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Analysis of Leaf's disease detection by improving the image quality using super resolution generative adversial networks
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ABSTRACT

In most cases, the acquired pictures for agricultural disease image identification are not very clear, which might result in subpar identification outcomes when used in actual production settings. The identification accuracy of pre-trained image classifiers is greatly affected by the picture quality. We suggest DATFGAN, a generative adversarial network that combines topology-fusion with dual-attention, to solve this issue. With this network, even low-resolution photographs may be improved to a much higher standard. Our suggested network also has a weight sharing method that may drastically cut down on parameters. The experimental findings show that compared to state-of-the-art approaches, DATFGAN produces better outcomes in terms of visual appeal. Furthermore, identification tasks are used to assess the altered pictures. The findings show that the suggested strategy is strong enough for real-world applications and performs far better than competing methods.

INTRODUCTION

One important aspect that restricts the production of crops is crop disease. The agricultural industry stands to lose a substantial amount of money if crop diseases cause precipitous decreases in output. Hence, in order to reduce crop loss and pesticide usage, early disease detection in crops is essential for choosing the best treatments. Crop diseases reduce crop output and quality, and they may impact any crop. Nevertheless, drug residues and environmental degradation might result from too relying on chemical control. There has never been a higher demand for high-quality crops, driven by rising living standards. Consequently, there are problems that need fixing, and they pertain to the early detection and treatment of agricultural illnesses. Disease detection in agriculture has been a popular area of study as of late. Using deep convolutional neural networks (DCNN), Cheng et al. [1] achieved a reasonable recognition result by classifying and identifying diseases caused by agricultural pests via the use of the fine-tuning approach. In order to restore and identify diseases caused by agricultural pests, Yue et al. [2] created a super-resolution approach. Using a convolutional neural network (CNN), Kawasaki et al. [3] developed a system for diagnosing plant illnesses. Their goal was to detect two leaf diseases in cucumber plants. To detect a wide variety of leaf illnesses, Sun et al. [4] enhanced the classic AlexNet [5] model with CNN models that included batch normalisation and global pooling. These experiments show that using DCNNs to identify leaf diseases is both possible and useful. Pictures taken on farms, however, tend to be fuzzy. Due to their training on clean, high-resolution datasets, pre-trained classifiers have a much lower identification accuracy when images of poor quality.

In order to enhance the precision of agricultural disease picture classification, it is necessary to super-resolve low-resolution photos in order to raise the spatial resolution and recreate the high-

FIGURE 1. Super-resolved image generated by DATFGAN (right)

frequency specifics of acute angles. To improve upon low-resolution farm photos, we present a generative adversarial network (GAN) that uses topology-fusion and dual-attention techniques. A DATFGAN network is the one that has been suggested. In order to assess the suggested approach, we compare its classification accuracy after picture transformation to that of state-of-the-art approaches. Our studies showcase the use of eight traditional classification networks on a dataset consisting of crop leaf disease photos categorised into a total of twenty-seven different ways. In Figure 1 we can see a super-resolution picture of a crop leaf disease that was created using DATFGAN. Transforming pictures using super-resolution approaches improves classification accuracy, according to experimental data. With a 3% gain in accuracy on average, DATFGAN outperforms the state-of-the-art algorithms tested in this study. The following is an overview of our primary contributions.
1) We provide a new approach to picture super-resolution specifically designed for agricultural disease photos.

2) As far as we are aware, our approach represents the pioneering use of GANs in the field of agricultural disease picture processing.
3) In terms of visual quality and classification accuracy, benchmark testing show that DATFGAN surpasses state-of-the-art approaches.

I. RELATED WORKS

One of the biggest problems in agriculture is the need for accurate methods of detecting crop stress and pathogens [6, 7]. Using pattern recognition and image processing techniques, Zhang et al. [8] developed a system to identify apple leaf diseases. They used a dataset of 90 photos depicting sick apple leaves in their tests. They were able to get a recognition accuracy of over 90% using their method. Waghmare et al. [9] focused on a technique for detecting diseases in grape plant leaves. With only one leaf as input, their algorithm can remove the backdrop and then segment the image. Downy mildew and black rot are two of the most prevalent diseases in grape vines, and their research focused on these issues. They were 96.6% accurate using their method. In order to quickly, automatically, affordably, and accurately identify leaf diseases, Bashish et al. [10] created an image-based approach. There are four primary components to their approach: a structure for colour modification, picture segmentation using K-means clustering, texture feature computation, and a pre-trained neural network. They found that their system could identify and categorise illnesses with an accuracy of around 93% in experiments. Arivazhagan et al. presented a system to automatically identify and categorise plant leaf diseases in [11]. Their process is divided into four primary phases. An RGB input image's colour transformation structure is first built. Secondly, a segmentation procedure is carried out after masking and removing green pixels using a certain threshold value. Finally, segments that are valuable have their texture statistics calculated. The fourth step involves running the characteristics that have been retrieved through a classifier. With a 94% success rate, their technique accurately categorised the disorders under study. Convolutional neural network (CNN) based deep learning approaches outperform classical machine learning techniques [12]-[17], which need intricate picture preparation and classification procedures. Numerous academics have investigated deep learning-based agricultural disease identification in recent years with the goal of better crop management and health. A new method for building plant disease detection models utilising deep convolutional networks for leaf image classification was suggested by Sladojevic et al. [18]. They were able to train their model to identify thirteen distinct plant illnesses and to differentiate between real and fake plant leaves. Their created model showed experimental accuracy values of 96.3% for distinct class tests, ranging from 91% to 98%. The process of disease classification in banana leaves may be automated using a deep learning-based method [19] established by Amara et al. They used the LeNet [20] architecture as a convolutional neural network (CNN) to categorise picture collections. Even in difficult situations like lighting change, complicated backdrops, and varying real-world picture resolutions, sizes, positions, and orientations, their first findings showed that deep learning techniques work. To train a DCNN to detect 14 crop species and 26 illnesses (or lack thereof), Mohanty et al. [21] used a publicly available dataset consisting of 54,306 photos of healthy and sick plant leaves obtained under controlled circumstances. By using a held-out test set, their trained model was able to get an accuracy of 99.35%. Using a dataset of photos taken in the field of cassava illnesses in Tanzania, Ramcharan et al. [22] trained a deep convolutional neural network (DCNN) to detect three diseases and two kinds of pest damage (or absence thereof) using transfer learning. Brown leaf spot had a best-trained model accuracy of 98%, red mite damage of 96%, green mite damage of 95%, cassava brown streak disease of 98%, and cassava mosaic disease of 96%. An open collection including 87,848 photos containing 58 pairings of plants or diseases was used to train models by Ferentinos [23]. An AlexNet [5], VGG [24], and GoogLeNet [25] were among the model architectures developed; the highest accuracy for plant disease detection attained was 99.53%.

Research shows that convolutional neural networks (CNNs) are effective in identifying agricultural diseases, and these experiments have shown promising outcomes. Unfortunately, farms usually only provide low-resolution, hazy photographs of crop diseases, which makes it difficult to enhance the accuracy of crop disease image detection. Hence, improving crop disease pictures using super-resolution technologies is of the utmost importance. To improve low-resolution farm photos, we suggest a GAN that uses topology-fusion and dual-attention techniques.

II. PROPOSED METHOD

In Section III-A, we describe our network design in detail. In Section III-B, we then provide two attention processes, namely channel attention and texture attention. Section III-C concludes with a definition of adversarial training.

A. *NETWORK ARCHITECTURE*

The overall network architecture is described in Section III-A1, parameter sharing in Section III-A2, and topology fusion in Section III-A3. This section is divided into three sections. We begin by outlining DATFGAN's general design. As a second point, we provide the generator network with the procedures for sharing parameters. Third, talk about the ways in which dense and residual connections may be used.

1) **Overall architecture**
2) A generator and a discriminator are the two main components of DATFGAN. A shallow feature extraction network, a parameter-sharing attention-enhanced topology-fusion network, and a reconstruction network make up DATFGAN's generator network, as shown in Figure 2. Two convolutional layers retrieve shallow features from the generator network in the topology fusion network that is used for shallow feature extraction. Two branches of low-resolution pictures are sent into the generator network. The

generator network's initial convolutional layer is followed by an upscaling module, which receives one branch as input. For information after the second convolutional layer, the other branch feeds into the topology fusion network. In order to create high-resolution pictures, the reconstruction network uses upscaled images in conjunction with anticipated information, taking use of global residual learning [26]. In Figure 3, we can see the discriminator network. In order to train the discriminator network, we first issue it with a maximisation problem. Like the VGGNet [24], it has seven convolutional layers and a growing number of filter kernels, going from 64 to 512. Every time the number of features is increased, the picture resolution is reduced using striding convolutions. A final LeakyReLu activation function and two linear layers are used to boost the likelihood of sample classification using the 512 feature maps that

3) Parameter sharing

Some statistical properties of local information may be identical to those of other local information, which means that the features obtained by convolution operations may also be applied to other types of data. This is because convolution processes extract local information. This allows for the reusability of the learning features across several picture locations. One feature (one dimensional of input data) is extracted by a convolution kernel (filter) in a convolutional neural network (CNN). Parameter explosion in the convolution layer may occur if the input data has numerous features (dimensions), since this results in a large number of convolution kernels. Furthermore, every convolution kernel in the layer ignores local correlations in data when extracting features. Parameter sharing ensures that features are translationally invariant, which means that the same feature may exist in several places in different datasets and be extracted from all of these places using the same convolution kernel. In addition, a convolutional layer may share its convolution kernel and minimise the number of parameters by conducting weight sharing, which is based on the local correlations between the input. A deep neural network's ability to extract features is directly proportional to the number of layers it contains, as each convolutional layer may employ a unique convolution kernel. In order to create a deeper structure trainable, decrease the number of network parameters, and increase the chance of avoiding overfitting, we use parameter-sharing attention- enhancing topology-fusion networks in the DATFGAN generating network.

4) Topology fusion

ResNet [26] was proposed to solve the problem of degrada- tion in deep learning. When the number of layers in a model increases, the error rate decreases. The degradation problem is closely related to optimization. When the structure of a model becomes increasingly complex, optimization becomes increasingly difficult, resulting in unsatisfactory learning re- sults. The residual block in ResNet [26] was implemented using residual connections. The input and output of the blockwere added element-wise through the residual connections. This simple form of addition does not add any extra param- eters or calculations to the network, but it can significantly increase the training speed of the model, thereby improving the overall effectiveness of training. When the number of layers in the model increases, this structure can also solve the degradation problem.

ResNet [26] can train deep CNNs by establishing residual connections between front and back layers, which aids with the back-propagation of gradients during training. The basic idea of DenseNet [27] is the same as ResNet [26], but dense connections are established between all previous layers and latter layers. DenseNet [27] achieves better performance than ResNet [26] with fewer parameters and lower computational cost. Compared to ResNet [26], DenseNet [27] uses a more aggressive and dense connection mechanism of connecting all layers, meaning DenseNet [27] performs direct concatena- tion of feature maps from different layers, which can improvefeature reuse.

To take advantage of both residual and dense connec- tions, we combined both connections types in a single layer. Compared to residual networks, our proposed generator can preserve more information from previous states, providing

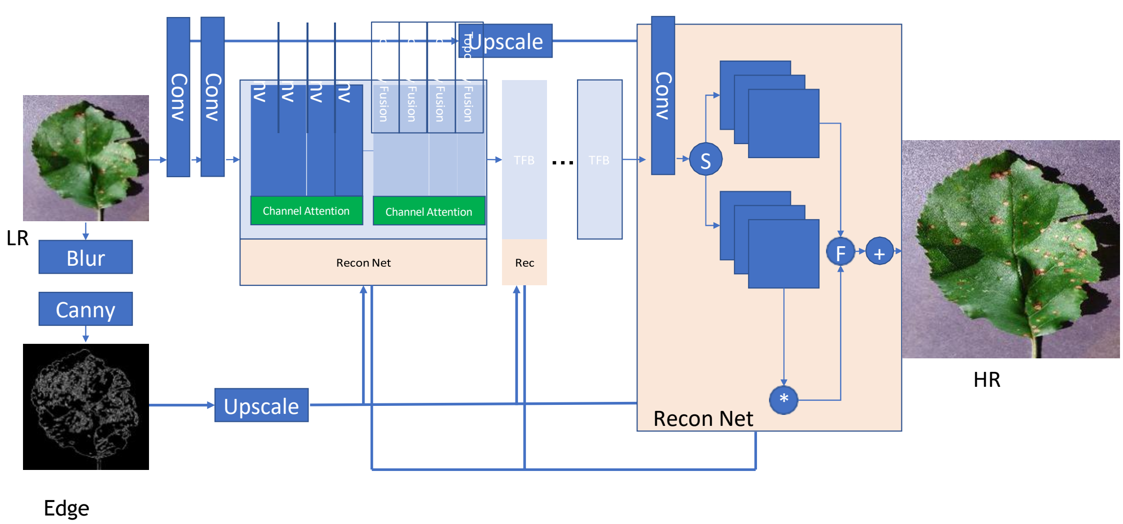


FIGURE 2. Generator network.

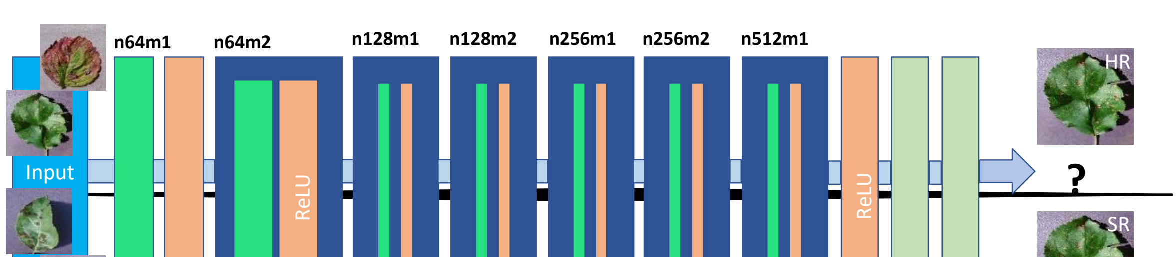


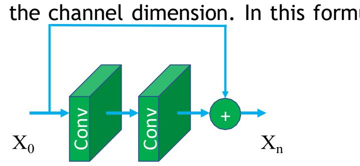
FIGURE 3. Discriminator network.

our network with contiguous memory. Compared to dense networks, our proposed structure can reduce the channel growth rate by half. This significantly reduces the number of network parameters and makes deeper structures trainable. Additionally, this topology can enhance the flow of informa-tion and gradients. Figure 4 presents the inner structure of the proposed mixed-link connections. The operator M in Figure 4

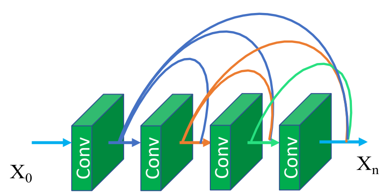
$$F^1, F^2 = Slice(W(F_{i-1}) + b), \quad (2)$$

In Formula 2, the output of one layer or unit is sliced into two equal parts in the channel dimension. In this formula, W

Xn



(a) Residual Block



(b) Dense Block

denotes the weight of a convolutional layer and b denotes the bias.

denotes a mixed-link operation, which yields a fusion of $F_{i+1} = C(C(F^1 + F^2, F^2), F^1$

) (3) residual and dense connections between the current layer and previous layer. Mixed-link operations can be calculated using i

will contain N/2 channels

where W_t denotes the weight of a 1×1 convolution for block-after the slicing operation. feature fusion, which can reduce the number of channels.

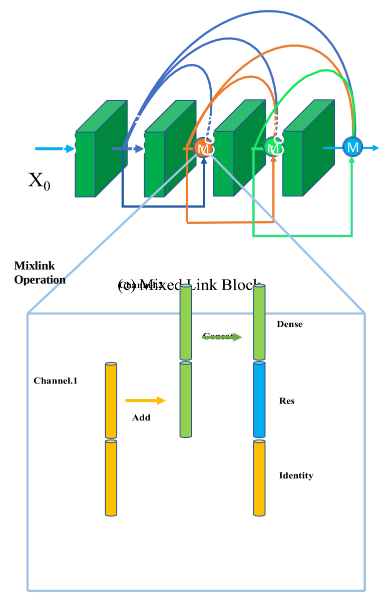


FIGURE 4. Topology fusion

F_{j-1} denotes the features of the preceding mixed-link block

operates according to Formulas 5 and 6:

and F_j denotes the output features of the current mixed-link

$H \quad W$

HW

block. Based on this mixed-link mechanism, our network can synchronously generate both residual and dense connections, which decreases parameter growth and improves network performance.

$$F_j = W_t(F_{j-1}) + b, \quad (4)$$

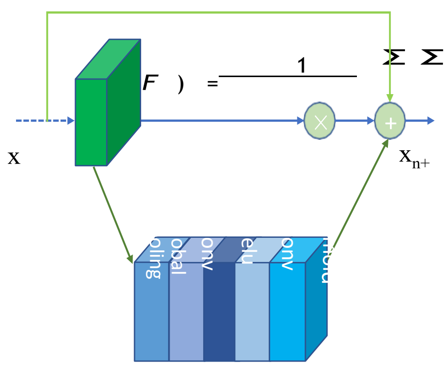
B. DUAL ATTENTION

We propose channel attention in Section III-B1 and texture attention in Section III-B2. Both of these mechanisms are used for improving the effectiveness of transforming images.

1) Channel attention

Our topology-fusion network models the interdependencies of convolution channels using channel attention, which may be autonomously taught to enhance vital channels and inhibit superfluous ones. In order to rebalance the gradient and information flow across networks, this mechanism acts as a filter. Figure 5 shows the components of the channel attention module. One of them is a global average pooling layer, which uses spatial feature compression to retrieve channel-level data. The next step is to create a bottleneck using two 1 1 convolutions. In the end, the data is normalised using a Sigmoid layer, and the resulting outputs are reweighted to provide self-trained channel-wise attention. Focus efforts

$$F \quad) = \frac{1}{\quad} \sum \sum F \ (i, \ j),$$



Channel Attention

FIGURE 5. Channel attention

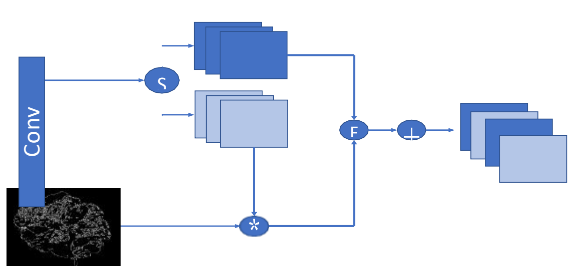


FIGURE 6. Texture attention Texture

The idea behind this approach is that if you put in the same data, you should get the same results. A modest modification to an input should have a correspondingly minimal effect on the output. Consequently, making sure that many inputs produce the same result is the best approach to applying this regularisation. Building a confrontation sample and minimising the cross entropy between the output and ground truth may be achieved by first trying to find the disturbance that creates the most loss.

(9)

(5)

$i \quad j$

where $S(.)$ is a squeeze operation that pools the features in each channel into a global mean, and H and W denote the height and width of the input feature map, respectively.

$$A(F \quad) = \delta(W_u\sigma(W_dS(F \quad))) * F, \quad (6)$$

where $A(.)$ denotes the channel attention function, σ denotes the ReLU function, and W_u and W_d denote two 1 1 convolutions. W_d first reduces the channels to 1/16th of their original size, then W_u expands the tensor to the original shape, which forms a bottleneck. δ denotes the sigmoid function, which normalizes the weights for each channel to values between zero and one. We use these weights to boostuseful information and suppress useless information.

2) Texture attention

As shown in Figure 6, texture is a very important feature in plant images and is very useful for image super-resolution tasks. Additionally, the high-frequency details of an image are typically located around edges, meaning it is important toassign attention with guidance from edges. Therefore, we usetexture attention in our reconstruction network.

We utilize edges as global spatial attention components for image reconstruction according to Formula 7-8, where W_{exp} represents expanding the original number of channels. In this process, the number of global features is doubled. Half of the

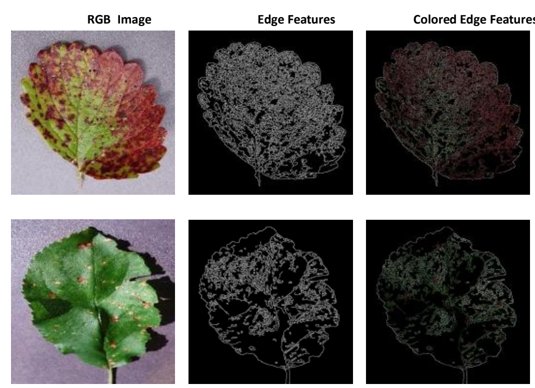


FIGURE 7. Edge features

landscape's loss function. We were surprised that this approach enhanced our model's generalizability, but there may be ways to simplify prediction functions that work better with actual data.

one set of channels is weighted based on global information while the other set is kept local. In order to combine global and local data, the two parts are averaged and added together. To improve the aesthetic quality of the output photos, we used adversarial training rather than simply optimising the mean squared error between the input images and the targets. The following formula defines advertising loss:

C. ADVERSARIAL TRAINING

The core principle of adversarial training is direct confrontation. The pedagogical and instructional aims of two modules may be met via confrontational learning. One way to make a model's output more consistent is to use adversarial training, which involves smoothing down the

$$F^{1}, \quad F^{2} = Slice(W_{exp}(F_{i-1})), \quad (7)$$

$$L = E[D(G(I \quad))] - E[D(I \quad)],$$

GAN LR HR

$$F_{i+1}^{0} = Up(Canny(F_0)) * F^1 + F^2, \quad (8)$$

As shown in Formula 8, Up denotes an up-sampling operation and Canny denotes an operator for extracting edge features. F_0 denotes the initial input features. The resulting edge features following up-sampling are multiplied by half ofthe initial input features using large-scale pixel maps to guidesmaller maps. The result of this operation is then added to theother half of the initial input features to perform fusion.

Figure 7 presents edge features obtained from an RGB image processed by the Canny operator. We also present colored edge features for the sake of clarity.where D(.) denotes the discriminator of DATFGAN and G(.) denotes the generator. I_{LR} denotes generated pseudo-high-resolution images and I_{HR} denotes real-world high-resolution images.

After incorporating adversarial loss, the total loss can be represented as follows:

$$L = aL_{GAN} + L_{content}, \quad (10)$$

Where L is the total loss and L_{GAN} is the adversarial loss. $L_{content}$ denotes the total perceptual loss for the target content. We set a to 0.01 in this work.

III. EXPERIMENTS

There were four parts to our experiments: preparation (Section IV-A), maintenance of the dataset (Section IV-B), training, and analysis.
DATFGAN (Section IV-C), and contrasting DATFGAN with cutting-edge approaches (Section IV-D). First, we established the software and hardware ecosystems. In the second phase, we gathered information for using in DATFGAN training and categorization. Using the acquired data, we trained DATFGAN in the third step. Our last step was to compare the outcomes of several super-resolution algorithms for picture transformation and then rank them according to their accuracy in image categorization.

A. EXPERIMENTAL SETUP

To train the suggested network, we used a PC with the software and hardware components shown in Table 1. The network was built using Pytorch, and acceleration was achieved using CUDA.

B. DATASETS

The suggested super-resolution model was pre-trained using the DIV2K dataset [28]. The photos were down-sampled using bicubic interpolation, and then we created pairs of clear and unclear images by adding additive Gaussian noise to the low-resolution images. Additionally, we drew on 1,350 photos of crop leaf diseases collected for the 2018 AI Challenger's Plant Disease Recognition Competition. Each of the twenty-seven categories has fifty photos. The CLDI dataset is the name we give to this group of data. Classification becomes more challenging and bias becomes less likely in the CLDI dataset since it includes photos of crop leaf diseases from both distinct species and from the same species with diverse images of diseases.

Forty photos were chosen for training the classification network models, and ten images were chosen for testing. In order to get better outcomes during training and testing, all photos were preprocessed. We enhanced the data by using batch normalisation and randomly rotating and flipping the photos. You can see the CLDI dataset in Figure 8. Table 2 further details the quantity and types of photos included in the CLDI collection.

TABLE 2. CLDI dataset

Name	Amount
Apple Scab	50
Potato Late Blight Fungus	50
Cedar Apple Rust	50
Strawberry Scorch	50
Cherry Powdery Mildew	50
Tomato Powdery Mildew	50
Cercospora Zeaemaydis Tehon and Daniels	50
Tomato Bacterial Spot Bacteria	50
Puccinia Polysora	50
Tomato Early Blight Fungus	50
Corn Curvularia Leaf Spot Fungus	50
Tomato Late Blight Water Mold	50
Maize Dwarf Mosaic Virus	50
Tomato Leaf Mold Fungus	50
Grape Black Rot Fungus	50
Tomato Target Spot Bacteria	50
Grape Leaf Blight Fungus	50
Tomato Septoria Leaf Spot Fungus	50
Grape Black Measles Fungus	50
Tomato Spider Mite Damage	50
Citrus Greening June	50
Tomato YLCV Virus	50
Peach Bacterial Spot	50
Tomato Tomv	50
Pepper Scab	50
Apple Frogeye Spot	50
Potato Early Blight Fungus	50
Total	1350

C. TRAINING DETAILS AND PARAMETERS FOR DATFGAN

We down-sampled the pictures using bicubic interpolation after training DATFGAN on an NVIDIA RTX2080Ti GPU with the DIV2K dataset [28]. In order to generate pairs of clear and unclear pictures, we further applied additive Gaussian noise to the low-resolution photos. In order to enhance the data, we flipped and rotated the photos at random. To optimise the model, we trained it for 200 epochs using the RMSProp optimizer, which minimised the loss function. After 60 epochs, we decreased the learning rate from its starting value of 0.0001. Both the momentum and the weight decay were set to 0.9 and 0.0001, respectively. Our team made advantage of 64 images as the mini-batch size to feed into the model. We also pre-trained our discriminative model using a VGG19 model trained in Pytorch to perform initialization and avoid undesired local optima.

D. COMPARISON TO STATE-OF-THE ART METHODS

We divided this stage into two phases of visual result inspection (Section IV-D1) and image classification (Sec- tion IV-D2). In Section IV-D1, we present super-resolution results and the ground truth images of crop leaf disease images. In Section IV-D2, we describe the training details and experimental results of images classification.

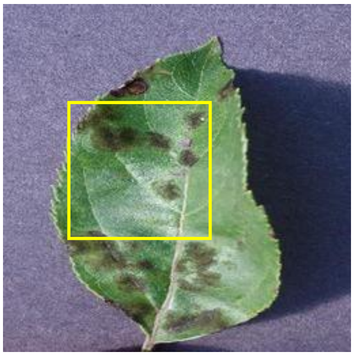
1) Visual result inspection

We compared our final models to state-of-the-art peak signal-to-noise ratio (PSNR)-oriented super-resolution methods, including Biubic, SRResNet [29], EDSR [30], SRDenseNet[31], VDSR [32] and LapSRN [33], using the CLDI dataset.Because there is no effective standard metric for perceptual quality, we present representative qualitative results in Fig-ure 9. PSNRs and structural similarity indexes are also pro- vided for reference. In Figure 9, one can see that DATFGANoutperforms previous approaches in terms of both sharpnessand details. For example, DATFGAN can produce sharperand more natural crop leaf disease image textures comparedto state-of-the-art PSNR-oriented super-resolution methods,which tend to generate blurry results with unnatural and noisy textures. Furthermore, previous PSNR-oriented super-resolution methods sometimes introduce unpleasant artifacts.DATFGAN eliminates such artifacts and produces natural

2) Image classification

We selected AlexNet [5], VGG-16 [24], Inception-v3 [34], ResNet-101 [26], Resnext50 [35], DenseNet-121 [27], MobileNet V2 [36], and ShuffleNet V2 [37] as classification networks. During the process of training these classification networks, we retained most of the weights in the original models and only trained softmax layers. We used 1080 im- ages from the CLDI dataset to train each model and 270 images from the CLDI dataset to test each model. Adam wasused as an optimizer and cross entropy was used as a loss function. Additional training details could be found in Table3.

Figure 10 presents the classification accuracies for imagestransformed by different super-resolution methods and raw images. In Figure 10, one can see that classification accuracy



Apple scab

Strawberry scorch

To

VDSR 30.06/0.79

Apple frogeye spot

Raw PSNR/SSIM

VDSR 26.63/0.70

Raw PSNR/SSIM

VDSR 30.48/0.84

Raw PSNR/SSIM

VDSR 28.42/0.79

EDSR 31.29/0.82

Bicubic 25.58/0.79

EDSR 26.75/0.73

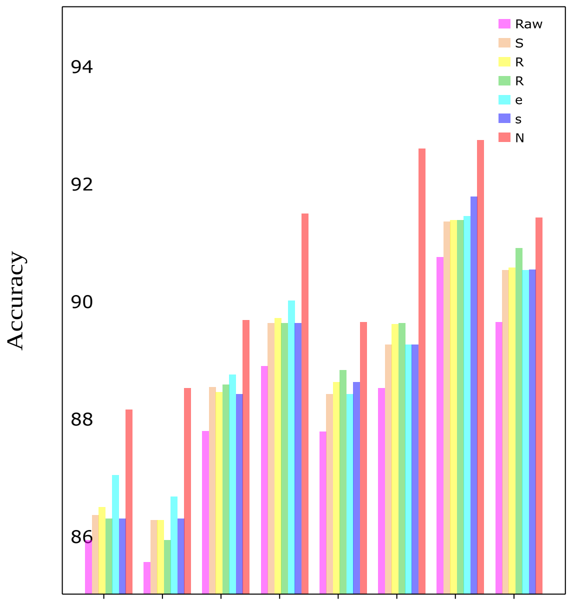
Bicubic 27.66/0.87

EDSR 30.53/0.85

Bicubic 27.34/0.85

EDSR 28.43/0.78

Overall classification accuracy



Alexnet VGG16 Inception-v3 Resnet101
Resnext50
Densenet121 MobileNet V2 ShuffleNet V2
Method

TABLE 3. Training details

Method	Learning rate	Batch size	Epochs
Alexnet	0.0001	20	50
VGG16	0.0001	20	50
Inception-v3	0.0001	20	65
Resnet101	0.0005	20	50
Resnext50	0.0005	20	60
Densenet121	0.0005	20	50
MobileNet V2	0.0001	20	60
ShuffleNet V2	0.0001	20	70

FIGURE 10. Overall classification accuracy

may be enhanced by using super-resolution techniques to the modified pictures. In this experiment, DATFGAN outperformed the state-of-the-art approaches and significantly improved classification accuracy compared to the other super-resolution methods. This was especially true for the ResNet-101 [26] and DenseNet-121 [27] classifiers. Table 4 displays the findings of imaging disease categorization for crop leaves.

DISCUSSION

Improving the spatial resolution of photographs of crop leaf diseases was suggested in this work using a super-resolution technique. Our findings show that compared to low-resolution photos acquired from farms, images altered using super-resolution approaches provide better categorization accuracy. This is due to the fact that, in comparison to low-resolution photos, photographs that have been processed using a super-resolution approach are able to transmit much more information, including specifics about lesions. Since the use of low-resolution photos led to reduced accuracy, our trials on the CLDI dataset clearly indicate this phenomenon. According to these findings, the super solution approaches were able to accurately recreate the intricate appearances of lesions, which greatly improved the process of disease detection. We found that DATFGAN enhances classification accuracy more than state-of-the-art algorithms when we compared them.

DATFGAN is a GAN that combines topology-fusion and dual-attention techniques. We combined dense and residual connections into one layer so that we might benefit from both kinds of connections. The DATFGAN generator is better at preserving information from earlier stages than residual networks, which allows our network to keep contiguous memory. Deeper structures can be trained with DATF-GAN since it can cut the channel development rate in half compared to dense networks, drastically reducing the number of network parameters. Two methods of paying attention, channel attention and texture attention, were used. Learned autonomously, channel attention may represent the interdependencies of convolution channels, allowing for the augmentation of relevant channels and the suppression of superfluous ones. In order to rebuild images, we may use edges as global spatial attention mechanisms since texture attention can direct attention depending on edges. Also, DATFGAN is great at making low-resolution photographs seem sharp and crisp. Beyond that, our suggested network's parameter sharing approach may drastically cut down on parameter counts. There are still several constraints that need to be solved, despite the fact that DATFGAN provides many benefits over earlier techniques. The use of average pixel locations in traditional deep-learning-based super-resolution algorithms results in excessively smooth pictures; yet, they do increase

TABLE 4. Classification Accuracy

Method	Accuracy(%)						
	Raw	SRResNet	EDSR	LapSRN	VDSR	SRDenseNet	DATFGAN(Ours)
Alexnet	85.92	86.35	86.48	86.29	87.03	86.29	88.14
VGG16	85.55	86.26	86.26	85.92	86.66	86.29	88.51
Inception-v3	87.78	88.53	88.44	88.57	88.74	88.41	89.67
Resnet101	88.88	89.62	89.70	89.62	90.00	89.62	91.48
Resnext50	87.77	88.41	88.61	88.82	88.41	88.61	89.63
Densenet121	88.51	89.25	89.60	89.62	89.25	89.25	92.59
MobileNet V2	90.74	91.34	91.37	91.37	91.44	91.77	92.73
ShuffleNet V2	89.63	90.52	90.56	90.89	90.52	90.53	91.41

PSNR. DATFGAN does not use averaging, resulting in better visual effects, but reducing PSNR compared to other super- resolution methods.

One of the most important techniques in deep learning, including CNNs, is transfer learning, which is also as knownas fine-tuning. In this study, we slightly modified state-of- the-art network architectures to avoid image size reduction and produce RGB images directly. In future studies, we willconduct network training using larger image datasets, such as ImageNet [38], and evaluate the resulting classification performance.

CONCLUSION

This research presents a new approach to crop leaf disease picture restoration. Our approach incorporates GANs with agricultural disease image processing in a way that no one has before seen. In order to make deeper structures trainable and drastically decrease the number of network parameters, we used both residual and dense connections. An additional performance improvement was achieved via a dual-attention method. Focusing on channels allows you to prioritise those that matter and downplay those that don't. By using textures as global spatial attention mechanisms during picture reconstruction, texture attention may allocate attention depending on the texture properties. Our experiments show that when compared to state-of-the-art approaches, DATFGAN achieves better outcomes in terms of visual quality and classification performance. With its foundation in topology fusion and excellent attention mechanisms, DATFGAN is able to decrease the amount of network parameters while simultaneously improving classification accuracy, making it very practical for real-world applications.

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