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# Agricultural Disease Identification Based on Feature Enhancement and Datfgan

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***Abstract*-The agricultural economy needs to identify farming diseases. For farming disease image identification, collected imagery are usually blurred, which can be reach to poor identification results in original invention environments. The quality of picture has a notable impact on the identification efficiency of pre-trained picture classifiers. To eliminate this difficulty, the proposed scheme can generative adversarial network with dual-attention and topology-fusion mechanisms called DATFGAN. This system can efficiently convert unclear images into bright and high-resolution images. In addition to this, the weight sharing plan in our advanced network can significantly decrease the number of parameters. Laboratory results explain that DATFGAN yields extra visually satisfying results than state-of-the-art methods. Furthermore, managed images are estimated based on identification tasks. Detection of plant leaf disease through some electronic procedure is beneficial as it reduces an extra effort of monitoring in large fields of crops, and at the very early stage itself it identifies the marks of diseases i.e. when they arrive on plant leaves.**

***Key words*-Crop leaf disease, attention, generative adversarial networks, super-resolution, identification.**

## I.INTRODUCTION

Nowadays, plant crop disorders are one of the main principal intimidations to crop production and also more to food protection. Plant leaf diseases identified using conventional techniques that are not give good results. The farming landmass is higher than just being feeding sourcing in today's world. Indian economy is extremely dependent on farming productivity. Consequently, in the department of horticulture, the detection of infection in plants represents an essential role. To identify a plant infection in the very beginning stage, use of automated virus detection procedure is beneficial.

Crop infection is a major factor restricting crop cultivation. Crop infection can manage to pointed drop in productions, which can be leads to large losses in the horticultural economy. Therefore, immediate identification of crop disease is crucial for the choice of optimal medications and is an essential prerequisite for decreasing crop damage and pesticide usage. Total crops are susceptive to diseases and crop infections negatively affect yield and state. However, extreme chemical control can transmit drug excesses and lead to environmental contamination. Based on upgraded living principles, the order for crop superiority is greater than ever. Therefore, the early diagnosis and therapy of crop diseases are issues that must be determined.

In modern days, farming disease identification is a more hot research topic. Cheng et al. [1] used the fine-tuning technique to analyze and recognize agricultural pest's infection while by deep convolutional neural networks (DCNN), which can be achieve a reasonable identification outcome. Yue et al. [2] developed a super-resolution technique for farming pest's infection restoration and recognition.

A plant disease finding system was projected by Kawasaki et al. [3] to know two plant leaf infections in maize plants by using a CNN. Sun et al. [4] designed the traditional AlexNet [5] model by implementing CNN models combining batch normalization and global pooling to recognize many leaf diseases. These investigations illustrate the workability and effectiveness of implementing DCNNs in the field of plant leaf disease identification. However, images acquired from fields are typically unclear. Lower image quality significantly decreases the identification efficiency of pre-trained classifiers, which are typically trained on understandable high-resolution datasets.

To improve the advance accuracy of farming plant disease image classification, poor-resolution pictures must be super-resolved to enhance spatial resolution and rebuild the high-frequency facts of pointed boundaries. In this way, the advanced scheme introduce a generative adversarial network (GAN) with dual-attention and topology-fusion mechanisms to transform poor-resolution pictures obtained at farms. The proposed scheme is called DATFGAN. To decide the proposed method, we examine it to state-of-the-art methods in terms of classification accuracy when images are distributed. We present attempts using eight classic classification systems and crop leaf disease images with a total of 27 levels as a classification dataset. An instance of a leaf disease that

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was super-resolved using DATFGAN is displayed in Figure 1.

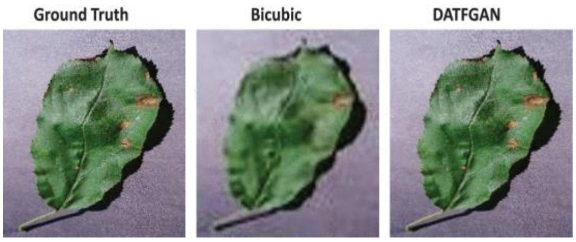


Figure.1 Super-resolved image generated by DATFGAN.

Experimental outcomes described that analysis efficiency should develop if images shall be transformed utilizing super-resolution techniques. Related to the state-of-the-art method considered in this investigation, DATFGAN presents excellent performance with medium accuracy improvement of 3%. Our main principal contributions can be resumed as follows.

- We suggest a novel image super-resolution approach for farming disease images.
- To the most excellent of our information, our system is the first to propose GANs into farming disease image processing.
- According to benchmark tests, DATFGAN defeats state-of-the-art techniques in terms of visible quality and classification accuracy.

## II. EXISTING SYSTEM

The secure identification and detection of plant crop diseases and crop force are a significant difficulty in the farming industry [6], [7].
The modern method for plant virus detection is generally naked eye inspection by professional experts through which classification and detection of plant infections are done. For performing so, a great team of professionals, as well as consecutive monitoring of plant, is required, which costs extremely high when we do with huge farms. At the same time, in some countries, farmers do not have special facilities or even the idea that they can interact with experts.

Due to asking the specialists, it’s high-priced as well as time-consuming too. In such conditions, the advised technique determines to be beneficial in recognizing large ranges of crops. Computerized detection of the diseases by just observing the marks on the plant leaves makes it easier as well as cheaper. This also helps machine vision to provide image-based computerized method control, examination, and robot guidance. Over the past few years, to develop crop management and health crop, several researchers have investigated plant crop disease identification based on deep learning techniques. Sladojevic et al. [17] introduced a unique method to the growth of plant disease identification models based on leaf image classification utilising deep convolutional networks. Their example could identify 13 various types of plant viruses and could recognise plant leaves from their surroundings.

## III. PROPOSED SYSTEM

### 1. Network Architecture

We separate this section into three sections to define the overall network architecture, parameter sharing, and topology fusion. First, we explain the overall structure of DATFGAN. Second, we propose parameter sharing services that are used in the generator network. Third, examine how to use the advantage of both residual and dense attachments.

### 1.1. Overall Architecture

DATFGAN can be classified into a generator and discriminator. Figure 2 displays the generator network of DATFGAN, which contains three components: a shallow feature extraction network, parameter-sharing attention-enhanced topology-fusion network, and reconstruction network. The shallow feature extraction network utilised for topology fusion has two convolutional layers for extract shallow characteristics from the generator system. Low level resolution imagery are employed as inputs for the generator system and split into two categories. One category serves into an upscaling module after the first convolutional layer in the generator network. Another category feeds into the topology fusion network to predict aspects following the second convolutional layer. The reconstruction network exploits global residual learning [25] and combines upscaled images with predicted aspects to generate high-resolution images.

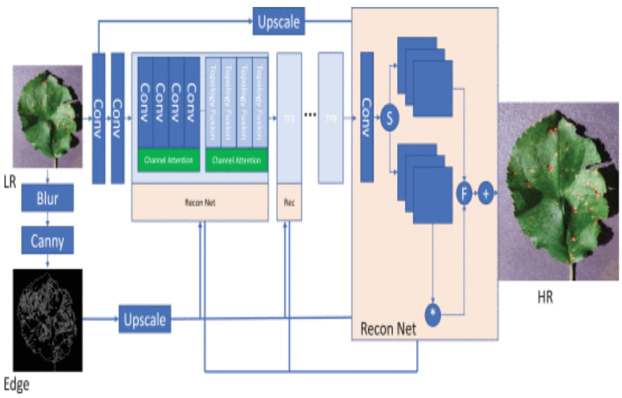


Figure 2 Generator network.

The discriminator network is shown in Figure 3. The discriminator network is trained to determine a maximization difficulty. It holds seven convolutional layers with a rising number of filter kernels. Striding convolutions used to decrease the image resolution every time the total number of features is multiplied. The resulting 512 feature plans are fed into an ultimate LeakyReLu activation function and two linear layers to improve the probability of individual classification.

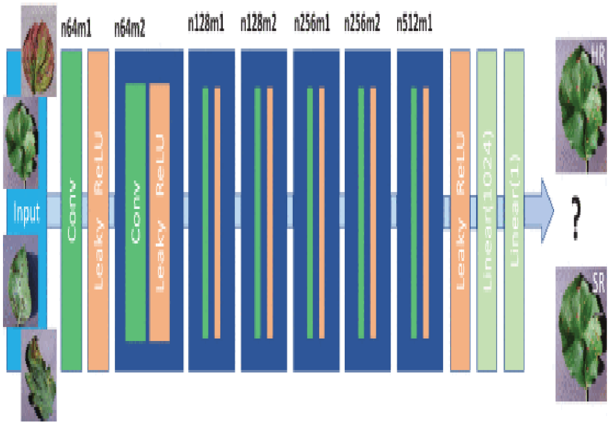


Figure 3 Discriminator network.

### 1.2. Parameter Sharing

A convolution process removes local data & some analytical properties of local data may be the same as those of other local data, meaning the features learned throughout convolution processes can also use for information. Consequently, the same learning features can be reused for many locations in the image. In a CNN, a convolution kernel (filter) is used to remove the feature. If the input information has many features, there will be several convolution kernels, beginning to parameter explosion in the convolution layer. Additionally, every convolution kernel in the layer that removes distinct features while neglecting the local associations among information.

### 1.3. Topology Fusion

ResNet [25] proposed to determine the difficulty of degradation in deep learning. The degradation difficulty is closely related to optimization. When the structure of design becomes increasingly difficult, optimization becomes increasingly difficult, appearing in unsatisfactory learning outcomes. The residual block in ResNet [25] was implemented employing residual associations. The input and output of the block were combined element-wise through the residual attachments. This simplistic form of addition does not combine any additional parameters or estimates to the network, but it can significantly improve the preparation speed of the design, thereby increasing the on the whole efficiency of training. When the amount of layers in the pattern develops, this arrangement can also resolve the degradation problem.

## 2. Dual Attention

### 2.1. Channel Attention

Channel attention used in topology fusion network to design the interdependencies of convolution channels, which can be acquired autonomously to support significant channels and suppress inefficient channels. This mechanism performs like a filter to recalibrate the report and gradient flow between networks.

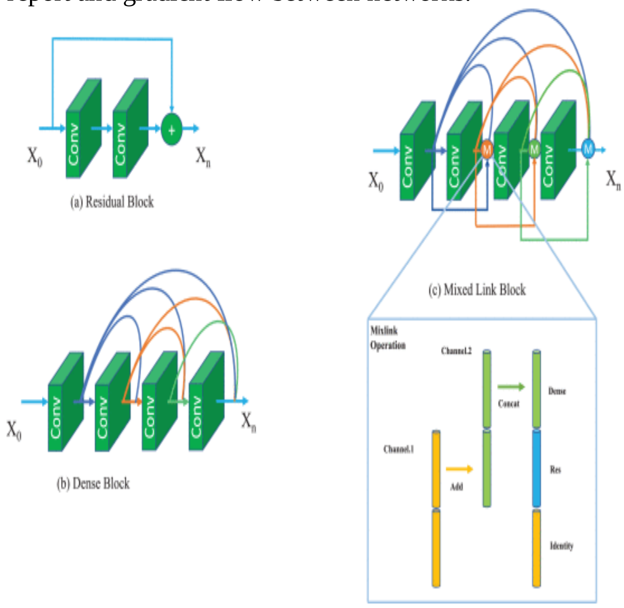


Figure 4 Topology fusion.

### 2.2. Texture Attention

As displayed in Figure 5, the texture is a very essential feature in crop images and is extremely useful for image super-resolution tasks. Furthermore, the high-frequency details of an image are typically positioned neighboring edges, expressing it is essential to assign awareness with directions from edges. Accordingly, we use texture attention in our reconstruction network.

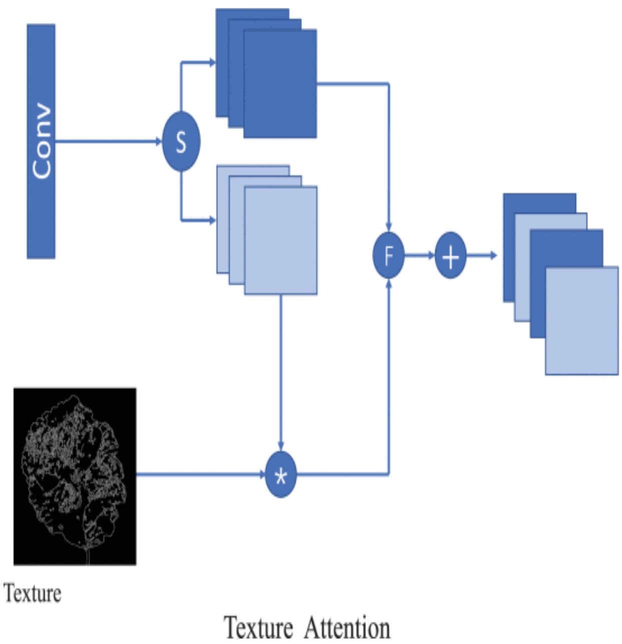


Figure 5 Texture attention.

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Figure 6 exhibits edge features taken from an RGB image prepared by the Canny operator. We further exhibit coloured edge features for the sake of purity.

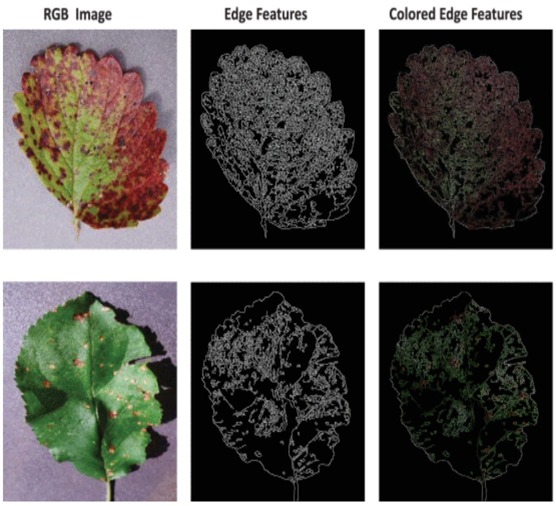


Figure 6 Edge features.

## IV. ALGORITHM METHODOLOGY

The block diagram of the introduced scheme is shown in the below figure. 7. The step by step advanced strategy consists of plant leaf and fruit image database collection, pre-processing of those pictures, segmentation, feature extraction of these pictures using Improved Deep Convolutional Neural Networks.

First, the pictures of multiple leaves obtained using a high-resolution camera to take more outcomes & capability. Then image processing procedures are implemented to these pictures to obtain valuable features which will require for additional analysis.

| |
|---|
| Image acquisition |
| Image pre-processing |
| Image Segmentation |
| Feature extraction |
| Statistical analysis |
| Classification |
| Diagnosis Results |

Figure 7 Block Diagram of proposed approach

### 4.1. Image Acquisition

Image acquisition is the principal system of digital image processing and it is described as catching the picture through the camera and holds it in digital media for further MATLAB methods. It is also a performance of regaining a picture from the machine, so it can be transformed by the additional process. In our work, utilising the digital camera we obtained healthy and diseased images of leaf & fruit as shown in fig. 4 for MATLAB image processing system.

Figure 8 Original image of diseased leaf and fruit.

### 4.2. Image Pre-Processing

The main objective of image pre-processing is to develop the image data contained unwanted distortions or to become some image characteristics for additional processing. Pre-processing process uses different ways such as adjusting image size and shape, filtering of noise, image conversion, improving the image and morphological operations. In this work, we used different MATLAB code to resize the image, to improve contrast and RGB to grayscale conversion as shown in fig. 5 for further operations like building clusters in segmentation.

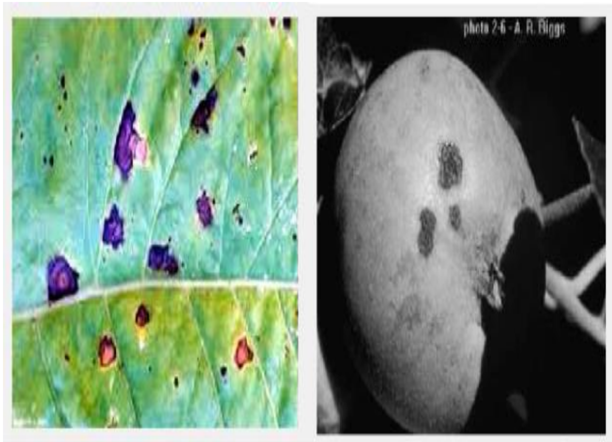

Figure 9 Contrast enhanced and RGB to gray converted image.

### 4.3. Image Segmentation

Image segmentation is the process for the reformation of the digital image into many segments and rendering of an image into something for more accessible analysis. Using image segmentation is used for finding the objects and bounding line of that image.

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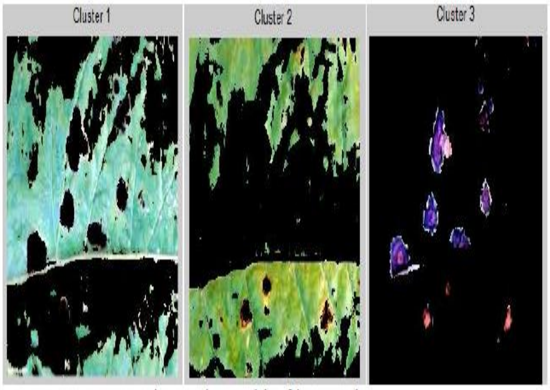


Figure 10 Diseased leaf image clusters.

### 4.4. Feature Extraction

In feature extraction, wanted feature vectors such as color, texture, morphology and structure are extorted. Feature extraction is a method for involving the number of resources required to define a large set of data exactly.

### 4.5. Image Classification

The convolutional neural network (CNN) is a type of deep learning neural networks. CNN represents a tremendous breakthrough in image recognition. They're most generally used to investigate visual representation and are continually working behind the scenes in image classification.

## V. EXPERIMENTAL RESULTS

Our analyses consisted of four stages: experimental setup, dataset management, training DATFGAN, and comparing DATFGAN to state-of-the-art methods. In the first stage, we described hardware and software environments. In the second stage, we gathered data for training DATFGAN and performing classification. In the third stage, we trained DATFGAN using the gathered data. In the last stage, we converted images using different super-resolution methods and correlated the results in terms of image classification efficiency.

### 5.1. Experimental Setup

We trained the advanced network utilising a computer furnished with the hardware and software listed in Table 1. Pytorch was used as a framework for building the network and CUDA was approved for acceleration.

| Hardware | Software |
|---|---|
| CPU: 8 Cores | Windows10 |
| RAM: 32 GB DDR4 | CUDA10.0 + CUDNN7.0 |
| GPU: NVIDIA RTX2080Ti (11GB GDDR6) | Pytorch1.0.1 + Python 3.7 |

### 5.2. Datasets

We applied the DIV2K dataset [27] for pre-training the advanced super-resolution model. We applied bicubic interpolation to down-sample pictures & we combined additive Gaussian noise to the low-resolution pictures to generate clear and unclear picture pairs. We also employed 1350 crop leaf virus models from the Plant Disease Recognition Competition of the AI Challenger 2018. These pictures hold 27 various categories & each section contains 50 images. We refer to this dataset as the CLDI dataset. The CLDI dataset holds both crop leaf disease pictures of several varieties and several disease images for the same species, which enhances the hardness of classification and overcomes the potential for bias.

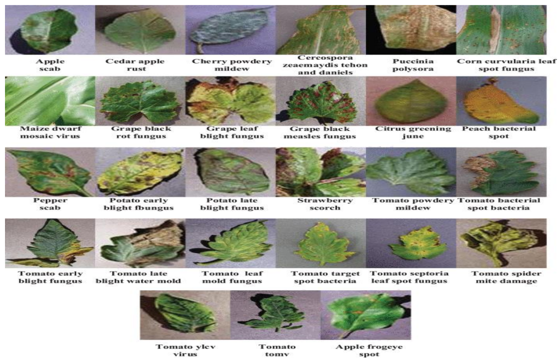


Figure 11 CLDI Dataset.

### 5.3. Training Details and Parameters for DATFGAN

We practised DATFGAN on an NVIDIA RTX2080Ti GPU utilising the DIV2K dataset [27] and worked bicubic interpolation to down-sample the images. We also combined additive Gaussian noise to the low-resolution pictures to create clear and unclear picture pairs. We randomly turned and flipped the pictures for data augmentation.

### 5.4. Comparison to State-of-the Art Methods

Transformed pictures handling different super-resolution techniques and analysed the results in terms of picture classification efficiency.

## VI. CONCLUSION

In this article, we introduced a new picture restoration approach for plant leaf disease images. To the biggest of our experience, our system is the beginning to introduce GANs into farming disease image processing. We preferred use of both residual and compact connections to decrease the number of network parameters significantly and make deeper structures trainable. Moreover, a dual-attention mechanism implemented a significant appearance boost. Channel attention can boost essential channels and suppress useless channels. Texture attention can indicate the attention based on the texture features and employ textures as global spatial attention mechanisms during picture reconstruction. According to our preliminary outcomes, DATFGAN outperforms state-of-the-art techniques in terms of both visual quality and classification performance. Based on topology fusion and effective attention mechanisms, DATFGAN can not only enhance classification accuracy but also decrease the number of network parameters, making it very useful for real-world applications.

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