RESEARCH ARTICLE

The impact of agricultural informatization on agricultural production efficiency and system application

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Received: April 2, 2024; **accepted:** June 20, 2024.

The development of agriculture is related to the stability of the country's economy. Changes in agricultural productivity have been one of the more complex current agricultural problems. To improve agricultural productivity, this study built a pest detection model based on agricultural information technology. This model used agricultural information technology to analyze agricultural pests and diseases. The results showed that crop yields were higher when using the research model in crop productivity. The training and testing of three crop pest and disease data showed that, in different models, the accuracy of the proposed model was 1.22%, 2.47%, 3.47%, and 1.68% higher than that of ResNet50, ResNet101, MobileNetV1, and MobileNetV2, respectively. In addition, the proposed model could process the data stably and reduce the error value. The utilization of an enhanced convolutional neural network method demonstrated the enhancement of green vegetables yield, while concomitantly reducing the impact of pests and diseases and improving the efficiency of agricultural production. This research provided a good reference value for the future improvement of agricultural production efficiency.

Keywords: agricultural informatization; agricultural productivity; pest and disease detection; computation model.

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Introduction

Agriculture has always played an important role as one of the most basic modes of production in human society [1]. However, the problem of pests and diseases during agricultural production has always been one of the major challenges plaguing farmers and agricultural development. The outbreak of pests and diseases will not only lead to crop yield reduction or even crop failure, but also cause serious damage to the ecological environment, bringing threats to the sustainable development of agriculture [2]. With the rapid development of information technology, agricultural informatization has emerged and is gradually playing an important role in agricultural production [3]. The agricultural information system monitors the agricultural environment, crop growth status, and pests and diseases in real time through sensors, remote sensing technology, and other means. It transmits data to a central database for analysis and processing, and by issuing real-time warning information, helps farmers to take corresponding prevention and control measures in a timely manner, effectively reducing the occurrence and spread of diseases and pests [4].

Convolutional neural network (CNN) is a deep learning model that is particularly good at processing multi-dimensional data such as images and videos. CNN is a more widely used image recognition method and is also an important tool for the identification of agricultural pests and diseases and the processing of agricultural information technology. To solve the problems of latency and energy consumption of mobile nodes in smart agriculture, Liu *et al*. proposed a solution that introduced edge computing. The mobile edge computing could offload some computational tasks to the edge of the core network, thus improving the network performance. Its system architecture contained three layers including physical sensing, information service, and intelligent application, which further defined the offloading model for smart agriculture. The results showed that the method could reduce latency and save energy consumption, which brought new opportunities and challenges for the development of smart agriculture [5]. To investigate the effects of super-absorbent polymers (SAPs) on water/nutrient retention characteristics and agricultural productivity of saline soils in the Yellow River Basin in China, Zhao *et al*. conducted soil column leaching and potting experiments. Three types of SAPs including commercial SAP, starch grafted SAP, and modified SGSP were used in the study with six treatments being set up in the leaching experiments including applications of MSSP only, fertilizer only, fertilizer and CSAP, fertilizer and SGSP, fertilizer and MSSP, and CF + 70% MS. The results showed that the application of SAP significantly reduced water and nutrient leaching losses from saline soils and increased maize yield and fertilizer efficiency [6]. To address the problem of backwardness in agricultural productivity in developing countries, the importance of studying the intangible and non-physical dimensions of agriculture has been raised. Through a field study in Nepal, the scientist collected the data from 262 smallholder farmers and established four regression models. The results showed that there was an association between high positive ratios and all four productivity indicators [7]. Sarpong *et al*. proposed the use of plant microbiomes, an environmentally friendly and sustainable agricultural productivity resource, to address the environmental problems associated with the excessive use of agrochemicals. The results showed that microbial inoculants and their interactions with mineral fertilizers could improve crop yields, but there were still some challenges [8]. Mrunalini *et al*. proposed nature-based solutions to improve soil quality and sustainability of agricultural productivity and proved that indigenous practices such as goat penning, pond sludge application, and green manure could restore and maintain soil fertility. Biofertilizers and biochar could increase soil nutrients and improve soil conditions, while biogas slurry could also increase soil fertility and reduce dependence on external resources [9]. Todmal analyzed the data of Maharashtra, India from the period of 1980 to 2014 to assess the monsoon rainfall variability in semi-arid regions and its linkages with El Niño/Southern Oscillation (ENSO), Indian Ocean Dipole (IOD), and agriculture. The results indicated that the main reasons for below average rainfall were El Niño and positive phase of the International Drought Zone [10]. To assess the effectiveness of ground cover cultivation methods in semi-arid regions, Li *et at*. conducted six different treatments and field trials for three years, and the results showed that the use of different tillage and mulch cover materials significantly increased soil water content, crop yield, ecological efficiency, and evapotranspiration rate. RPM treatments were effective methods for water conservation, CWP, and yield improvement [11]. Scaini *et al*. developed a method to quantify the 110 agricultural catchments in the United States over the period of 1987-2012 to increase agricultural productivity and reduce negative environmental impacts using nitrogen and phosphorus utilization efficiency (NPUE). The results suggested that climatic conditions and crop choice were important drivers of nutrient use efficiency in agricultural catchments [12].

In current agricultural production, pest and disease monitoring and control methods often fail to respond in a timely manner, making it difficult to accurately identify and locate pests and diseases, resulting in improper use of pesticides, increased production costs, and environmental pollution. In addition, existing information technology methods still have certain limitations in data processing and analysis and cannot fully utilize massive agricultural data to improve production efficiency. Therefore, the aim of this study was to propose an intelligent agricultural information processing model that provided accurate and timely monitoring and warning of pests and diseases to help farmers better cope with pest and disease problems and improve agricultural production efficiency. The research mainly utilized CNN combined with sensors, remote sensing technology, and agricultural big data analysis to achieve real-time monitoring and data analysis of farmland environment and crop growth status. CNN was applied to identify and detect crop diseases and pests in real-time by analyzing crop images, and in addition, to detect nutrient deficiencies by analyzing the color and morphology of crop leaves, thereby providing accurate fertilization recommendations. The proposed model would optimize resource utilization, reduce excessive use of pesticides and fertilizers, reduce environmental pollution, and promote sustainable development of agriculture. Consequently, this study would improve agricultural production efficiency and impact on agricultural production.

Materials and methods

Monitoring agricultural pest and disease

Agricultural pests and diseases are mainly identified by manual inspection and equipment detection. The manual inspection requires farmers to make judgement of pests based on their own experience. However, the discrimination of pests and diseases can be misjudged due to the diversity of pest species [13]. The equipment detection is to use drones or monitoring equipment to identify and judge agricultural pests and diseases, and based on the collected data, judge the pests and diseases to complete the identification and management. However, due to some deficiencies in data processing, image segmentation, and empirical judgment, there may be misjudgments of pests and diseases. Drones and monitoring equipment are mainly used to collect the information of farmland through high-definition cameras to complete the monitoring of farmland. Due to the large area of farmland, it is necessary to distribute different points of monitoring equipment to different locations to achieve the current monitoring of pests and diseases in farmland. In this study, managing monitoring equipment involved multiple tasks including real-time pest and disease monitoring, as well as regular maintenance and data queries. Management personnel should regularly check the equipment's operating status and manage faults. In addition, they also needed to regularly compile and query information on farmland maps. It is essential to complete the user login of the current equipment management personnel and the information related to system entry [14]. When adding a new monitoring device, the maintenance personnel should log in and enter their information to the system, which would then be displayed in the current monitoring system. The system would check the information for duplicate users. If no duplicates were found, the user was prompted to complete the registration of the new device. The use of monitoring equipment could complete the current farmland pest data information and image acquisition. The collection of pest data was typically structured using image data that was employed to express the information pertaining to pests and was achieved using image data to express the size, color, and other obvious characteristics of pests. The monitoring device would capture the pest information of the current farmland crops, achieve the collection of pest images by means of fixed-point data collection, and then upload the collected data to the background client data for storage. In the information acquisition of pest images, the farmland pictures were captured and stored to guarantee that the information could be queried and called up in the whole equipment. Through neural networks, current pest and disease information and images were obtained and

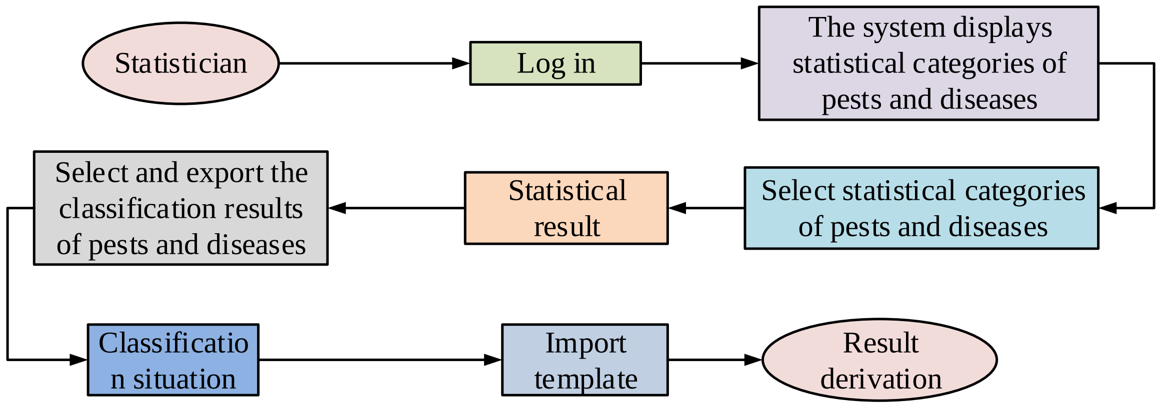

Figure 1. System flowchart of agricultural informatization processing.

analyzed, and corresponding pest and disease types and related information were obtained through information processing [15]. The statistician in charge of informative treatment would then log into the system and search for the current pest and disease pictures and data. After determining the type of pest and disease through neural network analysis, the statistician used an Excel (Microsoft, Redmond, WA, USA) table to compile statistics on the type of pest and disease before entering the statistical data into the data system. The data for current farmland areas affected by pests and diseases would then be available by the system and could be used to treat the farmland areas that were currently affected by pests and diseases (Figure 1). The system for pest detection needed to meet some of the current requirements including capable of handling a variety of transactions within the current system and short response time in addition to the authentication for each user account. The accounts that had not been logged into for a long time should be frozen to ensure security. For the processed data, it should be able to adapt to the parameter operation of neural networks to achieve the sharing of agricultural information. The stability of the system was required to be good without crashing and unresponsive problems. Also, the system needed to meet the operational simplicity to facilitate the various departments to complete the detection and analysis of pest and disease information.

Construction of CNN-based agricultural information technology pest monitoring system

The detection and analysis of pests and diseases required the storage and processing of current pest and disease data information. Therefore, the construction of the system needed to include several necessary data processing layers including data acquisition, data sensing, system application, and program processing (Figure 2). The data acquisition layer was primarily responsible for collecting current pest and disease images and information data and handled the image data collection of the farmland. Meanwhile, the data perception processed various types of financial data, images, and pictures. The system application layer was mainly responsible for analyzing and processing the monitoring equipment and some data information of the current system, which allowed for the integration of various applications into the application layer. The program processing layer was responsible for detecting and troubleshooting the current system's programs, which also handled the collection and logical analysis of the algorithmic model of the pests and diseases. The processing and analysis of pest and disease images was the most important part of the current system model, using CNN to complete the identification of pest and disease

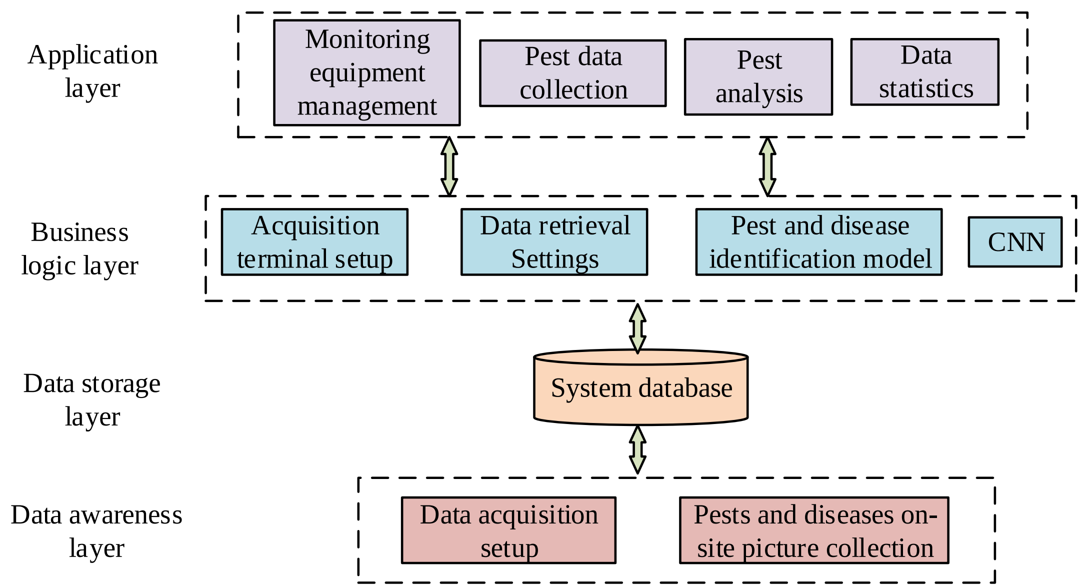

Figure 2. Schematic diagram of system structure framework.

images and data analysis. CNN in the detection of pests and diseases mainly extracted features of the entire system. The construction of a pests and diseases image dataset involved annotating images with the current type of pests and diseases, the location of their emergence, the number of occurrences, *etc*. The image data would be pre-processed and analyzed. Due to the image features of pests and diseases exhibited the characteristics of discrete data, a single leaf of a crop might be infested with a variety of pests and diseases. Therefore, in the analysis, these features should be added to the feature dataset to improve the clarity of identification. Through the operation of aggregating data features, the information would be projected into the dataset of image data features and expressed in equation (1) [16].

$$k_i = Z(SP(SC(x_i^1), SC(x_i^2), \cdots, SC(x_i^{n-1}), SC(x_i^n))) \quad (1)$$

where *n* was the number of image acquisition. x_i^1 was the acquired image data. $SC(\bullet)$ was the feature acquisition and projection of image data that could be achieved through the convolution operation of CNN. $Z(\bullet)$ was the set of functions for feature training. k_i was the result after feature convolution and feature projection. The resulting feature convolution yielded the $SP(\bullet)$ feature that was expressed in equation (2).

$$SP(\{k_c^j : j = 1, 2, \cdots, n\}) = SC(\{k_c^j : j = 1, 2, \cdots, n\}) \quad (2)$$

where k_c^j was the data value in the first j feature convolution. *c* was the combination of sequences in random order. Through a series of data feature maps, the transmission and replacement of the current data frame could be completed. The process of replacing the feature set of a function was shown below [17].

$$\begin{aligned} SP_1(\{k_c^j\}) &= \max(\{k_c^j\}) \\ SP_2(\{k_c^j\}) &= \min(\{k_c^j\}) \\ SP_3(\{k_c^j\}) &= \max(\{k_c^j\}) + \min(\{k_c^j\}) \end{aligned} \quad (3)$$

where $\max(\{k_c^j\})$ was the maximum value of feature convolution in the time dimension. $\min(\{k_c^j\})$ was the minimum value of feature convolution in the time dimension. Feature processing through the above formulas could get the feature data of the image. However, for complex pest images, it was difficult for a simple

CNN to improve image detection accuracy and performance. Therefore, the operation method of deep convolution was introduced for improvement. Additionally, the complexity of pest images was reduced by the dense data model, which helped to improve the accuracy of image recognition and diagnosis. Deep convolution primarily involved the convolution of each input channel, which not only reduced the number of parameters and computation, but also increased the size of the receptive field in the algorithm. This enhancement improved the expressive capability of the algorithm model and the clarity of image data processing. The output loss function value of deep convolution was shown in equation (4).

$$E=\sum\nolimits_{i=1}^{l(N)}\frac{1}{2}(O_i-y_i)^2 \tag{4}$$

where $l(N)$ was the number of neurons. y_i was the encoding result of the label. O_i was the average value of the activation time of the output layer on the i neuron. The formula for calculating the average value in equation (5) was obtained by the expected determination.

$$O_i=\frac{1}{T}\sum\nolimits_{t=1}^{T}S_i^{n-N,t} \tag{5}$$

where T was the length of time for training. S was the gradient calculation term. If the sample network was trained using minimal training, the loss function formula could be obtained as shown in equation (6).

$$L=\frac{1}{N}\sum\nolimits_{k=1}^{N}E_k \tag{6}$$

where N was the sample size of the minimum training sample. L was the average loss function value of the sample. The gradient formula was obtained by data optimization of the network as shown in equation (7) [18].

$$\bar{V}w_{i,j}^{n,t}=\frac{\sigma L}{\sigma w_{i,j}^{n,t}} \tag{7}$$

where $\bar{V}w_{i,j}^{n,t}$ was the gradient magnitude. $\frac{\sigma L}{\sigma w_{i,j}^{n,t}}$ was the derivative value expression after derivation. t was the time of the analyzed term. n was the number of neurons. Then the matrix analysis shown in equation (7) was obtained in equation (8).

$$\bar{V}w^{n,t}=\frac{\sigma L}{\sigma w^{n,t}} \tag{8}$$

Equation (8) showed the matrix post-derivative formula after the gradient had been minimally trained, and the propagation error and gradient size of the algorithm were then obtained by calculation using equation (9).

$$\frac{\sigma E}{\sigma h^{n,t}}=\sigma^{n,t} \tag{9}$$

When the change in time was the same as the output and input layers, the number of neurons, the number of input layers, and the minimum number of samples processed at this time were the same. Then the new error propagation formula obtained was shown in equation (10).

$$\sigma^{n,t}=\frac{\sigma E}{\sigma h^{N,T}}=\frac{\sigma E}{\sigma o}\text{g}\frac{\sigma o}{\sigma S^{N,T}}\text{g}\frac{\sigma S^{N,T}}{\sigma h^{N,T}}=(o-y)\text{g}\frac{1}{T}\text{g}\frac{\sigma g}{\sigma h^{N,T}} \tag{10}$$

where $\sigma^{n,t}$ was the error propagation term. T was the training time. N was the number of output layers. The error propagation formula obtained when the time of the analysis term was less than the training time was shown in equation (11) [19].

$$\sigma^{n,t}=\sigma^{n,t+1}\text{g}\frac{\sigma h^{N,t+1}}{\sigma h^{N,t}}+(o-y)\text{g}\frac{1}{T}\text{g}\frac{\sigma g}{\sigma h^{N,T}} \tag{11}$$

The error propagation relationship obtained when the time relationship was consistent, and

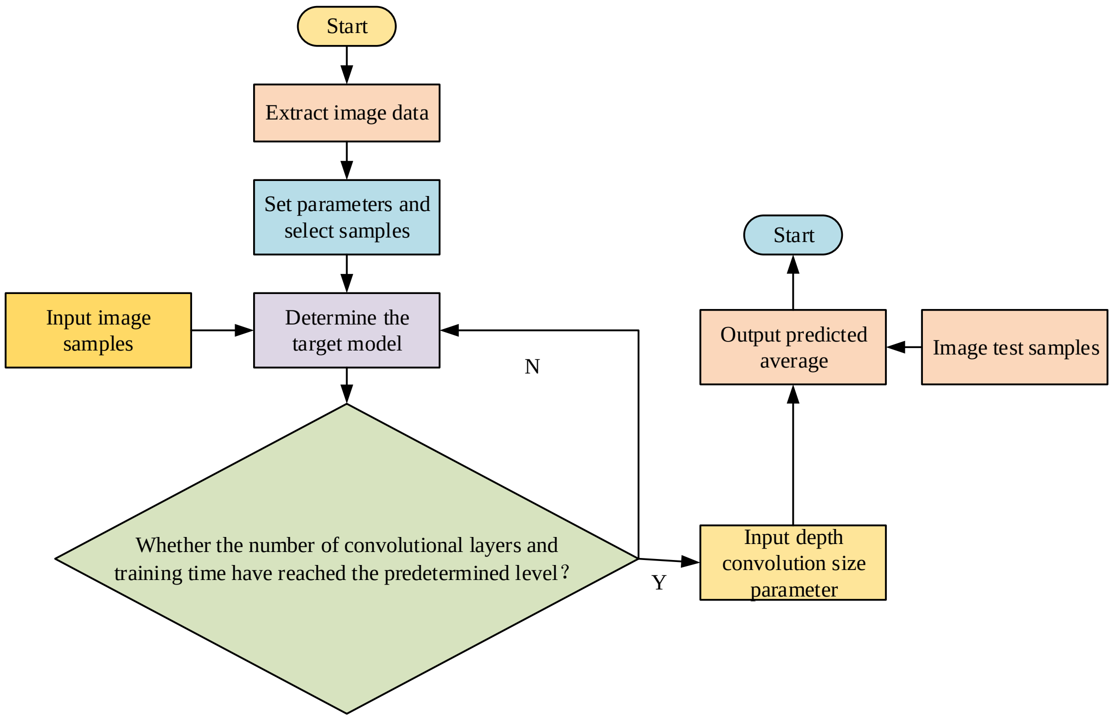

Figure 3. Improved convolutional neural network (CNN) image prediction model.

the quantity relationship was different was shown below.

$$\sigma^{N-1,t} = \frac{\sigma E}{\sigma h^{N-1,T}} = \frac{\sigma E}{\sigma h^{N,T}} g \frac{\sigma h^{N,T}}{\sigma S^{N-1,T}} g \frac{\sigma S^{N-1,T}}{\sigma h^{N-1,T}} \quad (12)$$

After calculating the propagation error of the algorithm, the error gradient expression of the algorithm was recalculated as shown in equation (13).

$$\frac{\sigma h^{n,t}}{\sigma w^{n,t}} = s^{n-1,t} \quad (13)$$

Using CNN and depth convolution could complete the feature extraction and data processing of the pest image. Therefore, the pest image processing model was built based on depth convolution and CNN (Figure 3). The model samples were first extracted from the image data. Then, the learning and training sample data that needed to be used and analyzed were selected. The data were analyzed and processed through the Kernel function in the CNN. The purpose of verifying the target image was achieved through the setting of the original parameters. Meanwhile, pest image samples were added in the step to better complete the comparison and processing. Afterwards, the depth of convolution was used to compare the parameters and determine whether the number of convolution layers, training time, and other data of the parameters had reached the set values. If the set values were reached, the model was trained, otherwise, then the model was re-validated. The size of the parameters for deep convolution was then input into the optimal parameters, and the predicted average value obtained by the output algorithm ended the algorithm model.

Validation of proposed model

The existing data sets of crop pests and diseases were downloaded and stored to verify the feasibility of the proposed model. The datasets of wheat (Global Agricultural Monitoring System (GLAM), https://glam.org/data/wheat), corn

Table 1. Number of training and test sets for different pest and disease types in three crops.

Crop	Types of pests and diseases	Test set	Training set	Total number
	Withered leaf	335	365	700
	Foxiness	330	354	684
Wheat	Stripe	452	431	883
	Leaf rust	426	431	857
	Measles	483	492	975
	Withered leaf	426	445	871
	Foxiness	482	429	911
Corn	Stripe	426	435	861
	Leaf rust	351	364	715
	Measles	425	462	887
	Withered leaf	445	483	928
	Foxiness	316	350	666
Sorghum	Stripe	426	453	879
	Leaf rust	425	439	864
	Measles	426	483	909

(Agricultural Data Science and Analysis Platform (AgData), http://agdata.org/datasets/maize), sorghum (International Center for Agricultural Research (ICAR), https://icar.org/data/sorghum) were selected as the research targets. All crops were grown at the same time and environment. Due to the various types of crop pests and diseases, five common pests and diseases of these crops were selected for analysis, which included withered leaf, foxiness, stripe rust, leaf rust, and measles. A total of 3,000 datasets were selected for each crop for comparative analysis. The training and testing datasets were allocated in a 4:1 ratio. The data of affected crops were shown in Table 1. To validate the current crop recognition accuracy of improved CNN, several image recognition algorithms including classification and regression tree (CART), support vector machine (SVM), and CNN algorithm were compared for recognition accuracy. The accuracy of data processing parameters between the improved algorithm model and other models including ResNet50 [20], MobileNetV2 [20], ResNet101 [21], and MobileNetV1 [21] models was also compared. The ResNet model is a CNN network that can reduce the gradient reduction problem of algorithms in training residual models. The MobileNet model is a CNN class model that can reduce the number of parameters and model variations. Green vegetables were further used to test the proposed model compared with traditional methods.

Results and discussion

Comparison of crop recognition accuracy among different models

The recognition accuracy of different algorithms for three crops increased with the increase of sample size. However, after reaching a certain number of samples, the accuracy began to decline. The results showed that the proposed improved CNN algorithm demonstrated a relatively higher accuracy rate than that of other algorithms, and its accuracy recognition curve was also more stable than others (Figure 4). Such results might be due to the increase of sample number reducing the data processing ability of the other algorithms, leading to a decrease in their recognition accuracy. However, the improved CNN could achieve deep convolution, which ensured its accuracy not being affected.

Analysis of the accuracy and effectiveness of model pest and disease query

The query accuracy of the model for different pests and diseases was further validated. Query

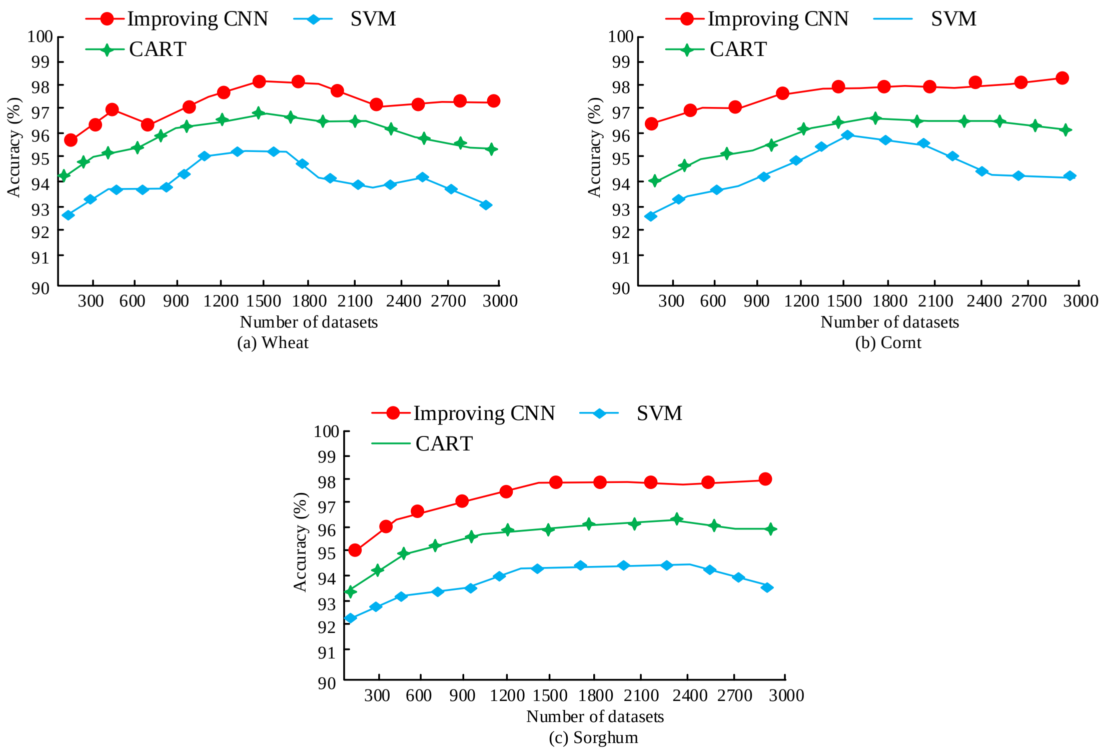

Figure 4. Comparison of accuracy of different algorithms for three crops.

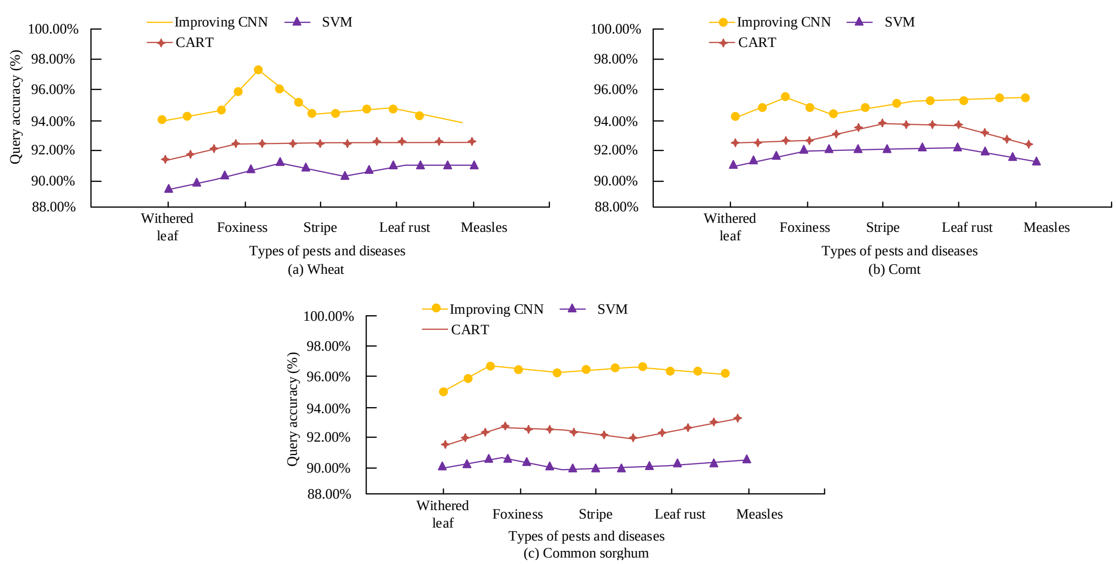

Figure 5. Comparison of the accuracy of disease and pest queries using three algorithms.

accuracy refers to the ability to accurately find disease and pest data during the sample recognition process. The query accuracy of the three algorithms signified that the algorithm model could accurately identify the current pest and disease images. In the comparison of the query accuracy of three algorithms for wheat diseases and pests, the improved CNN algorithm showed the higher trend in the change curve of query accuracy (Figure 5a), which indicated that

Table 2. Comparison of training accuracy for different model parameters.

Model name	ResNet 50	ResNet 101	MobileNet V1	MobileNet V2	Proposed model
Data-processing accuracy (%)	97.67	96.42	95.42	97.21	98.89
Number of training participants	8,452	8,472	8,325	8,631	8,854
Total number of training parameters	9,000	9,000	9,000	9,000	9,000

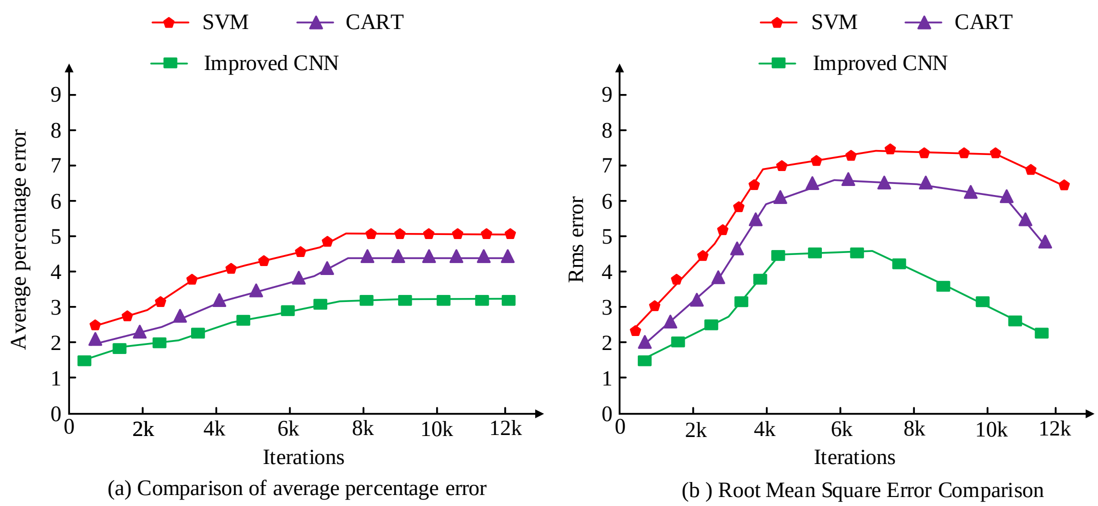

Figure 6. Comparison of average percentage error and root mean square error of the three algorithmic models.

the query accuracy of the algorithm would not undergo significant changes with changes in pests and diseases. There was not much difference in the trends of the three algorithms for analyzing corn pests and diseases compared to that of wheat (Figure 5b). The improved CNN algorithm showed the highest query accuracy. However, it was lower than that of wheat. The query accuracy of the three algorithms for sorghum demonstrated that the improved CNN was better than other algorithms (Figure 5c). The results confirmed that, among the three algorithms for pest and disease identification of crops, the improved CNN algorithm model was the most effective one.

Comparison of parameters for different types of CNN data

The comparison of the five algorithmic models showed that the accuracy of the proposed model performed the best among the five models with an accuracy of 1.22%, 2.47%, 3.47%, and 1.68% higher than that of ResNet50, ResNet101, MobileNetV1, and MobileNetV2 (Table 2). The results indicated that the proposed model outperformed other models based on CNN algorithms in data training and parameter processing, which might be due to different processing methods of proposed model. The number of training parameters for the proposed model was significantly higher than that of the other four models in terms of parameter training and processing.

Performance comparison of different models

To compare the training and recognition errors of the current algorithm models, the average percentage error and root mean square error of the proposed algorithm were compared with SVM and CART algorithms. The average percentage error trend of the three algorithms showed that, after the error value stabilized, the trends of the three algorithms first increased with the increase of iteration times. The

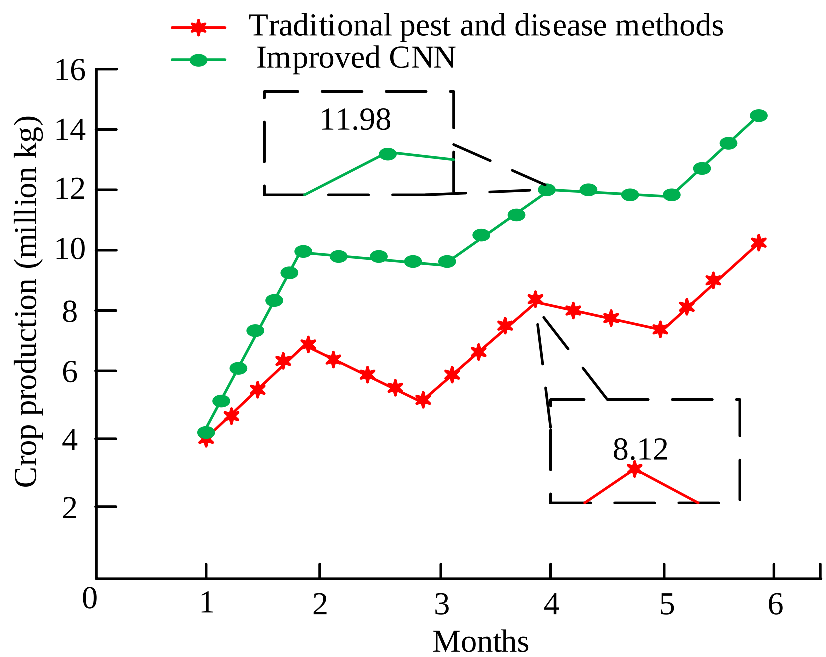

Figure 7. Comparison of yield changes after using improved CNN method for green vegetables.

improved CNN algorithm had the smallest error margin after reaching stability, which was around 2.8 (Figure 6a). In the comparison of root mean square errors, the trends of the three algorithms first increased with the increase of iteration times, and then decreased with the increase of iteration times, which might be due to the instability of the algorithms in calculating the root mean square error during the middle of the iteration (Figure 6b). However, the error value of the improved CNN algorithm was still the optimal one.

The impact of models on agricultural economic efficiency

The monthly yield of green vegetables was employed to test the impact of the current algorithm on the economic efficiency of agriculture. The data in April was randomly selected as the current comparison of green vegetable yields. The results showed that the improved CNN method significantly increased the yield of green vegetables compared to traditional methods with an increase of 3.86M kg (Figure 7). The results indicated that the use of improved CNN algorithms could improve the recognition of pests and diseases, thereby reducing their impact and improving agricultural production efficiency.

Conclusion

This research mainly focused on the study of the impact of pests and diseases on crop production efficiency and introduced agricultural information technology tools into pest management to improve agricultural production efficiency by reducing pests and diseases. After analyzing the occurrence and general control methods of agricultural pests and diseases, a new data collection system was constructed with the improvements of traditional CNN based method. The proposed method could recognize and analyze pest and disease images, improved the accuracy of current pest and disease identification, and thus achieved the goal of reducing pests and diseases and improving agricultural production efficiency. The results showed that the improved CNN had higher recognition accuracy than other algorithm models either for the recognition of disease and pest images or the recognition and analysis of datasets. The accuracy of the proposed model was higher than that of other different models. The crop production yield was higher when using the new method model. The results confirmed that using the proposed improved CNN model could improve the efficiency of current agricultural production and reduce the damage of pests and diseases. However, this research still had some shortcomings, which included that the information size of the crop dataset used in this study was small. More and larger datasets should be analyzed in the future.

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