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A Smart Mobile Diagnosis System for Citrus Diseases Based on Densely Connected Convolutional Networks

WENYAN PAN[1], JIAOHUA QIN[1], XUYU XIANG[1], YAN WU[1], YUN TAN[1], AND LINGYUN XIANG[2]

[1]College of Computer Science and Information Technology, Central South University of Forestry and Technology, Changsha 410004, China
[2]School of Computer and Communication Engineering, Changsha University of Science and Technology, Changsha 410114, China

Corresponding authors: Jiaohua Qin (qinjiaohua@163.com) and Xuyu Xiang (xyuxiang@163.com)

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ABSTRACT Citrus is one of the most widely cultivated fruit in the world. However, citrus diseases are becoming more and more serious, which has caused substantial economic losses to citrus growers. With the rapid developments of mobile device, mobile services computing play an increasingly important role in our daily lives. How to develop an intelligent diagnosis system for citrus diseases based on mobile services computing and bridge the gap between citrus growers and plant diagnostic experts is worth studying. In this paper, we build an image dataset of six kinds of citrus diseases with the help of experts and realize an intelligent diagnosis system for citrus diseases by constructing the simplified densely connected convolutional networks (DenseNet). The system is realized using the WeChat applet in the mobile device, with which users can upload images and receive diagnostic results and comments. The experimental results show that the recognition accuracy of citrus diseases exceeds 88% and the predict time consumption has also been reduced by simplifying the structure of the DenseNet.

INDEX TERMS DenseNet, intelligent diagnosis, citrus diseases, mobile service computing.

I. INTRODUCTION

The development of mobile devices and wireless technology further pushed the advance of other fields [1]. Mobile service computing enables us to provide and access services anytime and anywhere through mobile devices, such as mobile phones. Its convenient service can be effectively applied in our life and bring us convenience [2]. This paper aims to use mobile services computing to provide services to citrus growers through mobile phones.

Due to the high performance of convolutional neural networks (CNNs), it becomes a general trend to apply them to practical application scenarios. However, it is hampered by their large number of computational costs and a lack of datasets, that makes it becomes a hot topic for researchers.

Recently, the idea of feature reuse is prevalent, which is used to design deep networks, such as ResNet [3] and DenseNet [4]. This idea makes the network be substantially deeper, more accurate, and efficient.

According to incomplete statistics, Citrus is grown in more than 140 countries around the world. Due to climate warming, the prohibition of the use of highly toxic pesticides, aging of citrus trees, abuse of herbicides and other factors, citrus pests and diseases are increasingly serious. Common Citrus diseases include Citrus huanglongbing (HLB) [5], Anthracnose [6], Canker [7], Black spot [8], Sand paper rust and Scabies [9]. These citrus diseases usually affect leaves, branches, flowers, fruits, and stalks, affecting fruit quality and damaging economic benefits.

Citrus is cultivated on a large scale in China. However, the professional quality of fruit growers is generally not high, and it is inconvenient for them to communicate with experts. When encountering difficult diseases, it is impossible

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to find the causes and solutions in time, resulting in economic losses. Citrus diseases are widely spread and rapidly transmitted. It is inefficient and low accurate to recognize by the human eye alone. Using deep learning technology can effectively improve the efficiency and accuracy, and save human resources.

To solve above problems, the idea of this paper is to combine mobile computing with deep learning, so we proposed an intelligent mobile diagnosis system for citrus diseases based on DenseNet and mobile service computing to break the barrier between citrus growers and experts. A citrus disease recognition model based on DenseNet is trained and the intelligent diagnosis of citrus disease is realized by using mobile WeChat applet. User can take the photo of suspected citrus disease case and upload it to our system through the WeChat applet. Then it will feedback the intelligent diagnosis result. At the same time, the system can provide a positioning service to facilitate users to set up monitoring points for further tracking. The system also enables users to communicate directly with experts online.

The main contributions of this paper are as follows:

1.Image dataset for 6 kinds of Citrus diseases is constructed with the help of the experts.

2.Citrus disease dataset was used to train the simplified DenseNet network, which improved classification accuracy and reduced prediction time consumption.

3.Intelligent diagnosis of citrus diseases is realized using WeChat applet, which bridges the gap between citrus growers and experts.

II. RELATED WORKS

The convenience brought by mobile service computing not only exists in our life [10], but also can be effectively applied in industrial production [11], agriculture [12], transportation [13] and other fields [14], bringing great convenience to these fields.

Recently CNNs have achieved great success in the field of image processing. Compared with traditional image recognition algorithms, deep learning has a strong ability of learning and efficient feature expression. More importantly, it can extract information layer by layer from pixel-level original data to abstract semantic concepts, which has prominent advantages in extracting global features and context information of images [15].

With the development of the CNNs, the network are going deeper. However, the information in the network training process may gradually disappear after repeating convolution. To solve this problem, DenseNet designed Dense block structure, which connects each layer to other layers, and each layer takes the feature map of the previous layer as input. The structure of the 5-layer Dense block is shown in Figure 1.

The input of the model is x_0. Dense block consists of L layers and the nonlinear transformation function of each layer is $H_l(\cdot)$, where l represents the number of layers, the output of layer l is denoted as x_l. The relationship between the $l-1$ layer and the l layer is shown in Equation 1:

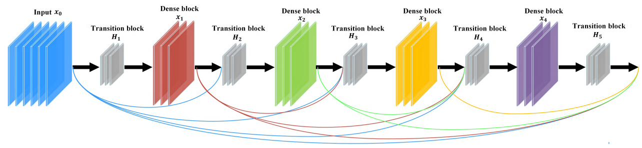


FIGURE 1. The structure of the 5-layer Dense block.

$$x_l = H_l([x_0, x_1, \ldots, x_{l-1}]) \tag{1}$$

where $[x_0, x_1, \ldots, x_{l-1}]$ represents that the Dense block makes concatenation the output feature map from 0 to $l-1$ layers.Because of the excellent performance of DenseNet, In this paper we use dataset to train the DenseNet network.

Traditional citrus disease detection based on the image is usually used traditional manual features of the image, such as color histogram, texture feature and color feature [16], [17]. Now CNNs can be applied to practical scenarios, such as medically assisted diagnosis [18], agriculture [19], and detection of plant diseases is no exception. References [20]–[22] use CNNs to detect and diagnose plant diseases. Reference [23] constructed a new three-channel CNN for the identification of leaf blight. However, few papers reported the application of CNNs in citrus diseases. Reference [24] use CNN to detect citrus and other crops and trees from UAV images. Reference [25]combined deep learning with network technology to set up an expert system for remote diagnosis of citrus diseases.

The citrus disease detection method described above usually use the image acquisition system to collect datasets, but they lacks the environmental background, and are not suitable for the actual situation of directly collecting images. However, the citrus disease detection methods based on CNNs failed to combine disease identification with the diagnosis system based on mobile service computing, so they cannot provide convenient services for growers. These are exactly the problems we want to solve by this paper.

III. A SMART MOBILE DIAGNOSIS SYSTEM FOR CITRUS DISEASES

The purpose of mobile computing is to provide useful, accurate and timely information to customers at any time and place through mobile devices. We use WeChat applet to set up the system on the mobile device so that users can use the system anytime and anywhere diagnose citrus diseases, monitor their orchards, and get some information about citrus diseases. Figure 2 shows the structure of smart mobile diagnosis system for citrus diseases. The system mainly realizes the following main functions:

1.Users can take photos of citrus diseases through the system and directly upload images to the server. The system not only feeds back the disease types of citrus but also displays relevant information of the disease, such as disease symptoms and causes. Also, the system will also propose the corresponding treatment plan for the disease, which can help to prevent and cure the disease. At the same time, users

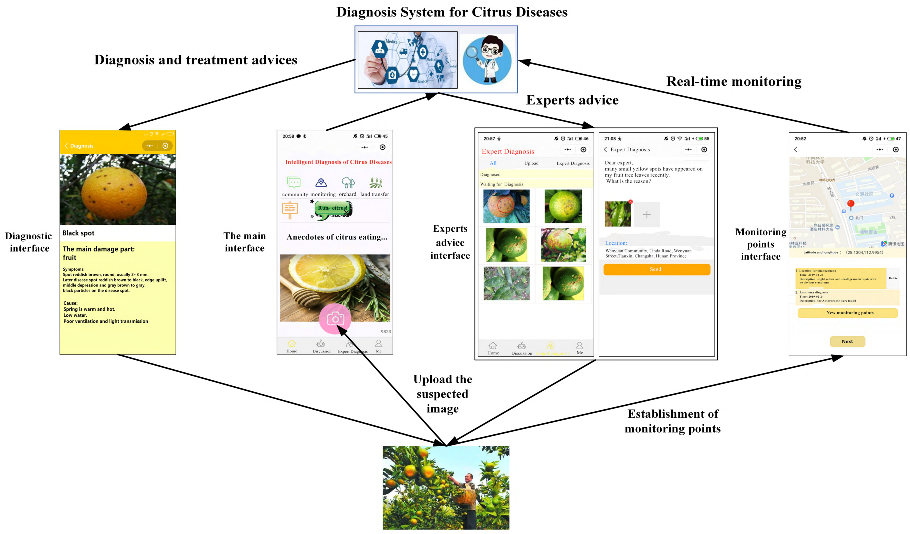


FIGURE 2. The structure of Smart Mobile Diagnosis System for Citrus Diseases.

can search the case of citrus diseases that they are interested in. Diagnostic information can be sent to the corresponding expert by clicking on the expert avatar.

2.In order to facilitate the users to monitor the citrus, the system provides the function of setting monitoring points. Users can accurately locate and set up monitoring points, so as to detect diseases as early as possible and deal with them in time.

3.To narrow the gap between citrus growers and experts, the system sets up expert consultation, and users can send difficult and complicated diseases to experts in the form of pictures and language text for expert diagnosis.

The data transfer between the client and the Nginx server is shown in Figure 3. Firstly, the client shakehands with the server through the network encrypted transport protocol "SSL/TLS protocol" and the public key is generated after the handshake is successful. Then the client sends HTTPS requests and encrypts image file information with the public key. The server receives the encrypted image and decrypts it with its private key. Finally, after a series of processing by the server, the data is sent to the client.

IV. DATASET ESTABLISHMENT

Due to the lack of citrus disease dataset, we collected related images through the network, local materials, access to experts and other ways, and then constructed the citrus disease dataset, annotate the dataset with the help of experts. The dataset contains 6 kinds of common citrus diseases: HLB, Anthracnose, Canker, Black spot, Sand paper rust, and Scab. Each category includes the corresponding images of the fruit and leaf with the symptom and most images contain the surrounding environment. The number and proportion distribution of each category of samples are shown in Table 1 and sample images of the experimental datasets are shown in Table 2.

TABLE 1. Number and proportion of citrus diseases.

Disease types	Number	Proportion
HLB	496	23.65%
Anthracnose	201	9.59%
Canker	746	35.57%
Black spot	279	13.30%
Sand paper rust	198	9.44%
Scab	177	8.44%

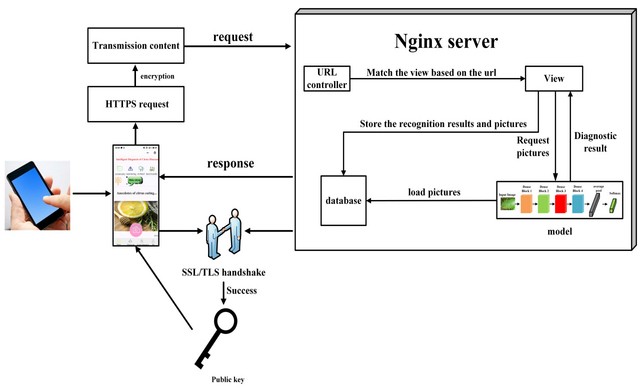


FIGURE 3. The data transfer between the client and the Nginx server.

Since our dataset is not enough, the training network is prone to overfitting. In order to avoid this problem, the dataset can be processed to generate new images and increase the size of the dataset [26], data augmentation has proved to be effective in deep learning image classification [27]. Therefore, we use 5 general ways to augment our training set and test set:

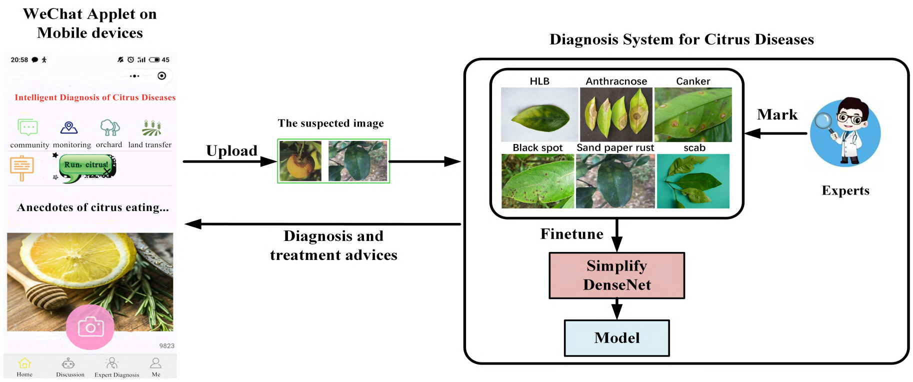
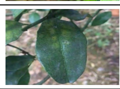
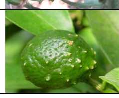


FIGURE 4. The process of Smart Diagnosis for Citrus Diseases.

TABLE 2. Image samples of citrus diseases.

Disease type	Sample	
HLB		
Anthracnose		
Canker		
Black spot		
Sand paper rust		
Sand paper rust		

horizontal flip, vertical flip, horizontal - vertical flip, increase brightness and contrast. In this way, the size of the training set and test set is increased by five times. The data augmentation methods and examples are shown in Table 3 and Table 4. The number and proportion distribution of each category after data augmentation are shown in Table 5.

To increase brightness and contrast, we use Equation 2 below for calculation:

$$dst = img1 \times \alpha + img2 \times \beta + \gamma \tag{2}$$

where dst is the target image, which is equivalent to the linear combination of $img1$ and $img2$. $img1$ and $img2$ are two images of the same size. We can change the contrast and brightness of images by changing α, β, γ. In our experiment, $img1$ is the original image, $img2$ is the image of the same size as the original image, and all pixel values are 0. In the experiment of increasing the contrast of the image, we select $\alpha = 1.5$, $\beta = 3$, $\gamma = 0$. In the experiment of increasing the brightness of the image, we select $\alpha = 1$, $\beta = 2$, $\gamma = 40$.

V. THE PROPOSED SMART MOBILE DIAGNOSIS SYSTEM FOR CITRUS DISEASES BASED ON DENSENET

A. SYSTEM ARCHITECTURE

The framework of the Smart Mobile Diagnosis System for Citrus Diseases based on DenseNet is shown in Figure 4. We use the dataset to train the simplified DenseNet and upload the model to the diagnosis system in the cloud server. Users collect images of citrus diseases and upload images to our system through the WeChat applet in the mobile device. The system recognizes the uploaded images through the trained model and returns the diagnosis results and treatment advice to users.

B. SIMPLIFY DENSENET

To reduce the possibility of overfitting reduce the prediction consumption, We appropriately removed the layers of DenseNet.

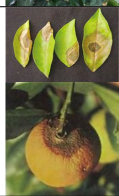
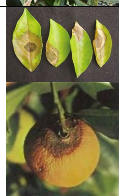
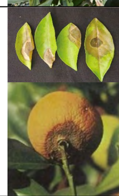
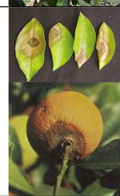
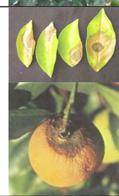
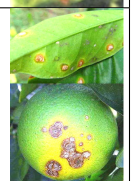
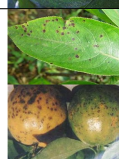
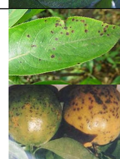
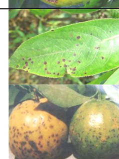
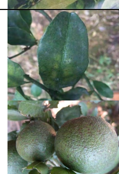
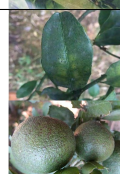
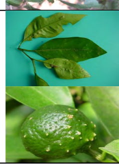
Figure 5 is the framework of DenseNet model training process. The main structure of the DenseNet-201 consists of four different Dense blocks and the transition Layer which connect each Dense block. Each Dense Block consists of 6, 12, 48, and 32 Bottleneck layers, respectively. Each Bottleneck layer consists of BN-ReLU-Conv(1×1)-BN-ReLU-Conv (1×1) [4], where BN is the Batch Normalization, ReLU is the rectified linear unit and Conv(1×1) is the convolution of 1×1. In the last Dense Block, we removed five Bottleneck layers and added the Batch Normalization, activation function, global average pooling, and softmax layers to form the simplified DenseNet. We use the original dataset and data augmentation dataset to fine-tune the simplified DenseNet to get our model.

VI. EXPERIMENTAL RESULTS AND ANALYSIS

A. SYSTEM ARCHITECTURE

The experiments were conducted with the Intel(R) Core(TM) i7-7800X CPU @ 3.50GHz, 64.00 GB RAM and one Nvidia GeForce GTX 1080 Ti GPU. In order to avoid repeated

TABLE 3. Data augmentation samples of citrus diseases.

Disease types	Original images	Data augmentation Samples				
		Horizontal flip	Vertical flip	Horizontal-vertical flip	Increasing brightness	Increasing contrast
HLB						
Anthracnose						
Canker						
Black spot						
Sand paper rust						
Scab						

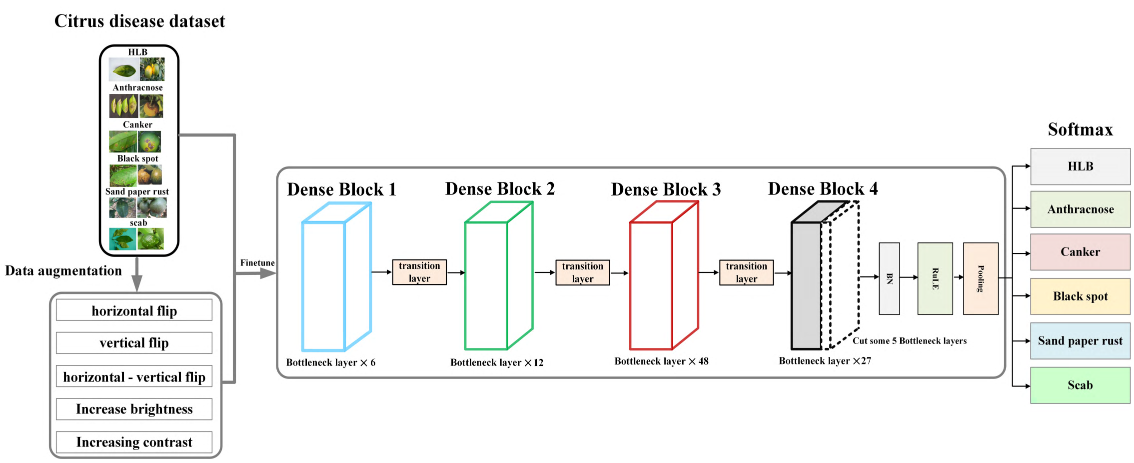


FIGURE 5. The structure of simplified DenseNet.

TABLE 4. Date augmentation methods.

Methods	Specific operations
Flipping	horizontal flip, vertical flip, horizontal - vertical flip
Increasing contrast	$dst = img1 \times \alpha + img2 \times \beta + \gamma$ $\alpha = 1.5, \beta = 3, \gamma = 0$
Increasing brightness	$dst = img1 \times \alpha + img2 \times \beta + \gamma$ $\alpha = 1, \beta = 2, \gamma = 40$

TABLE 5. Number and proportion of citrus diseases after data augmentation.

Disease types	Number	Proportion
HLB	2501	23.65%
Anthracnose	1016	9.61%
Canker	3761	35.56%
Black spot	1409	13.32%
Sand paper rust	998	9.44%
Scab	892	8.43%

development work, deep learning has a large number of frameworks. In this paper, we used the Keras framework.

B. TRAINING

The training set, validation set, and test set are constituted by randomly extracting images from the dataset with the ratio of 6:2:2 for each category. We use the training set and validation set to train the network, and the test set is used to evaluate the performance of the trained model.

We first train the DenseNet with the dataset, save the model, then reload the model and delete some Bottleneck layers for further training. All the networks are trained using stochastic gradient descent (SGD), and momentum is set to 0.9. On our dataset, we train using batch size 8 and 50 epochs. The initial learning rate is set to 0.001 and multiplied by 0.94 every two epochs. Our initial weight adopt the weight of DenseNet on the ImageNet.

C. EXPERIMENTAL COMPARISON AND PERFORMANCE EVALUATION

We use the dataset with data augmentation to training different networks. The accuracy of different networks for test sets is shown in table 6.

1) ACCURACY

The results show that the classification accuracy of our dataset with data augmentation is improved in different networks(+0.75%, +1.14%, +0.25%, +2%, +1%). The classification accuracy of the simplified DenseNet-201 is higher than that of the original network(+1%, +0.26%). The highest classification accuracy is 88.53%, which used data augmentation dataset with simplified DenseNet-201. This is because, in data augmentation the three image flips methods are designed to increase the number of training samples. Increasing colors and contrast can provide different color features and increasing the diversity of dataset, to improve the generalization ability of the model. Simplifyed DenseNet can alleviate the problem of excessive network complexity for our dataset and alleviate overfitting.

TABLE 6. The classification accuracy of the different network.

Methods	Original Dataset	Data augmentation
InceptionResNetV2	80.55%	81.30%
ResNet50	85.39%	86.53%
InceptionV3	86.53%	86.78%
DenseNet201	86.53%	88.28%
Simplify DenseNet201	86.53%	**88.77%**

TABLE 7. The classification accuracy of the simplified DenseNet201 for each category.

Methods	Original Dataset	Data augmentation
HLB	94.93%	95.79%
Anthracnose	65.79%	65.79%
Canker	90.21%	93.01%
Black spot	92.45%	94.34%
Sand paper rust	73.68%	73.68%
Scab	82.53%	85.29%

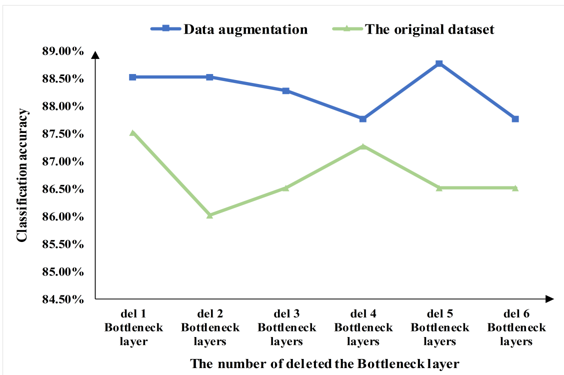


FIGURE 6. The impact of cutting the Bottleneck layers on the classification results.

We also investigated the classification results of each class with the simplified DenseNet201 network, which are shown

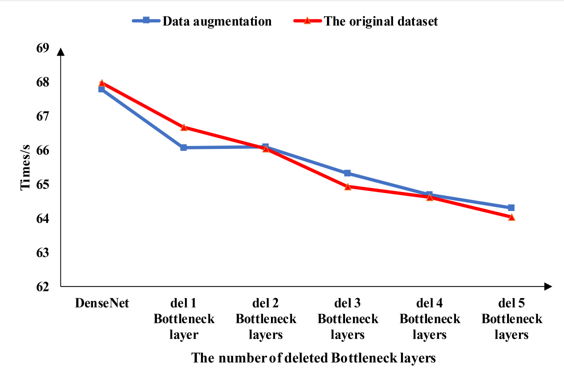


FIGURE 7. The comparison of time consumption.

in table 7. It can be seen that the classification accuracy of HLB, Canker and Black spot reaches more than 90%, while that of Anthracnose, Sand paper rust and Scab is lower. That is because, as we can see in table 1 and table 5, Anthracnose, Sand paper rust and Scab occupy less proportion in the dataset, resulting in poor training results. Moreover, some characteristics of citrus diseases are similar, which increase the difficulty of recognition. At the same time, different environment background and equipment will also affect the classification results.

We set up experiments on the impact of the classification accuracy with cutting different number of Bottleneck layers. The experimental results are shown in figure 6. In the experiments, the influence of the removal of 1, 2, 3, 4, 5, 6 Bottleneck layers is tested respectively. Experimental results show that the highest classification accuracy is obtained with the removal of five Bottleneck layers (88.78%).

2) TIME CONSUMPTION

In mobile service, the time consumption and real-time of the diagnosis system is a very important issue. In Figure 7, we compare the time consumption with different Bottleneck layers for the original dataset and the dataset with data augmentation.

3) OTHER EVALUATIONS

Recall, F1-score and MCC were used to evaluate our methods. The original DenseNet was trained with the original dataset and dataset after data augmentation. The simplified DenseNet network was trained using the same datasets. As we can see from figure 8, the values of the three evaluations show an upward trend, indicating that the method we proposed has advantages over other methods. In general, the proposed method has high classification accuracy for our citrus disease dataset.

VII. DISCUSSION

A. HELP FOR FRUIT GROWERS

The purpose of our method is to break the barrier between growers and experts so that growers can easily and quickly determine the type of citrus disease and the treatment of citrus diseases. Fruit farmers often have trouble communicating with experts. Besides, Citrus diseases are widely spread and rapidly transmitted, which will lead to economic loss if not effectively treated in time. The detection, monitoring and expert consultation functions set by our system can effectively help farmers manage their orchards.

B. CNNS APPLIED TO CITRUS DISEASES

The traditional diagnosis method of citrus diseases is to judge by the corresponding symptoms of fruits and leaves. Usually, the image-based detection method of citrus diseases uses the manual features of images, such as color features and texture features. The lower layers of CNN can learn the low-level image features, such as the edge and texture of citrus fruit or leaf, while the higher layers can learn lower layers features, and then form the high-level features (such as the shape and texture of disease spots), and so on. This allows

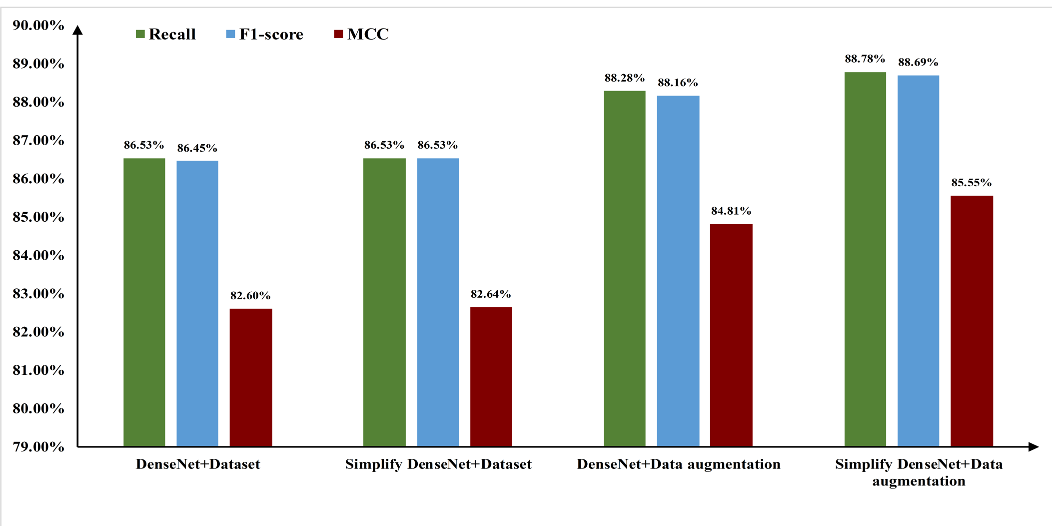


FIGURE 8. The comparison of other evaluation.

CNNs to learn increasingly complex and abstract visual concepts efficiently. This makes features of deep learning more representative of image content and better detection effect than traditional manual features.

C. SIMPLIFY NETWORK AND DATA AUGMENTATION

With the increase of network depth, overfitting may occur, resulting in poor classification effect. Besides, the lack of training samples may also cause this problem. Therefore, we use the method of data enhancement and simplified network to alleviate the overfitting phenomenon and improve the precision of the citrus disease detection system.

VIII. CONCLUSION

In this paper, deep learning is applied to the identification of citrus diseases. We construct a model to identify citrus diseases using dense connection networks. At the same time, the WeChat applet is used to realize the automatic identification of citrus diseases and provides patent disease prevention and treatment suggestions for fruit growers. Next, we will continue to expand the dataset and further optimize our method to achieve higher accuracy with the consideration of the similarity and confusion of some disease characteristics.

REFERENCES

[1] T. Qiu, J. Liu, W. Si, and D. O. Wu, "Robustness optimization scheme with multi-population co-evolution for scale-free wireless sensor networks," *IEEE/ACM Trans. Netw.*, to be published. doi: 10.1109/TNET.2019.2907243.

[2] J. Miranda, N. Mäkitalo, J. Garcia-Alonso, J. Berrocal, T. Mikkonen, C. Canal, and J. M. Murillo, "From the Internet of Things to the Internet of people," *IEEE Internet Computing*, vol. 19, no. 2, pp. 40–47, Mar. 2015.

[3] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jun. 2016, pp. 770–778.

[4] G. Huang, Z. Liu, L. van der Maaten, and K. Q. Weinberger, "Densely connected convolutional networks," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. (CVPR)*, Jul. 2017, pp. 2261–2269.

[5] J. M. Bové, "Huanglongbing: A destructive, newly-emerging, century-old disease of citrus," *J. Plant Pathol.*, vol. 88, no. 1, pp. 7–37, 2006.

[6] L. Deng, K. Zeng, Y. Zhou, and Y. Huang, "Effects of postharvest oligochitosan treatment on anthracnose disease in citrus (*Citrus sinensis* L. Osbeck) fruit," *Eur. Food Res. Technol.*, vol. 240, no. 4, pp. 795–804, 2015.

[7] H. Jia, Y. Zhang, V. Orbovic, J. Xu, F. F. White, J. B. Jones, and N. Wang, "Genome editing of the disease susceptibility gene *CsLOB1* in citrus confers resistance to citrus canker," *Plant Biotechnol. J.*, vol. 15, no. 7, pp. 817–823, 2017.

[8] N. T. Tran, A. K. Miles, R. G. Dietzgen, M. M. Dewdney, K. Zhang, J. A. Rollins, and A. Drenth, "Sexual reproduction in the citrus black spot pathogen, *phyllosticta citricarpa*," *Phytopathology*, vol. 107, no. 6, pp. 732–739, 2017.

[9] P. M. Bushong and L. W. Timmer, "Evaluation of postinfection control of citrus scab and melanose with benomyl, fenbuconazole, and azoxystrobin," *Plant Disease*, vol. 84, no. 11, pp. 1246–1249, 2006.

[10] S. Arshad, M. A. Azam, S. H. Ahmed, and J. Loo, "Towards information-centric networking (ICN) naming for Internet of Things (IoT): The case of smart campus," in *Proc. Int. Conf. Future Netw. Distrib. Syst. (ICFNDS)*, 2017, p. 41. doi: 10.1145/3102304.3102345.

[11] T. Qiu, H. Wang, K. Li, H. Ning, A. K. Sangaiah, and B. Chen, "SIGMM: A novel machine learning algorithm for spammer identification in industrial mobile cloud computing," *IEEE Trans. Ind. Informat.*, vol. 15, no. 4, pp. 2349–2359, Apr. 2018.

[12] H. Hu and X. Su, "General agriculture mobile service platform," in *Proc. 4th IFIP TC 12 Conf. Comput. Comput. Technol. Agricult. IV (CCTA)*, Nanchang, China, Oct. 2010, pp. 22–25.

[13] T. Qiu, X. Wang, C. Chen, M. Atiquzzaman, and L. Liu, "TMED: A spider-Web-like transmission mechanism for emergency data in vehicular ad hoc networks," *IEEE Trans. Veh. Technol.*, vol. 67, no. 9, pp. 8682–8694, Sep. 2018.

[14] L. Y. Xiang, X. B. Shen, J. H. Qin, and W. Hao, "Discrete multi-graph hashing for large-scale visual search," *Neural Process. Lett.*, vol. 49, no. 3, pp. 1055–1069, Jun. 2019.

[15] Y. LeCun, Y. Bengio, and G. Hinton, "Deep learning," *Nature*, vol. 521, no. 7553, pp. 436–444, May 2015.

[16] X. Zhao, T. F. Burks, J. Qin, and M. A. Ritenour, "Digital microscopic imaging for citrus peel disease classification using color texture features," *Appl. Eng. Agricult.*, vol. 25, no. 5, pp. 769–776, 2009.

[17] H. Ali, M. I. Lali, M. Z. Nawaz, M. Sharif, and B. A. Saleem, "Symptom based automated detection of citrus diseases using color histogram and textural descriptors," *Comput. Electron. Agricult.*, vol. 138, pp. 92–104, Jun. 2017.

[18] H. Greenspan, B. V. Ginneken, and R. M. Summers, "Guest editorial deep learning in medical imaging: Overview and future promise of an exciting new technique," *IEEE Trans. Med. Imag.*, vol. 35, no. 5, pp. 1153–1159, Mar. 2016.

[19] A. Kamilaris and F. X. Boldú, "Deep learning in agriculture: A survey," *Comput. Electron. Agricult.*, vol. 147, pp. 70–90, Apr. 2018.

[20] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Comput. Electron. Agricult.*, vol. 145, pp. 311–318, Feb. 2018.

[21] S. P. Mohanty, D. P. Hughes, and M. Salathé, "Using deep learning for image-based plant disease detection," *Frontiers Plant Sci.*, vol. 7, p. 1419, Sep. 2016. doi: 10.3389/fpls.2016.01419.

[22] S. Sladojevic, M. Arsenovic, A. Anderla, D. Culibrk, and D. Stefanovic, "Deep neural networks based recognition of plant diseases by leaf image classification," *Comput. Intell. Neurosci.*, vol. 2016, May 2016, Art. no. 3289801. doi: 10.1155/2016/3289801.

[23] S. Zhang, W. Huang, and C. Zhang, "Three-channel convolutional neural networks for vegetable leaf disease recognition," *Cogn. Syst. Res.*, vol. 53, pp. 31–41, Jan. 2018.

[24] O. Csillik, J. Cherbini, R. Johnson, A. Lyons, and M. Kelly, "Identification of citrus trees from unmanned aerial vehicle imagery using convolutional neural networks," *Drones*, vol. 2, no. 4, p. 39, 2018. doi: 10.3390/drones2040039.

[25] X. Laisheng, W. Zhengxia, P. Xiaohong, W. Min, and Y. Guangzhou, "Remote diagnosis and control expert system for citrus agricultural diseases and insect pests based on BP neural network and WebGIS," in *Proc. 2nd Int. Conf. Intell. Comput. Technol. Automat.*, vol. 4, Oct. 2009, pp. 88–93.

[26] W. Ma, J. Qin, X. Xiang, Y. Tan, Y. Luo, and N. N. Xiong, "Adaptive median filtering algorithm based on divide and conquer and its application in CAPTCHA recognition," *Comput., Mater. Continua*, vol. 58, no. 3, pp. 665–677, 2019.

[27] L. Perez and J. Wang, "The effectiveness of data augmentation in image classification using deep learning," *CoRR*, vol. abs/1712.04621, pp. 1–8, Dec. 2017.

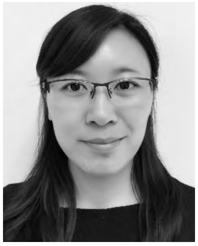
[28] D. C. Cireşan, U. Meier, L. M. Gambardella, and J. Schmidhuber, "Deep, big, simple neural nets for handwritten digit recognition," *Neural Comput.*, vol. 22, no. 12, pp. 3207–3220, 2010.

WENYAN PAN received the B.S. degree in electronic and information engineering from Hunan City University, China, in 2017. He is currently pursuing the M.S. degree in computer technology with the College of Computer Science and Information Technology, Central South University of Forestry and Technology, China. His research interests include machine learning and image processing.

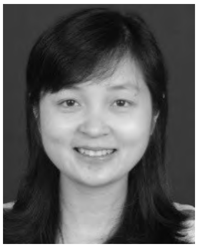
JIAOHUA QIN received the B.S. degree in mathematics from the Hunan University of Science and Technology, China, in 1996, the M.S. degree in computer science and technology from the National University of Defense Technology, China, in 2001, and the Ph.D. degree in computing science from Hunan University, China, in 2009. She is currently a Professor with the College of Computer Science and Information Technology, Central South University of Forestry and Technology, China. Her research interests include network and information security, image processing, and pattern recognition.

XUYU XIANG received the B.S. degree in mathematics from Hunan Normal University, China, in 1996, the M.S. degree in computer science and technology from the National University of Defense Technology, China, in 2003, and the Ph.D. degree in computing science from Hunan University, China, in 2010. He is currently a Professor with the Central South University of Forestry and Technology, China. His research interests include network and information security, image processing, and the Internet of Things.

YAN WU was with the Hunan Branch, China Telecom, where she was focused on mobile services for more than ten years. She is currently pursuing the M.S. degree in agriculture and information engineering with the College of Computer Science and Information Technology, Central South University of Forestry and Technology, China. Her research interests include mobile service, machine learning, and image processing.



YUN TAN received the M.S. and Ph.D. degrees from the Beijing University of Posts and Telecommunications (BUPT), China, in 2004 and 2016, respectively. She is currently a Lecturer with the College of Computer Science and Information Technology, Central South University of Forestry and Technology. Her research interests include information security, compressive sensing, and the Internet of Things.



LINGYUN XIANG received the B.E. degree in computer science and technology and the Ph.D. degree in computer application from Hunan University, Hunan, China, in 2005 and 2011, respectively. She is currently a Lecturer with the School of Computer and Communication Engineering, Changsha University of Science and Technology. Her research interests include information security, steganography, steganalysis, machine learning, and pattern recognition.