A Data Augmentation Method Based on Generative Adversarial Networks for Grape Leaf Disease Identification

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\textbf{ABSTRACT} The identification of grape leaf diseases based on deep learning is critical to controlling the spread of diseases and ensuring the healthy development of the grape industry. Focusing on the lack of training images of grape leaf diseases, this paper proposes a novel model named Leaf GAN, which is based on generative adversarial networks (GANs), to generate images of four different grape leaf diseases for training identification models. A generator model with degressive channels is first designed to generate grape leaf disease images; then, the dense connectivity strategy and instance normalization are fused into an efficient discriminator to identify real and fake disease images by utilizing their excellent feature extraction capability on grape leaf lesions. Finally, the deep regret gradient penalty method is applied to stabilize the training process of the model. Using a total of 4,062 grape leaf disease images, the Leaf GAN model ultimately generates 8,124 grape leaf disease images. The generated grape leaf disease images based on Leaf GAN model can obtain better performance than DCGAN and WGAN in terms of the Fréchet inception distance. The experiment results show that the proposed Leaf GAN model generates sufficient grape leaf disease images with prominent lesions, providing a feasible solution for the data augmentation of grape leaf disease images. For the eight prevailing classification models with the expanded dataset, the identification performance based on CNNs indicated higher accuracies, whereby all the accuracies were better than those of the initial dataset with other data augmentation methods. Among them, Xception achieves a recognition accuracy of 98.70% on the testing set. The results demonstrate that the proposed data augmentation method represents a new approach to overcoming the overfitting problem in disease identification and can effectively improve the identification accuracy.

\textbf{INDEX TERMS} Generative adversarial networks, convolutional neural networks, data augmentation, grape leaf disease identification.

\section{I. INTRODUCTION}

Grape leaf diseases greatly influence the growth and yield of grapes. Hence, the quick and accurate identification of grape diseases is of significant importance for early prevention and treatment. With the development of artificial intelligence, convolutional neural networks (CNNs), which are one of the most momentous branches of deep learning, have made important breakthroughs in plant disease identification. Rather than manually selecting features to feed traditional
machine learning classification methods, CNNs provide end-to-end pipelines to automatically extract advanced robust features and thus significantly improve the usability of plant leaf identification. In [1]–[16], various kinds of CNN-based models are applied in the plant leaf disease recognition field which demonstrates deep-learning-based models have become the prevailing methods. However, sufficient training images are an important requirement in the high generalization capability of CNN-based models. In the grape leaf disease identification field, the collection of disease images is labor-intensive and time-consuming, which results in the lack of training disease images. Thus, insufficient training images are the main factor that hinders further improvement in the identification accuracy of grape leaf diseases.

Researchers have attempted to address this challenge by using traditional data augmentation. In general, data augmentation methods such as random flipping and cropping and color jitter are the most common choices [17], [18]. However, little additional information can be gained from these methods. In this paper, a novel and robust data augmentation method based on the generative adversarial network model named Leaf GAN is proposed to perform data augmentation for grape leaf disease images and overcome the overfitting problem faced by the identification model. The proposed data augmentation method can provide sufficient and high-quality grape leaf disease images for various training models.

The main contributions of this paper are summarized as follows:

- A Leaf GAN model for generating grape leaf disease images is proposed. To adapt to the requirements of training models for image big data, the generator model is first recomposed with degressive channel layers. Then, the dense connectivity strategy and instance normalization are applied to the discriminator model for distinguishing real and fake disease images due to its excellent feature extraction capability. In addition, to stabilize the training process and generate clear grape leaf disease images with prominent lesions, the discriminator and generator models are trained together with a deep regret analytic gradient penalty algorithm.

- The GAN-based hybrid dataset is established, and a data augmentation method based on GAN is first employed to diagnose grape leaf diseases. The initial grape leaf disease images selected from the Plant-Village dataset and the generated grape leaf disease images are mixed into the training set. With the synthetic dataset, the identification performance of the classification models based on CNNs obtain higher accuracies and are all better than that of the initial dataset.

The experimental results demonstrate that the generated grape leaf disease images of Leaf GAN are of higher quality than those of the DCGAN and WGAN in terms of the Fréchet inception distance. With the proposed data augmentation method, the GAN-based hybrid dataset, which contains 8,124 grape leaf disease images, is established. Trained with the new dataset, the four common classification models show better recognition performance. The proposed method can provide a high-quality solution for the data augmentation of grape leaf disease images and can improve the identification accuracy of grape leaf disease images.

The remainder of this paper is organized as follows: In Section II, the background is introduced. In Section III, the details of the Leaf-GAN-based data augmentation method and the detailed structure of the Leaf GAN model are presented. In Section IV, experiments are described, and the results are analyzed. In Section V, related work is introduced. Finally, this paper is summarized in Section VI.

II. BACKGROUND

The basic principle of GAN is to obtain a probability distribution $P_G$ of the generator so that the probability distribution is as similar as possible to that of the initial dataset, which is assumed to be $P_{data}$. The generator $G$ maps the random data to the target probability distribution as shown in Figure 1:

$$G^* = \arg \min_{G} \text{Div}(P_G, P_{data})$$

However, under real-world conditions, as the dataset cannot include all the information in the world and $P_G$ cannot always simulate $P_{data}$ perfectly, the generator model of the GAN cannot perfectly fit the probability distribution of the dataset in practice. This property allows the generated images to be used as data augmentation so that further training can improve the recognition accuracy.

The information generated by the GAN is effective. The GAN generator model attempts to simulate the probability distribution of the dataset; even if it cannot fit perfectly, its probability distribution should be very close to the probability distribution of the dataset. As shown in Figure 2, the red points in the right-most distribution are the noise information. These points are close to the real data. The new information generated in this way is practicable.

III. DATA AUGMENTATION METHOD BASED ON GAN FOR GRAPE LEAF DISEASE IMAGES

A. DATA ACQUISITION

A total of 4,062 images of grape leaves with typical symptoms were collected from Plant-Village [19], which...
TABLE 1. Grape leaf disease dataset.

| Class         | Total |
|---------------|-------|
| Black rot     | 1180  |
| Esca measles  | 1383  |
| Leaf spot     | 1076  |
| Healthy       | 423   |
| **Total**     | **4062** |

FIGURE 3. The four types of grape leaf diseases. (a) Black rot. (b) Esca measles. (c) Leaf spot. (d) Healthy.

difficult to identify. Generating highly differentiated lesion ability is required for the generator model. To generate differentiated features continuously, the generator model should maintain a balance between the discriminator and generator model in training. Therefore, a generator model similar to the original DCGAN [20] is implemented. With seven deconvolution layers that decreasing the number of channels through layers, the generator model has the expected output RGB grape diseased images with a resolution of 256×256 pixels. Besides, the common ReLU activation is implemented empirically.

The detailed generator model of Leaf GAN is shown in Figure 4 and related parameters are shown in Table 2. The generator model consists of a series of deconvolution layers. The input of the model is a 128×1×1 latent vector which is drawn from a gaussian distribution. The size of the input vector is changed to 2048×4×4 by the deconvolution of the first layer. Then, the number of channels is decreased, and the subsequent deconvolution is carried out layer by layer to generate disease features smoothly. The number of channels of each deconvolution layer is halved, and the output tensor is doubled. Finally, the last generated image is output by the tanh activation layer.

2) THE DISCRIMINATOR MODEL FOR GRAPE LEAF DISEASE IMAGES

For Black rot and Leaf spot diseases, the tiny lesion features of the grape leaf images are a vital factor that impacts the results of the grape leaf disease identification models instead of the image background. However, these tiny lesion features will vanish during forwarding propagation in neural networks. Therefore, the dense connectivity strategy from DenseNet [21] is applied to the discriminator model to extract lesion features effectively and alleviate the vanishing-gradient problem. Analogously, the differences in individual grape leaf disease images are preferentially focused on in the identification process, instead of common characteristics such as the green color and leaf shapes. As a result, instance normalization [22] is applied to the discriminator model to focus on the differences in individual grape leaf disease images. The discriminator model mainly consists of a transition layer and two dense blocks with instance normalization layers. The detailed discriminator model of Leaf GAN is shown in Figure 5, and the related parameters are shown in Table 3.

According to the dense connectivity strategy, for each layer, the feature maps are used as inputs of the latter layers.
TABLE 2. The generator model and related parameters.

| Name         | Type            | Input Size     | Output Size    |
|--------------|-----------------|----------------|----------------|
| CovTranspose0| ConvTranspose   | 128×1×1        | 2048×4×4       |
| Norm0        | Normalization   | 2048×4×4       | 2048×4×4       |
| RelU0        | Activation      | 2048×4×4       | 2048×4×4       |
| CovTranspose1| ConvTranspose   | 2048×4×4       | 1024×8×8       |
| Norm1        | Normalization   | 1024×8×8       | 1024×8×8       |
| RelU1        | Activation      | 1024×8×8       | 1024×8×8       |
| CovTranspose2| ConvTranspose   | 1024×8×8       | 512×16×16      |
| Norm2        | Normalization   | 512×16×16      | 512×16×16      |
| RelU2        | Activation      | 512×16×16      | 512×16×16      |
| CovTranspose3| ConvTranspose   | 512×16×16      | 256×32×32      |
| Norm3        | Normalization   | 256×32×32      | 256×32×32      |
| RelU3        | Activation      | 256×32×32      | 256×32×32      |
| CovTranspose4| ConvTranspose   | 256×32×32      | 128×64×64      |
| Norm4        | Normalization   | 128×64×64      | 128×64×64      |
| RelU4        | Activation      | 128×64×64      | 128×64×64      |
| CovTranspose5| ConvTranspose   | 128×64×64      | 64×128×128     |
| Norm5        | Normalization   | 64×128×128     | 64×128×128     |
| RelU5        | Activation      | 64×128×128     | 64×128×128     |
| CovTranspose6| ConvTranspose   | 64×128×128     | 3×256×256      |
| Tanh0        | Activation      | 3×256×256      | 3×256×256      |

The dense connectivity strategy shares weights from prior layers and improves the feature extraction capability. In grape leaf disease images, the lesions are illegible features that impact the results of identification models. The tiny lesions are expected to be extracted effectively by the discriminator model. The dense connectivity can provide a strong ability to take advantage of the extracted features and reuse the prior information. The shorter connections alleviate the vanishing-gradient problem. Because one of the problems hindering the training process of the GAN is the discriminator model’s vanishing-gradient, the dense connectivity strategy is supposed to contribute to stabilizing the model training. Considering training both the generator and the discriminator requires more memory and is time-consuming, the discriminator is supposed to be a pruned DenseNet. The proposed discriminator model is built with two dense blocks that have enough layers for feature extraction. The first dense block has 6 dense layers so that it can be initialized from ImageNet-pretrained weights to accelerate the model convergence. The second dense block has 9 dense layers to further feature extraction within proper memory. Since only two dense blocks are used, the light model has a small number of parameters, and the total number of parameters is 1,001,057, which is approximately one-eighth that of DenseNet-121. The ReLU activation function is implemented as its stability. A schematic diagram of the dense connectivity strategy is shown in Figure 6.

For the normalization layer, instance normalization is utilized to replace the usual batch normalization [23]. Instance normalization focuses on a single image instance, whereas batch normalization focuses on the overall distribution of data and ensures a consistent data distribution. Batch normalization is often affected by other grape leaf disease images, and the instability of each batch’s mean and standard deviation can affect the correctness of individual grape leaf images. The noise will weaken the independence among grape leaf image instances. In image generation problems, the overall information obtained by batch normalization will not provide any benefits. Instance normalization learns information directly from a single image so that it can maintain the independence of each image instance. The identification of lesions that contain more edge and corner features can benefit from instance normalization.

C. STABILIZING THE MODEL TRAINING

1) LOSS FUNCTION

The training performance on previous layers strongly impacts the latter layers, which requires the generator to be highly stable. The volatility of the layers will negatively impact the generation of grape leaf lesions, which result in blurry lesions. Therefore, to stabilize the generator training process, LeafGAN model implements the loss function with the gradient penalty method of DRAGAN proposed by Kodali et al. [24]. The loss is less strongly disturbed by confusing lesion features, as it has been limited by the deep regret gradient penalty method. The method can produce more satisfactory results in generating grape leaf disease images than other GANs such as the series of WGANs.

The adversarial loss of the discriminator model is defined based on the original GAN model, and the formula is as shown in Eq. (2):

$$L_{adv} = -E_{x \sim P_{data}} \log D(x) - E_{z \sim P_{G}} \log(1 - D(G(z)))$$  \hspace{1cm} (2)$$

$P_{data}$ indicates the distribution of the real data. G and D indicate the generator model and discriminator model, respectively. z is the input noise, while x is a grape leaf image as real data.
The gradient penalty loss of the discriminator is defined as shown in Eq. (3):

$$L_{gp} = E_{x \sim P_{data}, \delta \sim N_d(0,cI)} || \nabla_x D(x + \delta) ||_2^2 - 1^2$$

where $c \sim 10$ is set empirically.

The loss of the discriminator is the sum of the adversarial loss and the gradient penalty loss. $\lambda_{gp}$ is the balance factor for the gradient penalty loss, which is defined as 10. The formula is defined as shown in Eq. (4):

$$L(D) = L_{adv}(D) + \lambda_{gp} L_{gp}(D)$$

The loss of the generator is the same as the original GAN. The formula is defined as shown in Eq. (5):

$$L(G) = L_{adv}(G) = E_{z \sim P_{noise}} [\log(1 - D(G(z)))]$$

2) LABEL SMOOTHING

Aside from the generator model, the discriminator model also requires a stable training process. When the discriminator model cannot extract practical information and discriminate between blurred and clear lesions, the discriminator training will be degraded. The label smoothing technique was independently rediscovered by Szegedy et al. [25] and was shown to be able to reduce the vulnerability of GAN’s discriminator model [26] caused by the above-mentioned reason.

When training one class of grape leaf diseases, there are two target labels. In typical GAN training, the label of the real image is 1, while that of the fake image is 0. For the reason that the training set is limited and cannot cover all the grape disease images, such coding often leads to overfitting. Moreover, this coding approach can cause model overconfidence about its prediction [27]. Therefore, the labels of the real images are replaced by a random number between 0.7 and 1.2, and the labels of the fake images are replaced by a random number between 0.0 and 0.3 to make the training process more stable.

3) WEIGHT INITIALIZATION

Leaf GAN learns latent representations from grape leaf disease images based on unsupervised learning technology, and the linear layer in the discriminator model outputs the explicit representations of the information that the generator model has learned. The model layer the previous feature information of the grape leaf lesions into a single output, which is significant for examining the results of Leaf GAN model. Because the grape lesion features are small and easily cause confusion during the disease identification, the discriminator model with the reliable weight initialization is expected to accurately guide the image signal.

Common weight initialization methods include random initialization, Xavier initialization [28], Kaiming initialization [29], etc. Considering that weight initialization is supposed to be implemented in the linear layer that directly outputs the explicit representations of grape leaf disease features, Xavier normalization, which maintains good distributions of the output, is the most suitable weight normalization method in the training process. The biases are initialized to be zero, and the weights $W_{ij}$ at each linear layer, are as shown in Eq. (6):

$$W_{ij} \sim U[-\frac{\sqrt{6}}{\sqrt{n_{in} + n_{out}}}, \frac{\sqrt{6}}{\sqrt{n_{in} + n_{out}}}]$$

$n_{in}$ is the number of input channels, and $n_{out}$ is the number of output channels.

IV. EXPERIMENT

In this section, the experimental setup is first introduced, and the details of the experiments are provided. Finally, the experimental results are analyzed and discussed.

A. EXPERIMENTAL SETUP

The experiments were conducted on a deep learning server that contained two Tesla P100 processors (16 GB memory) with the Ubuntu operating system. In addition, the PyTorch deep learning framework was used to implement the proposed model. Additional configuration parameters and the training hyperparameters are listed in Table 4.

B. EXPERIMENTAL RESULTS AND ANALYSIS

1) IMAGE QUALITY EVALUATION

The proposed Leaf GAN is evaluated from two different perspectives: the Fréchet inception distance score [30] and
TABLE 4. Software and hardware environment.

| Configuration Item | Value                      |
|--------------------|----------------------------|
| CPU                | Intel® Xeon CPU E5-2650 v4 |
| GPU                | NVIDIA GTX P100 16 GB      |
| Hard disk          | 1TB                        |
| Operating system   | Ubuntu 16.04.1 LTS (64-bit)|
| Python             | 3.7.2                      |
| PyTorch            | 1.0.1.post2                |
| Batch size         | 32                         |
| Learning rate      | 0.0001                     |
| Optimizer          | Adam (beta1=0.9, beta2=0.999)|
| Weight decay       | 0.00001                    |

general overviews. The Fréchet inception distance score is a prevailing method to evaluate the generated images of GANs.

a: **FRÉCHET INCEPTION DISTANCE**

In this paper, the Fréchet inception distance evaluation method is selected to compare the generated image quality of the generated grape leaf images of DCGAN, WGAN and Leaf GAN. Under the feature space of a specific layer in the pretrained Inception Net, the Fréchet inception distance is the distance between the distribution of the original data and the generated data. Better images should have a lower Fréchet inception distance. The formula is shown in Eq. (7):

$$FID(x, x^*) = \|\mu_x - \mu_{x^*}\|^2_2 + Tr(C_x + C_{x^*} - 2(C_x C_{x^*})^{1/2})$$  (7)

The qualities of the images generated by DCGAN, WGAN, and Leaf GAN are analyzed using the evaluation method of the Fréchet inception distance in Table 5. As the assumption of Leaf GAN is based on the seven degressive-channel deconvolution layers, Leaf GANs with different discriminator architectures are included in the experiment as well. As Leaf GAN’s discriminator has two dense blocks with 6, 9 dense layers respectively, it can be noted as LG-[6, 9]. Several network sizes such as LG-[6, 3], LG-[6, 12] are tested. While the proposed Leaf GAN’s discriminator model applies ReLU, Leaf GAN with leaky ReLU (LG-LR) and Leaf GAN with PReLU (LG-PR) are tested. Both LG-LR and LG-PR has the same network size as the proposed Leaf GAN.

From Table 5, it can be seen that, in the generation of Black rot, Leaf spot, and healthy images, Leaf GAN clearly achieves better average results than DCGAN and WGAN, while for Esca measles, the leaves show a slightly worse result. The small difference between the results of Esca measles disease may be caused by the diversity of Leaf GAN’s generated images and the inability of Fréchet inception distance’s overfitting examination. WGAN has bad results as its strong gradient penalty method limited its ability to generate high-resolution images. For Leaf GAN with different kinds of activation functions in the discriminator, leaky ReLU and PReLU have bad performance as their activation for negative values increase the difficulty of model learning. For the different network sizes of the discriminators, the discriminator model of LG-[6, 3] is weak to extract sufficient features, while LG-[6, 12] with more dense layers converge quickly so that the generator cannot follow its steps. Among these models, Leaf GAN outperforms and get a balance between the generator and discriminator.

b: **THE OVERVIEW OF GENERATED IMAGES**

As shown in Figure 7, it can be seen that under the same training settings, the images generated by the DCGAN fit high-resolution but are similar to the oil painting, and the lesion is not obvious, while the leaf images generated by Leaf GAN model have obvious lesion characteristics.

![Figure 7. The generated Black rot grape leaf images.](image)

The mode collapse phenomenon of the DCGAN-generated images is serious, which means that the generator collapses, producing limited varieties of samples. As shown in Figure 5(a), the images in the red frame are almost the same, and the other images look very similar. The image diversity generated by Leaf GAN is obviously better. Furthermore, without the gradient penalty method, DCGAN is more sensitive to different colors. Some flavescent grape leaf images in the initial Black rot dataset can make the generated Black rot images significantly yellower. Therefore, Leaf GAN is suitable for the generation of grape leaf disease images as it can generate grape leaf disease images in higher quality than WGAN and has less mode collapse than DCGAN.

As shown in Figure 8, comparing with DCGAN, Leaf GAN can always generate high-quality images with clear lesions,
which is expected to be significant in improving classification model accuracy. WGAN has difficulty generating clear high-resolution grape leaf disease images. In addition, leaf spot disease images are the most difficult class to generate. Both DCGAN and Leaf GAN have trouble generating leaf spot disease images; however, Leaf GAN’s generated leaf spot images have more prominent lesions. Comparing with other kinds of architectures of the discriminator, Leaf GAN can generate slightly clearer lesions than LG-LR, LR-PR, and LG-[6, 12] and much better images than LG-[6, 3]’s. The bad performance of LG-[6, 3] is caused by its discriminator’s weak ability of feature extraction, so its generator can learn little information from it.

2) THE IDENTIFICATION ACCURACY COMPARISON

a: THE WORKFLOW OF GAN-BASED DATA AUGMENTATION

The generated data were synthesized through the GAN model with real data. Then, the generated data were added to the training set. For these datasets with generated images, all the generated images were placed in the training set, and all the images in the testing set were from the initial dataset. The testing set was completely derived from the initial data set and was guaranteed not to be used in the GAN models for data augmentation. The flowchart of the data augmentation method is shown in Figure 9:

To train the classification model, the three datasets were split into training and testing sets with a ratio of 9:1. The numbers of images in each class and dataset are shown in Table 6.

b: THE IDENTIFICATION PERFORMANCE ON FOUR CLASSIFICATION MODELS

Initialized by ImageNet-pretrained weights, eight common image classification models (AlexNet [31], VGG-11 [32], ResNet-34 [33], DenseNet-121 [21], Xception [34], ResNext-50 [35], SEResNet-50 [36], EfficientNet-b0 [37]) were implemented to train and test these datasets. These prevailing models are selected to show the robustness of the proposed data augmentation method as their various characteristics: AlexNet and VGGNet are composed of plain convolutional neural networks with a number of layers; ResNet and DenseNet are the typical models that implement skip connections by different ways; Xception and ResNext apply depth-wise separable convolutions and group convolutions respectively to extract features in channel-wise; SEResNet implements squeeze-and-excitation modules which inspired by the attention mechanism; EfficientNet is a recent AutoML work that searching typical network architectures through compound scaling which including depth, width and resolution dimensions. The proposed data augmentation method based on Leaf GAN is supposed to obtain great performance on different kinds of models.

For the initial dataset1, five basic data augmentation technologies (random horizontal flip, random vertical flip, random contrast, random saturation, and random hue) are composed during the training process. The probability of applying these random operations was set to 10%. For the initial dataset2 and the initial dataset3, the state-of-art data augmentations MixUp [38] and random erasing [39] are applied. For the rest hybrid datasets, the datasets were...
V. RELATED WORK

In recent years, the generative model has become a research hotspot and has been applied to a variety of fields. In [40], Kingma et al. proposed a deep learning technique named variational autoencoder (VAE) for learning latent representations. The model was used to generate data based on semi-supervised learning technology. VAEs can pair a differentiable generator network with a recognition model based on neural networks. The recognition model applied to approximate inference. The variational sampling approach achieved some success; however, the samples often suffered from blur. In [41], Ian Goodfellow et al. proposed a GAN model that was used for learning latent representations based on unsupervised learning. The model could generate images through an iterative forward diffusion process with the framework that specific training algorithms could be yielded for many types of models and optimization algorithms. It could overcome the difficulty of approximating many intractable probabilistic computations that arose in maximum likelihood estimation and related strategies. In [20], Radford Alec et al. proposed DCGAN, which utilized deep neural networks to extract hidden features and generate data. The model learned a hierarchy of representations from object parts to scenes in both the generator and discriminator. It had been verified that DCGAN could be used as a feature extractor to learn useful feature expressions from unlabeled data and then be applied to supervised learning. In [42], Zhang et al. proposed StackGAN to generate photorealistic images from text descriptions. StackGAN used the Stage-I GAN to sketch the primitive shape and colors of the object from a given text description and used the Stage-II GAN to generate high-resolution images with photorealistic details. In [43], Larsen et al. presented an autoencoder that leveraged learned representations to better measure similarities in data space and combined a variational autoencoder with a generative adversarial network so that the model could learn an embedding in which high-level abstract visual features could be modified using simple arithmetic. In [44], Qu et al. proposed an enhanced pix2pix dehazing network to reduce the image dehazing problem to an image-to-image translation problem and generate haze-free images without relying on the physical scattering model. The model was embedded by a GAN model and an enhancer inspired by visual perception global-first theory. The experimental results showed that the model is superior to the other methods in terms of PSNR, SSIM, and PI. In [45], Zhu et al. proposed the Cycle GAN model to implement image domain transformation directly. The model could learn a mapping from the source domain to the target domain using an adversarial loss and cycle consistency loss. Cycle GAN achieved a breakthrough in image-to-image translation. In [46], Wu et al. proposed an enhanced TripleGAN (EnhancedTGAN) model to improve both instance synthesis and classification in learning class-conditional data distributions. The model achieved superior performance on multiple benchmark datasets and demonstrated the effectiveness of the mutual reinforcement between the generator model and classification models in facilitating semi-supervised instance synthesis and classification. In [47], Karras et al. proposed a progressive GAN to generate high-resolution images. The model started from low-resolution images and gradually increased the number of network layers of the generator and discriminator, increasing the resolution of the generated image. The method could generate images of 1024 × 1024 pixels. In [48], Yang et al. proposed SAVAE-DNN for network intrusion detection. The model used WGAN-GP instead of vanilla GAN to learn the latent distribution of the original data. The experimental results showed that the model was a suitable choice for the data augmentation operation than other data oversampling methods.

To take advantage of the latent representations learned by the GAN and apply them to supervised learning, researchers have attempted to propose data augmentation methods based on GAN models. In [49], Xian et al. proposed the f-VAEGAN-D2 model to address any-shot learning problems in a unified feature-generating framework. The model was developed with a generator model that combined the advantages of VAE and GAN and a discriminator model that learned the marginal feature distribution of unlabeled images. The experimental results showed that the model learned highly discriminative features on five different datasets. In [50], Zheng et al. improved the DCGAN for generating reID pedestrian images. The experiments showed that adding the GAN-generated data effectively improved the discriminative ability of the learned CNN embeddings, and the model achieved a 0.6% improvement over a strong baseline. In [51], Zheng et al. proposed a joint learning framework to improve
learned re-ID embeddings by better leveraging the generated data. The proposed DG-Net model was coupled with re-ID learning and data generation in an end-to-end manner. In the experimental results, DG-Net achieved gains of 8.3% and 10.3% mAP on Market-1501 and DukeMTMC-reID, respectively, indicating the advantage of the proposed joint learning. In [52], Lee et al. proposed an any-time-of-day camera-based BSD system and generated synthetic nighttime siderectilinear images to improve the nighttime performance of the hand-crafted feature-based BSD system. The framework with a conditional GAN for data augmentation was built, and the nighttime detection performance was improved. In [53], Ali-Gombe et al. proposed a GAN-based data augmentation approach to handle the class imbalance problem. The method used multiple fake classes to ensure fine-grained generation, and the results showed that the method could generate diverse minority class instances. In [54], Ge et al. proposed a scheme for improving glioma subtype classification. The pairwise GAN model was used for data augmentation in a bidirectional cross-modal fashion. The results which obtained average 88.82% accuracy on the testing set for gliomas subtypes demonstrated the scheme was effective and robust.

Although deep convolution networks make the GAN structure strong in terms of feature extraction, model training is well known for being delicate and unstable. Its sensitivity to the training process produces a mode collapse phenomenon, that is, the generator generates a large number of almost identical images, resulting in a lack of diversity in the generated images. The basic idea for solving the problem is deploying the gradient penalty algorithm and evaluating the distribution in different ways. In [55], Arjovsky et al. proposed the Wasserstein GAN (WGAN), which could balance the sensitive gradient loss between the generator and the discriminator. The WGAN replaced the Kullback-Leibler distance with the Wasserstein distance to measure the probability distribution so that the WGAN did not require a careful design of the network architecture and careful balance in the training of the discriminator and generator. In [56], Gulrajani et al. proposed WGAN-GP to further solve the vanishing-gradient problem of the WGAN. The model used the gradient penalty to update the weights. This ensured the continuous optimization of the weights, significantly improved the training speed, and solved the problem of slow convergence of WGAN. In [57], Qi proposed LS-GAN to limit the gradient explosion problem, which regularized the loss function with a Lipschitz regularity condition on the density of real data, thereby yielding a regularized model that could better generalize the data to produce new data from the classic GAN. In the experiments, LS-GAN achieved better performance than many other classical GAN models in terms of the minimum reconstruction error (MRE). In [58], Din et al. proposed a GAN-based network to remove mask objects in facial images. The model used two discriminators where one helped learn the global structure of the face and then another come in to focus on learning the deep missing region. The experimental results outperformed other state-of-the-art image editing methods.

### VI. CONCLUSION

This paper has proposed a high-quality generative adversarial network called Leaf GAN model to generate sufficient training images for the identification of grape leaf diseases. With the decreasing-channel generator model, Leaf GAN can make good use of features and generate better grape leaf disease images with prominent disease lesions. Furthermore, a discriminator model based on a dense connectivity strategy and instance normalization is employed to achieve excellent feature extraction performance from the original grape disease images. Finally, the deep regret loss function is applied to stabilize the training process.

In image quality valuation, the generated images of Leaf GAN obtain a better average score than DCGAN and WGAN with respect to the Fréchet inception distance evaluation standard. Furthermore, while other data augmentation methods focus on the global context features, Leaf GAN focuses more on lesion features which are significant in grape leaf disease identification. In the accuracy comparison, Leaf GAN’s dataset has a higher average recognition accuracy than other state-of-the-art image editing methods.
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