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Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network

Mrs.T. Aruna Jyothi[1], P. Sai Krishna Sri Charan[2], S. Meghansh[3], B. Dinesh[4]

Assitant Professor, Department of Information Technolgy, MECS, Hyderabad, India[1]

Student, Department of Information Technolgy, MECS, Hyderabad, India[2-4]

Abstract: Many major grain-producing nations have implemented steps to limit their grain exports as COVID-19 has expanded globally; food security has sparked significant worry from several stakeholders. One of the most crucial concerns facing all nations is how to increase grain output. Crop infections, however, are a challenging issue for many farmers, thus it's critical to understand the severity of crop diseases promptly and properly to support staff in taking additional intervention steps to reduce plants being further affected. This paper proposed a hybrid deep learning model that combines the benefits of deep residual networks and dense networks to identify tomato leaf disease. This model can reduce the number of training process parameters to increase calculation accuracy and improve the gradients and information flow. Since the original RDN model was developed for image super-resolution, we must modify the input image characteristics and hyperparameters to reorganize the network architecture for classification tasks. On the Tomato test dataset in the AI Challenger 2018 datasets, experimental findings demonstrate that this model can obtain a top-1 average identification accuracy of 95%, confirming its good performance. In terms of crop leaf recognition, the reconstructed residual dense network model can outperform the majority of the state-of-the-art models while using significantly less computing power.

Index Terms: Agricultural artificial intelligence; tomato leaf diseases; residual dense network; identification of leaf diseases

I. INTRODUCTION

Every government must take steps to ensure food security, the Directors-General of the FAO, WHO, and WTO stated in a joint statement released in March 2020 as countries moved to execute policies intended to slow the COVID-19 pandemic. Food security has received more attention recently, and many nations and organizations are attempting to boost food production. An important field for research is how to control agricultural diseases and insect pests more precisely and successfully. Particularly, leaf diseases have a significant impact on crop growth and output. Effectively determining the severity of crop diseases has required a lot of research. At the moment, there are essentially two issues that makeup research on crop disease identification. One is the conventional approach to computer vision, which mostly relies on spectral Detection and feature extraction for illness classification. diverse diseases produce diverse leaf characteristics, which results in a variety of leaf shapes and colors when diseased and healthy crops are compared. The other topic identifies photos of leaves using machine learning. In other words, sickness images are retrieved using supervised or unsupervised learning algorithms, and the recognition is done utilizing the many characteristics of sick and healthy plants. The accuracy and effectiveness of crop leaf disease identification have further improved with the advancement of machine learning and the technology of the Internet of Things (LOT) in agriculture, which automatically identifies plant diseases and insect pests. The disease traits on tomato leaves, such as spot blight, late blight, and yellow leaf curl disease, were extracted by Jiang et al. using a deep learning technique. The accuracy of the suggested method rose by 0.6% and 2.3% in the training set and test set following continuous iterative learning to predict the category of each disease. For the purpose of automatic plant leaf disease detection and classification, P. Sharma et al. proposed a picture collection, image preprocessing, segmentation, and classification method based on artificial intelligence. This method can swiftly and efficiently identify crop illnesses in agriculture. A leaf disease identification technique based on the AlexNet architecture was proposed by M. Lv et al. . The design of an AlexNet architecture network named DMS-Robust AlexNet improved the capability of feature extraction combined with dilated convolution and multiscale convolution after first creating a framework for improving the maize leaf feature under the complex environment. A generative adversarial network-based leaf disease identification model was put out by Liu, B. et al. For training, this model created photos of four different leaf diseases. It then combined DenseNet with instance normalization to distinguish between authentic and fraudulent disease images and to extract feature information from grape leaf lesions. Finally, the approach applied a deep regret gradient penalty to stabilize the training process. The findings show that the GAN-based

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data augmentation strategy can successfully address the overfitting issue in disease identification, and this method can also effectively improve identification accuracy.A three-part multiple-classifier integration method for picture recognition was put forth by S. Liang et al..In order to classify several plant diseases that were assessed independently, CNN was first utilized to classify a public dataset of damaged and healthy plant leaves. Finally, the combined three models were assessed for their accuracy in diagnosing plant diseases. According to experimental findings, the top-1 accuracy on a split test set was close to 99.92%.

II. RELATED WORKS

Identification of leaf diseases is a crucial component of crop growth situation awareness, which enables individuals to take action as soon as feasible. The two primary techniques are deep learning-based leaf image detection and conventional machine learning algorithm detection.

A. TRADITIONALLY USED MACHINE LEARNING METHOD

The following diagram illustrates the most common classical machine learning approach used to identify crop leaf diseases.

1) SUPPORT VECTOR MACHINE

One of the most effective and potent machine learning techniques is the support vector machine. Given a small sample size, it can exactly strike a balance between model complexity and classification ability. SVM is superior to other machine learning techniques in many ways; it can perform without any prior information and ignore the effects of noise .

Modern models using SVM classifiers are widely used to identify crop diseases. A cotton leaf disease diagnosis method based on image processing and SVM was proposed by N. R. Bhimte et al. For the purpose of classifying cotton leaf diseases, this system first chooses the suitable picture attributes, such as color and texture, and then applies an SVM classifier.

Results from the experiments indicate that good performance was attained. In order to help with grape leaf disease identification and classification using an SVM classifier, Padol et al. first identified the damaged area for segmentation by KNN, and then they extracted features for the color and texture of the grape leaves.

By using classification approaches, they were able to identify the specific type of leaf disease. On the test set, this system had an accuracy of 88.89%.

2) K-MEANS

One of the first and most often used clustering algorithms is the k-means algorithm . K-means has received a lot of attention in the literature and has been used in a wide range of substantive fields .

Superpixel clustering-based leaf segmentation using K-means clustering and PHOG algorithms was proposed by S. Zhang et al. In the segmentation and recognition of images of plant sick leaves, this approach performed amazingly well. A diagnosis technique for brinjal leaf disease based on image processing and machine learning was put out by R. Anand et

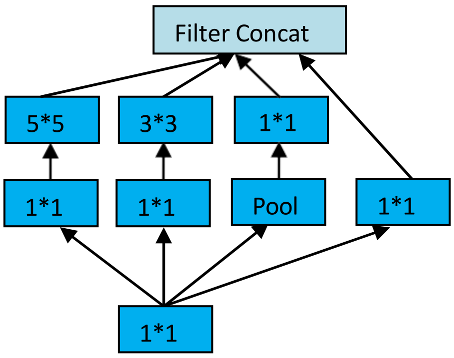

FIGURE 1. The original Inception network model

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al. This technique was particularly successful at identifying leaf illnesses because it used a K-means clustering algorithm to segment brinjal leaf disease. C. U. Kumari and others presented using image processing techniques, a leaf spot identification system. picture capture, picture segmentation, feature extraction, and classification were the four stages of this procedure. The illness features were computed using K-means. The target location of cotton leaf disease and the accuracy of bacterial leaf spots were 90% and 80%, respectively. A Kmeans clustering-based leaf disease and classification approaches were proposed by F. A. P. Rani et al. By collecting color and texture data and fed them to a multiclass SVM classifier. SVM was shown to have an average classification accuracy of more than 95%.

B. DEEP LEARNING

Numerous picture recognition models have been put forth as a result of the advancement of deep learning, and they can successfully address the issue of crop leaf identification. The extensively utilized deep convolutional neural network models at this time are listed below.

1) ALEXNET

The creation of AlexNet was one of the major advances in deep convolutional networks . It took first place in the field of vision in the ILSVRC2012 competition. The impact significantly outperforms the conventional method on the millions of ImageNet datasets, by more than 70% to 80%. Three convergence layers, three complete connection layers, and five convolution layers make up AlexNet. These include solving the gradient dispersion problem using the ReLU activation function rather than the sigmoid function or logistic function. In order to prevent overfitting and overlapping, local response normalization is employed for normalization, and dropout is applied at the fully connected level
.

2) INCEPTION NETWORK

Layer by layer, the prior networks conduct convolutions, and the output is input to the following layer. However, Inception defines a module that performs various convolution operations and, as an output, combines various convolution operations. According to experimental findings, it performs well. The output of the Inception network, as seen in FIGURE 1, is the depth stitching of the feature map, which distinguishes it from the typical convolution neural network in that it uses several convolution kernels of various sizes in its convolution layer.

3)RESIDUAL NETWORK

The residual network has advanced significantly in both depth and architecture over the earlier networks. It adds shortcut connections that transform the network into a relic of its former self. When the input and output have the same dimensions, identity shortcuts can be applied immediately. The ImageNet detection, ImageNet localization, COCO detection, and COCO segmentation tasks were all won by deep residual networks.

4)DENSE NETWORK

A feedforward connection is made between each layer and every other layer via the dense convolutional network (DenseNet). Our network features L(L+1)/2 direct connections as opposed to standard convolutional networks with L layers having L connections, one between each layer and its following layer. The feature-maps of all layers before it are inputs for that layer, and the feature-maps of all layers after it are inputs for that layer.

III. RESTRUCTURED RESIDUAL DENSE NETWORK

The residual dense network (RDN) was first proposed to address problems in image superresolution and image denoising. The residual dense block (RDB) extracts abundant local features via dense connected convolutional layers. RDB further allows direct connections from the state of the preceding RDB to all the layers of the current RDB, leading to a contiguous memory (CM) mechanism .

In this paper, we propose RRDN to solve the problem of crop leaf disease identification. As the original model was used in image superresolution, the input images have no dimension reduction operation, which may work well in a single block. But in the image classification task, tens of thousands of images are input, which will require considerably more computing resources, as well as low efficiency. So in this paper, the input image is convolved first in Res-Dense-Block (RDB)and the tensor is batch normalized after the convolution in the RDB block is useful in image SR. However, in the classification task, it takes a very large weight, which affects the classification efficiency and accuracy. To solve this

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problem, we abandon the tensor T2 that has no residual concatenation in RDB and finally use it for residual concatenation.Where T2 is activated by the LeakyReLU function, and T1 is the residual concatenate tensor by T2 and the input layers.

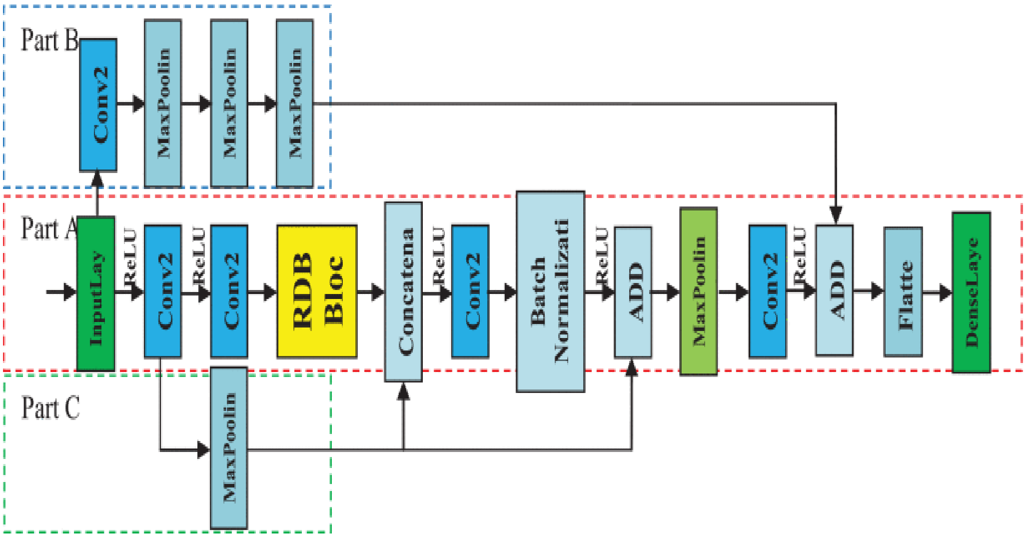

FIGURE 2. The architecture and workflow of RRDN.

T=N(C(I))…(1)

In Formula (1), the operators N and C stand for normalisation and convolution, respectively, while I stands for the input layer. The normalised tensor in RDB is denoted by the letter T.

This approach is helpful in image SR since it can be utilised throughout the whole model life cycle and uses T1 as the output tensor from RDB in the original RDB block. However, it carries a significant amount of weight in the classification task, which has an impact on the efficiency and accuracy of the classification. We finally use the tensor T2, which does not have residual concatenation in RDB, for residual concatenation in order to resolve this issue.

T1=Concate(T,I)

T2= L(T) ….(2)

Concate in Formula (2) stands for the residual concatenation operation. T2 is the tensor following the LeakyReLU operation and has an alpha of 0.3. T1 is the tensor that has been concatenated between T and I, where L signifies the LeakyReLU operation.

The tensor input size in this experiment is 196*196*64, and the 3-layer RDB is then input for feature extraction. The output size is then 98*98*64, which is suitable for residual addition. The initial input tensor and the block produced by the 3-layer RDB are then combined to produce the residual connection operation and a new tensor (T3).

T3=R3(C(C(I))) …(3)

Operator R3 in Formula (3) stands for the 3-layer RDB operation. After three pooling procedures, the input layer can be reloaded for residual connection to increase classification accuracy; the output image size is 1*1*128. Then, as shown in Formula (4), the residual connected operation is carried out with tensor T3 and tensor T4 is output, preparing for classification.

T4=Concate(T3,P3(C(I))) ..(4)

P3 (.) stands for three pooling operations. To classify the layer, we add a dense one. The loss function is cross-entropy, the optimizer is the adadelta function, and an L2_regularizer is introduced in the dense layer to avoid overfitting.

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IV. EXPERIMENT AND ANALYSIS

A. EXPERIMENTAL ENVIRONMENT

The experiment environment list is shown in TABLE 1

TABLE 1 Experimental Environment

Equipment	Specifications
System	Ubuntu18.04
Framework	Tensorflow2.3.1, Cuda10.1
Language	Python3.8
CPU	Inter(R) Xeon(R) E5-2620 v4@2.10GHz
RAM	20G
GPU	NVIDIA GeForceG TXTITAN Xp(12G)

B. DATASETS

This experiment uses the AI CHALLENGER dataset for tomato leaf diseases, which consists of 13,185 photos divided into 9 classes and all have the identical dimensions of 196*196 pixels. TABLE 2 displays the specific problems.

TABLE 2 Dataset Details

Classes	Number of images
Tomato_Healthy	1,381
Tomato_EarlyBlightFungus	792
Tomato_LateBlightWaterMold	1,569
Tomato_LeafMoldFungus	1,126
Tomato_PowderyMildew	1,469
Tomato_SeptoriaLeafSpotFungus	1,403
Tomato_SpiderMiteDamage	929
Tomato_TargetSpotBacteria	74
Tomato_YLCVVirus	4,442

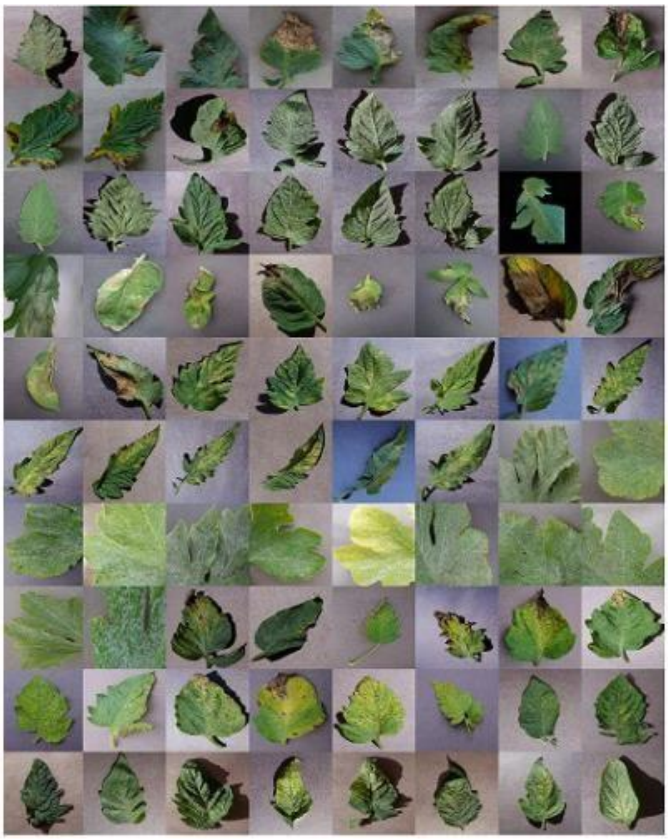

FIGURE 3. Some of the tomato leaf disease images.

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C. Training Details

1) Dataset Partition

In this paper, we trained RRDN on NVIDIA GeForceG TXTITAN Xp GPU using the tomato dataset in AI CHALLENGER 2018. The dataset was randomly divided into 3 parts, 60% for training, 20% for the validation set, and 20% for the test set.

2) RDB Activation Function

In the RDB block, the ReLU activation function is used after the convolution operation in every layer and the LeakyReLU function is used in the tensor after normalization to solve the dead neuron phenomenon.

3) Loss Function

One of the crucial instruments for determining the difference between network output and targets is the loss function. The cross-entropy loss function was employed in the loss layer and the softmax activation function was used in the output layer to more effectively address the multiclassification issue.

loss(x,class)=−x[class]+log(∑j=0K−1exp(x[j]))

where x is the input and class is the index of range[0, K-1], K is the total of elements

4) Optimizer Function

The loss function was minimised and the learning rate was adaptively adjusted with an initial learning rate of 0.0001 in the optimisation layer using the adadelta optimizer.

5) Batch Size and Epochs

We choose between 8, 16, or 32 as the batch size. We set the value to 8 as the batch size to feed into the model because there was a gradient fluctuation phenomena when the batch size was 16 or 32. Additionally, we trained the model for 200 epochs because the loss convergence was no longer obvious at higher epoch counts.

V. CONCLUSION

The tomato is a staple food that is consumed all across the world for both food and spice. even for amusement. Tens of thousands of revellers from all over the world throw tonnes of tomatoes at each other during the "Tomatina," which is celebrated annually on the final Wednesday in August. The tradition began in Spain. The issue of plant infections must be solved if people are to grow tomatoes of higher quality. Plant diseases typically manifest on the leaves first, making the detection of leaf diseases particularly crucial.

A. Result Analysis

In this study, we analyse the original residual dense network model in order to create a collection of models for accurately recognising leaf illnesses. RDN design, as opposed to residual networks or dense-based architectures, is distinct. The network is structured using ResNet principles, and the RDB block is dense-based. By combining all of the earlier and later layers, DenseNet can perform better while requiring fewer parameters. Gradient disappearance can be addressed by ResNet by employing a residual block to connect the front and rear layers.

We redesigned the RDN model that was proposed in superresolution in order to take advantage of the residual block collection and DenseNet in the task of tomato leaf disease identification. A DenseLayer is utilised for the classification task after the input pictures have been normalised, the RDB tensor has been optimised, and a residual convolution layer module has been added. The results demonstrate that our method may increase the identification accuracy on the dataset for tomato leaf diseases. Experiments demonstrate that the RRDN can achieve good performance on the tomato dataset as high as 95%.

B. Discussion

The paper developed a residual dense network-based model for the diagnosis of tomato leaf diseases, which draws inspiration from RDN in the task of picture superresolution. We changed the model's design to create a categorization model, which outperformed the most recent models in terms of accuracy. We will attempt to execute transfer learning from the tomato dataset to other plants through the model adjustment as this model is appropriate for the tomato dataset.

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This will improve the generalization ability. We intend to put this research to use in the future in order to contribute in some little way to the advancement of agricultural intelligence.

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