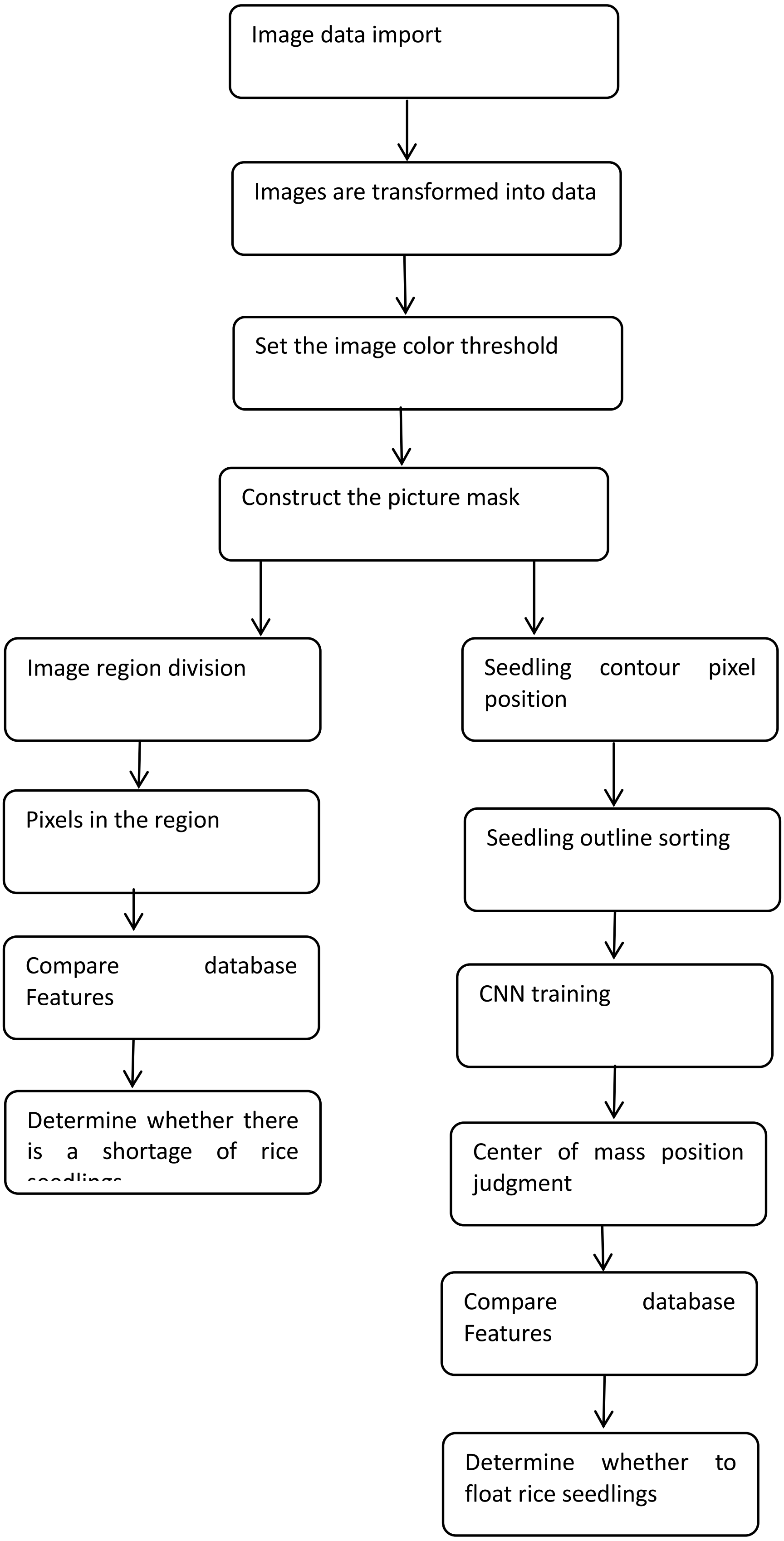

Figure 2. Identification algorithm process of lacking and drifting rice seedlings

1) The process of seedling deficiency recognition: filter the number of pixels of the collected image, and then construct the mask; Secondly, find out the contour pixel position of each seedling, and arrange in order from the largest to the smallest; Finally, the centroid position of each seedling was calculated, and the distance between two adjacent seedlings was calculated according to the column, and the threshold value was set to determine whether there was seedling deficiency.

2) Steps of drift seedling recognition: the first step is to find the contour pixel position of each seedling and sort it from the largest to the smallest, so as to build the database; Second, the samples are divided into training sample set and test sample set. Third, the RCNN network was constructed to train the seedling training database. In the fourth step, the trained network model was used to verify the model of seedling test samples.

4.2. Application of Machine Learning Algorithm in Agricultural Machine Vision Monitoring System

In this paper, 50 rice seedling images of paddy field were used for experimental testing, and the image size was 1292*964. Three seedling recognition algorithms, RCNN, SVN and decision tree, were used to recognize and test the shot seedling images, and F1 was combined to analyze the performance of the algorithm. The results of the algorithm for seedling deficiency recognition are shown in Table 2:

Table 2. Results of identifying seedling deficiency by algorithm

Model	RCNN	SVN	The decision tree
10	88.89%	85.45%	77.21%
20	90.12%	86.17%	75.39%
30	92.78%	91.25%	80.14%
40	94.25%	89.14%	78.28%
50	91.54%	92.16%	77.99%

It can be seen from the data in FIG. 3 that the accuracy rate of RCNN, SVN and decision tree in identifying the lack of rice seedlings in the 10 paddy field seedling images is 88.89%, 85.45% and 77.21%, respectively. The accuracy rate of RCNN, SVN and decision tree was as high as 90.12%, 86.17% and 75.39%, respectively. The accuracy rate of RCNN, SVN and decision tree was 92.78%, 91.25% and 80.14%, respectively. The accuracy rate of RCNN, SVN and decision tree was 94.25%, 89.14% and 77.99%, respectively. The accuracy rate of RCNN, SVN and decision tree was as high as 91.54%, 92.16% and 77.99%, respectively.

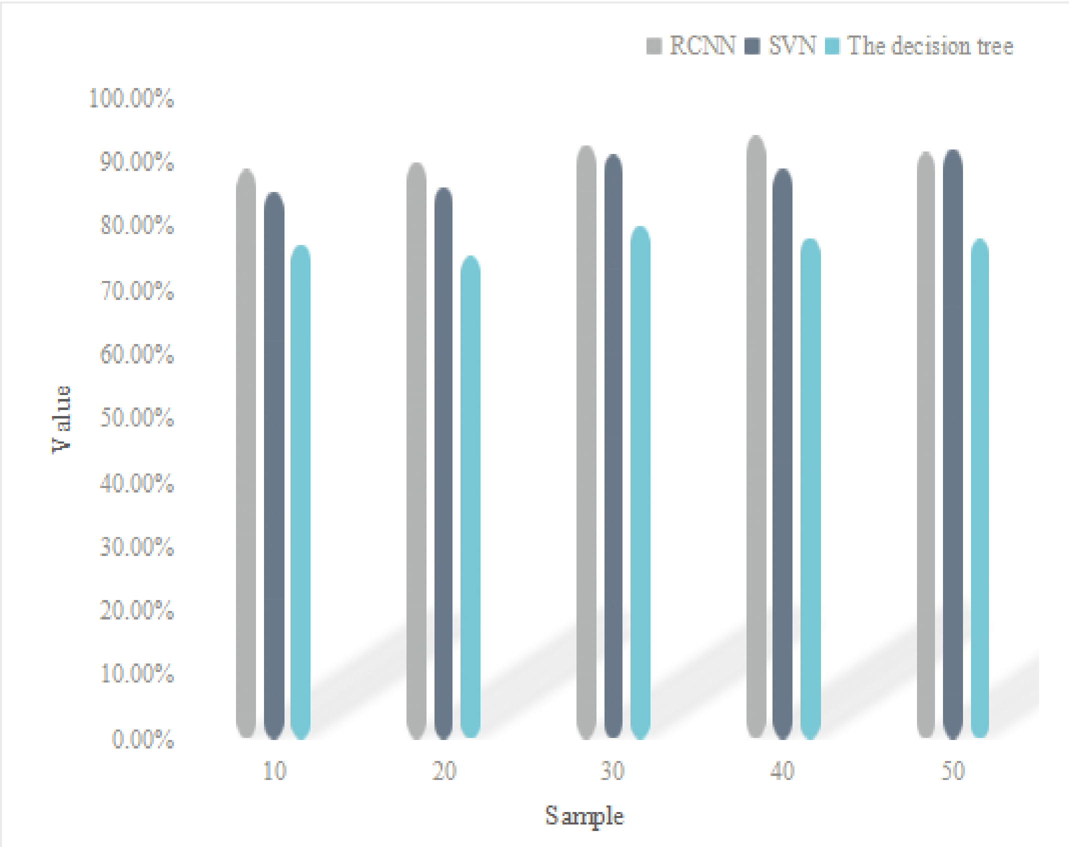

Figure 3. Comparison of results of algorithm identification of seedling deficiency

5. Conclusion

The tide of artificial intelligence and machine learning promotes the development of the present era and society. The intellectualization and networking of machines are irreversible trends. If this technology is applied to the agricultural machine vision monitoring system, the operation of the agricultural machine vision system can be more intelligent and humanized. This paper studies and designs agricultural machine vision monitoring system based on machine learning. Based on image processing, K-means algorithm image classification technology, camera timing shooting technology and RCNN seedling status recognition technology are integrated. According to the functional requirements of agricultural machine vision monitoring system, the whole monitoring system is divided into three parts: information acquisition system, remote communication system and remote monitoring system. These three systems complete the functions of seedling image acquisition, image upload and image recognition respectively. The three systems cooperate closely with each other.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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