Journal of Informatics and Web Engineering

Vol. 2 No. 1 (March 2023) eISSN: 2821-370X

A Data Augmented Method for Plant Disease Leaf Image Recognition based on Enhanced GAN Model Network

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Abstract - The identification of plant disease leaves based on deep learning is the key to control the development and spread of plant diseases. In this paper, the existing problems of traditional classification and recognition of plant disease leaves and the limitations of deep learning-based plant disease leaf training are analysed. An enhanced GAN model network based on the Wasserstein GAN loss function has been developed to address the limited training images of plant disease leaves. The self-attention layer is added into the self-encoding structure of the generating network. The effectiveness of data generated by the encoder is increased after the self-attention layer is added after the convolution. Finally, the model's training process is stabilised using the depth gradient punishment method. Three types of corn disease photos and 100 health images from the PlantVillage dataset were used as data sets in the experiment. An AWGAN model was applied to generate around 3000 images. Several data improvement techniques were applied to augment the same datasets. Comparative tests are conducted using AlexNet, VGG16, and ResNet18. The results indicate that the proposed AWGAN model is capable of generating sufficient images of maize leaf diseases with apparent lesions, making it a viable solution for data augmentation of plant disease images. The training model's recognition accuracy is significantly increased. The proposed awGAN-based image identification method for plant leaf disease efficiently resolves the over-fitting problem in the small sample training set. The model recognition accuracy in the ResNet18 network achieves 98.4%.

Keywords— Image Recognition, Deep Learning, Agricultural Disease, AWGAN Model

Received: 26 September 2022; Accepted: 11 November 2022; Published: 16 March 2023

I. INTRODUCTION

Global climate change deteriorates the natural environment, increasing food production susceptibility to disease and insect pests. Pests and diseases have an easier time spreading since the natural growing environment of crops has deteriorated. Soybean crops. Therefore, acquiring and identifying pest and disease information in crops promptly is necessary to increase crop productivity. In traditional crop production, human eyes are used to judge and diagnose diseases and pests. This requires skills, professional knowledge, and experience [1],[2],[3]. To solve the traditional artificial plant diseases

Journal of Informatics and Web Engineering
https://doi.org/10.33093/jiwe.2023.2.1.1

Published by MMU Press. URL: https://journals.mmupress.com/jiwe

and insect pests such as slow recognition method, high misdiagnosis rate, and high non-response rates, many researchers are using image processing technology and agriculture plant diseases and insect pests' recognition.

In recent years, Artificial Intelligence (AI), Big Data, the Internet of Things (IoT), Cloud Computing, and other technologies have significantly advanced manufacturing, medical, entertainment, and transportation industries [4]. Machine learning has already made huge breakthroughs in computer vision, speech recognition and robotics. The rise and excellent performance of generative adversarial networks in recent years have attracted the interest of many researchers [5]. Among them, compared with the data enhancement method based on geometric transformation and image manipulation, which can effectively alleviate the neural network, the method of generating adversarial network to generate new samples is much more complicated but can enrich the diversity of samples [6]. It supported agricultural development modernization and enhanced crop productivity and quality. Image processing and AI technology have increasingly become an efficient approach to aid in the identification, monitoring, and detection of crop diseases.

Extensive research has been done on image recognition for agricultural plant diseases but there are still many deficiencies. It is difficult to practice application and agricultural production activities. There are numerous local feature images of different crop diseases and insect pests had been stored in the repository. However, when disease images are acquired against a variety of different backgrounds, weather conditions, and degrees of damage, their applicability is frequently compromised, and the recognition effect is distinctly average [7]. The look, posture, form, and amount of numerous target items in an image may vary. They are also distorted by various factors such as illumination and occlusion, increasing the complexity of target detection [8]. The multiple positions of the appearance form, the uncertainty associated with illumination changes, and the diversity of the background all lead to lower robustness and generalizability of manual feature design methods [9], while the complicated algorithm steps result in low detection efficiency and accuracy.

Although large amounts of data can be collected in some fields, data annotation is time-consuming and complicated, and poor data annotation will have a direct impact on the model's generalisation effect [10]. A large amount of labelled data is necessary to train the model. The entire monitoring procedure involves human input since agricultural pests and diseases take on different shapes and features at different times of the year. As a result, traditional crop pest methods must develop multiple classification standards for various crops and diseases.

Traditional machine learning disease recognition starts with image acquisition and uses image processing techniques such as denoising, image segmentation, swelling, and corrosion to pre-process the image. Then, image features were extracted and analysed using classical machine learning algorithms such as the least square method, Support Vector Machine (SVM), principal component analysis (PCA), and K-means clustering algorithm (K-MEANS clustering algorithm), and maximum inter-class variance method (McOvariance). Thermal imagery and depth information were integrated to generate a row feature set from local and global locations and to increase the detection accuracy of unhealthy plants [11]. [12] used deep CNN to classify 26 illnesses affecting 14 crops with a 99.35% accuracy. The CNN model was trained on 87,848 images from 25 distinct plants and obtained 99.53% accuracy in identifying healthy leaves from damaged crop leaves.

With the advent of GPUs, big data, cloud servers, and the Torch, TensorFlow, Pytorch, and Caffe frameworks, deep learning has found applications in image recognition, text recognition, speech recognition, automatic driving, and cancer detection, among other fields. Similarly, deep learning can compensate for the disadvantages of traditional agricultural disease identification by offering high accuracy, a fast detection time, and a high degree of stability. [13] used transfer learning and a selective convolutional kernel module to replace global average pooling with global average pooling to improve the recognition rate and recognition time of apple disease spots due to their small size. As a result, the model had a good recognition effect on small disease spots.

[14] proposed a method for detecting cucumber disease using multi-scale convolutional neural networks to improve DCNNs by using global average pooling instead of a full connection layer when training time for traditional image recognition is lengthy and generalisation ability is limited. Deep learning, like standard recognition, comprises three steps. Pre-processing of data, design and development of models, and training data. However, convolutional neural network feature extraction typically takes a considerable amount of data. In most circumstances, while studying data from a small sample size, the recognition rate will fall short of the required level. As a result, only data expansion can enable the application of the limited sample field in deep learning.

To address this issue, and A-WGAN model was proposed for the generation of images of plant disease leaves. Deep learning is utilised to train the image identification model, which is based on a large amount of plant disease leaf image data. The purpose of data enhancement is to mitigate the over-fitting phenomena of neural network models through the use of conventional image processing techniques such as spatial affine transformation and colour transformation on existing image data sets. The WGAN network model is utilised to ensure that training is stable and unaffected by hyperparameters. By incorporating a self-attention layer into the self-coding structure of the generative network, the limitations associated with traditional feature extraction via convolution and transformation between feature graph and matrix can be alleviated, while also enhancing the global feature in image processing.

In this study, an image recognition experiment on plant disease leaves in a small sample scenario, demonstrating and analysing the difficulties associated with the image identification task on small sample disease leaves. For the image recognition job of small sample plant leaves, a Wasserstein loss function was introduced, and the phenomena of pattern collapse were successfully improved [15]. Finally, in comparison to the conventional data enhancement method, the proposed method is shown to be effective at identifying small samples of plant diseases.

II. RELATED WORKS

The recognition ability to exist in image recognition models depends on training on a large number of data sets containing manually labelled images. In many practical application scenarios of image recognition, some categories often lack or even have no samples. In addition, in some application scenarios, the target categories of image recognition are increasing. It is impractical and time-consuming to select and label valid sample images for the ever-increasing target categories [16]. Therefore, research in unsupervised and semi-supervised learning can better address the problem of lack of labeled data. However, due to the large variety of plant disease image data, the training of the deep network model requires a large number of training samples. A small number of plant disease leaf image sample data is not enough to train the huge weight of network parameters [17]. Only small samples of plant leaves are used as the training set to train the deep neural network model, which is easy to over-fit and has poor generalization ability, resulting in low accuracy of lithology identification and unsatisfactory effect of intelligent identification model in image recognition of plant disease leaves. In addition, the commonly used data enhancement methods are usually geometric transformation of the original image, such as flipping, rotating, clipping, scaling and color transformation of the image of plant disease leaves, such as changing colors, adding noise, blur processing & erasing [18].

GAN has attracted much attention as an emerging generative model for unsupervised learning, and there is a growing desire to use GAN in many fields [19]. So far, GAN has been studied and applied in image generation, speech synthesis, target detection, style migration, privacy protection, etc. Generative Adversarial Network (GAN) mainly generates samples with the same distribution as the target input through the game between generator and discriminator. It is widely used in image generation, image style migration and other image tasks [20]. The generative adversarial network had been widely implemented by many researchers [21]. Finally, the discriminant network needs to be "in the game equilibrium" by probability value is infinitely close to 0.5 make sure the game results generate against the network to determine the specific model. Here discrimination network is essentially similar to a two classifiers [16], because each input sample discrimination in the network will be a probability value of the said amount of the samples from the real sample or generate sample judgment if the probability value in the range of [0, 1] slants big, comes from the real sample, if small probability value, If the probability value is infinitely close to 0.5, it means that the discriminant network cannot judge the source of the sample, that is, the generative adversarial network is in the training equilibrium state at this time. The generative network and adversarial network in generative adversarial network are independent from each other: the input of generative network is noise Z selected from random distribution, and the output is data $G(z)$ synthesized by feature extraction of generative network. The input of the discriminant network is $G(z)$ and the real data X, and the output is a probability value, representing the probability that each sample is close to the real data. Figure 1 shows the principle of the generative adversarial network.

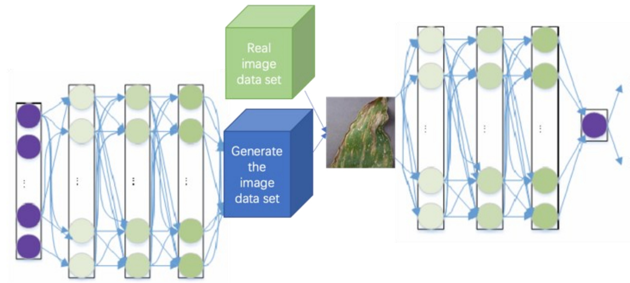

Figure 1. Principle of the Generative Adversarial Network

Over the network operation generated in the process, the main purpose of the resulting network is to maximize the discriminant network error probability, which is originally discriminant network input for the real sample, identifying network is identifying it as false samples, or samples of the original input discrimination network is false, identifying network is identifying it as a real sample. Functions *G* and *D* can take many possible forms, but there is only one condition that keeps the generative adversarial network in equilibrium. *D(x)* means *x* comes from the real sample. If the training generation network can make real samples and generated samples get the correct allocation, and the probability of correct allocation reaches the maximum, then the value of log(1−D(G(z))) can be minimized, so the discriminant network needs to be trained at the same time. While training *G*. This is the minimax game used to determine the function *V (G, D)* in the operation principle of generative adversarial networks. Figure 2 shows the Schematic of generating adversarial network training.

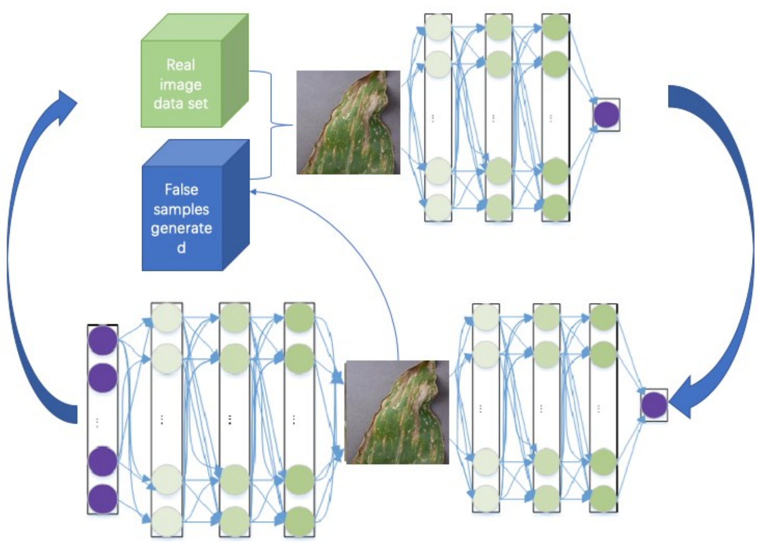

Figure 2. Schematic of Generating Adversarial Network Training

The value function of GAN is shown in the Equation (1) below:

$$\min_{D} \max_{G} V(D, G) = E_{x \sim p_{data(x)}}[\log D(x)] + E_{x \sim p_{z}(x)}[\log(1 - D(G(z)))] \tag{1}$$

As shown in Figure 2, at the beginning of the training of the generative adversarial network, the distribution of real samples, the distribution of generated samples Pg(*G*) and the change of discriminant distribution are closely related to the training process. The random noise *Z* is the input, the sample distribution in the noise is uniform in the initial state, and the real sample *X* is the reference. The whole training process represents the method of *x*=G(*z*) adding non-uniformly distributed

Pg to uniform noise. At the beginning, the gap between real samples and generated samples is the largest, so the discriminant network cannot distinguish them correctly at this time. First of all, the generative network remains unchanged and only the discriminant network is trained. At this time, the discriminant network has improved its discrimination effect on real samples and generated samples. Then, the discriminant network remains stationary and only trains the generative network, to confuse the discriminant network so that it is impossible to distinguish whether the sample belongs to the real sample or the generated sample. After such training methods keep iterating until finally converges to the corresponding loss, and the discriminant network has reached the state of being completely undistinguishable. At this time, the training of generative adversarial network is finished, and the model is determined accordingly.

III. RESEARCH METHODOLOGY

A. Self-Attention

In this paper, the introduction of self-attention layer [22] is to add the self-attention layer into the self-coding structure of the generation network. At present, convolutional neural network (CNN) often appears in deep learning, but the standard and conventional CNN algorithm still has loopholes in some occasions, so many scholars will make different improvements based on the standard CNN structure. The core process of encoder-decoder network structure is to first obtain a potential vector by convolution, activation and pooling of the input image, and then restore the size of the output image through a series of deconvolution to make it consistent with the size of the input image [23]. It can be seen intuitively that the codec structure is symmetric, and its main component is the convolution layer, which is characterized by simple principle and relatively accurate processing results. Therefore, many researchers choose the codec structure. Enlarging the filter or deepening the network layer to overcome this shortcoming, but not only the result does not get outstanding advantages.

In this paper, attention generation adversarial network is used as the infrastructure, and the main body of the generation network is also self-coding structure. Therefore, adding the self-attention layer after the convolutional layer can enhance the effectiveness of the original network to generate images of plant disease leaves, and add feature superposition on the basis of the original self-attention layer structure. The inspiration of self-attention mechanism is derived from the field of natural language processing. Based on the unique structural design of self-attention mechanism, the limitations of traditional feature extraction by convolution, transformation between feature graph and matrix can be alleviated, and the global feature in image processing can be enhanced. This helps improve the network structure and improve network performance [24].

There are three convolution channels, F, G and H, which are dispersed from the feature graph extracted from the output $x \in R^{C \times N}$ of the previous convolution layer [25]. They can also be called the three feature Spaces, whose purpose is to obtain the content associated with attention in a more comprehensive way. Among them $F(x) \rightarrow W_{F^x}$, $G(x) \rightarrow W_{G^x}$. See Equation (4) below for explanation.

$$\beta_{j,i} = \frac{\exp\,(S_{ij})}{\sum_{i=1}^{N} \exp\,(S_{ij})}, S_{ij} = F(x_i)^T G(x_j) \tag{4}$$

$\beta_{j,i}$ in the formula means that the network divides the picture into different detail parts in the process of generating the picture. If the J part needs to be generated, the attention weight of the I part should be given. The output of the self-attention layer is $o = (o_1, o_2, \dots o_j, \dots o_n) \in R^{C \times N}$. C represents the size of the convolution parameter channel.

$$o_j = v\left(\sum_{i=1}^{N} \beta_{j,i} h(x_i)\right), h(x) = W_{hx_i}, v(x_i) = W_{vx_i} \tag{5}$$

In the above Equation (5), $W_G \in R^{C\times C}$,$W_F \in R^{C\times C}$, $W_H \in R^{C\times C}$ is the weight to be updated during the whole process. Here, F G, H three feature space used by the convolution kernel size is 1, because the number of channels in the experimental process step by step C has been reduced, until the number of channels into $\frac{C}{8}$, the end result can be found bad degree is small, also the part of the training data set, the specific purpose was to help determine the best effect of k value, C. Through observation and analysis, $\frac{C}{8}$ was selected for training.

B. Wasserstein distance

Wasserstein distance is a fictitious term that refers to the difference between the data distribution pr and the model distribution pg. Wasserstein distance is proposed in the WGAN (Wasserstein GAN) algorithm [26]. Instead of using the Jen-Sen-Shannon (JS) scatter, the algorithm uses the earth-mover distance to calculate the similarity between the probability distribution of the real data and the generated data. It is able to solve problems such as training instability and gradient disappearance. For binary classification, the original GAN output is true or false, while the WGAN output is the Wasserstein distance, which is used in regression tasks to represent the distance between the generated distribution and the true distribution.The Wasserstein distance becomes smaller because the generated image is closer to the true diseased leaf image [6] as depicted in Equation 6.

$$W\left(p_r, p_g\right) = \underset{y\in\prod(p_r,p_g)}{inf} \square_{(\hat{j},j)\sim y}[||\hat{j} - j||]. \tag{6}$$

$\prod\left(p_r, p_g\right)$ indicates the set of the joint distribution of data distribution $p_r$and model distribution p_g for edge distribution of （$\hat{j}, j$） .As found on（$\hat{j}, j$） liable to Y distribution, the minimum expected of to $\|\hat{j} - j\|$ is the Wasserstein distance.

The Equation (6) of the abovementioned loss function can be expressed as follows (see Equation (7)):

$$W\left(p_r, p_g\right) = \underset{G}{min}\,\underset{D}{max}\, \mathbb{E}_{x\sim p_r}[D_\theta(x)] - \mathbb{E}_{\hat{j}\sim p_g}[D_\theta(G(x))] \tag{7}$$

Where $W\left(p_r, p_g\right)$ is the distance between real image data set distribution p_r and generated image data set distribution p_g.

C. AWAGN Network structure

The attention waserstein generative adversarial network (AWGAN) is a specially designed image generation network that solves the overfitting problem in image-based plant leaf disease recognition tasks by efficiently generating pseudo-training images with large variations.AWGAN is built on the traditional GAN using Wasserstein distance and introducing a self-attentive mechanism that enables the network to transform relevant regions (e.g., leaf regions) while preserving the background.AWGAN focuses only on the leaf area, producing natural and convincing images.

Attention generative adversarial network and feature fusion generative adversarial network are both enhanced based on attention generative adversarial network. The final layer of a convolutional neural network that classifies images is typically a softMax layer whose maximum value corresponds to the classification category. If the backward propagation begins at the node of the category with the highest probability of classification, the gradient of the final convolutional layer can be obtained, and the region of the image that the neural network focuses on when classifying the category can be observed. AWGAN Two discriminators must learn the actual data of their respective domains to determine whether the data generated by the respective domain generator is local domain data. The discriminator is a binary neural network model designed to differentiate between real and generated data. The attention block produces the attention-activation graph A(x) of the leaf after receiving A healthy leaf image X, which represents the image region on which the generator should concentrate, namely the leaf part.

As illustrated in Figure 3, the AWGAN model structure is as follows: the left input images are awaiting processing of plant leaves; the input to the note - loop module obtains attention and concentration distributions; the concentration degree is also different due to the different training time in different time steps; the concentration distribution in the note below mapping attention more, disease areas are more prominent. Then, it is combined with the sample and input into the middle self-coding structure, where the image with disease is generated. Finally, it is fed into the discriminant network, which performs the discrimination. Figure 4 shows the overall network architecture of AWGAN.

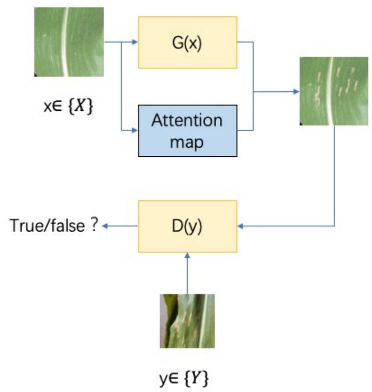

Figure 3. Schematic of Generating Adversarial Network Training

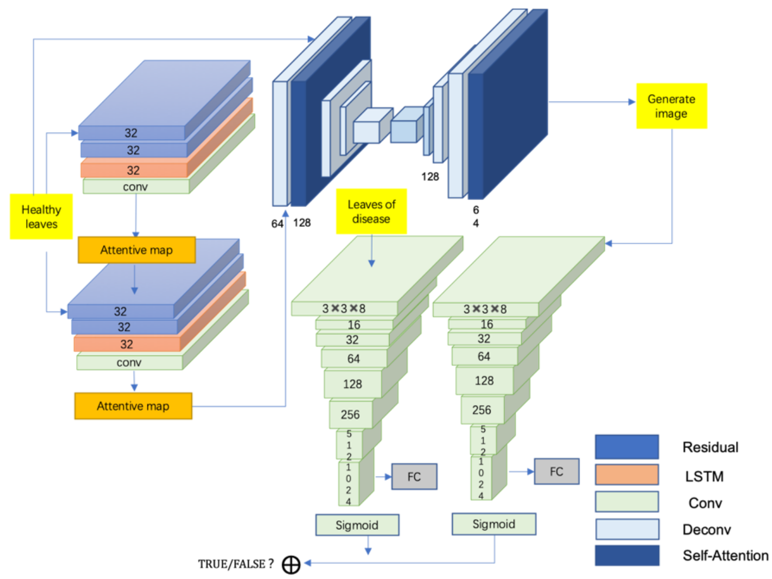

Figure 4. AWGAN Network Structure

IV.RESEARCH DESIGN

In order to test the effectiveness of AWGAN network data enhancement, experiments were designed to compare and analyse the correctness of different training models on the same experimental data set in the identification of plant leaf diseases.

A. Data Set

Around 50,000 images of 38 pests and diseases are included in the PlantVillage dataset. It is difficult to obtain images of crop disease leaves in the majority of real-world scenarios. Although the PlantVillage data set contains disease information for a variety of crop varieties, each crop may be infected with numerous diseases. However, obtaining image data of healthy leaves is quite simple. To more accurately simulate the actual scene, which lacks images of diseased leaves, the experiment employs an AWGAN network model to generate images of diseased plant leaves to compensate for the training set's data deficiency. The experimental data set consisted of 300 images of corn leaves from the PlantVillage data set B. The training data, validation data and test data are divided according to the ratio of 6:2:2. The experimental platform configuration is shown in Table 1.

Table 1. Experimental Environment

The Operating system	Window 10
CPU	3.8GHz
GPU Memory	GTX3090 32G
Deep Learning Framework	Tensorflow. OpenCV

B. Experimental Steps

Images of healthy corn leaves were used as input in this experiment to generate images of diseased spots (See Figure 5). Since WGAN networks are mostly used for style migration, and CycleGAN [27] and LeafGAN [28] models have shown advancement in the field of plant leaf data enhancement, they were used as the baseline model for this experiment. and then the improved attentional activation graph-based model was used for comparative experiments. Two models were used to add 500 pieces to the unbalanced corn data set. The classical deep learning network models VGG16 , and ResNet18 were then used to identify the unbalanced maize dataset separately, and the recognition accuracy before data expansion was compared.

Figure 5. Data Set Construction

C. Comparative experiment on enhancement effect of corn disease recognition data

In the unbalanced classification task, the categories with large sample size were defined as multi-category or negative category, while the categories with small sample size were defined as few categories or positive category. Even if the classifier predicts all the sub-class samples incorrectly in the training process, its recognition accuracy is as high as 99%. Such high accuracy will lead to the failure of the target loss function to provide enough gradient for the model to train. In order to avoid this problem, the number of healthy leaves of each crop is also limited to 10 when training the small sample crop classification experiment, and a large number of healthy leaves are needed as the source domain data to be converted in the leaf image recognition experiment of small sample. Therefore, only 100 healthy leaf images are randomly selected. In this way, different data enhancement methods are adopted in the experiment to construct a small sample leaf image data set in this experiment. The training data set consists of 3 categories with a total of 3000 pieces, and the corresponding test set of each category is 1000 pieces. In the comparative experiment of crop data enhancement effect, AlexNet, VGG16 and ResNet18 CNN models were selected as the image recognition models of crop leaf diseases. As shown in Table 2, the original small sample crop disease identification data set consists of three categories, 100 for each category, including healthy leaves. Traditional Data Augmentation is such as flipping, rotating, clipping, scaling and color transformation of the image.

Table 2. Corn disease Leaf Image Recognition Dataset

DataSet	Quantity
Original Data	100
Traditional Data Augmentation	10000
AWGAN	30000
CycleGAN	20000
LeafGAN	30000
Test Data Set	10000

V. RESULTS AND DISCUSSIONS

Three groups of experiments (See Figures 6,7 and 8) of the same CNN model selected the same initial network learning rate, optimization algorithm, and the same number of iterations. Softmax has often been used in traditional machine learning model and CNN model classification task, more as a model of the output layer, it will be a number of neurons in the output is mapped to [0, 1] within the scope of the network output is more like a legitimate probability distribution, and these different labels corresponding probability value accumulation and classification of 1. The label corresponding to the output maximum probability value is the final classification result of the network. Softmax not only gives the network output interpretability, but also simplifies the gradient derivation process and solves the problem of unstable numerical calculation of cross entropy loss function. In this experiment, 128 X 128 pixel leaf images were used.

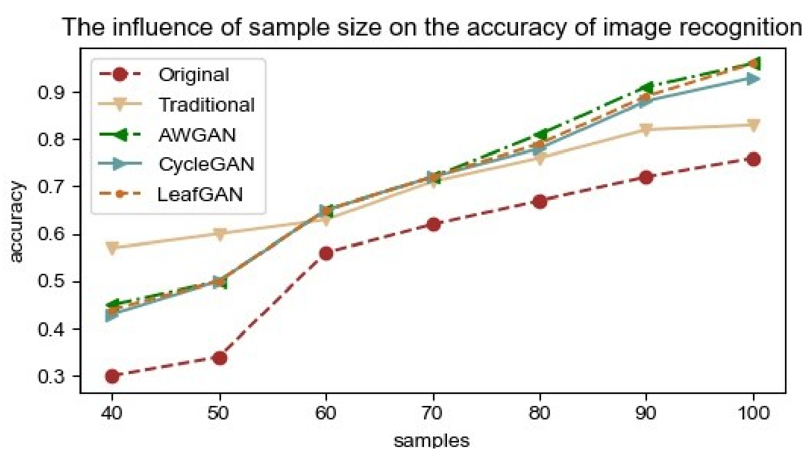

Figure 6. The Accuracy of Different Data Enhancement (Alexnet)

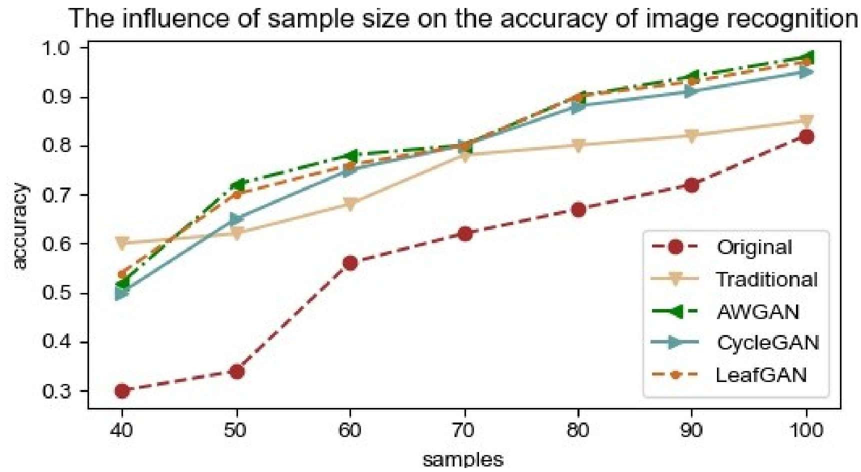

Figure 7. The Accuracy of Different Data Enhancement (VGG16)

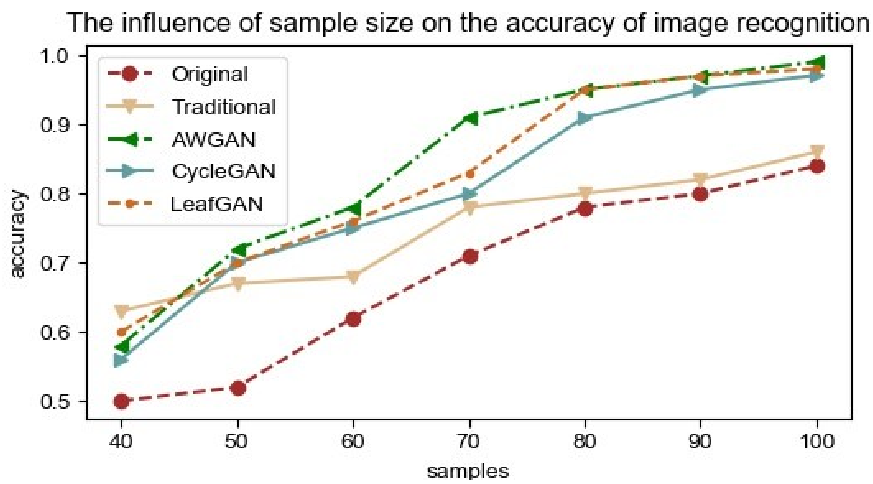

Figure 8. The Accuracy of Different Data Enhancement (ResNet18)

When the number of various images is 50, the effect of data enhancement by using various GAN is not good. Taking ResNet18 as an example (See Figure 8 and Table 3) , the recognition accuracy of original data set is 84.33%, and the accuracy of data expansion by using Traditional Data Augmentation method is improved to 98.4%. However, the recognition accuracy of GAN model after expansion is not significantly higher than that of original data set.

Table 3. Comparison Table of Identification Accuracy of Maize Disease Leaves

NetWork	AlexNet	VGG16	ResNet18
Original Data	76.4%	82.4%	84.3%
Traditional Data Augmentation	83.2%	85.1%	86.2%
AWGAN	96.2%	98.3%	98.4%
CycleGAN	93.7%	95.4%	97.1%
LeafGAN	96.1%	97%	98%

It can be seen from the data results that the data set enhanced with data can obtain better identification accuracy of disease leaves. Even with the Traditional Data Augmentation method, such as flipping, rotating, clipping, scaling and color transformation of the image, The accuracy of the model trained with original data is only 76.4%. the accuracy of the model is improved by about 4%. Three improved GAN models all show high performance. In addition, compared with CycleGAN and LeafGAN models, the AWGAN model proposed in this paper can improve the accuracy of the three deep learning models by 1% to 2%.

In this paper, the important role of plant disease detection on healthy growth of plants was analyzed from the promotion of intelligent interconnection technology to plant disease detection technology for the first time, and the existing problems of traditional disease detection technology were summarized. Secondly, the plant disease detection method based on deep learning is introduced, and the reason of over-fitting problem of its training data is analyzed. An improved GAN network is proposed to enhance the training data and fill the training data set. Finally, the effectiveness of the proposed algorithm on training set data enhancement is verified by experiments. This paper proposes that AWGAN network uses Earth-Mover distance to calculate the probability distribution of real data and the similarity of generated data. Compared with traditional GAN network, AWGAN network has better stability, and adds self-attention layer after convolution to solve the problem of local results after convolution, resulting in the lack of global information and affecting the accuracy of results. The self-attention layer was added to the convolutional layer to generate self-coding structure of the network to enhance the global dependence of the image, and then a discriminator was introduced to make the generated image of the disease blade closer to the real image. Compared with the existing methods, this method has the advantages of low cost and real effect. At the same time, the generation speed meets the requirement of real time. Furthermore, the effectiveness of the training data set of plant disease leaves can be improved, and the high-precision recognition model can be obtained from the training data set of small samples. Experimental analysis shows that the plant disease leaf data enhancement method proposed in this paper shows high recognition accuracy in AlexNet, VGG16, ResNet18 CNN model training plant disease recognition tasks.

IV. CONCLUSION

In this paper, the important role of plant disease detection on healthy growth of plants was analyzed from the promotion of intelligent interconnection technology to plant disease detection technology for the first time, and the existing problems of traditional disease detection technology were summarized. Secondly, the plant disease detection method based on deep learning is introduced, and the reason of over-fitting problem of its training data is analyzed. An improved GAN network is proposed to enhance the training data and fill the training data set. Finally, the effectiveness of the proposed algorithm on training set data enhancement is verified by experiments. This paper proposes that AWGAN network uses Earth-Mover distance to calculate the probability distribution of real data and the similarity of generated data. Compared with traditional GAN network, AWGAN network has better stability, and adds self-attention layer after convolution to solve the problem of local results after convolution, resulting in the lack of global information and affecting the accuracy of results. The self-attention layer was added to the convolutional layer to generate self-coding structure of the network to enhance the global dependence of the image, and then a discriminator was introduced to make the generated image of the disease blade closer to the real image. Compared with the existing methods, this method has the advantages of low cost and real effect. At the same time, the generation speed meets the requirement of real time. Furthermore, the effectiveness of the training data set of plant disease leaves can be improved, and the high-precision recognition model can be obtained from the training data set of small samples. Experimental analysis shows that the plant disease leaf data enhancement method proposed in this paper shows high recognition accuracy in AlexNet, VGG16, ResNet18 CNN model training plant disease recognition tasks.

ACKNOWLEDGEMENT

This work was supported by Heilongjiang Provincial Natural Science Foundation of China: LH2020F039

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