IEEE Access
Multidisciplinary | Rapid Review | Open Access Journal

Received January 13, 2021, accepted February 8, 2021, date of publication February 12, 2021, date of current version February 24, 2021.

Digital Object Identifier 10.1109/ACCESS.2021.3058947

Tomato Leaf Disease Identification by Restructured Deep Residual Dense Network

CHANGJIAN ZHOU[1], SIHAN ZHOU[2], JINGE XING[1], AND JIA SONG[3]
[1]Department of Modern Educational Technology, Northeast Agricultural University, Harbin 150030, China
[2]College of Electrical and Information, Northeast Agricultural University, Harbin 150030, China
[3]Key Laboratory of Agricultural Microbiology in Heilongjiang Province, Northeast Agricultural University, Harbin 150030, China

Corresponding authors: Jinge Xing (xingjinge@neau.edu.cn) and Jia Song (songjia@neau.edu.cn)

This work was supported in part by the National Natural Science Foundation of China under Grant 31700067, in part by the Special Project of Educational Informatization of the China Association of Higher Education under Grant 2016XXYB06, and in part by the 2021 Project of the 14th Five Year Plan of Educational Science in Heilongjiang Province under Grant GJB1421224 and Grant GJB1421226.

ABSTRACT As COVID-19 spread worldwide, many major grain-producing countries have adopted measures to restrict their grain exports; food security has aroused great concern from various parties. How to improve grain production has become one of the most important issues facing all countries. However, crop diseases are a difficult problem for many farmers so it is important to master the severity of crop diseases timely and accurately to help staff take further intervention measures to minimize plants being further infected. In this paper, a restructured residual dense network was proposed for tomato leaf disease identification; this hybrid deep learning model combines the advantages of deep residual networks and dense networks, which can reduce the number of training process parameters to improve calculation accuracy as well as enhance the flow of information and gradients. The original RDN model was first used in image super resolution, so we need to restructure the network architecture for classification tasks through adjusted input image features and hyper parameters. Experimental results show that this model can achieve a top-1 average identification accuracy of 95% on the Tomato test dataset in AI Challenger 2018 datasets, which verifies its satisfactory performance. The restructured residual dense network model can obtain significant improvements over most of the state-of-the-art models in crop leaf identification, as well as requiring less computation to achieve high performance.

INDEX TERMS Residual dense network, leaf disease identification, agricultural artificial intelligence, tomato leaf diseases.

I. INTRODUCTION

In March 2020, a joint statement by the Directors-General of FAO, WHO and WTO, as countries move to enact measures aiming to halt the accelerating COVID-19 pandemic, every country must take measures to ensure food security [1]. Food security has been increasingly addressed; many countries and institutions are working to increase food production. How to master crop diseases and insect pests more accurately and effectively is an important research area. Specifically, leaf diseases greatly influence crop growth and yield. Researchers have performed considerable work to effectively identify the severities of crop diseases.

The associate editor coordinating the review of this manuscript and approving it for publication was Haruna Chiroma.

To present, the research on crop disease identification is mainly divided into two topics. One is the traditional computer vision method, which is mainly based on spectral detection and feature extraction to identify different diseases. Different types of diseases cause different leaf features, which leads to different shapes and colors of leaves eroded by diseases and healthy crops. The other topic uses machine learning technology to identify leaf images. That is, the identification of disease images is extracted by using supervised or unsupervised learning algorithms and the recognition is carried out through the different features of diseased and healthy plants.

With the development of machine learning and the technology of Internet of things (LOT) in agriculture [2], [3], which automatically identifies plant diseases and insect pests, especially for the application of deep learning, the accuracy and efficiency of crop leaf disease identification have further improved.

Jiang *et al.* [4] used a deep learning method to extract the disease features on tomato leaves, such as spot blight, late blight and yellow leaf curl disease. The proposed method predicted the category of each disease after continuous iterative learning, and the accuracy showed in the training set and test set increased by 0.6% and 2.3%. Sharma *et al.* [5] introduced an image collection, image preprocessing, segmentation and classification method based on artificial intelligence for the task of automatic plant leaf disease detection and classification, which can easily and quickly detect and classify crop diseases in agriculture. Lv *et al.* [6] proposed a leaf disease recognition method based on the AlexNet architecture. A maize leaf feature enhancement framework was designed first which enhanced the maize features under the complex environment and then designed an AlexNet architecture network named DMS-Robust AlexNet, which improved the capability of feature extraction combined with dilated convolution and multiscale convolution. Liu *et al.* [7] proposed a generative adversarial network-based leaf disease identification model. This model generated images of four different leaf diseases for training, then fused DenseNet and instance normalization to identify real and fake disease images as well as feature extraction capability on grape leaf lesions. Finally, the method stabilized the training process by applying a deep regret gradient penalty. The results showed that the GAN-based data augmentation method can effectively overcome the overfitting problem in disease identification, and this method can also effectively improve identification accuracy. Liang *et al.* [8] proposed a multiple classifier integration method for image recognition, which was divided into 3 parts. First, a public dataset of diseased and healthy plant leaves was adopted, and then CNN was used to classify different plant diseases which were evaluated separately. Finally, it was evaluated for accurately diagnosing plant diseases by the integrated three models. Experimental results showed that on a split test set the top-1 accuracy approached 99.92%. Jaisakthi *et al.* [9] designed a grapevine detection system based on image processing and machine learning. This system can segment grape leaves from the background by the grab-cut segmentation method. Global thresholding and a semisupervised technique were used by segmenting the diseased region from segmented leaves, and then extracted features from the segmented diseased part, which were classified as healthy, rot, esca, and leaf blight by different machine learning methods. Notably, the method obtained a better testing accuracy of 93% by SVM. Huang *et al.* [10] proposed an end-to-end plant disease diagnostic model-based deep neural network, which can reliably classify plant types and plant diseases. This model consists of two components: the leaf segmentation part that separates the leaves in the original image from the background, and the plant disease classifier, which is based on a two-head network that classifies plant diseases with the features extracted by various popular pretrained models. Experimental results demonstrate that this method can achieve a 0.9807 plant classification accuracy and a 0.8745 disease recognition accuracy. Waheed *et al.* [11] proposed an optimized corn leaf identification model based on DenseNet, which uses few parameters to improve work efficiency. Experimental results showed that this method has a good effect on corn leaf disease identification.

It can be seen from the above state-of-the-art methods that the research in crop leaf disease identification is mainly concentrated in computer vision and machine learning, particularly the recent development of deep learning used in agriculture. However, methods are rarely applied to crop leaf disease identification that can balance accuracy and efficiency. In this paper, we propose a restructured dense residual network that adjusts the structure and parameters. The purpose of this model is to improve the performance in crop leaf identification and reduce the impact of the disease on the crop as much as possible.

The main contributions of this paper include the following five points:

1) A *batch normalization* operation is added to the tensor after convolution in the RDB block.
2) The tensor (named T1) connected by residuals output by RDB is abandoned because in the whole model, this tensor has a very large weight, which has few contributions to classification accuracy.
3) The tensor (named T2) with no residual connected output by RDB can be used to make the final residual connection. After the convolution operation, the size of the image is (98*98*64).
4) The original images are reloaded instead of T1 to prevent excessive weight by the pooling operation and output the image (1*1*128).
5) Because RDN was originally used for image superresolution, we reduce the upscale layer and output layer as well as added a dense layer with a *softmax* function for the classification task.

The rest of the paper is organized as follows, Section 2 presents related works. Section 3 presents the structure of the restructured residual dense network (RRDN). Section 4 presents the experimental results and analysis, and Section 5 presents the conclusions.

II. RELATED WORKS

Leaf disease identification is an important part of crop growth situation awareness, which can allow people to take measures as soon as possible. The main methods are traditional machine learning algorithm detection and deep learning detection based on leaf images.

A. TRADITIONAL MACHINE LEARNING ALGORITHM

The most popular traditional machine learning algorithm applied in crop leaf disease identification can be shown as follows.

1) SUPPORT VECTOR MACHINE

Support vector machine is one of the strongest and most powerful machine learning algorithms [12], [13]. It can precisely find a balance between model complexity and classification ability when given limited sample information [14]. SVM has many advantages compared with other machine learning methods; it can also overcome the impact of noise and work without any prior knowledge [15].

In crop disease identification, there are many state-of-the-art models using SVM classifiers. Bhimte and Thool [16] proposed a cotton leaf disease diagnosis system based on image processing and SVM. This system selects appropriate features such as color and texture of images and then uses an SVM classifier for cotton leaf disease classification. Experimental results show that good performance was achieved. Padol *et al.* [17] intended to aid grape leaf disease detection and classification by using an SVM classifier; they first located the diseased region for segmentation by KNN, and then extracted grape leaves color and texture features. Finally, they detected the type of leaf disease by classification techniques. This system achieved an accuracy of 88.89% on the test set.

2) K-MEANS

It is known that the k-means algorithm is one of the oldest and most popular clustering methods [18], [19]. K-means has been widely studied with various extensions in the literature and applied in a variety of substantive areas [20]–[23].

Zhang *et al.* [24] proposed a fusion of superpixel clustering-based leaf segmentation method by K-means clustering and PHOG algorithms. This method achieved a wonderful performance in plant diseased leaf image segmentation and recognition. Anand *et al.* [25] proposed a brinjal leaf disease diagnosis method based on image processing and machine learning. This method segmented brinjal leaf disease by a K-means clustering algorithm and was very effective in recognizing leaf diseases. Kumari *et al.* [26] proposed a leaf spot identification system by image processing techniques. This method was divided into four stages: image acquisition, image segmentation, feature extraction and classification. K-means was used to compute disease features. The accuracy of bacterial leaf spot and target spot of cotton leaf disease was as high as 90% and 80% respectively. Rani *et al.* [27] proposed a K-means clustering-based leaf disease and classification algorithm by extracting color and texture features and feeding them to a multiclass SVM classifier. The classification accuracy on average for SVM was found to be greater than 95%.

B. DEEP LEARNING

With the development of deep learning, a variety of image recognition models have been proposed, which can effectively solve the problem of crop leaf identification. At present, the popular deep convolutional neural network models that are widely used are as follows.

1) ALEXNET

One of the main breakthroughs in deep convolutional networks was the development of AlexNet [28], [29]. It won the championship of the ILSVRC2012 competition in the field of vision. On the millions of ImageNet datasets, the effect greatly exceeds the traditional method, from more than 70% to 80%. AlexNet consists of 5 convolution layers, 3 convergence layers and 3 full connection layers. These include using the *ReLU* activation function instead of the sigmoid function or logistic function to solve the gradient dispersion problem. Local response normalization is used for normalization and dropout is used at the fully connected level to avoid overfitting, as well as overlapping.

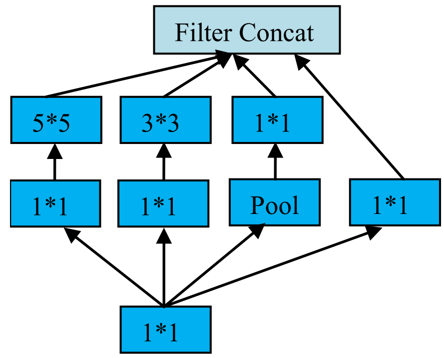

FIGURE 1. The original Inception network model.

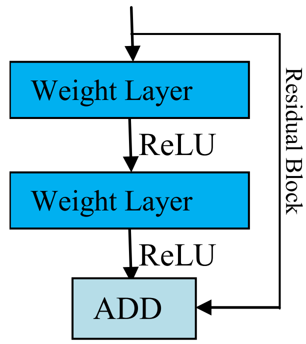

FIGURE 2. Residual network model.

2) INCEPTION NETWORK

The previous networks perform convolutions layer-by-layer, and the results are input to the next layer. However, inception defines a module that carries out different convolution operations, and finally splices different convolution operations as output. Experimental results show that it has a good performance. As shown in FIGURE 1, the Inception network is different from the general convolution neural network in that it contains multiple convolution kernels of different sizes in its convolution layer, and the output of Inception is the depth stitching of the feature map [30].

3) RESIDUAL NETWORK

The residual network, as shown in FIGURE 2, has not only made great progress in depth but the architecture is also different from the previous networks. It inserts shortcut connections, which turn the network into its counterpart residual version. The identity shortcuts can be directly used

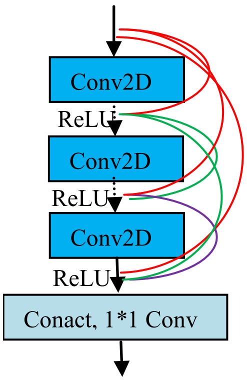

FIGURE 3. Dense network model.

when the input and output are of the same dimensions [31]. Deep residual nets won 1st place on the ImageNet detection tasks, ImageNet localization, COCO detection, and COCO segmentation.

4) DENSE NETWORK

The dense convolutional network (DenseNet, as shown in FIGURE 3) connects each layer to every other layer in a feed-forward fashion. Whereas traditional convolutional networks with L layers have L connections-one between each layer and its subsequent layer-our network has L(L+1)/2 direct connections. For each layer, the feature-maps of all preceding layers are used as inputs, and its feature-maps are used as inputs into all subsequent layers [32].

III. RESTRUCTURED RESIDUAL DENSE NETWORK

The residual dense network (RDN) was first proposed to address problems in image superresolution and image denoising. As shown in FIGURE 4. The residual dense block (RDB) extracts abundant local features via dense connected convolutional layers. The structure of the RDB is shown in FIGURE 5. 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 [33], [34].

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, which is shown in FIGURE 6.

Where T2 is activated by the LeakyReLU function, and T1 is the residual concatenate tensor by T2 and the input layers.

$$T = N(C(I)) \tag{1}$$

In Formula (1), the operator N denotes the *normalization* operation, and the operator C denotes the convolution operation, and I denotes the input layer. T is the tensor that has been normalized in RDB.

In the original RDB block, T1 as the output tensor by RDB, this block is used to transitive tensor to next RDB block, which can be used in the whole model life cycle, this method is useful in image SR. However, in the classification task,

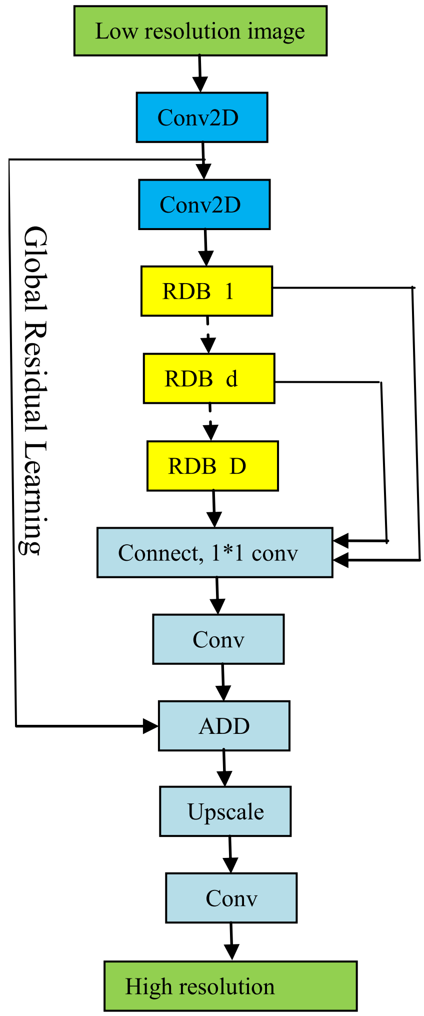

FIGURE 4. Residual dense network for image superesolution.

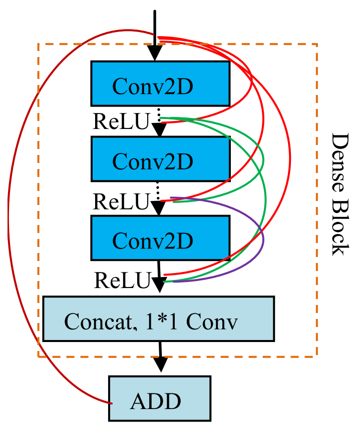

FIGURE 5. The original RDB block structure.

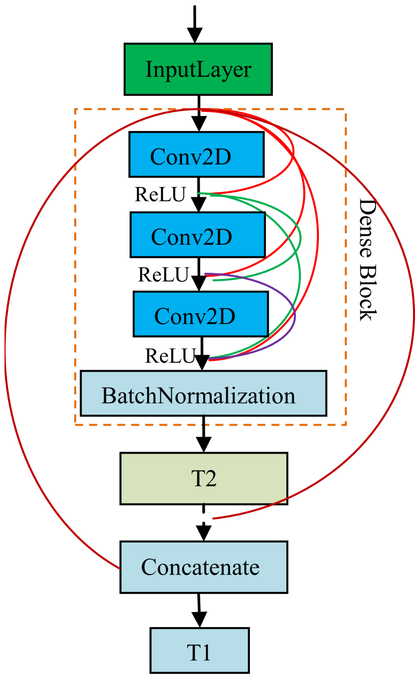

FIGURE 6. The RDB block structure of RRDN.

it takes a very large weight, which affects the classification efficiency and accuracy. To solve this problem, we abandon the tensor T2 that has no residual concatenation in RDB and finally use it for residual concatenation.

$$T1 = Concate(T, I)$$
$$T2 = L(T) \tag{2}$$

In Formula(2), *Concate* denotes the residual concatenate operation. $T1$ is the tensor that has been concatenated between T and I, where L denotes the *LeakyReLU* operation, $T2$ is the tensor after *LeakyReLU* with an alpha of 0.3.

In this experiment, the input size of the tensor is 196*196*64, then input the 3-layer RDB for feature extraction. Then the output size is 98*98*64, which can be used for residual added. After that, the block output by the 3-layer RDB and the initial input tensor create the residual connection operation and output a new tensor(T3).

$$T3 = R^3(\mathrm{C}(C(I))) \tag{3}$$

In Formula (3), Operator R^3 denotes the 3-layer RDB operation. To improve the classification accuracy, the input layer can be reloaded for residual connection, after 3 pooling operations; the output image size is 1*1*128. Then, the residual connected operation is performed with tensor *T3*, tensor T4 is output, which prepares for classification, as shown in Formula (4).

$$T4 = Concate(T3, P^3(C(I))) \tag{4}$$

where P^3(.) denotes 3 pooling operations. We add a dense layer for classification. To prevent overfitting, an L2_regularizer is added in the dense layer, the *adadelta* function is used for the optimizer, and the loss function is *cross-entropy*. The architecture and workflow of this proposed method can be seen in FIGURE 7.

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)

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

IV. EXPERIMENT AND ANALYSIS

A. EXPERIMENTAL ENVIRONMENT

The experiment environment list is shown in TABLE 1.

B. DATASETS

The tomato leaf diseases dataset in AI CHALLENGER is used for this experiment, which includes 13,185 images within 9 classes; the images are the same size of 196*196 pixels. The detailed issues are shown in TABLE 2. Part of the tomato leaf disease images is shown in FIGURE 8.

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

The loss function is one of the important tools to measure the gap between network output and targets. To deal with the multiclassification problem more conveniently, the cross-entropy loss function was used in the loss layer and the *softmax*

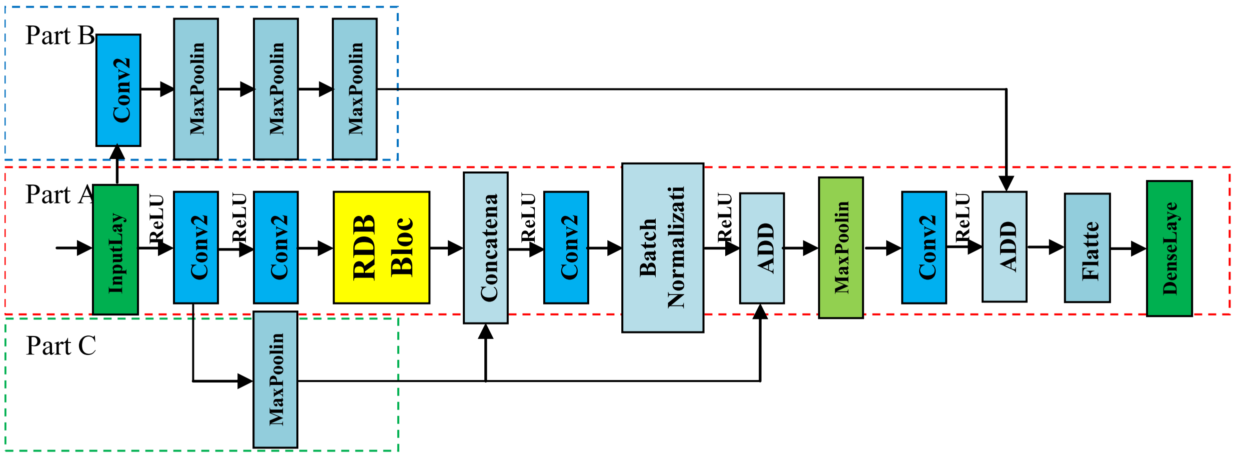

FIGURE 7. The architecture and workflow of RRDN.

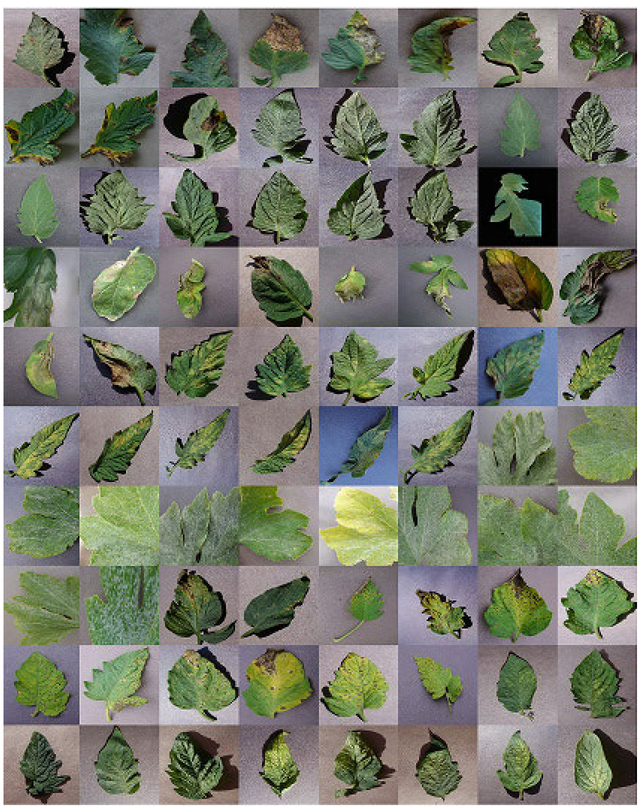

FIGURE 8. Some of the tomato leaf disease images.

activation function in the output layer. The *cross-entropy* [35] loss can be denoted in Formula (5).

$$loss(x, class) = -x[class] + \log\left(\sum_{j=0}^{K-1} \exp(x[j])\right) \quad (5)$$

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

4) OPTIMIZER FUNCTION

In the optimization layer, the *adadelta* optimizer was used to minimize the loss function and adjust the learning rate adaptively with the initial learning rate of 0.0001.

5) BATCH SIZE AND EPOCHS

We set the value of the batch size to 8, 16 or 32. When the batch size is 16 or 32, there was a gradient fluctuation phenomenon, so we set the value to 8 as the batch size to feed into the model. In addition, when the epochs were more than 200, the loss convergence was no longer obvious, so we trained the model for 200 epochs.

D. ABLATION STUDY AND MODEL COMPARISON

To evaluate the accuracy of the alternative models, this paper commonly used top-1 accuracy for classification. This can be shown in Formula (6).

$$acc = \frac{f}{N} \quad (6)$$

where N is the number of samples, and f is the number of correct predictions.

1) ABLATION STUDY

To validate the impact of the hyperparameters and the basic components in RRDN, an ablation study is necessary. As seen in FIGURE 7, part A is the main body of the RDN; we reduced the upscale layer and output layer in FIGURE 4 and added a flatten layer and dense layer for the classification task. Only in this way can the model work for image classification.

Part B is the unprocessed image tensor, with a size of (196*196*3), the input to the convolution layer with filters is 256, the kernel_size is 256, the stride is (1, 1), and then 3 *maxpooling* operations are performed to make a residual connection with the ADD layer in FIGURE 7.

Part C is the residual block; because our work to extract features for classification, a *maxpooling* layer with pooling_size 3, and stride (2, 2) is necessary for residual concatenation to Part A.

To validate the effect of the RRDN components, the model was divided into 4 parts:

i) The original RDN model is shown in Part A in FIGURE 7.

TABLE 3. Result of every part in RRDN.

	Validate accuracy	Test accuracy
Part A	90%	88.76%
Part A + B	94%	94.19%
Part A + C	94%	93.87
Part A+ B + C(RRDN)	95%	95%

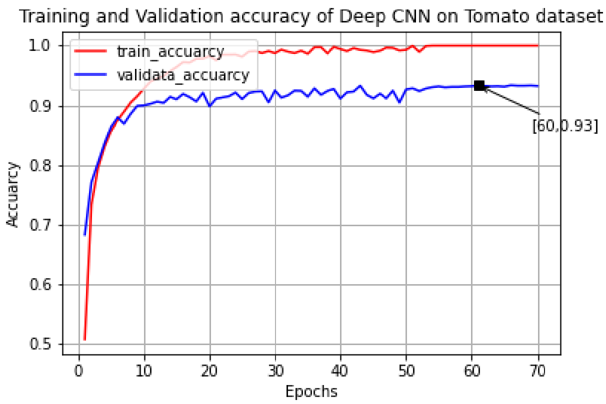

FIGURE 9. Training and validation accuracy of deep CNN.

ii) Part A + Part B.
iii) Part A + Part C.
iv) Part A + Part B + Part C, which is RRDN.

The same environment and dataset were used for every part. The results are shown in TABLE 3.

As seen in TABLE 3, the origin RDN model (Part A) only had 90% accuracy on the validation set and 88.76% on the test set; the model with Part A and Part B achieved 94% accuracy on the validation set and 94.19% on the test set; the model with Part A and Part C achieved 94% accuracy on the validation set and 93.87% on the test set. Our method RRDN(Part A + B + C) achieved 95% on both the validation set and test set separately.

After the ablation experiment, our method achieved the highest validation and test accuracy, which verifies its effectiveness.

2) COMPARISON WITH STATE-OF-THE-ART MODELS

We select some classic deep learning models for comparison, Deep CNN [36], ResNet50, DenseNet121, in the experiment environment and datasets. FIGURE 9~FIGURE12 shows the training and validation accuracy of the four models.

As shown in FIGURE 9~FIGURE 12, with the increase in epochs, the accuracy in the deep CNN gradient fluctuation is obvious, and the phenomenon of overfitting occurs; in Resnet50, the highest accuracy is approximately 89%, which is significantly lower than other models. In DenseNet121 there is a smooth model curve, but the accuracy is 92%, lower than RRDN. In RRDN, training and validation are convergent; the accuracy is 95%, which is the best performance in all of the models, which is satisfactory performance.

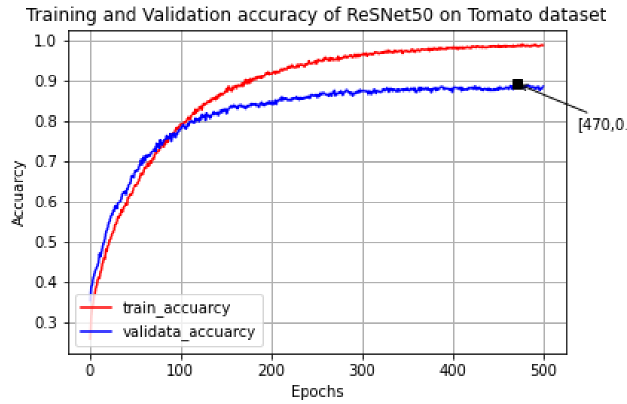

FIGURE 10. Training and validation accuracy of ResNet50.

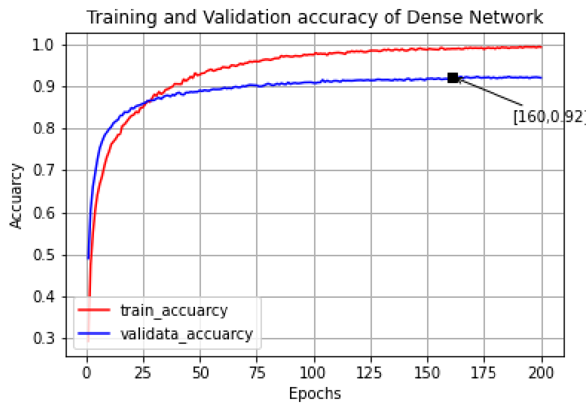

FIGURE 11. Training and validation accuracy of DenseNet121.

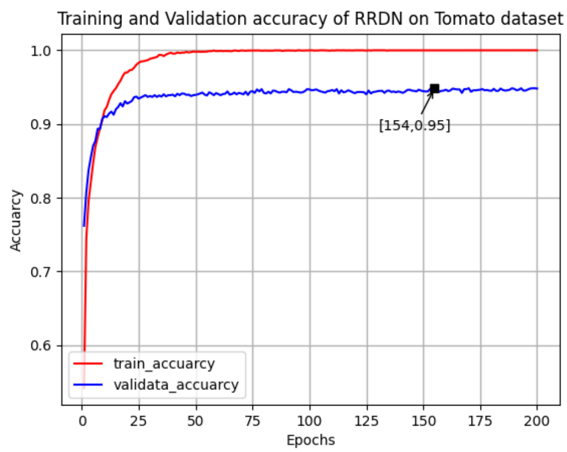

FIGURE 12. Training and validation accuracy of RRDN.

FIGURE 13~16 shows the training and validation loss by the four models.

As shown in FIGURE 13~FIGURE 16, with the increase in epochs in Deep CNN, the loss function fluctuates obviously on the tomato dataset; in ResNet50, when the validation loss is reduced to 0.5, it does not continue to decrease; in

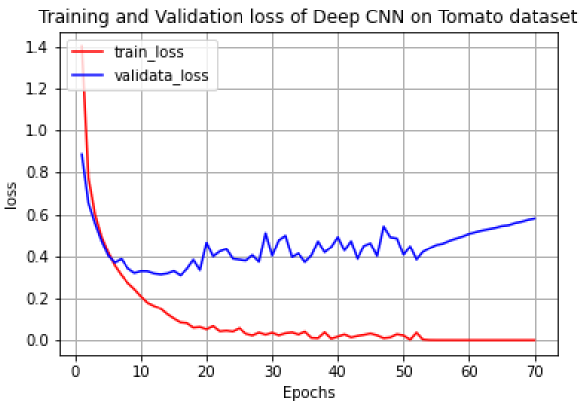

FIGURE 13. Training and validation loss in Deep CNN.

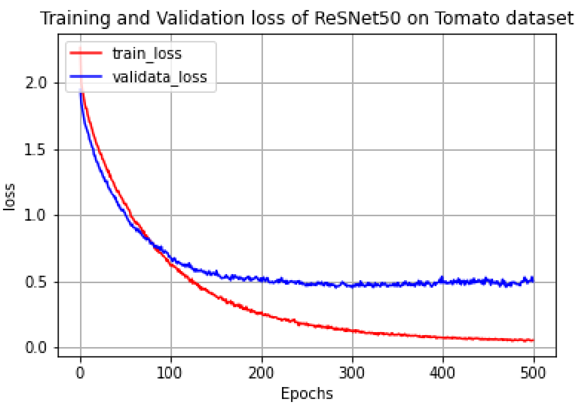

FIGURE 14. Training and validation loss in ResNet50.

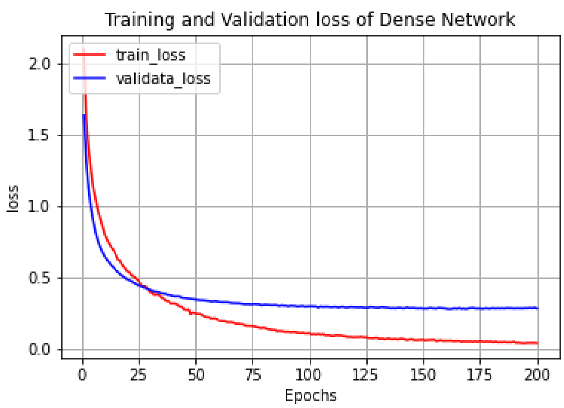

FIGURE 15. Training and validation loss in DenseNet121.

DenseNet121, the loss function and RRDN progress as well as RRDN; the RRDN training and validation loss is convergent and the gradient gradually decreases.

To better verify the prediction performance of the models, the accuracy on the test dataset can be shown in TABLE 4.

The comparison with the state-of-the-art study on tomato disease identification can be shown here. Raza *et al.* [37] proposed an SVM-based classifier on 71 tomato leaf images, which only achieved an accuracy of 89.93%. Prasad *et al.* [38] used a KNN based model on the tomato

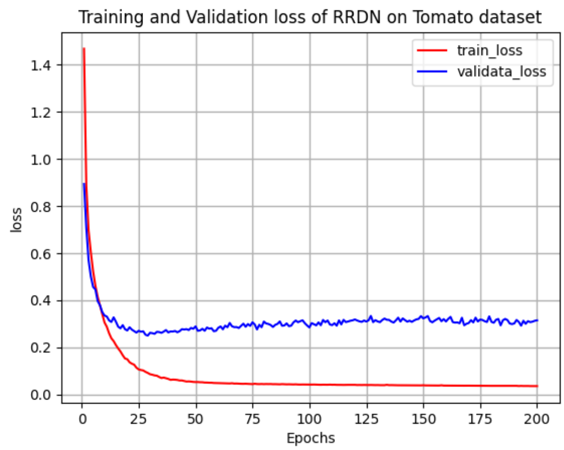

FIGURE 16. Training and validation loss in RRDN.

TABLE 4. Accuracy on test dataset.

Models	Accuracy
Deep CNN	93.21%
ResNet50	88.49%
DenseNet121	91.96%
RRDN	95%

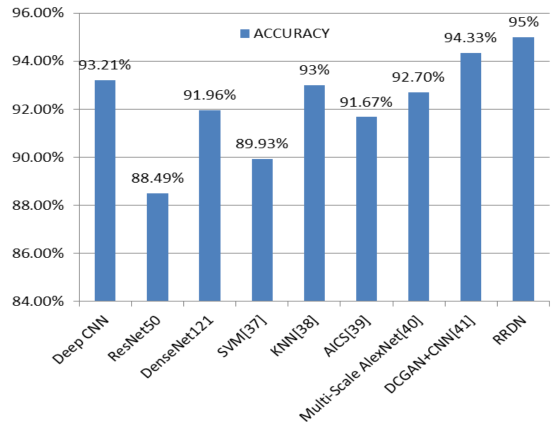

FIGURE 17. Comparison with the state-of-the-art on the tomato disease identification.

data of 14,529 images in 10 classes and achieved an accuracy of 93%. Luna *et al.* [39] proposed an automated image capturing system that achieved an accuracy of 91.67% on the tomato dataset. Guo *et al.* [40] designed a new model named multiscale AlexNet, which achieved 92.7% accuracy on 5,766 images in 8 classes of the tomato dataset. Wu *et al.* [41] proposed a DCGAN+CNN model, which achieved an accuracy as high as 94.33%. Our method named the RRDN model, t achieved up to 95% accuracy on a dataset of 13,185 images within 9 classes. The comparison with the state-of-the-art study can be shown in FIGURE 17.

V. CONCLUSION

Tomato is a very popular food worldwide for food or for seasoning; it is one of the necessities of life. Even for entertainment. The "Tomatina" held each year on the last Wednesday in August originated in Spain where tens of thousands of revelers from around the world pelt each other with tons of tomatoes. To produce better quality tomatoes, people must overcome the problem of plant diseases. Generally, plant diseases appear on the leaves first, which makes the leaf disease identification particularly important.

A. RESULT ANALYSIS

In this paper, we strive to develop a set of models for identifying leaf diseases with high accuracy, through analyzing the original residual dense network model. According to the RDN architecture, which is different than residual networks [31], [42] or dense-based models [43], [44]. The RDB block is dense-based and the network is structured considering the rules of ResNet. DenseNet can collect all of the previous and latter layers, which can achieve better performance with fewer parameters. ResNet can connect front and back layers using a residual block, which can solve the problem of gradient disappearance.

To take advantage of the residual block collection and DenseNet in the task of tomato leaf disease identification, we restructured the RDN model which was proposed in superresolution. After normalizing the input images, optimizing the RDB tensor, adding a convolution layer residual module, a DenseLayer is used for the classification task. Experiments show that the RRDN can achieve satisfactory performance on the tomato dataset as high as 95%; the results show that our method can improve the identification accuracy on the tomato leaf diseases dataset.

B. DISCUSSION

This paper proposed a residual dense network-based tomato leaf disease identification model; this inspiration comes from RDN in the image superresolution task. By adjusting the model architecture, we transformed it into a classification model, which obtained a higher accuracy than state-of-the-art models. Because this model is suitable for the tomato dataset, we will attempt to perform transfer learning from the tomato dataset to other plants through the model adjustment to improve the generalization ability. In the future, we hope to apply this work in practical work to make a small contribution to developing agricultural intelligence.

ACKNOWLEDGMENT

The authors would like to thank SeeTaaS Deep Learning Cloud Platform developed by Beijing Seetatech Technology Company Ltd. and the High Performance Computing Platform of Northeast Agricultural University for providing computing resources and technical support. *(Changjian Zhou and Sihan Zhou contribute equally to this work.)*

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CHANGJIAN ZHOU was born in Shandong, China, 1984. He received the M.S. degree from the College of Computer Science and Technology, Harbin Engineering University. He is currently an Engineer with the Department of Modern Educational Technology, Northeast Agricultural University. His research interests include machine learning and computer vision, agricultural artificial intelligence, and agricultural image processing.

SIHAN ZHOU was born in Zhejiang, China, 1998. He is currently pursuing the B.S. degree with the College of Electrical and Information, Northeast Agricultural University. He is also a Leader of the High Performance Computing Innovation Team, College of Innovation and Entrepreneurship, Northeast Agricultural University. His research interests include machine learning and computer vision, and deep learning and agricultural image processing.

JINGE XING was born in Heilongjing, China, 1972. He received the M.S. degree from the College of Engineering, Northeast Agricultural University. He is currently a Senior Engineer with the Department of Modern Educational Technology, Northeast Agricultural University. His research interests include cyberspace security, intelligent information processing, and agricultural artificial intelligence.

JIA SONG was born in Heilongjing, China, 1984. She received the B.S. degree from Northeast Agricultural University, in 2007, and the M.S. and Ph.D. degrees from the Harbin Institute of Technology, Harbin, China, in 2009 and 2014, respectively. She is currently a Visiting Scholar with the Cell and Molecular Biology, University of Gothenburg, Sweden, from 2011 to 2013. Since 2014, she has been a Lecturer with Northeast Agricultural University. Her research interests include plant protection and secondary metabolite of actinomycetes, plant disease, and computational biology.