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# Depthwise Separable Convolution architectures for the identification of leaf diseases in Tomato Crop

**D Sandhya Rani[1], K Shyamala[2]**

[1]Research Scholor, [2]Professor

[1]Department of Computer Science and Engineering

[1]Osmania University, Hyderabad, India

***Abstract.*** The early prevention of crop diseases and identifyingthem at early stage is very important for crop production. The usage of fertilizers and chemicals is causing a negative effect on the agriculture eco-system and causes economic loss. A reliable method to identify and diagnose the diseases will benefit the farmers. In this paper, a new model is introduced with depthwise separable convolution architecture for tomato plant disease detection using leaf images. The models were trained and tested on a subset of publicly available plant village dataste containing six different classes of healthy and diseased leaves. These depthwise separable convolutions achieved high gain in convergence speed and the accuracy is also improved. A novel model called CNNLDD is proposed and it is compared with reduced CNNLDD model and this reduced model achieved a classification accuracy of 98.39% with fewer parameters. The satisfactory accuracy and small size of this model makes it suitable for real time crop diagnosis with less computation cost and the training time is also minimized. The standard CNN model requires a huge number of parameters, computation cost is high and also the training time is more. Standard convolution is replaced with the depth wise separable convolution in order to minimize the number of parameters and computation cost.

***Key words:*** Plant diseases, Deep learning, point wise convolution, convolutional neural network, depth wise convolution, classification

## I. INTRODUCTION

The normal growth of the plant is distributed by plant disease. Several types of plant diseases could cause several loss to the production of crops. The early identification of diseaseswill help in taking action to prevent losses and produce a high quality tomatoes and results in good crop prodcution. Generally, the detection of plant diseases is achieved by researchers and experts with academic background and a practical experience on symptoms and causes of diseases[1]. The plant diseases are categorized into three different types of diseases like fungal, bacterial and viral. Automated quality analysis of plant health with the images of plant leaves, characterized by its color, shape and size is an accurate and reliable method for the increased productivity.

A machine learning approach involves the extraction of the features by ML algorithmsto associaite correct labels to the given attributes. With the advacement if deep learning algorithms, the quality of the crop is determined and there is an increase in the crop quantity in real time without human intervention. These deep learning algorithms yield high accuracy with different types of datastes. Particularly, convolutional neural networks (CNN's) gained much attention in the fruit detection [2], disease identification [3-5], weed detection [6] and pest recognition [7]. These models are popularly used becuse of the automatic extraction of appropriate features from the dataset. Several deep learning models such as GoogleNet, AlexNet, VGGNet, ResNet and DenseNet have been developed for identification of plant diseases. Deep learning models requires large amounts of date to train the network. If an available dataset does not contain enough images the performance

degrades, whereas transfer learning doesn not need a large amount of data to train the network. Transfer learning improves learning a new task through knowledge transfer from a similar task that had already been learned.
Various computational methods like handcrafted and deep learning based feature sets are proposed by the researchers. Hand crafted feature extraction techniques are used to extract the most important features from the leaf images to train the machine learning classifiers for image recognition tasks. Image pre-processing methods such as segmentation, noise reduction, image enhancement, image scaling and color transformation is essential before extracting the features from the images. After feature extraction, classifiers like K nearest neighbour, Random forest, histogram of oriented gradients , Support Vecot Machine, Logistic Regression , decision tree can be used. Random Forest is a commonly used supervised learning algorithm that is mainly used in classification problems. It can handle large datasets with high dimensionality and prevents the overfitting issue. SVM is also one among the popular supervised machine learning algorithm used for the classification purpose. KNN is one of the machine learning technique mostly used in the classification problems.
The main contributions of the paper are as follows:
1.A novel CNNLDD architecture is proposed to diagnose the pant diseases on the basis of healthy and diseases leaf images.
2.The reduced CNNLDD model is based on a depthwise seperable convolution network which has been explicitly incorporated in CNNLDD model.
3.The implemented reduced CNNLDD model use fewer parameters and ltakes less time for training and is faster than the CNNLDD, ResNet50 and VGG16 models.
The paper is structured as below: Section 2 discusses literature review of leaf disease detection of Tomato crop. Section 3 illustrates the methods that are used in the experiments. The results are discussed in Section 4. And the paper in Section 5 is concluded.

## II. RELATED WORK

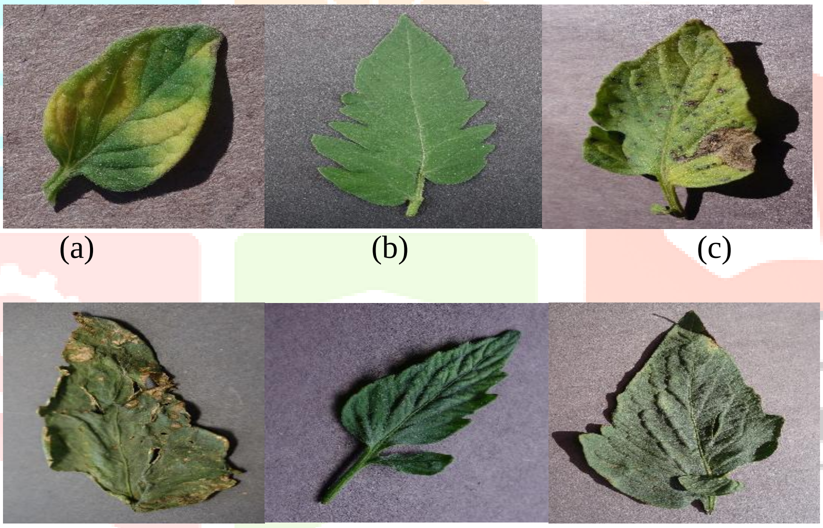
This section discusses about the existing techniques for identifying diseased leaves and to increase the crop production. Yafeng Zhao et al [8] used VGG16, ResNet, DenseNet models to identify plant diseases from the plant village dataset. To increase the dataset size, they used a double generative adversarial network (Double GAN), which improved the performance results. Rice and maize leaf diseases are identified by Chen et al [9] using the INC-VGGN method. The last convolution layer of VGG19 is replaced with two inception layers and one global average pooling layer. Bhatt et al [10] proposed automated low cost early detection of crop diseases, deep convolution models with high accuracy, satisfactory inference time and model size suitable for real time crop state diagnosis on a large scale with limited network capabilities.
Geetharamani and Pandian [11] introduced a novel nine layer deep learning model to identify diseased leaves of 13 different plants from the publicly available Plant Village Dataset and attained an accuracy of 96.40%. Many research works on plant diseases detection are done on public datasets. 11 out of 19 studies realized by boulent et al [12] are performed on public datasets known as plant village dataset which contains 87,848 images of healthy and diseased crop plants. Sladojevic et al [13] proposed a model to automatically classify and detect plant diseases from the leaf images. The data is gathered from the internet and formed a datset of thirteen different classes corresponding to different diseases.
Atabay.H.A [14] proposed occlusion technique and it consists of sliding a black windows on the input image and analyze the change of the output probability. A heatmap is generated by this method that highlight the pixels that are most sensitive to a specific class. Kamal KC et al [15] proposed a depthwise separable convolution architectures for plant disease classification. Several models were trained and tested of which Reduce MobileNet model achieved a classification accuracy of 98.34% with 29 times fewer parameters compared to VGG and 6 times lesser than that of MobileNet.
SK Mahmudul Hassan et al [16] developed a novel convolutional neural network for plant disease identification by implementing depthwise separable convolution to reduce the number of parameters. The proposed model has been trained and tested on three different plant disease datasets. The performance accuracy obtained on plant village dataset is 99.39% , on rice disease dataset is 99.66% and on cassava dataset is 76.59%. With less number of parameters the proposed model achieved higher accuracy when compared with the state of the art deep learning models.A robust model is proposed by Ghosan et al [17] to identify, classify and quantify a diverse set of foliar stresses in soyabean using a large and diverse dataset of unseen test samples achieved an overall classifcation accuracy of 94.13%.

Ferentinos et al [18] used different CNN architectures to identify 58 different plant diseases, achieving high levels of accuracy. The authors also tested the CNn architectures with real time images. Authors in [19] proposed two classification handcrafted feature extraction methods namely Random Forest and Bayesian Optimized SVM. Here for the selection of features Particle Swarm Optimization is used to get simulation results. The maximum accuracy achieved is 96.1% for detecting the leaf diseases of tomato, corn, apple, potato and rice plants. The authors in [20] proposed a nine-layer CNN model to identify plant diseases. The plant village dataset is used experimentally and data augmentation techniques are used to increase the size of the data and to analyze the performance.Ramcharan et al [21] used a transfer learning approach for the identification of three diseases and two pest damage types in cassava plants. The authors in [22] used a self attention convolutional neural network to identify several crops diseases. For examining the robustness of the model, the authors added different noise levels in the test image set.

## III. MATERIALS AND METHODS

### 3.1 Dataset Description

The plant leaf images that are used in this paper are collected from the publicly available repository known as plant village dataset to evaluate the performance of the model. It consists of 20,639 healthy and unhealthy leaf images divided into 15 categories. Among them, tomato plant disease consists 7447 images that are divided into six classes namely 2127 Bacterial Spot, 1000 Early Blight, 952 Leaf Mold, 1404 Target Spot, mosaic virus, 1591 tomato healthy images. The dataset consisting of 7447 images is randomly divided into 80% training set and 20% testing set. The sample images are shown in figure 1.



(a) (b) (c)

(d) (e) (f)

**Fig.1.** Tomato leaf images. a. Tomato_leaf_Mold b. healthy c. Tomato_Early_Blight d. Tomato_Bacterial_spot e. Tomato_mosaic_virus f. Tomato_Target_Spot

Table 1 shows the details of dataset with disease names and scientific names

**Table 1.** Data description of tomato leaf diseses

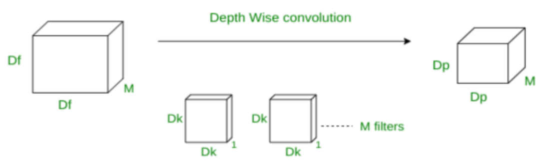
| Class | PlantName | Disease name | Scientific name | Type | No.of.images |
|---|---|---|---|---|---|
| C1 | Tomato | Leaf Mold | Fulvia fulva | Fungal | 952 |
| C2 | Tomato | Healthy | ---------- | -------- | 1591 |
| C3 | Tomato | Early Blight | Alternaria solani | Fungal | 1000 |
| C4 | Tomato | Bacterial Spot | Xanthomonas campestris | Bacterial | 2127 |
| C5 | Tomato | Mosaic Virus | Tomato mosaic virus | Viral | 373 |
| C6 | Tomato | Target spot | Corynespora Cassiicola | Fungal | 1404 |

### 3.2 Convolutional neural network

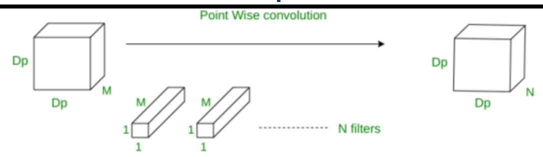
Convolutional Neural Network is widely used in many computer vision applications namely classification and object detection. In traditional approaches, features are extracted manually from images whereas CNNs can extract the features directly. The convolutional neural network performs better when compared with the traditional feature extraction methods in the identification of leaf diseases.

### 3.3 Depthwise Separable Convolution

Chollet [23] introduced depthwise separable convolution in the Xception model. It is divided into two separate kernels: the depth wise and point wise convolution. This method is used to reduce the number of parameters and computations in a convolutional neural network, making the network more efficient. Depth wise separable convolution block diagram is represented in figure 2. The kernels size is of Dk x Dk x 1. For M channels in the input data, M filters are needed and the output size is of Dp x Dk x M.




Depth Wise Convolution




Pointwise Convolution

**Fig. 2.** Depthwise separable convolution

The computation cost of Depth Wise Separable convolution is computed as:

$$M * Dk^2 * Dp^2 + N*M*Dp^2 \qquad \text{-----------} \ (1)$$

And the computation cost of standard convolution is computed as:

$$Dp^2 * N*M * Dk^2 \qquad \text{-----------} \ (2)$$

where $D_k$ is the input image dimension, $D_p$ is the kernel dimension, N is the no. of kernels, M is represented as the number of channels.

### 3.4 Proposed Novel CNNLDD model for detection of tomato leaf diseases

A novel architecture called CNNLDD is created from scratch and this is called as standard convolutional neural network model. Using depth wise separable convolution, Reduced CNNLDD model is implemented instead of conventional convolution layers. The results are compared with CNNLDD and pretrained models. The plant village dataset is split into two sets: training and validation. Validation data was used to tune the network parameters and hyperparameters to prevent overfitting. Adam optimizer is used to evaluate training and validation accuracies. The training hyperparameters are batch size is 16 and learning rate is 0.001. All the convolutional layers were followed by the ReLU activation function. Novel CNNLDD architecture comprises of a building block as shown in figure 3(a), whereas Reduced CNNLDD makes use of a building block as shown in figure 3(b). Table 2 and 3 define the model architectures of CNNLDD and Reduced CNNLDD respectively used in the study.

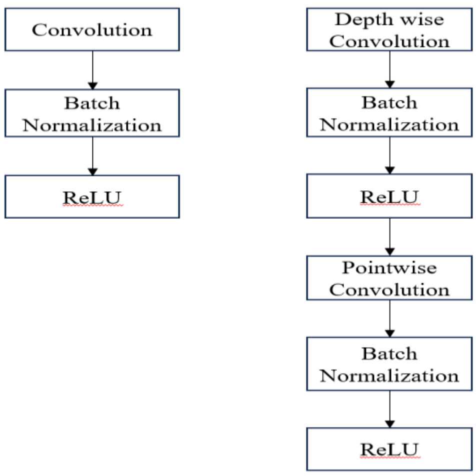



**Fig. 3.** Building blocks of deep neural network. (a) Standard Convolution as core layer. (b) Depth wise Separable Convolution as proposed in Reduced CNNLDD as core layer.

To generalize the model and to ensure a robust model these image datasets were augmented using different data augmentation process, such as flipping, rotations, shifts and a combination of these techniques. The main aim of data augmentation is to prevent overfitting by training the model to large data created artificially.

**Table 2:** CNNLDD architecture

| Layer Size/Stride | Output Shape | Parameters |
|---|---|---|
| 3,3 Conv, 32/S1 | 224,224,32 | 896 |
| Batch Normalization | 224,224,32 | 128 |
| 2,2 Maxpooling/S1 | 112,112,32 | 0 |
| Dropout(0.25) | 112,112,32 | |
| 3,3 Conv, 64/S1 | 112,112,64 | 18496 |
| Batch Normalization | 112,112,64 | 256 |
| 3,3 Maxpooling | 37,37,64 | 0 |
| Dropout(0.25) | 37,37,64 | |
| 3,3 Conv 64/S1 | 37,37,64 | 36928 |
| Batch Normalization | 37,37,64 | 256 |
| 2,2 Maxpooling/S1 | 18,18,64 | 0 |
| 3,3 Conv, 64/S1 | 18,18,64 | 36928 |
| Batch Normalization | 18,18,64 | 256 |
| 2,2 Maxpooling/S1 | 9,9,64 | 0 |
| 3,3 Conv, 64/S1 | 9,9,64 | 36928 |
| Batch Normalization | 9,9,64 | 256 |
| 2,2 Maxpooling/S1 | 4,4,64 | 0 |
| 3,3 Conv, 64/S1 | 4,4,64 | 36928 |
| Batch Normalization | 4,4,64 | 256 |
| 2,2 Maxpooling/S1 | 2,2,64 | 0 |
| Dropout(0.25) | 2,2,64 | |
| Dense | 1,1,64 | 16448 |
| Dense | 1,1,64 | 390 |
| Softmax | 1,1,6 | 0 |

**Table 3:** Reduced CNNLDD architecture

| Layer Size/Stride | Output Shape | Parameters |
|---|---|---|
| 3,3 DepthwiseConv, 32/S1 | 224,224,32 | 155 |
| 1,1 PointwisConv , 32/S1 | | |
| Batch Normalization | 224,224,32 | 128 |
| 2,2 Maxpooling/S1 | 112,112,32 | 0 |
| 3,3 DepthwiseConv, 64/S1 | 112,112,64 | 2400 |
| 1,1 PointwiseConv, 64/S1 | | |
| Batch Normalization | 112,112,64 | 256 |
| 2,2 Maxpooling | 56,56,64 | 0 |
| 3,3 DepthwiseConv , 64/S1 | 56,56,64 | 4736 |
| 1,1 PointwiseConv, 64/S1 | | |
| Batch Normalization | 56,56,64 | 256 |
| 2,2 Maxpooling/S1 | 28,28,64 | 0 |
| 3,3 DepthwiseConv, 64/S1 | 28,28,64 | 4736 |
| 1,1 PointwiseConv, 64/S1 | | |
| Batch Normalization | 28,28,64 | 256 |
| 2,2 Maxpooling/S1 | 14,14,64 | 0 |
| 3,3 DepthwiseConv, 64/S1 | 14,14,64 | 4736 |
| 1,1 PointwiseConv, 64/S1 | | |
| Batch Normalization | 14,14,64 | 256 |
| 2,2 Maxpooling/S1 | 7,7,64 | 0 |
| 3,3 DepthwiseConv, 64/S1 | 7,7,64 | 4736 |
| 1,1 PointwiseConv, 64/S1 | | |
| Batch Normalization | 7,7,64 | 256 |
| 2,2 Maxpooling/S1 | 3,3,64 | 0 |
| Dense | 1,1,64 | 36928 |
| Dense | 1,1,64 | 390 |
| Softmax | 1,1,6 | 0 |

## IV. RESULTS

CNNLDD achieved training accuracy of 99.93%, training loss 0.0209, validation accuracy 98.25, validation loss 0.0617, Reduced CNNLDD achieved training accuracy of 99.93%, training loss 0.0247, validation accuracy 98.39%, validation loss 0.0755 f or six classes of subset of plant village dataset of Tomato leaves dataset. The implemented Reduced CNNLDD model is compared with the CNNLDD standard convolutional model and the pretrained models like VGG, Efficient Net B0, ResNet50 and is shown in Table 4.

**Table 4:** Comparing accuracies (%) of Plant Village Dataset

| Model | Training accuracy | Training Loss | Validation accuracy | Validation Loss | No. of. Parameters |
|---|---|---|---|---|---|
| VGG | 98.84% | 0.2460 | 95.49% | 0.2024 | 14.7M |
| ResNet50 | 99.88% | 0.0320 | 99.60% | 0.0182 | 23.6M |
| InceptionV3 | 99.95% | 0.0125 | 99.53% | 0.0128 | 21.8M |
| Reduced CNNLDD | 99.93% | 0.0247 | 98.39% | 0.0755 | 60,225 |
| CNNLDD | 99.93% | 0.0209 | 98.25% | 0.0617 | 1,85,350 |

Figure 4 depicts the model accuracy and model loss of implemented Reduced CNNLDD model.

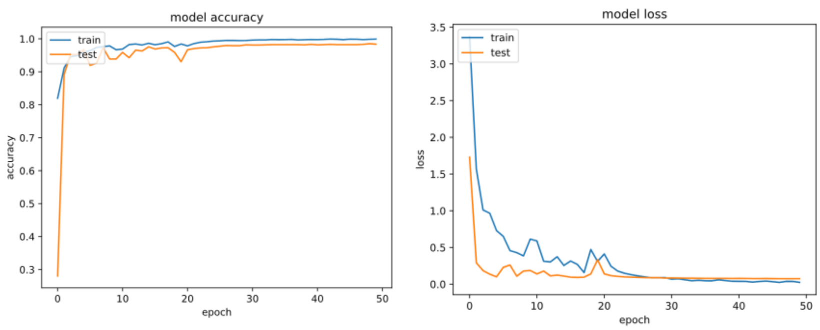



**Fig 4:** Model accuracy and model loss of Reduced CNNLDD architecture

## V.CONCLUSION

In this work various deep learning models were developed and compared based on different CNN architectures for efficient classification of plant diseases based on healthy and diseased leaf images. A Separable CNN model matched the accuracy of conventional CNN with drastically lesser parameters, thereby making it an ideal model to be used. The Reduced CNNLDD model achieved success rate of 99.93% with few parameters when compared with other pretrained models. The classification of six different classes from the tomato leaf images using separable convolution is efficient task and the first of its kind. However, implementation of this model on large databases could be time consuming hence outperforming the other models could be a challenging aspect. The proposed deep learning approach showed higher efficacy on the available dataset, and its potential depends on the quality and quantity of available data. The study explored the potential of efficient network architecture and various network models, which can easily satisfy the design requirements for mobile and embedded vision applications.

## REFERENCES

[1] P.K.Sethy, N.k.Barpanda, A.K.Rath and S.K.Behera. Aug 2020. Deep feature-based rice leaf disease identification using support vector machine. Computer Electron. Agriculture. Vol 175, Art no. 105527

[2] Farjon.G, Krikeb.O, A.B. Hillel and V. Alchanatis. 2019. Detection and counting of flowers on apple trees for better chemical thinning decisions. vol 21. pp 1-19.

[3] S.P. Mohanty, D.P. Hughes and M.Slathe. 2016. Using deep learning for image-based plant disease detection. Frontiers Plant Science. Vol 7, pp 1419.

[4] Chen, J. Chen, J. Zhang, D. Sun, Y. Nanehkaran, Y.A. 2020. Using deep transfer learning for image-based plant disease identification. Computer electronics Agriculture, vol 173, 105393.

[5] K. P. Ferentinos, K.P. 2018. Deep learning models for plant disease detection and diagnosis. Computer. Electronic Agriculture, vol 145, pp 311-318.

[6] V. Hong Trong, Y. Gwang-hyun, D. Thanh Vu and K. Jin-young. 2020. Late fusion of multimodal deep neural networks for weeds classification. Vol 175. Art no. 105506.

[7] F.Ren, W. Liu and G.Wu. 2019. Feature reuse residual networks for insect pest recognition. IEEE Access vol.7. pp 122758-122768

[8] Zhao, Y.Chen, Z. Gao, X.Song, W. Xiong, Q. Hu, J. Zhang, Z. 2021. Plant disease detection using generated leaves based on DoubleGAN. IEEE/ACM Trans. Comput. Biol. Bioinform.

[9] Chen, J. Chen, J. Zhang, D. Sun, Y. Nanehkaran, Y.A. 2020. Using deep transfer learning for image-based plant disease identification. Computer electronics Agriculture, vol 173, 105393.

[10] Bhatt, P. Sarangi, S. Pappula, S. 2017. Comparison of cnn models for application in crop health assessment with participatory sensing. IEEE Global Humanitarian Technology Conference. PP 1-7.

[11] Geetharamani, G. Pandian, A. 2019. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Computer Electronic Eng.vol. 76, pp 323-338.

[12] J. Boulent, S. Foucher. 2019. Convolutional neural networks for the automatic identification of plant diseases, Frontiers in plant science, vol. 10.

[13] S. Sladojevic, M. Arsenovic, A. Anderla, D.Culibrk and D. Stefanovic. 2016. Deep neural networks-based recognition of plant diseases by leaf image classification, Computational intelligence and neuroscience.

[14] H. A. Atabay. 2017. Deep residual learning for tomato plant leaf disease identification, Journal of Theoretical and Applied Information Technology, vol. 95: pp 24.

[15] kamal K.C. Zhendong Yin. Mingyang Wu. Zhilu Wu. 2019. Depth wise separable convolution architecture for plant disease classification. Computers and Electronics in Agriculture. Vol 165. Art no.104948

[16] SK Mahmudul Hassan and Arnab Kumar Maji. 2022. Plant Disease identification using a novel convolutional neural network. Vol 10.

[17] Ghosal, S. Blystone, D. Singh, A.K. Ganapathy Subramanian, Singh, A. Sarkar, S. 2018. An explainable deep machine vision framework for plant stress phenotyping. Vol 115, pp 4613-4618.

[18] Ferentinos, K.P. 2018. Deep learning models for plant disease detection and diagnosis. Computer. Electronic Agriculture, vol 145, pp 311-318.

[19] Ashutosh K.S., SVN S., Himanshu S., Evans A.: 2022 .Hybrid Feature-based disease detection in plant leaf using convolutional neural network , Bayesian optimized SVM and Random Forest Classifier, Hindawi, Art No. 2845320, Journal of Food Quality.

[20] Geetharamani, G. Pandian, A. 2019. Identification of plant leaf diseases using a nine-layer deep convolutional neural network. Computer Electronic Eng.vol. 76, pp 323-338.

[21] Ramcharan, A. Baranowski, K. McCloskey, P. Ahmed, B. Legg, J. Hughes, D.O. 2017.Deep learning for Image-Based Cassava Disease Detection. Frontiers in plant science. Vol 102, pp 9-21.

[2] Zeng, W. Li, M. 2020. Crop leaf disease recognition based on Self-Attention convolutional neural network. Computer Electronic. Agric. Vol 178, 105803

[23] Francois Chollet.2017. Xception: Deep Learning with Depthwise Separable Convolutions. IEEE Conference on Computer Vision and Pattern Recognition (CVPR).