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A transfer-learning-based feature classification algorithm for UAV imagery in crop risk management

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ABSTRACT

The development of precision agriculture puts forward higher requirements for the construction of an ecological irrigation area, some of which are the control of crop risk and the good circulation of the environment. In this paper, a method for extracting crops and weeds using remote sensing images of unmanned aerial vehicle (UAV) is proposed. The main three crops (wheat, peanut, maize) and three weeds (*Chenopodium album*, *Humulus scandens*, *Xanthium sibiricum* Patrin ex Widder) in the ecological irrigation area are collected by UAV. By manual labeling, 2,287 training sets and 979 test sets are formed. AlexNet, a transfer neural network, is trained in a single central processing unit (CPU), single graphics processing unit (GPU), and double GPUs to test the complexity of the algorithm. The classification results show that the accuracy of the *Chenopodium album* is 100%, *Humulus scandens* is 99.07%, *Xanthium sibiricum* Patrin ex Widder is 100%, wheat is 99.49%, peanut is 100%, and maize is 99.05%. The overall accuracy rate is 99.69%. The method proposed in this paper can accurately extract crops and weeds and calculate the quantity. The density of each weed can also be calculated in conjunction with the proposed density calculation method. It can provide a reference for the precise application of pesticides, thereby improving crop risk management capabilities.

Keywords: Ecological irrigation area; UAV; Weed classification; Convolutional neural network (CNN); Crop risk management; Remote sensing

1. Introduction

The ecological irrigation area is a system that is ecologically self-sustaining, economically sound, and has no negative impact on the environment for a long time and has a high level of productivity. The ecological irrigation area requires a high water resource utilization rate and has high standards for the ecosystem, pollution control, and management of irrigation areas. The ecological irrigation area is an important base for the development of modern agriculture and important support for regional economic development. It is also support for local ecological environment protection. To achieve modernization of irrigation area, one of the goals is to establish an effective barrier to remove agricultural pollution. At present, one of the causes of farmland pollution is the massive use of pesticides. According to the statistics from the Food and Agriculture Organization of the United Nations, there are more than 8,000 kinds of weeds in the world, and more than 250 kinds of weeds harming crops. At present, chemical weeding is widely applied. Extensive spraying of pesticides can control weeds, but it not only pollutes the environment, increases the cost of agriculture, but also poses a threat to food safety. Therefore, it is very important to achieve precise weeds prevention and control. Many scholars have conducted researches on weeds extraction, which are

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summarized as follows. Zheng et al. [1] proposed an automatic method for the detection of corn and weeds. In this paper, the traditional image segmentation method based on red-green-blue (RGB) value was abandoned, and a post-processing algorithm was used to distinguish maize and weeds. The accuracy rate was 93.87%. Shahbudin et al. [2] used Gabor wavelet and fast Fourier transform to extracting feature vectors of weeds image, then classified it based on the support vector machine (SVM). Sa et al. [3] presented an approach for dense semantic weed classification with multispectral images collected by a micro aerial vehicle, to realize the classification of weeds in the beet field. Ahmad et al. [4] implemented a real-time weed classification algorithm based on the Haar wavelet transform, which achieved 94% accuracy through segmentation, feature extraction, and classification. Vesali et al. [5] researched the weed identification of potato Tanaka. The machine vision method was used to extract primary colors from different plants and classified them by discriminant function. This paper also used a decision tree method to compare the results with discriminant analysis, and the highest accuracy rate was 87%. Lavania and Matey [6] proposed that the weed classification was divided into two steps: first, crop row monitoring. It was divided into image segmentation, double thresholding based on the 3D Otsu's method, and cropped row detection; and then used the principal component analysis method to realize the classification. The classification of weeds was achieved through these two steps.

In conclusion, most of the current weeds classification methods are based on the ground carrier, and complex image processing algorithms are used for feature extraction and classification. It induces such a method with poor adaptability and robustness. Fortunately, a convolutional neural network (CNN) can avoid these problems. The early model of CNN is called the neurocognitive machine. It is a bio-physical model inspired by the neural mechanism of the visual system. CNN has made a rapid development since its appearance in the field of deep learning. It has shown excellent performance in the field of image recognition [7], target location [8] and detection [9]. At present, CNN has been studied by many scholars and applied in many fields. Zhao et al. [10] proposed a 15 level CNN called "Fire_Net", which was used for fire classification, and it could be implemented effectively in wildfire detection. Li et al. [11] proposed that the well-known AlexNet CNN architecture was utilized in combination with a sliding window object proposal technique for palm tree detection and counting.

Unmanned aerial vehicle (UAV) is an aerial robotic system that can operate directly or remotely to complete flight behavior and other specific actions without direct operation by the driver. At this stage, the UAV is mainly divided into three types: single rotor [12,13], multi-rotor [14] and fixed-wing [15,16]. UAVs are widely used for their high automation, low cost, and high stability. UAV is used in monitoring [17], power line inspection [18], precision agriculture [19], surveying and mapping [20], rescue [21], wildlife protection [22] and other fields, and has achieved excellent effect. Among them, in the field of agriculture, Wang et al. [23] proposed a crop information collection system using UAV. Through the Django framework, the system could collect coordinate data and sensor data of UAV in real-time, and finally achieved the collection of crop growth information. Wei et al. [24] proposed a small-scale UAV for low-cost dynamic monitoring of terraces, which helped decision-makers to grasp the situation of farmland more comprehensively. Zhang et al. [25] proposed to use the UAV to spray the citrus, and compared the UAV spray with the artificial spray. Compared with the manual operation, the UAV was more efficient in spraying and lower in cost. At this stage, the use of UAVs in the agricultural sector has achieved a good effect, but more intelligent operations are still a challenge. Combining UAVs with deep learning is a trend to promote the intelligence of UAVs. In this paper, based on low-altitude plant images captured by UAV, a CNN method is proposed for weed classification. The method proposed in this paper aims to accurately calculate the number of weeds and the number of crops in the field, provide crop growth information for precision agriculture, and contribute to crop risk management. At the same time, the field information provided by the method can also provide reference for precise application of pesticides and reduce the use of pesticides, which reduces agricultural pollution and production costs, and improves food safety. The rest part of this paper is organized as follows. Section 2 introduces the principle and algorithm of CNN. Section 3 makes a series of pre-processing on the low-altitude plant image to prepare as the input of CNN. Section 4 implements the pre-trained AlexNet network by fine-tuning to classify 6 plants and puts forward a method for calculating the density of weeds. Section 5 concludes the whole work.

2. Convolutional neural network

CNN is a kind of multi-layer sensor which is originally inspired by neural mechanisms underlying visual system and was designed in view of the two-dimensional shape's identification. In 1962, Hubel and Wiesel [26] proposed the concept of the field concept through the study of cat visual cortex cells. In 1984, Miyake and Fukushima [27] proposed the Neocognition model based on the concept of the receptive field, which is regarded as the first realization of the CNN. In 1989, LeCun et al. [28] used the weight share technology for the first time. In 1998, LeCun et al. [29] combined the convolution layer and lower sampling layer to form the main structure of the CNN, which is the rudiment of the modern CNN.

2.1. Convolutional layer

The convolution layer is the core part of the CNN. Its main function is to extract local features of the input through the fixed-step movement of the convolution kernel. The core of the convolutional layer operation is to reduce unnecessary weight connections, introduce sparse or partial connections, and bring the weight sharing strategy to reduce the number of parameters greatly. The mathematical expression of the convolutional layer is as follows:

$$x_j^n = f\left(\sum_{i \in M_i} x_i^{n-1} * k_{ij} + b_j^n\right) \tag{1}$$

where x_j^n represents the jth feature map of the nth convolutional layer, $f(.)$ represents the activation function, M_i

represents the selected input feature map combination, x_i^{n-1} represents the ith output feature of the n–1 th layer, "*" represents the convolutional operation, k_{ij} represents the convolution kernel between the ith feature map of the previous layer and the jth feature map of the current layer, and b_j^n is the bias of the current layer.

2.2. Pooling layer

The pooling layer obtains the invariant properties of the higher level by the function transformation of the non-overlapping rectangular region on the upper output characteristic graph. Essentially, the perform space of pooling operation or the aggregation of feature type can reduce spatial dimensions. The mathematical expression of the pooling layer is as follows:

$$x_j^n = f\left(\beta_j^n * \text{down}\left(x_j^{n-1}\right) + b_j^n\right) \tag{2}$$

where x_j^n represents the jth feature map of the nth pooling layer, $f(.)$ represents the activation function, down represents the pooling process, β_j^n is a multiplicative weight value (its general value is 1), and b_j^n is additive bias (its general value is zero matrices).

2.3. Softmax regression

This paper deals with the classification of 6 different plants and adopts the softmax classification. Softmax classification is a kind of multi-classification problem which is similar to logistic regression, namely the label y can take k values. The softmax classification function is as follows:

$$h_\theta(x) = E\left[T(y) \mid x;\theta\right] = E\left[\begin{array}{c|} 1\{y=1\} \\ 1\{y=2\} \\ \vdots \\ 1\{y=k-1\} \end{array}\; x;\theta\right] = \begin{bmatrix} \phi_1 \\ \phi_2 \\ \vdots \\ \phi_{k-1} \end{bmatrix} = \begin{bmatrix} \dfrac{\exp\left(\theta_1^T x\right)}{\sum_{j=1}^{k}\exp\left(\theta_j^T x\right)} \\ \dfrac{\exp\left(\theta_2^T x\right)}{\sum_{j=1}^{k}\exp\left(\theta_j^T x\right)} \\ \vdots \\ \dfrac{\exp\left(\theta_{k-1}^T x\right)}{\sum_{j=1}^{k}\exp\left(\theta_j^T x\right)} \end{bmatrix} \tag{3}$$

$$\ell(\theta) = \sum_{i=1}^{m} \log p\left(y^{(i)} \middle| x^{(i)};\theta\right) = \sum_{i=1}^{m} \log \prod_{j=1}^{k} \left(\frac{e^{\theta_l^T x^{(i)}}}{\sum_{j=1}^{k} e^{\theta_l^T x^{(i)}}}\right)^{1\left\{y^{(i)}=l\right\}} \tag{4}$$

where the sample set is $\{x^{(1)},y^{(1)}\}$, $\{x^{(2)},y^{(2)}\}$, $\{x^{(3)},y^{(3)}\}$, …, $\{x^{(m)},y^{(m)}\}$. m is the number of training samples. 1 is an indicator function or an assertion function. 1{True1} = 1, 1{False} = 0. θ_1, θ_2, θ_3, …, θ_j are the fitting parameter of the model. The likelihood function for θ is used and the maximum of the function is found. Then, θ is brought into the classification function, which corresponds to output with highest probability value as the final classification result.

3. Data

3.1. Image acquisition

In this paper, the classification of 6 types of plants is realized. As shown in Fig. 1a, we collect 3 kinds of weeds and 3 kinds of crops, including *Chenopodium album*, *Humulus scandens*, maize, peanut seedlings, wheat, *Xanthium sibiricum* Patrin ex Widder, which are used for the classification of crop and weed by the CNN. The selection of maize, peanuts, and wheat is the main crop in the ecological irrigation area we studied. The type of weed selected is also the main weed that threatens crop growth in the region. The weed size targeted for this study is mid-plant growth morphology, the ground is dry, the light conditions are good, and the wind speed is less than 10 m/s. In the process of image acquisition, DJI-M100 UAV is used to fly at a fixed altitude of 2 m. For subsequent processing, all plant images taken at low-altitude are cut by the square base. The cropping images are shown in Fig. 1b.

3.2. Image processing

Because the AlexNet CNN input image size is 227 × 227 × 3, after cropping the image, the resolution is also handled as 227 × 227. For further expanding data set, the processed image should be rotated by 90°, 180°, 270°, respectively. The image of 6 rotated plants are shown in Fig. 2. The number of final data sets and the classification labels are shown in Table 1.

4. Experiments and discussion

4.1. Classification experiments

This paper classifies plants based on the pre-trained AlexNet CNN. AlexNet [30] was put forward by Alex in 2012. It greatly improves accuracy and reduces over-fitting through overlapping pooling, partial response normalization, and dropout. Pre-trained AlexNet has trained more than one million images on the ImageNet database and identified 1,000 categories of objects. The network has learned rich feature representations for a wide range of images. This paper adopts a transfer learning approach to learn new tasks on the pre-trained AlexNet. Transfer learning is a transfer of trained model parameters to a new model to help train the new model. Through transfer learning, the learned model parameters can be shared with the new model to speed up and optimize the learning efficiency of the model, instead of training a network with randomly initialized weights from scratch. Finally, the best classification effect is achieved using fewer training sets.

Fig. 3 shows the structure of the AlexNet, where the first layer is the input of the image, and the next five consecutive layers are convolutional, then the two layers are fully

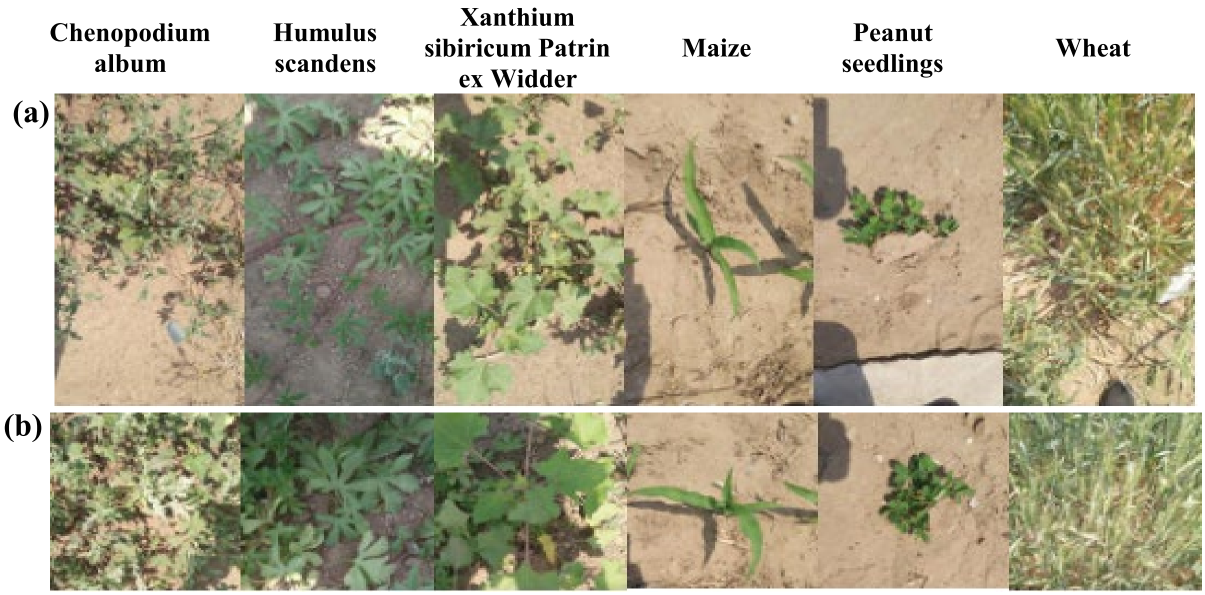

Fig. 1. (a) Low-altitude captured image and (b) cropped image.

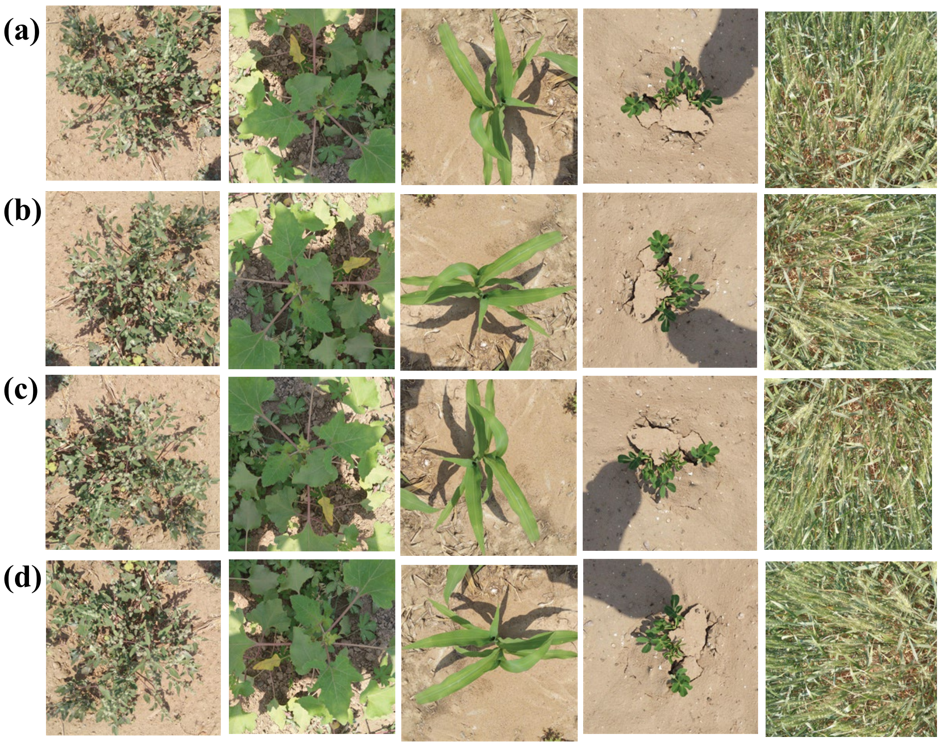

Fig. 2. (a) Non-rotation, (b) 90°, (c) 180°, and (d) 270°.

connected, and finally, the softmax layer implements six types of output. Since the pre-trained AlexNet network finally implements 1,000 categories, we reject the last 3 layers and re-establish a fully connected layer, a softmax layer, and a classification output layer for our task. At the same time, to make the new 3-layer training faster, "WeightLearnRateFactor" and "BiasLearnRateFactor" are both set to 20. Finally, the fast convergence of the neural network is realized.

The experiments are run on the matlab2018(a) platform. The hardware environment of the platform is a Lenovo workstation with double Intel(R) Xeon(R) CPU E5-2620 v4 dual-core CPU, double Nvidia GeForce GTX 1080 Ti and 64GB memory.

The experiments are conducted on a single CPU, single GPU, and multiple GPUs respectively to verify the training efficiency of the network. The number of iterations per

Table 1
Collection of sample set and label

	Chenopodium album	*Humulus scandens*	*Xanthium sibiricum* Patrin ex Widder	Maize	Peanut seedlings	Wheat	Total
Label	100,000	010000	001000	000100	000010	000001	–
Train set	370	252	227	490	490	458	2,287
Test set	158	108	97	210	210	196	979

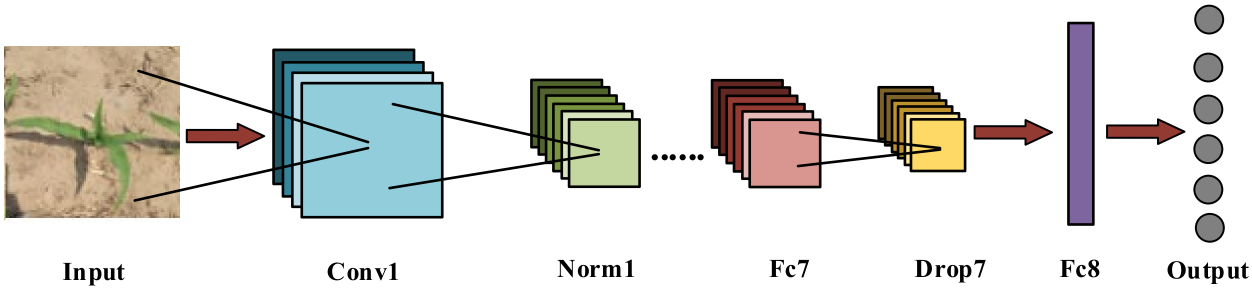

Fig. 3. Structure of the AlexNet CNN.

training is set to 430, and the consumption time and accuracy of each training are shown in Table 2.

From Table 2 it can be seen that training with a single CPU takes a lot of time, the training time with only a single GPU can be reduced to 20% of a single CPU, and that of using double GPUs can be reduced to 60% of a single GPU. Using double GPUs to train the neural network can greatly reduce training time. During the training process, two GPUs separately train a part of the network and only need to communicate with each other in the second convolutional layer and fully connected layer.

To test the effect of different iterations on the accuracy rate, the number of input pictures in a single batch is set to 50, the learning rate is set to 0.001, and experiments with iterations of 43, 86, 129, and 172 are performed. The consumption time and accuracy are shown in Table 3, and the accuracy and loss value in the training process are shown in Fig. 4.

As shown in Fig. 4, the network gradually converges to a better state when the iteration is about 10 times. With the further increase of iterations, the loss value further converges, and the accuracy rate also increases slowly. From Table 3, it can be obtained that when the number of iterations is 129 and 172, the network is optimal and the accuracy rate reaches 99.69%. However, to avoid overfitting and save training time, 129 times are selected as the optimal number of iterations. The accuracy rate of each type after 129 optimal iterations is shown in Table 4.

For further comparison, this paper uses the HOG + SVM [31] experiment. Histogram of oriented gradient (HOG) feature is a feature descriptor used for object detection in computer vision and image processing. It consists of calculating and counting the gradient direction histogram of the local area of the image. In this paper, the cell size is set to 6 × 6 pixels, and the block size is set to 2 × 2 with a 50% overlap. The basic model of SVM is to find the best separating hyperplane in the feature space to maximize the interval between positive and negative samples in the training set. HOG feature combined with the SVM classifier has been widely used in image recognition and detection. The accuracy rate of each type by HOG + SVM is shown in Table 4. From the number of classifications, it can be seen that the number of our method classifications is closer to the ground truth no matter which plant is classified. The accuracy of HOG + SVM is less than 90% for 5 categories, only one category is higher than 90%, and the total accuracy is less than 90%. In summary, our method is far superior to HOG + SVM.

4.2. Estimate of weeds density

The precise spraying depends on accurate weed density information. In the process of weed classification, the classification results can be used to estimate weed density. This paper uses the ratio of the number of weeds to the total low-altitude images to achieve the weeds density calculation. The equation is as follows:

Table 2
Single CPU, single GPU, and double GPUs experiments

Subject	Single CPU	Single GPU	Double GPUs
Consume time (s)	3,892	730	468
Accuracy (%)	99.69	99.69	99.57

Table 3
Effect of different iterations

Number of iteration	43	86	129	172
Consume time (s)	41	76	112	142
Accuracy (%)	96.02	98.59	99.69	99.69

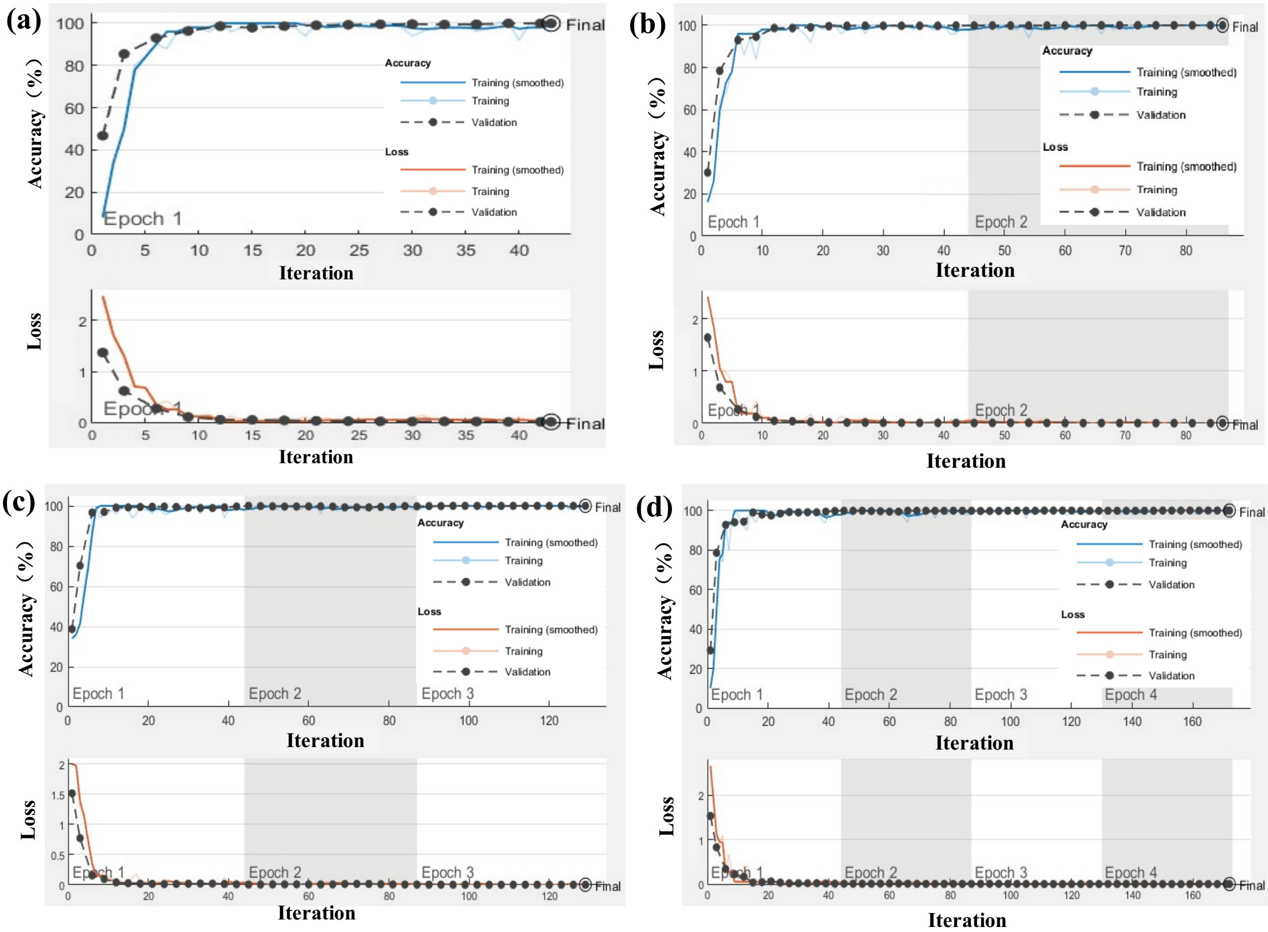

Fig. 4. Accuracy and loss value in different iterations during training (a) 43, (b) 86, (c) 129, and (d) 172.

$$\rho = \frac{\sum_{j=1}^{m} X_i^j}{\sum_{i=1}^{m}\sum_{j=1}^{m} X_i^j} \quad (5)$$

where j represents the number of samples of a type of plant, i represents the total types of plant, and ρ represents the density of weeds. Through this equation, the weed density in ecological irrigation areas can be calculated at low cost and convenience.

5. Conclusions

At present, the development of ecological irrigation areas is combined with the expressive needs of the people. The promotion of the concept of green development and

Table 4
Accuracy rate of each type after 129 optimal iterations

Subject		*Chenopodium album*	*Humulus scandens*	*Xanthium sibiricum* Patrin ex Widder	Maize	Peanut seedlings	Wheat
Ground truth		158	108	97	210	210	196
Experiment	Ours	158	109	97	208	210	197
	HOG + SVM	135	132	80	185	238	209
Accuracy	Ours	100%	99.07%	100%	99.05%	100%	99.49%
	HOG + SVM	85.44%	77.78%	82.47%	88.10%	86.67%	93.37%
Total accuracy	Ours	99.69%					
	HOG + SVM	85.64%					

the deepening of the concept of sustainable development allows more attention to focus on the development of modern agriculture. The low-altitude images captured by UAV are used in this paper, and the weed classification is implemented by using a CNN. Its accuracy rate can reach 99.69%, and it has the characteristics of good real-time and convenience. The main application scenarios of the method proposed in this paper are the ecological irrigation areas where maize, wheat, and peanut are planted. *Chenopodium album*, *Humulus scandens*, maize, peanut seedlings, wheat, *Xanthium sibiricum* Patrin ex Widder and three weeds can be accurately calculated. At the same time, this paper is based on Matlab 2018(a) fine-tuning pre-trained AlexNet network by using a single CPU, a single GPU, and double GPUs, and gives hardware parameters in detail, which provide a practical reference for remote-sensing deep learning based on Matlab. Using the density obtained in this paper, a set of evaluation indicators can be established to provide a reference for the application of variable spraying of pesticides in the later stage. In turn, it reduces the use of pesticides, reduces the production costs of agricultural products, improves food safety and ultimately achieves a good cycle of ecological irrigation area. However, this paper also has system limitations. When UAV acquires plant images, the wind speed is less than 10m/s, and the ground illumination is sufficient. At present, this method can only collect the number of main crops and weeds in the ecological irrigation area. Collecting more sample sets to achieve more crop and weed identification is also our next research direction.

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References

[1] Y. Zheng, Q. Zhu, M. Huang, Y. Guo, J. Qin, Maize and weed classification using color indices with support vector data description in outdoor fields, Comput. Electron. Agric., 141 (2017) 215–222.

[2] S. Shahbudin, A. Hussain, S.A. Samad, M.M. Mustafa, A.J. Ishak, Optimal Feature Selection for SVM Based Weed Classification via Visual Analysis, IEEE Region 10 Annual International Conference, 1 (2010) 1647–1650.

[3] I. Sa, Z. Chen, M. Popovic, R. Khanna, F. Liebisch, J. Nieto, R. Siegwart, WeedNet: dense semantic weed classification using multispectral images and MAV for smart farming, IEEE Rob. Autom. Lett., 3 (2018) 588–595.

[4] I. Ahmad, M.H. Siddiqi, I. Fatima, Weed Classification Based on Haar Wavelet Transform via K-nearest Neighbor (k-NN) for Real-time Automatic Sprayer Control System, International Conference on Ubiquitous Information Management and Communication, 1 (2017) 17.

[5] F. Vesali, M. Gharibkhani, M.H. Komarizadeh, Performance evaluation of discriminant analysis and decision tree, for weed classification of potato fields, Res. J. Appl. Sci. Eng. Technol., 4 (2012) 3215–3221.

[6] S. Lavania, P.S. Matey, Novel Method for Weed Classification in Maize Field Using Otsu and PCA Implementation, IEEE International Conference on Computational Intelligence and Communication Technology, 1 (2015) 534–537.

[7] S. Zhi, Y. Liu, X. Li, Y. Guo, Toward real-time 3D object recognition: A lightweight volumetric CNN framework using multitask learning, Comput. Graphics (Pergamon), 71 (2018) 199–207.

[8] K. Yanai, R. Tanno, K. Okamoto, Efficient Mobile Implementation of A CNN-based Object Recognition System, MM 2016, Proc. 2016 ACM Multimedia Conference, 1 (2016) 362–366.

[9] A. Qayyum, A.S. Malik, N.M. Saad, M. Iqbal, M.F. Abdullah, W. Rasheed, T. AB Rashid Abdullah, M.Y.B. Jafaar, Scene classification for aerial images based on CNN using sparse coding technique, Int. J. Remote Sens., 38 (2017) 2662–2685.

[10] Y. Zhao, J. Ma, X. Li, J. Zhang, Saliency detection and deep learning-based wildfire identification in UAV imagery, Sensors, 18 (2018) 712.

[11] W. Li, H. Fu, L. Yu, A. Cracknell, Deep learning based oil palm tree detection and counting for high-resolution remote sensing images, Remote Sens., 9 (2017) 22.

[12] J.S. Moon, C. Kim, Y. Youm, J. Bae, UNI-Copter: A portable single-rotor-powered spherical unmanned aerial vehicle (UAV) with an easy-to-assemble and flexible structure, J. Mech. Sci. Technol., 32 (2018) 2289–2298.

[13] X. Qi, J. Qi, D. Theilliol, D. Song, Y. Zhang, J. Han, Self-healing control design under actuator fault occurrence on single-rotor unmanned helicopters, J. Intell. Rob. Syst., 84 (2016) 21–35.

[14] X. Zhang, X. Li, H. Pei, R. Huang, Design of self balancing anti disturbance system for multi rotor UAV, Telkomnika (Telecommunication Computing Electronics and Control), 14 (2016) 363–371.

[15] S. Wang, Z. Zhen, J. Jiang, X. Wang, Flight tests of autopilot integrated with fault-tolerant control of a small fixed-wing UAV, Math. Prob. Eng., 2016 (2016), https://doi.org/10.1155/2016/2141482.

[16] C. Li, J. Shen, S. Zhai, C. Wang, J. Yang, Active flow vector flight control using only SJAs for a fixed-wing UAV, IEEE Access, 6 (2018) 76535–76545.

[17] A. Oscar, C.T. Calafate, Z.N. Roberto, N. Enrico, H.O. Enrique, C. Juan-Carlos, M. Pietro, A discretized approach to air pollution monitoring using UAV-based sensing, Mobile Network Appl., 23 (2018) 1693–1702.

[18] M. Shi, K. Qin, K. Li, Y. Zheng, Design and testing on autonomous multi-UAV cooperation for high-voltage transmission line inspection, Autom. Electr. Power Syst., 41 (2017) 117–122.

[19] C. Nived, L. Thomas, S. Cyrill, Robust long-term registration of UAV images of crop fields for precision agriculture, IEEE Rob. Autom. Lett., 3 (2018) 3097–3104.

[20] D. Yin, L. Wang, Individual mangrove tree measurement using UAV-based LiDAR data: possibilities and challenges, Remote Sens. Environ., 223 (2019) 34–49.

[21] B. Mesay Belete, Z. Abdallah, N. Abdelhamid, M. Farid, A convolutional neural network approach for assisting avalanche search and rescue operations with UAV imagery, Remote Sens., 9 (2017) 100, https://doi.org/10.3390/rs9020100.

[22] L.F. Gonzalez, G.A. Montes, E. Puig, S. Johnson, K. Mengersen, K.J. Gaston, Unmanned aerial vehicles (UAVs) and artificial intelligence revolutionizing wildlife monitoring and conservation, Sensors, 16 (2016) 97–115.

[23] X. Wang, H. Sun, Y. Long, L. Zheng, H. Liu, M. Li, Development of visualization system for agricultural UAV crop growth information collection, IFAC-Papers On Line, 51 (2018) 631–636.

[24] Z. Wei, Y. Han, M. Li, K. Yang, Y. Yang, Y. Luo, S. Ong, A small UAV based multi-temporal image registration for dynamic agricultural terrace monitoring, Remote Sens., 9 (2017) 904, https://doi.org/10.3390/rs9090904.
[25] P. Zhang, K. Wang, Q. Lyu, S. He, S. Yi, R. Xie, Y. Zheng, Y. Ma, L. Deng, Droplet distribution and control against citrus Leafminer with UAV spraying, Int. J. Rob. Autom., 32 (2017) 299–307.
[26] D.H. Hubel, T.N. Wiesel, Receptive fields, binocular interaction and functional architecture in the cat's visual cortex, J. Physiol., 160 (1962) 106–154.
[27] S. Miyake, K. Fukushima, A neural network model for the mechanism of feature-extraction, Biol. Cybern., 50 (1984) 377–384.
[28] Y. Lecun, B. Boser, J.S. Denker, Backpropagation applied to handwritten zip code recognition, Neural Comput., 1 (2014) 541–551.
[29] Y. Lecun, L. Bottou, Y. Bengio, Gradient-based learning applied to document recognition, Proc. IEEE, 86 (1998) 2278–2324.
[30] K. Alex, I. Sutskever, G. Hinton, ImageNet Classification with Deep Convolutional Neural Networks, NIPS Curran Associates Inc., 2012.
[31] A. Radman, N. Zainal, S.A. Suandi, Automated segmentation of iris images acquired in an unconstrained environment using HOG-SVM and GrowCut, Digital Signal Process, 64 (2017) 60–70.