

PAPER · OPEN ACCESS

## 15 Development of Concise Convolutional Neural Network for Tomato Plant Disease Classification Based on Leaf Images

To cite this article: Arnes Sembiring *et al* 2021 *J. Phys.: Conf. Ser.* **1845** 012009

3  
View the [article online](#) for updates and enhancements.

### 15 You may also like

- 3 - [Multiscale space-time-frequency feature-based multitask learning CNN for motor imagery EEG classification](#)  
19  
Xiuling Liu, Linyang Lv, Yonglong Shen et al.
- 5 - [Automated diagnosis of prostate cancer in multi-parametric MRI based on multimodal convolutional neural networks](#)  
5
- 11 - [Hung Le, Jingyu Chen, Liang Wang et al.](#)
- [A CNN identified by reinforcement learning-based optimization framework for 14-based state evaluation](#)  
14  
Yuxuan Yang, Zhongke Gao, Yanli Li et al.

## Development of Concise Convolutional Neural Network for Tomato Plant Disease Classification Based on Leaf Images

Arnes Sembiring<sup>1,3</sup>, Yuwaldi Away<sup>1,2</sup>, Fitri Arnia<sup>1,2</sup>, Rusdha Muharar<sup>1,2</sup>

Doctoral Program, School of Engineering, Universitas Syiah Kuala, Banda Aceh, Indonesia<sup>1</sup>

Department of Electrical and Computer Engineering, Universitas Syiah Kuala, Banda Aceh, Indonesia<sup>2</sup>

Department of Informatics Engineering, Universitas Harapan Medan, Medan, Indonesia<sup>3</sup>

Email: arnes2018@mhs.unsyiah.ac.id, yuwaldi@unsyiah.ac.id, f.arnia@unsyiah.ac.id, r.muhaarar@unsyiah.ac.id

**Abstract.** Early detection of plant diseases is one of the main keys to handling diseases quickly and successfully. The purpose of this study is to find out a simpler CNN architecture and meet an acceptable compromise between accuracy and simplification to detect diseases in tomato plants based on leaf images. This simpler architecture will allow the development of standalone and independent system model in the field to classify and identify the tomato plants diseases in low price and limited resources. This proposed architecture was developed from the CNN architecture baseline and is intended to classify 10 classes of tomato leaves consist of one healthy class and 9 classes of leaves diseases taken from the PlantVillage dataset. In this study, the performance of the proposed architecture and comparative architectures are examined in the same dataset. Comparative architectures used are some existing CNN architectures that are commonly used namely VGG Net, ShuffleNet and SqueezeNet. The results indicated that the proposed architecture can achieve competitive accuracy compared with the existing architecture while the proposed architecture is much shorter than the existing architecture and better in terms of performance time.

### 1. Introduction

Agriculture has significant role in the growth and economic development of a country [1]. The agriculture sector contributed 6.4% of total world economic production in 2018 and Indonesia is the fifth largest contributor country together with China, India, US and Brazil [2]. Based on the annual report of the Indonesian Central Statistics Agency through the Official Statistics, Indonesia's economy in the third quarter of 2018 against the third quarter of 2017 grew 5.17 percent. The agriculture, forestry and fisheries sectors donated 13.53% of the total growth, the second largest after the Manufacturing Industry sector which contributed 19.66% [3].

In terms of increasing agricultural productivity, environmental factors and production resources such as temperature, humidity and labor in the agricultural process are important to consider. On the other hand, plant disease causes a reduction in agricultural productivity significantly by 20-30% so that it becomes the main cause of the reduction in production and economic value in the agricultural industry worldwide [4]. Therefore, monitoring plant health conditions becomes an important task and a crucial aspect in controlling the spread of disease and enabling effective treatment [5].



Content from this work may be used under the terms of the Creative Commons Attribution 3.0 licence. Any further distribution of this work must maintain attribution to the author(s) and the title of the work, journal citation and DOI.

plant diseases is also a task that requires a lot of time, money and labor, especially if supervision must be carried out routinely and the area of supervision is quite extensive [6].

For the reliability of the monitoring system, the ability to recognize various plant diseases automatically is needed in the field. Various algorithms for the identification of plant diseases have been developed based on the appearance of colors, textures, shapes and other features that appear on plant leaves. Among the methods widely used are image segmentation, feature extraction and pattern recognition, image processing techniques, support vector machines (SVM), artificial intelligence and artificial neural networks [7, 8]. However, the performance of these methods has not been very satisfactory due to the still limited differentiating description capabilities of the extracted leaf features. It is also quite difficult to determine which features are optimal and appropriate for the recognition of plant diseases, especially when the background image of the diseased leaf is complex and segmentation is difficult [9].

The presence of deep learning, especially Convolutional Neural Network (CNN) has raised the accuracy standard to very high even close to 100% [10]. This success has made CNN widely implemented in fields such as business, agriculture, the automotive industry and other fields for object detection and image classification [11]. The use of CNN is also driven by CNN's ability to extract features automatically, especially from datasets in the form of image, video and voice data. Expert segmentation of important and interesting parts of the image is also unnecessary [12] [13]. In particular, the use of deep learning in the agricultural domain for identification and classification has also shown better results than other techniques [14].

One of the challenges of the CNN realtime deployment in agricultural field is the computational burden caused by the large number of CNN architectural parameters [15]. To address the challenges, this research proposed a simpler CNN architecture than the existing architecture with competitive classification accuracy. This simpler architecture is expected to be implemented at a low cost and limited resources in agriculture field.

## 2. Related Works

Several studies that have been carried out previously on disease detection in plant leaves focus on the use and fine tuning of existing architecture to achieve the best identification and classification accuracy. Generally, these studies adopt existing architectures such as the AlexNet architecture [10] [16] [17] [18] [19] [20], GoogleNet architecture [21] [10] [18] and VGGNet architecture [17] [18] [19] [5].

Although the accuracy of classification using CNN is very high, the size of the parameters involved in the CNN architecture makes CNN training time very long even though the training is done on a computer with very abundant resources [10] [18]. The deep and wide CNN architecture also requires numerous operations which increase inference time and limited use of CNN in applications that use limited data sources, low memory and are limited by time [22]. Many classification tasks in real field applications such as automated vehicles, robotics, healthcare and mobile applications work on resource-constrained environments [23].

Research for a concise architecture with a small number of parameters for specific needs has been researched based on the GoogleNet architecture. The new architecture, which is much more concise than GoogleNet, called AgNet is used to identify grasses and new plants that grow with an identification accuracy of  $88.9 \pm 0.4\%$  and involve 250,000 parameters. AgNet is then implemented in AgBot II agricultural robots which have limited computing resources [21].

CNN's light weight has also been investigated for its use in classifying the image of cucumber leaves into three classes of "fully leaf", "not fully leaf" or "none leaf". The purpose of this classification is to determine the boundary box of "fully leaf" so that it can be used at the diagnosis stage. CNN light weight used consists of 3 convolution layers, each layer followed by a batch normalization layer and the second and third convolution layers followed by a pooling layer. The output of this CNN is 2 fully connected layers. This study reaches a value of 78.0% F1-score [24].

Research to compare the effect of depth and width of CNN architecture on classification performance on tomato leaf disease has been carried out on AlexNet and SqueezeNet. The dataset used is the PlantVillage dataset with 10 target classes. The accuracy obtained is almost the same as the

SqueezeNet inference time three times faster than AlexNet [25]. This shows that the same accuracy can be obtained on a shorter CNN architecture with faster inference times and of course fewer resources.

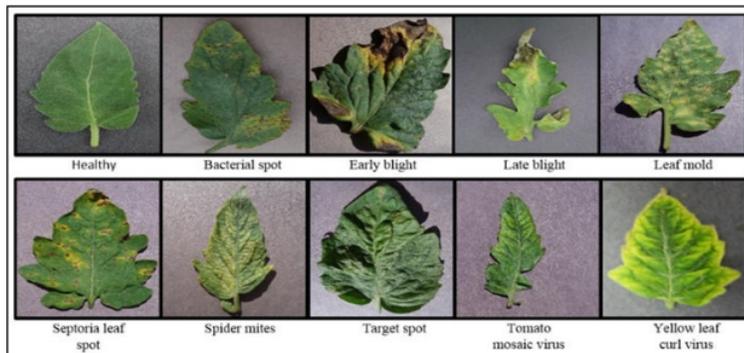
### 3. Proposed Work

The dataset used as training and testing material is the PlantVillage dataset with 10 target classes consisting of one image class of healthy tomato leaves and 9 classes of tomato leaves exposed to 9 types of diseases commonly found in tomato plants namely bacterial spot, early blight, late blight, leaf mold, Septoria leaf spot, spider mites, target spot, tomato mosaic virus and yellow leaf curl virus. Table 1 shows the breakdown of the amount dataset used in this study.

**Table 1.** The dataset are used as training and testing data.

	Healthy	Bacterial spot	Early blight	Late blight	Leaf mold	Septoria leaf spot	Spider mites	Target spot	Tomato mosaic virus	Yellow leaf curl virus
<b>The amount of data</b>	1.733	1.702	1.913	1.727	1.882	1.745	1.741	1.653	1.584	1.961

Figure 1 shows an example image of each leaf class mentioned in table 1 earlier. All images in this dataset are color images (RGB images) with a uniform resolution that is 256x256 pixels.



**Fig. 1.** Example image of each leaf class

The proposed architecture is shown in Figure 2. The proposed CNN input is an RGB image with 256x256 resolution, the same as the input image dimension of the dataset. This similarity makes the input image of the dataset no longer need to resize. And CNN output in the form of 2 fully connected layers consisting of 32 and 10 nodes, softmax and classification layer for 10 classes.

This proposed architecture consists of 4 layers of convolution, each of which is followed by a layer of batch normalization and activation of ReLU. Then followed by the pooling layer except the fourth convolution layer. The first, second, third and fourth convolution layers consist of kernels of the same size, 3x3, stride 2 and padding 2 but different amounts. The first layer has 8 kernels, the second layer has 16 kernels, the third layer has 32 kernels and finally the fourth layer consists of 64 kernels. The whole pooling layer consists of 3x3 maxpooling2d and stride 2. The total parameters involved in this architecture are 43.562.

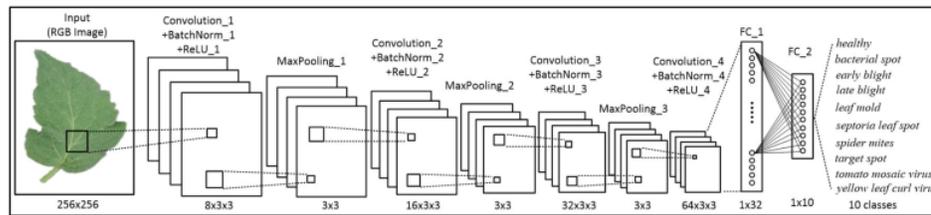


Fig. 2. The proposed architecture

As a comparison of the performance of the proposed architecture, three existing CNNs that are commonly used are VGG Net (VGG16), ShuffleNet and SqueezeNet. VGG16 consists of 16 convolution layers with a large number of kernels and 138 million parameters while shufflenets and squeezeNETs have 1.4 million and 1.25 million parameters, respectively. Although the VGG16 architecture has a very large size compared to the proposed architecture, VGG16 has been tested to have the best accuracy when compared to AlexNet and GoogleNet when tested on the PlantVillage tomato leaf dataset [18]. While ShuffleNet and Squeezenet are CNNs that consist of a concise architecture but have a high accuracy value [25].

#### 4. Training And Testing

The proposed architecture training and fine tuning existing architecture uses the same input image without any preprocessing images. Distribution of data sets is 70% of the dataset for training or fine tuning and the remaining 30% for testing.

The training was conducted in 50 epochs for the proposed architecture with a initial learning rate of 0.05 and the stochastic gradient descent with momentum (sgdm) optimization function. There was no use of minibatches for proposed architecture. While the comparison architecture was fine tuned with minibatch size 10 in maximum 6 epochs on the same dataset as the dataset used in the proposed architecture. The initial learning rate used in fine tuning is 0.0003 and the 'sgd' optimization function as well. In this fine tuning, the final layer of the existing CNN was replaced with a 7-w fully connected layer which classified ten classes, equal to the number of classes in the dataset. The fully connected layer parameter of Weight, LearnRateFactor and BiasLearnRateFactor was set to 10. Training, fine tuning and testing are carried out on a personal computer with an Intel Core i5, 8 GB RAM, Windows 10 Home Operating System with Matlab R2019a.

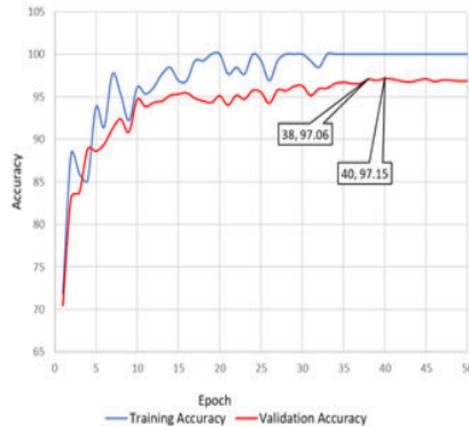
#### 5. Result

Table 2 shows the summary of training result of proposed architecture and fine tuning existing CNN. The highest achievement in terms of accuracy achieved by VGG16 is 98.28% but this takes more than 5 hours. Further, followed by a solution approved by SqueezeNet that is 96.64%. This achievement value takes 1 hour 23 minutes and 39 seconds. The accuracy value approved by the proposed architecture is 97.15%, slightly different from Squeezenet but with the shortest performance time of 1 hour 10 minutes 21 seconds. In addition, the ShuffleNet reached 97.01% and the training time was 2 hours 51 minutes 36 seconds.

Table 2. The training result of proposed architecture and fine tuning existing CNN

Model CNN	Epoch	Training Accuracy	Validation Accuracy	Training Loss	Validation Loss	Elapsed Time (hh:mm:ss)	Amount of parameter
Proposed Architecture	40	100	97.15	0.0011	0.1112	01:10:21	43.56k
VGG16	3	100	98.28	0.0804	0.0489	05:33:06	138M
ShuffleNet	6	100	97.01	0.0059	0.0955	02:51:36	5.4M
SqueezeNet	6	100	97.64	0.0433	0.0731	01:23:39	1.25M

Figure 3 and figure 4 show the results of training and testing of the proposed CNN architecture at 50 epochs. At the 38<sup>th</sup> epoch, the validation accuracy reached 97.06% with a validation loss of 0.1213. At the 40<sup>th</sup> epoch, this proposed architecture achieves the highest validation accuracy of 97.15% with a validation loss of 0.1112 with training time of 1 hour 10 minutes and 21 seconds. This validation accuracy value is quite stable above the 35<sup>th</sup> epoch with a validation value exceeded 97.0%. The addition of more than 40 epoch training does not seem to contribute anymore to increasing of the accuracy value.



13 Fig. 3. Training and validation accuracy of proposed architecture at 50 epochs.

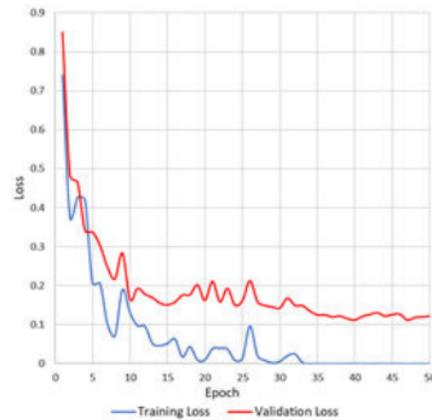


Fig. 4. Training and validation loss of proposed architecture at 50 epochs.

### 6. Conclusion

Based on discussion above, it can be concluded that using CNN's proposed architecture in the detection of tomato plant disease with the tomato leaf dataset from Plantvillage is quite promising and its performance can compete in terms of validation accuracy and better in terms of performance time with the existing CNN architectures.

The challenge in subsequent studies is to improve the accuracy of concise CNN while maintaining a short training time on limited resources and adding a dataset with leaf images taken from direct agricultural fields so that practical use in agriculture can be realized.

**Acknowledgments**

This research was granted by Ministry of Research and Technology/National Research and Innovation Agency of Republic Indonesia (Kementerian Riset Dan Teknologi/Badan Riset Dan Inovasi Nasional Republik Indonesia) under scheme of *Penelitian Disertasi Doktor* (PDD) 2020 with contract number of 43/UN11.2.1/PT.01.03/AMD/DPRM/2020.

**References**

- [1] A. Khamparia, *et al.*, "Seasonal Crops Disease Prediction and Classification Using Deep Convolutional Encoder Network," *Circuits, Systems, and Signal Processing*, vol. 39, pp. 818-836, 2020/02/01 2020.
- [2] CIA. (2018, 20 Nov 2018). *The World Factbook (GDP)*. Available: <https://www.cia.gov/library/publications/resources/the-world-factbook/fields/209.html>
- [3] B. P. S. BPS, "Pertumbuhan Ekonomi Indonesia Triwulan III-2018," in *Berita Resmi Statistik* vol. No. 90/11/Th.XXI, B. P. Statistik, Ed., ed. Jakarta, 2018, pp. 1-12.
- [4] H. Park, *et al.*, "Crops Disease Diagnosing Using Image-Based Deep Learning Mechanism," in *2018 International Conference on Computing and Network Communications (CoCoNet)*, 2018, pp. 23-26.
- [5] J. Lu, *et al.*, "An in-field automatic wheat disease diagnosis system," *Computers and Electronics in Agriculture*, vol. 142, pp. 369-379, 2017/11/01/ 2017.
- [6] J. Ma, *et al.*, "A recognition method for cucumber diseases using leaf symptom images based on deep convolutional neural network," *Computers and Electronics in Agriculture*, vol. 154, pp. 18-24, 2018.
- [7] J. G. A. Barbedo, "A review on the main challenges in automatic plant disease identification based on visible range images," *Biosystems Engineering*, vol. 144, pp. 52-60, 2016/04/01/ 2016.
- [8] X. Zhang, *et al.*, "Identification of Maize Leaf Diseases Using Improved Deep Convolutional Neural Networks," *IEEE Access*, vol. 6, pp. 30370-30377, 2018.
- [9] S. Zhang, *et al.*, "Three-channel convolutional neural networks for vegetable leaf disease recognition," *Cognitive Systems Research*, vol. 53, pp. 31-41, 2019/01/01/ 2019.
- [10] S. P. Mohanty, *et al.*, "Using Deep Learning for Image-Based Plant Disease Detection," *Frontiers in Plant Science*, vol. 7, 2016-September-22 2016.
- [11] E. C. Too, *et al.*, "A comparative study of fine-tuning deep learning models for plant disease identification," *Computers and Electronics in Agriculture*, vol. 161, pp. 272-279, 2019/06/01/ 2019.
- [12] Y. LeCun, *et al.*, "Deep learning," *Nature*, vol. 521, p. 436, 2015.
- [13] R. Yamashita, Nishio, M., Do, R.K.G. et al., "Convolutional neural networks: an overview and application in radiology," *Insights Imaging, Springer*, vol. 6, pp. 611 - 621, 2018.
- [14] A. Kamilaris and F. X. Prenafeta-Boldú, "Deep learning in agriculture: A survey," *Computers and Electronics in Agriculture*, vol. 147, pp. 70-90, 2018/04/01/ 2018.
- [15] K. R, *et al.*, "Attention embedded residual CNN for disease detection in tomato leaves," *Applied Soft Computing*, vol. 86, p. 105933, 2020/01/01/ 2020.
- [16] M. R. Howlader, *et al.*, "Automatic Recognition of Guava Leaf Diseases using Deep Convolution Neural Network," in *2019 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, 2019, pp. 1-5.
- [17] A. K. Rangarajan, *et al.*, "Tomato crop disease classification using pre-trained deep learning algorithm," *Procedia Computer Science*, vol. 133, pp. 1040-1047, 2018/01/01/ 2018.
- [18] E. Suryawati, *et al.*, "Deep Structured Convolutional Neural Network for Tomato Diseases Detection," in *2018 International Conference on Advanced Computer Science and Information Systems (ICACSIS)*, 2018, pp. 385-390.
- [19] K. P. Ferentinos, "Deep learning models for plant disease detection and diagnosis," *Computers and Electronics in Agriculture*, vol. 145, pp. 311-318, 2018/02/01/ 2018.
- [20] R. G. de Luna, *et al.*, *Automated Image Capturing System for Deep Learning-based Tomato Plant Leaf Disease Detection and Recognition*, 2018.

- [21] C. McCool, *et al.*, "Mixtures of Lightweight Deep Convolutional Neural Networks: Applied to Agricultural Robotics," *IEEE Robotics and Automation Letters*, vol. 2, pp. 1344-1351, 2017.
- [22] M. Shakeel, *et al.*, "Detecting Driver Drowsiness in Real Time Through Deep Learning Based Object Detection," ed, 2019, pp. Advances in Computational Intelligence, 283-296.
- [23] A. Khan, *et al.*, "A survey of the recent architectures of deep convolutional neural networks," *Artificial Intelligence Review*, vol. 53, pp. 5455-5516, 2020/12/01 2020.
- [24] H. Q. Cap, *et al.*, "A deep learning approach for on-site plant leaf detection," in *2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA)*, 2018, pp. 118-122.
- [25] H. Durmuş, *et al.*, "Disease detection on the leaves of the tomato plants by using deep learning," in *2017 6th International Conference on Agro-Geoinformatics*, 2017, pp. 1-5.

# Development of Concise Convolutional Neural Network for Tomato Plant Disease Classification Based on Leaf Images

## ORIGINALITY REPORT

18%

SIMILARITY INDEX

14%

INTERNET SOURCES

15%

PUBLICATIONS

%

STUDENT PAPERS

## PRIMARY SOURCES

1	<a href="http://eprints.utm.my">eprints.utm.my</a> Internet Source	3%
2	<a href="http://zaguan.unizar.es">zaguan.unizar.es</a> Internet Source	2%
3	<a href="http://iopscience.iop.org">iopscience.iop.org</a> Internet Source	2%
4	<a href="http://www.researchgate.net">www.researchgate.net</a> Internet Source	1%
5	Minh Hung Le, Jingyu Chen, Liang Wang, Zhiwei Wang, Wenyu Liu, Kwang-Ting (Tim) Cheng, Xin Yang. "Automated diagnosis of prostate cancer in multi-parametric MRI based on multimodal convolutional neural networks", Physics in Medicine & Biology, 2017 Publication	1%
6	<a href="http://www.jeeng.net">www.jeeng.net</a> Internet Source	1%

7

Roslidar Roslidar, Khairun Saddami, Fitri Arnia, Maimun Syukri, Khairul Munadi. "A Study of Fine-Tuning CNN Models Based on Thermal Imaging for Breast Cancer Classification", 2019 IEEE International Conference on Cybernetics and Computational Intelligence (CyberneticsCom), 2019

Publication

1 %

8

"Engineering Applications of Neural Networks", Springer Science and Business Media LLC, 2016

Publication

1 %

9

[doctorpenguin.com](http://doctorpenguin.com)

Internet Source

1 %

10

[www.mdpi.com](http://www.mdpi.com)

Internet Source

1 %

11

Luoyu Chen. "A Progressive and Joint Method for Micro and Macro Architecture Search", Journal of Physics: Conference Series, 2022

Publication

1 %

12

Hugo Araujo, Gustavo Carvalho, Mohammad Reza Mousavi, Augusto Sampaio. "Chapter 10 Multi-objective Search for Effective Testing of Cyber-Physical Systems", Springer Science and Business Media LLC, 2019

Publication

1 %

13

Md. Mehedi Hasan, Azmain Yakin Srizon, Abu Sayeed, Md. Al Mehedi Hasan. "High-Performance Object Recognition by Employing a Transfer Learned Deep Convolutional Neural Network", 2020 11th International Conference on Electrical and Computer Engineering (ICECE), 2020

Publication

---

1 %

14

Minglan Su, Baolin Liang, Sicong Ma, Chao Xiang, Chaoying Zhang, Jianxiu Wang. "Automatic Machine Learning Method for Hyper-parameter Search", Journal of Physics: Conference Series, 2021

Publication

---

1 %

15

Pushpalatha S. Nikkam, Archana Nandibewoor, Aijaz Qazi, Leena I. Sakri et al. "Comparative Analysis of DIP Techniques to Detect Leaf Diseases in Tomato Plant", IOP Conference Series: Materials Science and Engineering, 2021

Publication

---

1 %

16

[www.jabarprov.go.id](http://www.jabarprov.go.id)

Internet Source

---

1 %

17

Shanwen Zhang, Wenzhun Huang, Chuanlei Zhang. "Three-Channel Convolutional Neural Networks for Vegetable Leaf Disease Recognition", Cognitive Systems Research, 2018

&lt;1 %

18

Huu Quan Cap, Katsumasa Suwa, Erika Fujita, Satoshi Kagiwada, Hiroyuki Uga, Hitoshi Iyatomi. "A deep learning approach for on-site plant leaf detection", 2018 IEEE 14th International Colloquium on Signal Processing & Its Applications (CSPA), 2018

Publication

<1 %

---

19

Ilya Duboyskii, Aleksandra Shabanova, Oleg Sivchenko, Elizaveta Usina. "Architecture of cross-platform videoconferencing system with automatic recognition of user emotions", IOP Conference Series: Materials Science and Engineering, 2020

Publication

<1 %

---

20

Swapnil K. Gundewar, Prasad V. Kane. "Bearing fault diagnosis using time segmented Fourier synchrosqueezed transform images and convolution neural network", Measurement, 2022

Publication

<1 %

---

21

[depot.umc.edu.dz](http://depot.umc.edu.dz)  
Internet Source

<1 %

---