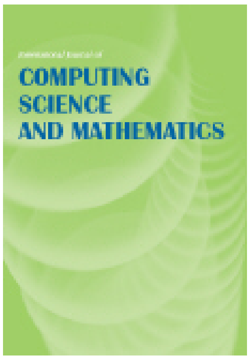

International Journal of Computing Science and Mathematics

ISSN online: 1752-5063 - ISSN print: 1752-5055
https://www.inderscience.com/ijcsm

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DOI: 10.1504/IJCSM.2023.10057854

Article History:

Received:	29 April 2022
Last revised:	14 March 2023
Accepted:	11 April 2023
Published online:	22 February 2024

Tea disease recognition technology based on a deep convolutional neural network feature learning method

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Abstract: China is a large tea country. Adopting more advanced science and technology to realise the intelligent identification of tea diseases will help to improve the planting, production and management of tea and carry out effective prevention and control of tea diseases. This research is based on the feature learning method of a deep convolutional neural network, introduces the optimal design of a high-order residual module, proposes an HRN algorithm, and combines self-attention mechanisms to improve the robustness of the HRN algorithm model. Through the simulation and comparative analysis with the other three algorithms, it can be seen that the HRN algorithm proposed in this study has better recognition efficiency and recognition accuracy, can effectively realise the recognition of tea diseases, and can be applied to the production and planting management of tea.

Keywords: convolutional neural network; tea; diseases; feature extraction; image recognition; high-order residual module; self-attention mechanism; tea tree disease spot.

Reference to this paper should be made as follows: Feng, Y. (2024) 'Tea disease recognition technology based on a deep convolutional neural network feature learning method', *Int. J. Computing Science and Mathematics*, Vol. 19, No. 1, pp.15–27.

Biographical notes: From 2004 to 2008, Yuhan Feng studied in Xinyang Normal University and received her Bachelor's degree in 2008. She received her Master's degree of Henan University of Science and Technology in 2014. From 2008, she works in Xinyang Agriculture and Forestry University. She has published 10 papers, one of which has been indexed by EI. Her research interests are IOT and AI.

1 Introduction

China has the longest history of tea planting and drinking. In ancient times, together with silk and porcelain, it was exported to other countries as a commodity represented by China. It is an important part of Chinese culture. At present, the Chinese are still the largest tea producer in the world, and the tea output in the world has always ranked first. Since 2014, China's tea production has shown a continuous growth trend, with the output of 204.93 million tons in 2014 and 2.97 million tons in 2020. As a big tea consumer, China has a huge tea consumption market. In the process of tea planting, there may be various diseases that affect the yield and quality of tea. In addition, the proliferation of modern pesticides makes more pesticide residues in tea. New diseases seriously affect the growth and yield of tea.

The traditional diagnosis of crop diseases mainly depends on the accumulation of long-term production experience, which has high technical and experience requirements for planting personnel. For some complex diseases, professional technicians are required to diagnose (Zhang et al., 2019; Camara et al., 2020; Goldstein et al., 2019). This requires a certain number of professional and technical personnel, which will be affected by the restrictions of time and place. It is difficult to effectively ensure the timely diagnosis of crop diseases, and it is easy to lose the best prevention and control opportunity. In this case, blindly taking a large number of pesticide spraying measures in the process of crop production may not only fail to obtain good treatment effect, but also cause serious environmental pollution when the yield is damaged (Mandal et al., 2019; Kim et al., 2020). The development of modern computer technology provides new technical support and ideas for the identification and management of tea diseases. The relevant algorithm technology for crop diseases has been gradually applied and achieved good control results.

The growing environment of tea is complex. Therefore, this paper uses convolutional neural network to identify tea diseases. Firstly, the traditional convolutional neural network is introduced and its basic structure is analysed. Then it is improved by introducing high order residual convolution neural network. On this basis, the self-attention mechanism is introduced to extract the global features of tea plant disease. Finally, the application effect of the improved depth convolution neural network in tea plant disease recognition is analysed.

This research has the following innovations:

1 The traditional convolutional neural network model is optimised and improved through the higher-order residual module, so as to learn the rich and detailed characteristics of tea plant diseases and improve the accuracy and robustness of the network model.

2 The self-attention mechanism is introduced to further extract the global features of the image, so as to improve the accuracy of tea plant disease recognition.

Higher order residual network can provide rich and detailed feature expression for disease appearance, and can effectively improve the disease identification accuracy of the model. At the same time, it also has a certain anti-interference ability, which can improve the robustness of the system to a certain extent. Self-attention network is mainly used to obtain the local features of the disease spot area, so as to achieve the extraction of effective features of tea plant disease spots and the high accuracy of tea plant disease recognition. By combining the advantages of the two, it can further improve the recognition accuracy and efficiency of tea plant diseases, and provide reliable technical support for tea plant disease management and control.

2 Research status at home and abroad

The damage of crop diseases to crops will directly affect the yield of crops, and serious diseases will even bring great losses. Therefore, it is necessary to carry out disease identification and prevention in time to reduce the losses caused by diseases as much as possible. Li et al. (2020) proposed the method of convolution neural network to identify common crop diseases. By building a common pest dataset of crops, they constructed a model for complex farmland scenes, which greatly promoted the research on the identification technology of crop diseases. Xin and Wang (2022) and others proposed to apply the deep learning algorithm to the identification of crop diseases, and creatively proposed a dcnn-g model. After testing and training 5000 samples, through simulation analysis, the recognition accuracy of the algorithm model can get the expected effect. Gajjar et al. (2022) proposed a machine learning method for crop disease prevention and elimination, and realised the positioning and recognition of leaves through convolution neural network combined with sensor technology, so as to realise the real-time recognition of crop diseases.

The intensification of agricultural ecology can greatly reduce the impact on the environment, and producers can obtain good benefits through less investment. Ecological agriculture will be the trend of agricultural development in the future. Adopting the method of ecological agriculture can effectively reduce the occurrence of diseases (Petit et al., 2020; Lei et al., 2021). Aminatun et al. (2020) analysed the impact of pesticides on the number and productivity of paddy crops through productivity data, used ANOVA test to understand the change relationship of different crop diseases, and analysed the relevant variables of crop diseases. Pokharel et al. (2021) proposed a deep learning algorithm for crop image recognition, and then for the prevention and control of farmland diseases. This algorithm is much higher than the recognition accuracy of the traditional DCNN basic algorithm model, which provides a new method and idea for the image quality evaluation of crop diseases. The application of remote sensing technology in disease management is becoming more and more mature. The use of remote sensing technology for relevant measurement and recording can collect relevant data of crops through the spectral behaviour of crops, help people formulate targeted pest management and reduce unnecessary pesticide use (El-Ghany et al., 2021).

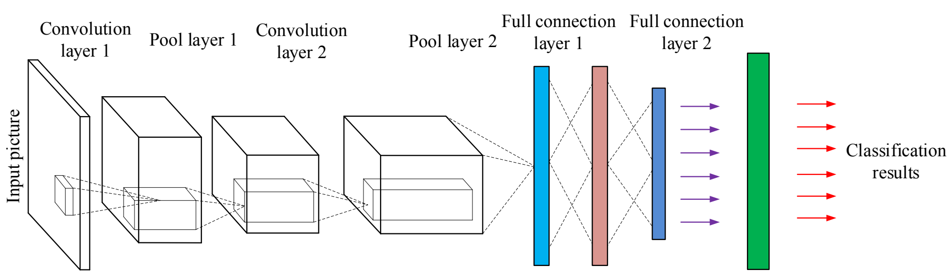
In the process of tea growth, gibberellin, a growth regulator, has potential harmful effects on human health. Jiang et al. (2020) used ultra-high performance liquid chromatography combined with mass spectrometry to analyse the degradation and metabolism of gibberellin in the process of tea growth and processing, and put forward measures to accelerate the degradation of gibberellin and promote the rapid growth of tea plants. Common tea diseases mainly include tea cake disease, tea ring spot disease, tea moire leaf blight, etc., and their location and manifestations will also be different. In the prevention and control of diseases and pests, we must be able to accurately identify them in order to suit the remedy to the case (Huang et al., 2020; Bharadwaj et al., 2021). It can be seen from the above literature that there are many kinds of tea plant diseases and it is difficult to identify them. In recognition methods, convolutional neural network, depth learning and remote sensing technology are widely used. Most of them are for image recognition of simple background, while the actual environment usually has various noises and complex background infection, which greatly reduces the accuracy of recognition. Therefore, considering the good performance of convolutional neural network in crop disease recognition, the study improved it by using high-order residuals, and introduced self-attention mechanism to jointly identify tea plant diseases, in order to further improve the recognition efficiency and accuracy.

3 Optimisation and improvement of a deep convolutional neural network

3.1 Deep convolutional neural network

Compared with the traditional neural network, convolutional neural network (hereinafter referred to as CNN) is a machine learning algorithm including multi-layer neural network, which can deal with complex background and large image problems, so it is very suitable for image recognition technology of tea diseases (Picon et al., 2019). Convolutional neural networks generally include convolution layer, pooling layer and full connection layer. Convolution neural network is characterised by using layer by layer convolution to realise weight sharing and pooling, which can gradually reduce the order of magnitude of network parameters, and finally realise the feature extraction and classification of targets. Its typical network structure is shown in Figure 1.

Figure 1 Structure diagram of typical convolutional neural network (see online version for colours)



The input layer in convolutional neural network is generally represented by the pixel matrix of the input image. The size of the input image is represented by the length and width value in the three-dimensional matrix, and the colour channel of the input image is represented by the depth of the three-dimensional matrix (Lanjewar and Panchbhai, 2023; Yang and Song, 2022; Jadhav et al., 2021). The most important part of convolutional neural network is convolution layer, in which each node input is a small block in the whole network structure. The pooling layer is to reduce the size of the matrix. Its essence is to convert the resolution of the picture to a lower resolution, and finally reduce the parameters of the network structure. The last layer is the full connection layer based on softmax activation function. After the operation of the previous convolution layer and pooling layer, the input image has been processed into information with significant characteristics. Finally, the classification needs to be realised through the full connection layer.

In the full connection layer, the function loss in the softmax model is represented by L, the output vector is S, its j value is S_j, y is a vector of $1*T$, and the loss function is:

$$L = -\sum_{j=1}^{T} y_i \log S_j \tag{1}$$

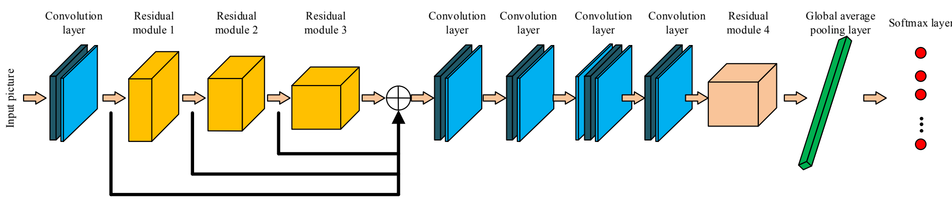
In equation (1), when j is limited to pointing to the real label of the current sample, it can be simplified as:

$$L = -\log S_j \tag{2}$$

3.2 Structure optimisation design of convolutional neural network

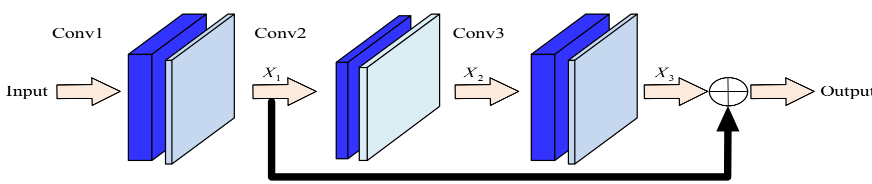
In order to cope with the complex environment in crop disease identification, a high-order residual convolution neural network (hereinafter referred to as HRN) is defined on the basis of convolution neural network, and its basic structure is shown in Figure 2. When inputting a tea image, the first convolution layer will be used to extract the low-level features, more image feature information will be extracted through three residual modules, and then the higher level image features are extracted through four convolution layers and a residual module. Finally, the recognition results of the image will be output through one pool layer and softmax layer to judge whether there is a disease problem.

Figure 2 HRN overall structure diagram (see online version for colours)



Since there are many kinds of diseases, it is necessary to define a high-order residual module that can effectively identify different disease characteristics. Its typical structure is shown in Figure 3.

Figure 3 Typical structure diagram of high-order residual module (see online version for colours)



In the residual module of Figure 3, there are three convolution layers Conv1, Conv2 and Conv3, and the corresponding outputs are X_1, X_2, X_3 according to the sequence. The residual sub network acquires more prominent micro information in the image by learning the residual function. The residual sub network realises that the low-level features extracted through convolution and the high-level details obtained through Conv1, Conv2 and Conv3 three-layer convolution are transferred to the following network structure at the same time to continue to extract more refined features. Their corresponding convolution kernel, step size and number of channels are shown in Table 1.

Table 1 Parameter setting of convolution layer of high-order residual module

Convolution layer	*CONV1*	*CONV2*	*CONV3*
Convolution kernel	3*3	1*1	3*3
Convolution kernel step	2*2	1*1	1*1
Number of channels	2x	x	2x
Output	X_1	X_2	X_3

Based on the idea of residual learning, it is assumed that:

$$H(x) = F(x) + X_1 = X_1 + X_3 \tag{3}$$

Therefore, the calculation formula of residual function can be obtained as follows:

$$F(x) = H(x) - X_1 - X_3 \tag{4}$$

More detailed and prominent small information can be obtained by using residual function $F(x)$. Through these three convolution layers, the image information can extract higher detail features, and transfer them to the subsequent network structure to extract more fine features, and finally obtain the global feature expression of tea image.

The Softamx function can calculate the gap with the labelled samples. The calculation is relatively simple and the effect is very significant. Therefore, softmax is selected as the final objective function of the network structure, and its expression is shown in formula (5). The expression formula of the objective function is:

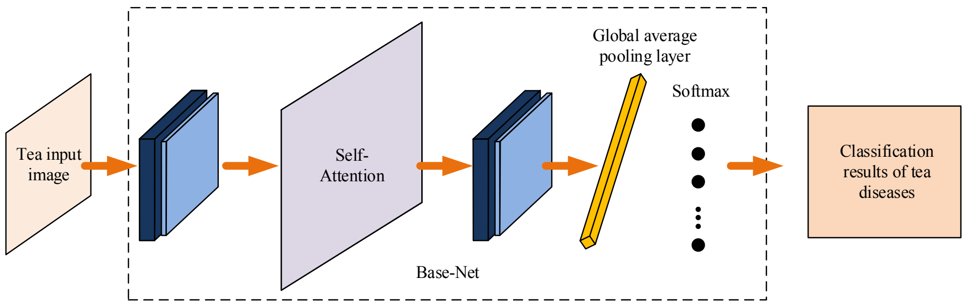
$$S(\theta) = -\frac{1}{L}\left[\sum_{L}^{l=1}\sum_{M}^{k=1} p(y_l == k)\log\frac{e^{\theta_p^L X_l}}{\sum_{p=1}^{M} e^{\theta_p^L X_l}}\right] \tag{5)}$$

In equation (5), $p(.)$ is the guiding function and y_l is the label corresponding to x_l, the number of training samples of the neural network is L, the number of categories of training samples is M, and the l training sample is x_l.

4 Tea disease identification technology based on improved HRN algorithm

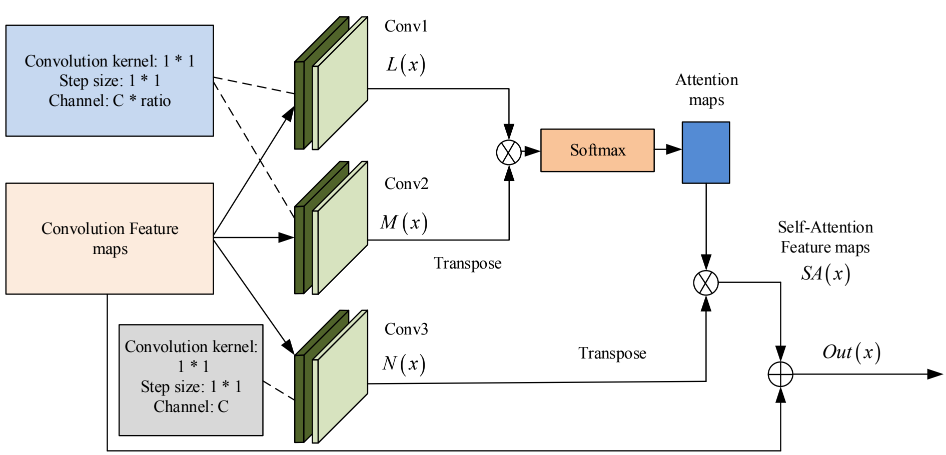
Tea disease image recognition based on improved depth convolution neural network needs to face more complex environmental noise interference and more influencing factors, especially the tea disease image has the particularity of small area and fuzzy background, so the algorithm model needs to have higher accuracy, better recognition efficiency and strong anti-noise ability (Zheng et al., 2020). The key of tea disease identification technology based on improved depth convolution neural network is to quickly lock the disease area and identify the disease types according to the sample data of the database (Estévez et al., 2020; Chen and Wu, 2023; Thangaraj et al., 2021). The attention mechanism in deep learning originates from the human attention mechanism, and its core is to select the information that is more critical to the current task goal from a large number of information, filter out the information that is not important to the target task, so as to save computing resources and improve processing accuracy. At the same time, the attention mechanism can add constraints to channel features to achieve feature recalibration. Therefore, the self-attention mechanism of deep learning is further introduced on the original basis to improve the processing accuracy and efficiency of the algorithm network (Turkoglu et al., 2022; Bao et al., 2020). The network framework constructed on this basis is shown in Figure 4.

Figure 4 CNN algorithm model architecture for tea disease identification based on self-attention mechanism (see online version for colours)



In Figure 4, the dotted box is the basic network structure, and the purple diamond is the self-attention module. It can be seen from Figure 4 that for the tea plant disease image to be identified, the probability of image category is calculated by introducing attention mechanism into the basic network, and then the classification result is obtained according to the probability calculation. After introducing the self-attention mechanism, the global features of tea diseases can be effectively extracted. The parameters of the convolution kernel are shown in Table 1. The over fitting can be effectively suppressed through three consecutive residual modules, and even if the sample data is not trained enough, it can have a good processing effect. The self-attention network structure introduced this time is shown in Figure 5.

Figure 5 Self-attention network structure diagram (see online version for colours)



Let the output via Conv1, Conv2 and Conv3 convolution layers be $L(x), M(x), N(x)$ respectively, so there are:

$$L(x) = W_l x \tag{6}$$

$$M(x) = W_m x \tag{7}$$

In equations (6) and (7), W_l, W_m is the weight parameter of the convolution layer. In order to carry out subsequent operations, it is necessary to convert the output of the convolution core, obtain attention maps through softmax layer processing, and finally obtain the key value Att_{ji} of SA (indicating the degree of participation of the model in the i position when synthesising the j region). Its calculation formula is:

$$Att_{ji} = \frac{\exp Fij}{\sum_{i=0}^{I} \exp(F_{ij})} \tag{8}$$

The calculation formula of F_{ij} in equation (8) is:

$$F_{ij} = L(x_i) M_{xj}^T \tag{9}$$

Let the output of attention map be $SA(x)$, and its calculation formula is:

$$SA(x) = N(x_j)^T Att_{ji} \tag{10}$$

It can be seen that the dimension corresponding to *SA* (*x*) is [Bitchsize, Area, Channel]. In order to perform and operate with *In*(*x*) to join the convolution layer of the subsequent network, you need to change the shape to [Bitchsize, Height, Width, Channel] and output it as *Out*(*x*):

$$Out(x) = \mu SA(x) + In(x) \tag{11}$$

After introducing SA, the robustness of the network structure will be significantly improved.

5 Simulation analysis

To analyse the application effect of the hrn algorithm proposed in this paper in tea disease identification, Leafsnap NN algorithm (Chompookham and Surinta, 2021; Bhagat and Kumar, 2022), SIFT SVM algorithm (Alamri et al., 2022) and traditional convolution CNN algorithm are selected for comparative analysis. Among them, Leafsnap NN method uses LEAR method to extract gist features, and then uses neural network to classify and recognise the extracted gist features of leaves. SIFT-SVM algorithm is a simple linear SVM classification method based on sparse coding linear space pyramid matching SPM core to recognise SIFI features. The experiment was carried out on a NVDIA GPU 1080i machine, and the HRN network parameters proposed in this paper are shown in Table 2.

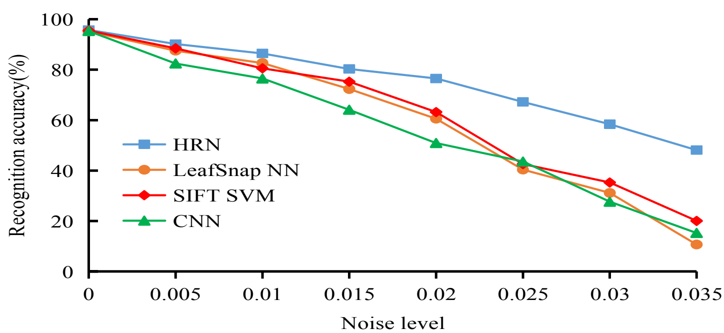
Table 2 The HRN network parameters proposed

Layer name (h/w/c)	*Output size (h×w)/stride*	*Filter size*
Convolute layer	256/256/8	3×3/1
Residual module 1	128/128/16	/
Residual module 2	64/64/32	/
Residual module 3	32/32/64	/
Feedback module	32/32/64	/
Residual module 4	16/16/128	/
Global average pooling layer	1×128	/
Softmax	1×6	/

Prepare 1000 photos of tea diseases. These photos have different factors such as environment, noise and light. The classification of diseases mainly includes five categories: Tea ring spot, tea moire leaf blight, tea white star disease, tea cake disease and other disease types.

Firstly, the four algorithms are simulated and analysed for the recognition accuracy of disease photos under different noise levels. The results are shown in Figure 6.

Figure 6 Comparative analysis of accuracy of four algorithms under different Gaussian levels (see online version for colours)



As can be seen from Figure 6, with the improvement of Gaussian noise level, the recognition accuracy of the four algorithms gradually decreases, but the reduction range of hrn algorithm proposed in this paper is the lowest. In the case of the same level of Gaussian noise, it always has higher recognition accuracy than the other three algorithms.

From 1000 pictures, 50 pictures of 5 types of tea diseases were selected, 250 in total. Then the four algorithms are used for image recognition and disease classification, and the classification results are shown in Table 3.

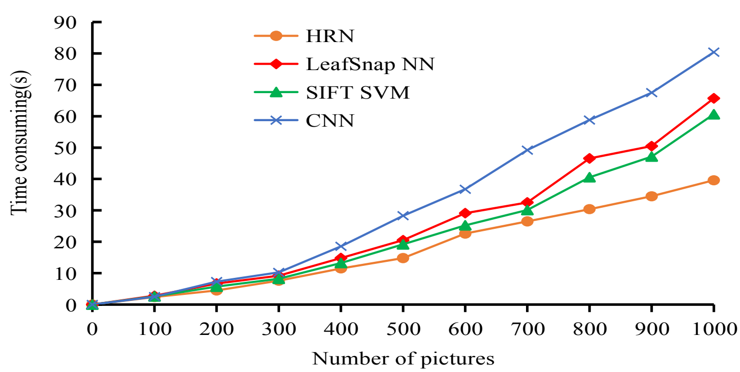
As can be seen from Table 3, the number of pictures accurately identified by HRN algorithm for tea ring spot disease, tea moire leaf blight, tea white star disease, tea cake disease and other disease types are 48, 47, 47, 49 and 49 respectively, the recognition accuracy is 96.0%, 94.0%, 94.0%, 98.0% and 98.0% respectively, and the comprehensive recognition accuracy is 96.0%. The highest recognition accuracy of Leafsnap NN algorithm, SIFT SVM algorithm and CNN is 82%, 84% and 76% respectively, which is far lower than the proposed HRN algorithm. This again shows that the improved hrn algorithm proposed in this paper has a good effect on tea disease recognition and classification.

Table 3 Image recognition and disease classification results of four methods

Method Type	*Disease type*	*Tea ring spot*	*Tea brown blight*	*Tea white star disease*	*Tea cake disease*	*Other disease types*
HRN algorithm	Accurately identify quantity	48	47	47	**49**	**49**
	Recognition rate	96.00%	94.00%	94.00%	**98.00%**	**98.00%**
Leafsnap NN	Accurately identify quantity	39	41	38	40	41
	Recognition rate	78.00%	82.00%	76.00%	80.00%	82.00%
SIFT SVM	Accurately identify quantity	38	42	37	39	39
	Recognition rate	76.00%	84.00%	74.00%	78.00%	78.00%
CNN	Accurately identify quantity	36	37	35	38	37
	Recognition rate	72.00%	74.00%	70.00%	76.00%	74.00%

Further analyse the recognition efficiency of the four algorithms, and compare and analyse the time required to realise the recognition of various diseases in 1000 pictures. The results are shown in Figure 7.

Figure 7 Comparative analysis of recognition efficiency of four algorithms (see online version for colours)



As can be seen from Figure 7, with the increase of the number of recognised pictures, the time consumption of the four algorithms is also gradually increasing. Compared with the other three algorithms, the HRN algorithm takes relatively less time and has significant differences in efficiency. Therefore, HRN algorithm has higher efficiency in tea disease image recognition.

Comprehensive analysis shows that the multi-layer image feature extraction and classification based on deep convolutional neural network can accurately realise the recognition and classification of tea diseases, has high accuracy and efficiency, and has more advantages than the other three algorithms.

6 Conclusion

The traditional convolutional neural network may have the problem of low recognition efficiency and accuracy in tea disease recognition, and the conventional crop disease recognition method is also difficult to deal with the image recognition in the complex environment of tea. In order to improve the robustness of the deep convolutional neural network algorithm and increase its effect on the extraction of tea image features, a high-order residual module is proposed to optimise and improve the network model, and the self-attention mechanism is used to improve the comprehensive performance of the algorithm model. In order to verify the feasibility of the hrn algorithm proposed in this paper, it is simulated and compared with Leafsnap NN algorithm, SIFT SVM algorithm and traditional convolution CNN algorithm. Under different noise levels, the HRN algorithm proposed in this paper has higher accuracy. The recognition accuracy of tea disease pictures reaches 96.0%, and its recognition efficiency is significantly higher than the other three algorithms. It can be seen from the research that after introducing the self-attention mechanism and high residual module, the deep convolutional neural network has better anti-interference ability, especially has a strong inhibitory effect on noise, and has a good application effect in tea disease identification.

Acknowledgement

This paper is supported by The Scientific and Technological Project of Henan Province (No. 222102210300):

Tea leaf disease recognition based on adaptive Meta-transfer learning and small samples.

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