Scalable Computing: Practice and Experience, ISSN 1895-1767, http://www.scpe.org

Volume 21, Issues 4, pp. 625–635, DOI 10.12694:/scpe.v21i4.1780

IDENTIFICATION OF TOMATO LEAF DISEASE DETECTION USING PRETRAINED DEEP CONVOLUTIONAL NEURAL NETWORK MODELS

ANANDHAKRISHNAN T* AND JAISAKTHI S.M †

Abstract. In this paper, we proposed a plant leaf disease identification model based on a Pretrained deep convolutional neural network (Deep CNN). The Deep CNN model is trained using an open dataset with 10 different classes of tomato leaves We observed that overall architectures which can increase the best performance of the model. The proposed model was trained using different training epochs, batch sizes and dropouts. The Xception has attained maximum accuracy compare with all other approaches. After an extensive simulation, the proposed model achieves classification accuracy better. This accuracy of the proposed work is greater than the accuracy of all other Pretrained approaches. The proposed model is also tested with respect to its consistency and reliability.The set of data used for this work was collected from the plant village dataset, including sick and healthy images. Models for detection of plant disease should predict the disease quickly and accurately in the early stage itself .so that a proper precautionary measures can be applied to avoid further spread of the diseases. So, to reduce the main issue about the leaf diseases, we can analyze distinct kinds of deep neural network architectures in this research. From the outcomes, Xception has a constantly improving more to enhance the accuracy by increasing the number of epochs, without any indications of overfitting and decrease in quality. And Xception also generated a fine 99.45% precision in less computing time.

Key words: Convolutional neural network, Architectures, Accuracy

AMS subject classifications. 68T05

1. Introduction. Deep CNN is a leading area of research in modern age and machine learning and has been already demonstrated and implemented successfully in different crop fields. Next shows the degree of machine learning techniques using specific layers of information processing to obtain and categorize features and evaluate patterns for supervised or unmonitored learning [20]. Sound processes, natural language and image vision, reinforcement were also tested [2]. It was also commonly used to identify objects and rank objects in multiple globe industries such as business,forestry,aerospace, etc. [15]. It has also been commonly used to identify objects and rank objects in multiple globe industries such as company, forestry, aerospace, etc. A number of CNN comparison analyzes with an increased number of margin layers were performed predominantly. Other works in which AlexNet, Google Inception V3, Inception V4, VGG network are shown [14]. Another job is the inner shift of the layer, trying to change the input details into a layer throughout practice. Furthermore, a range of optimization methods have been suggested to address issues properly, as well as to transfer teaching, CNN some technologies [4]. CNN has some methods of optimization that shown in. So that to improve batch standardization. Deep Learning throughout the classification of tomato plant disease image explains expertise in extending skillful picture handling study and implementation to the farming sector that has been shown. It is now possible to use CNN learning models to define Leaf disease and classify plant disease. Regulation of nutrition and plant safety are a major problem for the anticipated population increase in the world. In comparison, it is necessary to recognize plant diseases and to make appropriate comparison steps.In this research, in the assignment of defining and classifying crop disease a science evaluation of state-of the art profound learning designs is carried out [7]. Section 1 reviews related work in the agricultural sector. Section 2 describes the current art of Convolutional techniques and other equipment. Sections 3, 4 discusses the experimental set-up and findings. Section 5, 6 discusses the conclusion, as well as the methodology to achieve this task.

*Research Scholar, School of Computer Science and Engineering, VIT, Vellore, India (anandhakrishnan.t@vit.ac.in).
†Associate professor, School of Computer Science and Engineering, VIT, Vellore, India (jaisakthi.murugaiyan@vit.ac.in (Corresponding Author)).

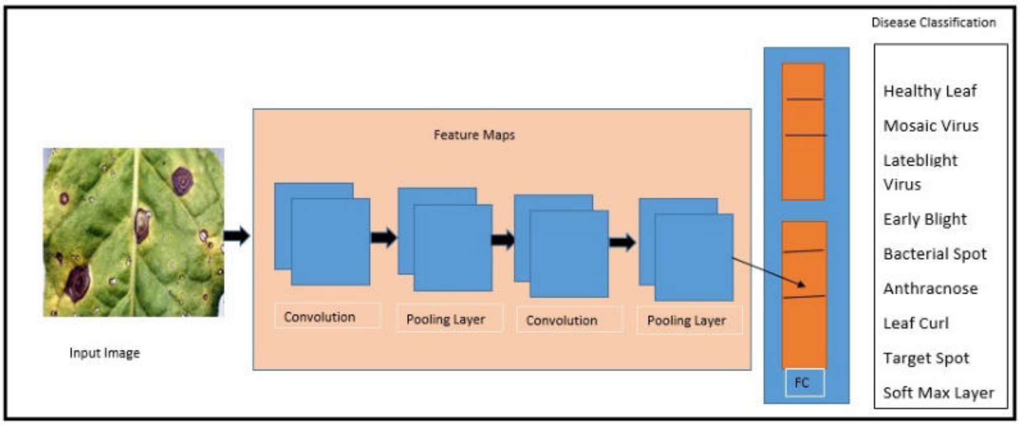

FIG. 1.1. *Deep convolutional neural network architecture*

2. Related Works. Many deep learning methods are used in crop fields and identification of images, including plant disease analysis and control of pests. Methodologies for deep learning and image processing have been expanded. Typical machine learning and deep learning approaches have been commonly adapted in the agricultural area. The paper [15] used a deep learning method in their work on developing a smartphone prognostic system for disease. Using data sources of 54,306 sample images of natural and contaminated plant leaves, they were using CNN to train their model. Sladojevic et al [3] addresses the plant leaves disease identification with 13 types of leafs with 4483 images and they used caffenet model for deeplearning the images for preprocessing they used Croppping the images and data augmentation technique is used and obtained the accuracy of 96.30% compare to the better results than SVM.

CNN were trained to use images to classify 14 species of crops and 26 diseases of the leaf..They assessed CNN's effectiveness for greenhouse and crop and disease classified problem. Two AlexNet and GoogleNet architectures have been implemented [4]. Their model was 99.35% valid. Even though their deep learning system achieved current art results, it was poorly performed when examined on image sets taken under numerous natural conditions. Similarly, [13] suggested that CNN use leaf images to identify plant diseases and validate the model. Their system was able to recognize from healthy leaves 14 various types of plant disease. Sladojevic etal Addresses the plant leaves disease identification with 13 types of leafs with 4483 images and they used caffenet model for deeplearning the images for preprocessing they used Cropping the images and data augmentation technique is used and obtained the accuracy of 96.30% compare to the better results than SVM. Mohanty et al. [14]. It focus on the plant leaves disease identification with 38 types of leafs with 54483 images and they used Alexnet model for deeplearning the images for preprocessing they resized to 224*224. No data augmentation technique is used and obtained the accuracy of 99.30% compare to the better results than other approaches.

But added, plants can be differentiated from their natural environment.On their investigation analysis, they accomplished an average 96.30% validity Probably used deep learning architectures to categorize plant species [6]. In their work, they presents a technique that can use colored images to produce plants and species. In their work, they were using CNN, which was tested on a total of 10,413 images of 22 species and crops.The CNN structure had such a problem in classifying certain plant species, and this is assumed to be limited to a small number of training datasets for those species [3]. The next method, called Deep Fruits, was introduced for tomato image detection in agriculture. They describe the CNN approach to tomato detection in their work using image data.Their intention was to construct an correct, reliable system of fruit identification and recognition,An important element of agricultural components for yield estimation and automatically generated processing.They trained their system and were able in the identification to accomplish an improvement of 0.838 accuracy and recall from the previous work. They trained to identify some fruits, taking four hours to annotate and train the new model per fruit all across the entire process [16]. Supervised learning techniques were applied same in classes on crop disease. The Artificial Neural Network [2] categorized the image of the potato leaf as sustainable or inconvenient. The results show that backpropogation could effectively detect blackspots Either

Fig. 2.1. *Sample Tomato leaf diseases in real field conditions*

explore the disease and detect the disease with a consistency of 92%. Four combinations of neural networks have been used to differentiate between wheat stripe rust and wheat leaf rust and grape downy mildew based on extraction techniques. Results revealed that plant disease identity and diagnosis could be achieved efficiently using image processing-based Neural networks. In contrast [19] proposes image analysis methodology for the detection of tomato scab disease. The sick images are collected from various vegetable fields and stored for improvement. In order to gain target regions for disease spots, the image segmentation is performed. Ultimately a specified region assessment disease spots is focused on a gray image processing approach

2.1. Materials and methods. Deep computer vision and image identification learning is currently progressing. The Deep-CNN standard comprises of a softmax or input and output layer, a categorization layer and hidden multiple layer. In general, CNN's hidden layers consist of convolution layers, pool layers, fc layers, and sometimes softmax layers. Lenet-5 architecture follows most CNN implementations. A number of CNN architectures were designed, by contrast [3]. During this work, A study comparing of the current neural network of convolution and its tuning to define and identify tomato plant disease using PlantVillage images is carried out. PlantsVillage contains 14528 images with open and free dataset, with 10 diseases for one crop plant. VGG 16, Xception V4, ResNet50, Alexnet, Lenet are the architectures evaluated. Quick and accurate Desired models for the detection of plant disease are desired so that specific primitive measures can be used soon in the categorization of leaf disease [22].

2.2. BenchMark Dataset. Image processing modules have been evaluated and practiced on sample tomato leaf images to classify and identify image disease that the CNN model had not seen before PlantVillage's data set [3] was used for this study openly and freely. Plant dataset has 14528 images for one crop plant with 10 diseases. For the first time, the images for the VGG network, ResNet and Alexnet architectures were resized to 224 * 224. The images are expanded to 299 * 299 pixels on both sides for both the Xception V4 architecture. Data standardization is performed by splitting all pixel values. Increase the aim or category variable to be used for the studied models very first, two parts of the data are available. First, the specific training data and then the highly classified data with a percentage ratio of 80 percent and 20 percent. The new range of the basically split current ratio is inspired by Mohanty et al work [21]. That test set is used to examine and formulate new models. The data is again divided into two training data and the validation data remains 80 percent and 20 percent and to assess if the model is overfitted in our approach, respectively. The training class included 14528 samples, validation samples, and a sample test set of 3632.

2.3. Progressive art of deep learning.

VGG net model. Deep teaching design has comparable methods, VGG net is one of the CNN systems designed for the ILSVRC-2014 assignment by [17]. The system may have reached a top-5 error level of 7.5 percent on verification, leading to an rise in some study job. As seen in [15] the template is generally used for its modesty. Figure 2.1 shows that overall model loss and accuracy with only 3 convolutionary layers on top of each other, the CNN system is increasingly consistency-sized. Max performs volume reduction (down sampling) for pooling. As seen in their work [16], our own initial softmax layer was overpassed And substituted

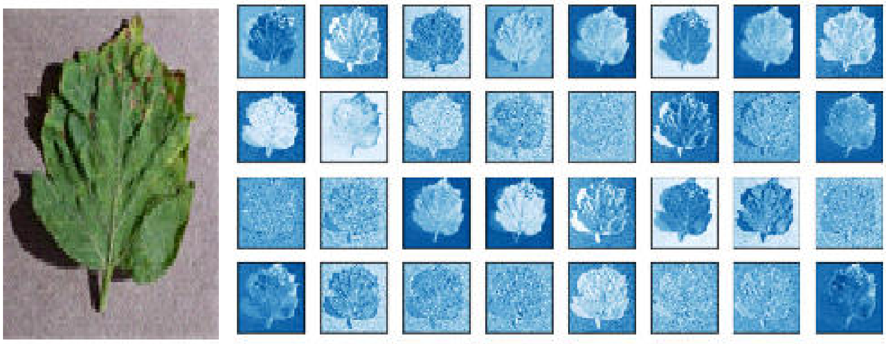

FIG. 2.2. *Visualization of convolution Filters*

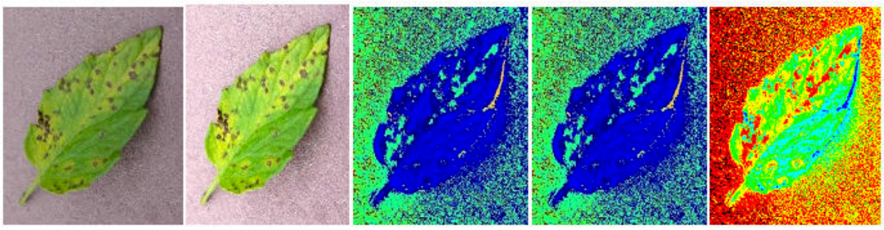

FIG. 2.3. *Action visualization learned weights by all layers*

by two fully embedded layers each of which has 4096 nodes and a classifier softmax. Our group's number 38 marks. A pre-trained ImageNet weight system was also used. Furthermore, on the sample set, the CNN system evaluated cross-entropy loss and accuracy.

ResNet. Very prominent in CNN [9]. ResNet design launched the ResNet system, the basis for the 2015 ILSVRC and 2015 classification contest.The suggested system of job took second position in the ImageNet classification with only a failure rate of 3.57 percent. The inability to understand different differential components for learning identification and degradation issues in different fields. Figure 2.2 shows that overall loss and accuracy of the model. This is an architecture that was incorporated as a network-in-network (NIN) into many full residual units. Such excess units are a set of basic components which are used to build networks.The result is a collection of basic residual unit types. ResNet architecture has resulted in a collection of basic residual unit types [5]. Convolution, pooling consists of residual units. A ResNet system has been created with 50, 101 and 50,101. Finally, a tailored crop illness detection layer of CNN was developed.

Xception V4. The later participation of GoogleNet architecture referring to the version amount was linked to Xception with few layers [8]. Stated architecture of Inception V3 also offers improvements to only the Inception module to increase the classification accuracy of ImageNet. In order to give primary importance to Inception V4 [16] strengthened the design.This architecture combines architectural design of activation with residual connections. Their objective is to combine training in network start-ups. The beginning-up module consists of a pooled layer stacked with convolution layers. The convolutions are 1 range, 3 range and 5 range in different sizes. The use of a bottle neck layer that is a bottle neck layer is another essential feature of the starting module. The bottleneck layer enables to reduce the computational demands that allow the required output to be produced. Within the unit, pooling layer is used in terms of size reduction [10]. The fusion of such parts as shown in requires a concatenation filter. Figure 2.3 shows that overall loss and accuracy of model. Xception v4 removes the concatenation stage with existing associations of the Inception architecture filter [13]. Finetuning of Inception V4 was carried out using ImageNet pre-trained weights. Furthermore, Avg pooling layer (88), dropout and softmax were used to transpose and describe a fresh template on the surface.

TABLE 2.1
Hyperparameters Settings

S.No	Hyperparameter	Settings
FD2	10^{-10}	26
FD4	10^{-12}	30
FD6	10^{-12}	30

TABLE 3.1
Hyperparameters Settings

S.No	Hyperparameter	Settings
1	Number of cnn layers	5
2	Number of neurons	500,100,7
3	Number of echos	30
4	Batch size	64
5	Activation functions	Relu
6	Optimizers	SGD
7	Learning rates	0.1
8	Momentum	0.9
9	Number of folds in cross-validation	10
10	Weight decay	0.004

2.4. Fine-tuning of models. Fine-tuning is an intrinsic notion of teaching to transfer the process of learning. Transfer teaching is an ML method, suggesting that acquiring expertise during practice is used in one type of issue to training in another associated assignment or field . The first few levels are taught in profound teaching to define the characteristics of the task. Most teaching involves fine-tuned teaching tests, Because the classes are much more faster than scratch [15]. Compared to scratch-trained designs they are also much more accurate. The CNN models have been carefully adjusted to verify and classify 10 crop disease types with previously trained designs to improve the leaf dataset in the training.The leafdataset provides about 1.2 million images and 1000 class entries.On the other hand, the Plantdataset contains 54,306 images and 38 classes. The Plantdataset is inadequate to train deep networks, although using the pre-trained weights of ImageNet. Fine tuning was achieved on both the plant dataset without any increase in information on CNN Inception v4, VGG16, ResNet. Fine tuning was achieved on the plant dataset without any increase in data from CNN Inception v4, VGG16, ResNet. The models were also developed and equipped with ImageNet pre-trained weights. By comparison, a new softmax layer on top layer truncated in the top layer [20]. Using the optimization SGD algorithm and the original learning frequency was 0.001, the system was also finely tuned.

2.5. Batch Normalization. Normalization is a method of deep learning that allows the inner change covariates to decrease layer problems [12]. When the yield of one layer is the source of the next layers during Deep Neural Networks practice. As the parameters of past layers shift during the learning phase of the CNN network, the dispersion of information information to layers differs dramatically over time. By having low learning prices, this method decreases instruction and makes it much easier to train those designs with regression swamping.When normalizing the CNN-Batch enables minimize the difficulties presented by the inner change of covariates. Changing the mean or width of input through one minibatch normalizes each layer's output, enabling higher learning prices to be used. All CNN tests are related to ReLU's batch normalization and activation feature.

3. DNN Settings. The DNN parameter settings consist of a number of all series of specific elements, that are presented in various architectures. DNN architectures shows pretrained architecture of a CNN, with its main elements, such as the input layer, convolutional layer, pooling layer, batch normalization and a process of flattening, where the information is entered into a set of dense layers, representing the result obtained in the output layer.

To continue a decent comparison between the experiments, an sample workflow attempt to standardize the hyper-parameters across the experiments was also made, using the following hyper-parameters, which are described in Table 3.1. DNN has unique significance and advanced in many research areas. Stochastic Gradient

Table 3.2
Machine Specifications

Hardware/software	Characteristics
Memory	64 Gb
Processor	Intel Core i7-7700
Graphics	GeForce GTX 1070 X 8 Gb
Operating system	ubuntu, 64 bits

Descent (SGD) has popular optimization algorithm and has been used in various architectures , and has proved to be an selective system between accuracy and efficiency [2]. The SGD is simple and effective, and it requires a tuning of the model hyper-parameters, particularly the initial learning rate, which is used in the optimization since it determines that the how fast the weights are adjusted in order to get a local or global to reduce the min loss function. The momentum helps to accelerate SGD in the suitable direction and reduces the overfitting [1]. In addition, the regularization is a very important technique to prevent the overfitting. The most common type of regularization is L2 Regularization, where the combination with SGD results in weight decay, in which each update the weights are scaled by a factor lightly smaller than one [18]. Each experiment runs a total of 30 epochs, where each epoch is the number of the training iteration. The choice was made due to the results of Mohanty et al work proposa because of its consistently converging after the first step down in the learning rate. Finally, all the CNNs are trained with the batch size of 32.Training these pretrained CNN architectures is extremely computational cost is very high intensive. Therefore, all the experiments are carried out on a workstation, presenting the details summarized in Table 3.2 [11]. The training process was conducted by Tensor flow using python with Deep Learning (DL) which provides a framework to design and implement CNNs, where applications and graphics help to visualize network activations and monitor the progress of network training. Meanwhile, the statistical analysis of each architecture was carried out with the Anaconda navigator–Spyder 3.2.

4. Results.

4.1. Experiment setup. The benchmark system used in our analysis is a GPU TiTan K40c workstation. The library of OpenCV, Keras, Theano, and CuDNN is used for implementation.

4.2. Training. From each DL- experiment, the model assessment uses accuracy metric and categorical cross-entropy loss (loss). The output is graphically designed with consistency and loss for each model. An overall experiment is computed using the test dataset to measure the loss score and accuracy and is used to determine the model performance. Table 4.1 introduces the measured results. For a total of 10 epochs and 30 epochs, each experiment runs. Where the epoch is the amount of iterations of training. The 10 and 30 iterations learning real choice was made to check which suitable model could mix with few iterations and which one is suffering from the problem of moral degradation. All popular deep learning networks have normalized the hyper-parameters. Stochastic Gradient Descent (SGD) is being used to train all network models, SGD runs better and diverges easily. They trained the networks with the batch size of 16 due to GPU memory limitations. Its learning rate for all networks was set at 0.001. They used 1e-6 weight from Decay and 0.9 momentum from Nesterov. Both experiments use batch standardized technique and ReLU activation function [13]. There is no data increase for all networks.

4.3. Results of the experiments. This experimental research has conducted an evaluation of the suitability of the distributed deep cnn to identify crop disease using pictures. Our focus was on the refining layers VGG 16, Inception V4, ResNet with 50, 101 and 152. Fine tuning and training of deep learning architectures as described in Section 2.1. Figures 4.1-4.8 explain the experiment's results. After good tuning, each document shows the precision and entropy loss of each DL design, all designs with 10 epochs except for VGG 16 were more than 90 percent accurate. By comparison, accuracy outcomes were achieved even after the 30th training cycle with systemically decreased log-loss. ResNet and designs continuously conduct better than VGG 16 and Inception V4. In addition, as viewed in The Deeper Models, they combined readily with stronger sample results as described in Table 4.1. Perform properly with fewer ResNet 50 and ResNet 101. On the other side, as shown in Figs. 4.1-4.8, ResNet 152 works badly with less iterations 4 and 5. However, with an enhanced amount of

Table 4.1
Results of Training and Testing and Execution time of the Proposed DCNN

CNN	Layers	Parameters	Training Loss	Validation Loss	time/sec
Alexnet	16	28.2M	0.0056	0.24	3Sec
Lenet	50	98.6M	0.009	0.56	2sec
Resnet	101	14.6M	0.0011	0.32	2.5sec
VGG 16	152	28.5M	0.99	0.0156	1.2sec
Proposed work	121	48.5M	0.17	0.24	2.9sec

Table 4.2
Hyperparameters Settings

Accuracy	Our proposed work	Alexnet	Lenet	Resnet	VGG16
%	99.45	90.1	88.3	98.40	90.1

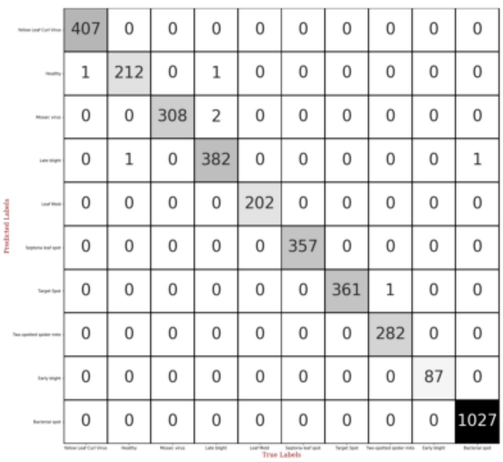

Fig. 4.1. *Results of the Proposed Confusion matrix*

Table 4.3
Classification accuracy of proposed CNN

Measures	Yellow	Healthy	Mosaic	Late Blight	Leaf mold	Septoria	Target
Accuracy	67	99	73	70	82	71	73
Precision	39	21	19	20	21	20	19
Sensitivity	98	90	99	85	79	89	78
Specificity	75	39	82	72	62	79	47

iterations as shown in Fig. 4.7, ResNet 152 continues to raise its precision and reduces its log-loss. Overall, Xception 121 performed well with the highest accuracy and low loss while VGG 16 performed badly with the lowest accuracy.

4.4. Discussions. The overall objective of this proposed work is to find the leaf disease in the images and to create an automatic classification of tomato leaf disease classification. Fast, accurate and detection of this disease can find out the diagnosis of disease. In this proposed Deep CNN, with TensorFlow and Keras model.Deep CNN we have analyzed from the Plant kaggle dataset it has 14528 images in that 1337 images are used validation and 3632 testing for one crop plant with 10 diseases. For the first time, the images for the VGG network, ResNet and Alexnet, Lenet, Xception architectures were resized to 224 * 224. The images

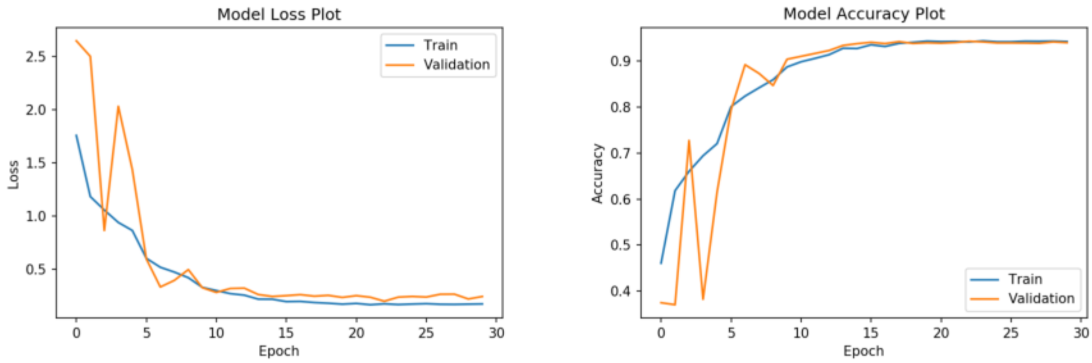

Fig. 4.2. *Results of ALEXNET Model: left Loss, right Accuracy*

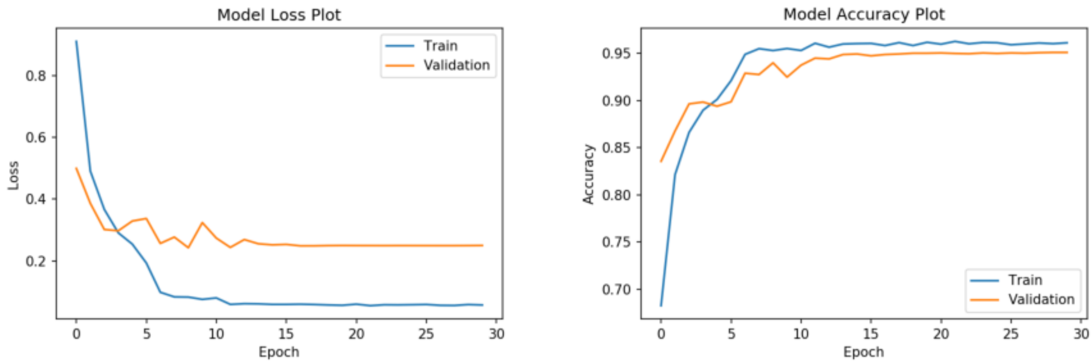

Fig. 4.3. *Results of LENET Model: left Loss, right Accuracy*

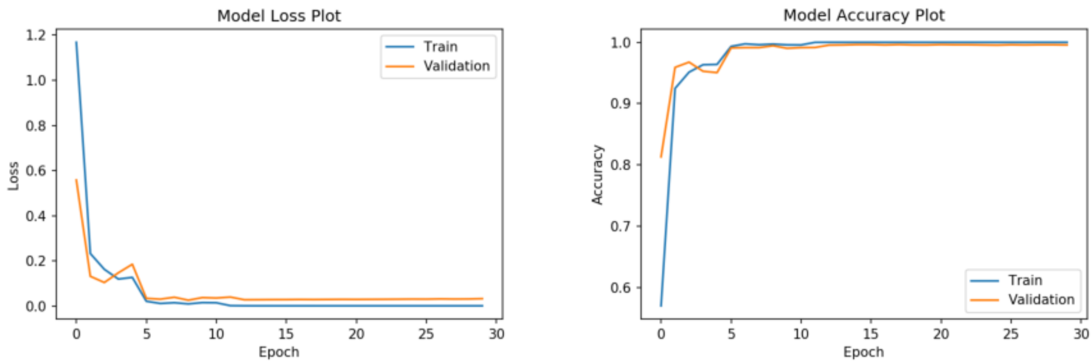

Fig. 4.4. *Results of VGG16 Model: left Loss, right Accuracy*

are enlarged to 299 * 299 pixels on both sides for both the Xception V4 architecture. Data standardization is performed by splitting all pixel values. Increase the aim or category variable to be used for the studied models very first, two parts of the data are available. First, the specific training data and then the highly classified data with a percentage ratio of 80 percent and 20 percent. The experimental results proved that the proposed method can reach a very high accuracy of 99.45% in the validation set and 95.03% in the test set with epochs equal to 30. The authors developed a classification of images from the kaggle plant village dataset, they used

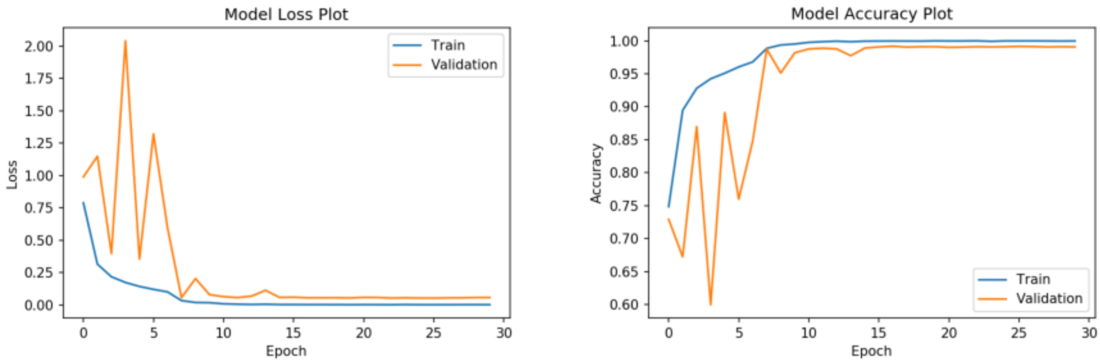

FIG. 4.5. *Results of Resnet Model: left Loss, right Accuracy*

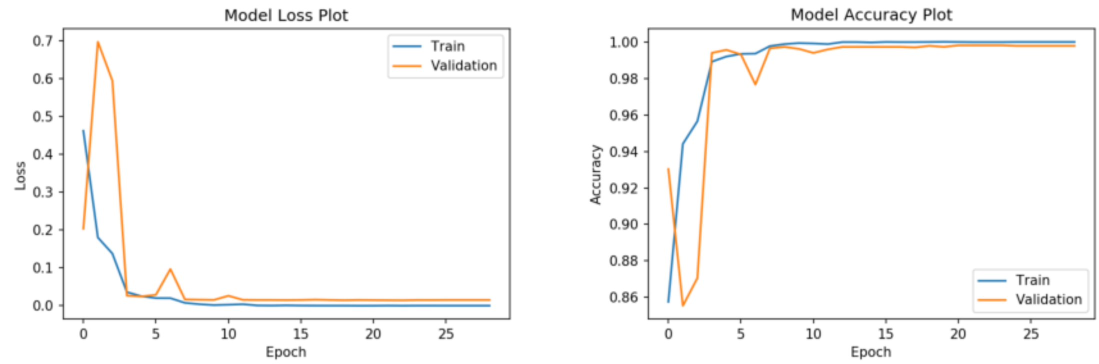

FIG. 4.6. *Results of Xception Model: left Loss, right Accuracy*

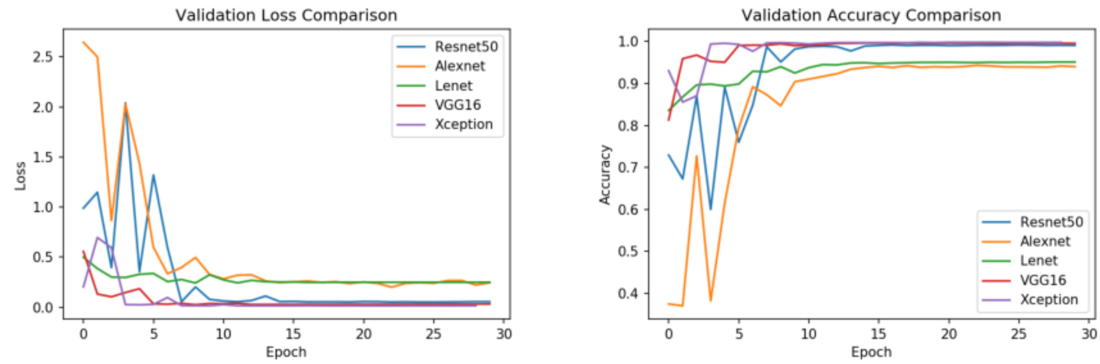

FIG. 4.7. *Left: Results of Loss Comparison; Right: Results of Accuracy Comparison*

convolution, pooling and full connection layers in the model created with the VGGNET architecture. In their research, the test phase of the educated model, class validation was obtained at 95.62%. In our work we have trained a CNN based on the ResNet50 architecture to classify leaf images of we have obtained a accuracy of 91% on the validation dataset. Therefore we have analyse differnt architectures of alexnet, lenet, VGGNET, resnet50 all of them Xception has attained a maximum accuracy of 99.45% of all rest of architectures.

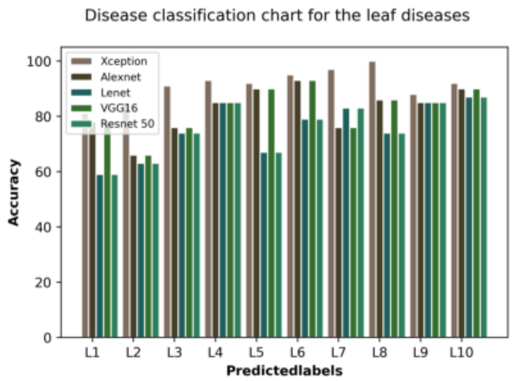

FIG. 4.8. *Disease Classification Plot for all Diseases*

TABLE 4.4
Parameters setting for proposed DCNN

Class	Images for training	Images for validation	Images for Testing
YLC Virus	1787	128	408
Healthy	787	120	213
Mosaic virus	1283	131	308
Late blight	1524	152	385
Leaf Mold	750	140	202
Septoria leaf spot	1414	185	357
Target Spot	1315	106	361
Two-spottedspider mite	1121	129	283
Early blight	286	56	87
Bacterial spot	4329	190	1028
Total	14528	1337	3632

5. Conclusion. From the above task, the refinement and analysis of the progressive deep convolutional neural network is performed for the identification of image-based plant disease. The architectures analyzed are VGG 16, Xception V4, ResNet 50, Alexnet, Lenet layers.From the analysis, Xception continues to yield consistent rises Throughout Precision with increasing number of epochs, with no signs of performance depletion and overfitting. In addition, Xception needs fewer numerical parameters and reasonable computing time to obtain the best outcomes in classified events. Xception's test accuracy for the 30th epoch is 99.45% percent, defeating the entire of all the architectures. Therefore, Xception v4 is a good model for image-based disease detection of plants. Even though the architecture's performance is good, increased research is needed to improve computational time.

REFERENCES

[1] S. Chetlur, C. Woolley, P. Vandermersch, J. Cohen, J. Tran, B. Catanzaro, and E. Shelhamer, *cudnn: Efficient primitives for deep learning*, arXiv preprint arXiv:1410.0759, (2014).
[2] L. Deng and D. Yu, *Deep learning: methods and applications*, Foundations and trends in signal processing, 7 (2014), pp. 197–387.
[3] K. He, X. Zhang, S. Ren, and J. Sun, *Deep residual learning for image recognition*, in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 770–778.
[4] G. Huang, Z. Liu, L. Van Der Maaten, and K. Q. Weinberger, *Densely connected convolutional networks*, in Proceedings of the IEEE conference on computer vision and pattern recognition, 2017, pp. 4700–4708.
[5] D. Hughes, M. Salathé, et al., *An open access repository of images on plant health to enable the development of mobile disease diagnostics*, arXiv preprint arXiv:1511.08060, (2015).
[6] S. Ioffe and C. Szegedy, *Batch normalization: Accelerating deep network training by reducing internal covariate shift*, arXiv preprint arXiv:1502.03167, (2015).
[7] D. S. Kermany, M. Goldbaum, W. Cai, C. C. Valentim, H. Liang, S. L. Baxter, A. McKeown, G. Yang, X. Wu,

F. Yan, et al., *Identifying medical diagnoses and treatable diseases by image-based deep learning*, Cell, 172 (2018), pp. 1122–1131.

[8] A. Krizhevsky, I. Sutskever, and G. E. Hinton, *Imagenet classification with deep convolutional neural networks*, Communications of the ACM, 60 (2017), pp. 84–90.

[9] Y. LeCun, L. Bottou, Y. Bengio, and P. Haffner, *Gradient-based learning applied to document recognition*, Proceedings of the IEEE, 86 (1998), pp. 2278–2324.

[10] M. Dyrmann, H. Karstoft, and H.S. Midtiby, *Plant species classification using deep convolutional neural network*, Biosystems Engineering, 151 (2016), pp. 72–80,

[11] S. Prasanna Mohanty, D. Hughes, and M. Salathe, *Using deep learning for image-based plant disease detection*, arXiv, (2016), pp. arXiv–1604.

[12] A. S. Rajput, S. Shukla, and S. Thakur, *Soybean leaf diseases detection and classification using recent image processing techniques.*

[13] A. K. Reyes, J. C. Caicedo, and J. E. Camargo, *Fine-tuning deep convolutional networks for plant recognition.*, CLEF (Working Notes), 1391 (2015), pp. 467–475.

[14] I. Sa, Z. Ge, F. Dayoub, B. Upcroft, T. Perez, and C. McCool, *Deepfruits: A fruit detection system using deep neural networks*, Sensors, 16 (2016), p. 1222.

[15] D. Samanta, P. P. Chaudhury, and A. Ghosh, *Scab diseases detection of potato using image processing*, International Journal of Computer Trends and Technology, 3 (2012).

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

[17] C. Szegedy, S. Ioffe, V. Vanhoucke, and A. Alemi, *Inception-v4, inception-resnet and the impact of residual connections on learning*, arXiv preprint arXiv:1602.07261, (2016).

[18] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, *Rethinking the inception architecture for computer vision*, in Proceedings of the IEEE conference on computer vision and pattern recognition, 2016, pp. 2818–2826.

[19] S. Prasanna Mohanty, D. Hughes, David and M. Salathe,, *Using Deep Learning for Image-Based Plant Disease Detection*, arXiv (2016), arXiv–1604.

[20] E. C. Too, L. Yujian, S. Njuki, and L. Yingchun, *A comparative study of fine-tuning deep learning models for plant disease identification*, Computers and Electronics in Agriculture, 161 (2019), pp. 272–279.

[21] H. Wang, G. Li, Z. Ma, and X. Li, *Application of neural networks to image recognition of plant diseases*, in 2012 International Conference on Systems and Informatics (ICSAI2012), IEEE, 2012, pp. 2159–2164.

[22] D. Yu, W. Xiong, J. Droppo, A. Stolcke, G. Ye, J. Li, and G. Zweig, *Deep convolutional neural networks with layer-wise context expansion and attention.*, in Interspeech, 2016, pp. 17–21.

Edited by: Rajkumar Rajasekaran
Received: Apr 4, 2020
Accepted: Dec 7, 2020