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Plant Disease Detection using VGG16

[1]Alok Kumar, [2]Ankit Kumar

[1]Research Scholar, [2]Assistant Professor

[1] Computer Science ,

[1]BMU, Rohtak, Haryana

Abstract: Plant disease detection is very important for healthy growth of plants. Plants play an important role in every living orgnisams life. Their by-products not only provide livehood to human beings but also contribute to a country's economy. Diseases have negative impact on both agricultural crop yield and health. Thus, it becomes important to monitor plants for any kind of diseases and take diagnostic actions according to reuirements. Disease detection can be done using machine learning algorithms. A novel plant disease detection technique based on deep learning is proposed in this work. VGG16 architecture is used for disease detection in tomato and potato plant species. This multi-class disease detection system significantly detect diseases and achieves an accuracy of respectively.

Index Terms **-VGG16, plant disease, plantvillage dataset and convolutional neural network.**

I. INTRODUCTION

For all living organisms on this earth, plants are a vital resource. They have the ability to heal, are a source of energy, guard the ecosystem, maintain environmental balance, and give food to all living organisms. A good agricultural yield support nation's economy. It helps in earning livelihood for its citizens and reduces risk of food scarcity. Thus, it is crucial to protect plants for the country's economy and natural life cycle. Plants should be regularly monitered for detecting diseases. This monitoring is carried out by team of experts by manual inspection. Manual inspection is time consuming. Diseases should be detected as early as possible and diagonistic actions if required, should be taken. Large-scale crop monitoring calls for close observation and thorough knowledge of diseases and their signs. In fields, disease can spread considerably more quickly and preventative measures may take some time to implement. Experienced agronomists are needed to monitor the crops since they must identify diseases through visual inspection.

Due to technological advancement, this manual inspection can be replaced by automated systems using artificial intelligence and machine learning. These fields try to mimic human activities and embib human intelligence in machines. Artificial intelligence and machine learning have provided solution to many pattern recognition problems. License plate detection, optical character recognition, health monitoring systems, biometric systems, natural language processing, fingerprint recognition, face recognition, signature verification etc , all these systems are developed using artificial intelligence and machine learning. Deep learning, a subset field of machine learning is an improvement over previously existing machine learning algorithms. A tremendous amount of improvement in recognition results in every field is achieved using deep learning technniques. Deep learning is end-to-end learning where features are extracted automatically.

In traditional techniques, feature extraction is done manually, in contrary, deep learning automatically extract features using kernels. The most common deep learning architecture is convolutional neural network. This network uses convolved filters for feature extraction of different levels at different layers. Lower layers extract low level features such as gradients, color, points which are transformed into higher level features such as edges, corners etc in higher layers of network. Convolutional neural networks take images as input and produces classes as their output in image classification tasks. Convolutional layers are mainly responsible for extracting features using convolved filters of different size. It also has pooling layers which help in dimensionality reduction. Pooling can be average pooling or max pooling depending upon the requirement. Softmax activation function is used in classification layer.

The most common CNN architectures are Alexnet, GoogleNet, VGG16, VGG19, Inception, ResNet etc. This work uses pretrained VGG16 network for disease detetction. Thus, VGG 16 is used for classification purpose. Tomato and potato images from plantvillage dataset are used in this work. The architecture of VGG 16 is explained in next section.

II. LITERATURE SURVEY

This section briefly reviews about the different state-of-art works of plant disease detection using deep learning.

The three types of apple diseases were detected and identified using an improved support vector machine (SVM), and the classification accuracy was 93%. Authors in [2] used the K-means clustering method to segment the lesions regions. They also combined the global colour histogram (GCH), colour coherence vector (CCV), local binary pattern (LBP), and completed local binary pattern (CLBP) to extract the colour and texture features of apple spots. Works in [3] and [4] explored the usage of individual lesions and spots rather than taking into account the entire leaf because each disease region has its unique features. The benefits of this approach include the ability to identify the presence of multiple diseases on the same leaf and the ability to enhance the data by segmenting the leaf picture into various sub-images. Authors in [5] employed the GoogLeNet model to identify 79 illnesses in 14 different plant species that were present in various field and experimental environments. Deep learning based Inception ResNet is used to detect yellow rust wheat disease in [6]. A technique was developed by [7] to automatically detect plant disease in images of maize plants that were captured in the field. In order to create an autonomous corn detector, authors in [8] trained a deep convolution neural network using 1632 images of corn kernels. A method for identifying rice infections was put forth by Lu et al. [9] and was based on deep convolutional neural network (CNN) technology. Using a deep learning technique, Zhang et al. created a network for recognising images of farm equipment [10]. In order to increase the precision of identifying maize leaf disease, Zhang et al. enhanced deep convolution neural network [11]. To conduct detection, images were fed into two deep learning-based architectures, namely AlexNet and VGG-16 net [12]. Coulibaly et al. proposed a technique to develop feature extraction using transfer learning [13]. The other methods for plant disease detection are based on support vector machines, guassian frameworks and k-neural networks. In [14], Directional Local Quinary Patterns (DLQP) were used to compute the keypoints in the input image in the first stage. The results of the plant disease classification were then obtained by training the SVM classifier on calculated key points. For the purpose of detecting tomato leaf disease, various deep learning models, including AlexNet, GoogleNet, and ResNet, were utilised in [15]. Using these deep learning networks, they experimented with the SGD and Adam optimizer, and the ResNet model attained the greatest accuracy of 97.28%.

By combining the deep architectures of Xception, MobileNet, DenseNet, and LeafNet, [16] proposed a multi-class disease detection method. Using Xception, it identified 26 distinct illnesses in 14 different plant species with a 99.81% accuracy rate. The accuracy of the detection of rice plant diseases by the authors in [17] using GLCM (Gray Level Co-occurrence Matrix) for feature extraction and probalistic neural network was 76.8%. Using several neural network classifiers and CNN, tomato illnesses were identified in [18]. For the purpose of weed and paddy detection, regional convolutional neural networks were used in [19].

Methods based on imaging techniques have also been used in literature. For foliar detection in barley plants, authors in [20] used probalistic topic modelling and hyperspectral imaging. Using region-based spectral reflentance, [21] was able to detect the mosaic virus in tobacco leaves. Different machine learning algorithms were employed to categorise these hyperspectral photos. [22] describes a method for detecting the yellow rust disease in wheat crops that combines spectroscopy and a multi-layer preceptron neural network. [23, 24, 25] provide a thorough overview of fluroscence and infrared spectroscopy.

III. VGG16

VGG 16 was introduced by Karen Simonyan and Andrew Zisserman of Oxford University [1]. The network receives a dimensioned image as input (64, 64, 3). The same padding and 64 channels with a 3*3 filter size are present in the first two layers. Then, two layers have convolution layers of 128 filters of size 3*3 followed by a max pool layer of stride (2, 2). The next layer is a max-pooling stride (2, 2) layer that is identical to the layer before it. There are then 256 filters spread across 2 convolution layers with filter sizes of 3*3.

There are then two sets of three convolution layers, followed by a max pool layer. Each layer has same padding and has 512 filters of size (3, 3). The stack of two convolution layers then receives this image. The filters we utilise in these convolution and max-pooling layers are 3*3 in size. We obtained a (4, 4, 512) feature map after adding a convolution and max-pooling layer to the stack. This output is flattened to create a (1, 2048) feature vector. Following this, there is dense layer which receives a vector of size (1, 2048) and produces a vector of size 4 channels. As there are 4 classes in the dataset for classification.

```
Layer (type)                 Output Shape              Param #
=================================================================
input_1 (InputLayer)         (None, 64, 64, 3)         0
_________________________________________________________________
block1_conv1 (Conv2D)        (None, 64, 64, 64)        1792
_________________________________________________________________
block1_conv2 (Conv2D)        (None, 64, 64, 64)        36928
_________________________________________________________________
block1_pool (MaxPooling2D)   (None, 32, 32, 64)        0
_________________________________________________________________
block2_conv1 (Conv2D)        (None, 32, 32, 128)       73856
_________________________________________________________________
block2_conv2 (Conv2D)        (None, 32, 32, 128)       147584
_________________________________________________________________
block2_pool (MaxPooling2D)   (None, 16, 16, 128)       0
_________________________________________________________________
block3_conv1 (Conv2D)        (None, 16, 16, 256)       295168
_________________________________________________________________
block3_conv2 (Conv2D)        (None, 16, 16, 256)       590080
_________________________________________________________________
block3_conv3 (Conv2D)        (None, 16, 16, 256)       590080
_________________________________________________________________
block3_pool (MaxPooling2D)   (None, 8, 8, 256)         0
_________________________________________________________________
block4_conv1 (Conv2D)        (None, 8, 8, 512)         1180160
_________________________________________________________________
block4_conv2 (Conv2D)        (None, 8, 8, 512)         2359808
_________________________________________________________________
block4_conv3 (Conv2D)        (None, 8, 8, 512)         2359808
_________________________________________________________________
block4_pool (MaxPooling2D)   (None, 4, 4, 512)         0
_________________________________________________________________
block5_conv1 (Conv2D)        (None, 4, 4, 512)         2359808
block5_conv2 (Conv2D)        (None, 4, 4, 512)         2359808
_________________________________________________________________
block5_conv3 (Conv2D)        (None, 4, 4, 512)         2359808
_________________________________________________________________
block5_pool (MaxPooling2D)   (None, 2, 2, 512)         0
_________________________________________________________________
flatten_1 (Flatten)          (None, 2048)              0
_________________________________________________________________
dense_1 (Dense)              (None, 4)                 8196
=================================================================
Total params: 14,722,884
Trainable params: 8,196
Non-trainable params: 14,714,688
_________________________________________________________________
```

Fig 1: VGG16 architecture for the proposed work

ReLU is used by every hidden layer as its activation function. Because ReLU promotes quicker learning and lessens the likelihood of vanishing gradient issues, it is more computationally efficient.

IV. EXPERIMENTAL RESULTS

PlantVillage dataset is used for experiments in the proposed work. The work is conducted on tomato and potato plant species. Figure 2 represents training and validation accuracies for tomato dataset. It achieves an overall accuracy of 88.6 % for tomato dataset. The system detects four kind of tomato diseases namely, leaf curl, mosaic virus, target spot and healthy leaves. Table 1 represents images of tomato plant species from plantvillage dataset.

Table 1: Images representing diseases of tomato plant species from plantvillage dataset.

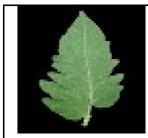		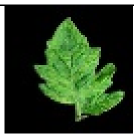	
Healthy	Target spot	Mosaic virus	Leaf curl

Figure 2 represents training and validation accuracy for tomato plant species. Losses are represented by figure 3.

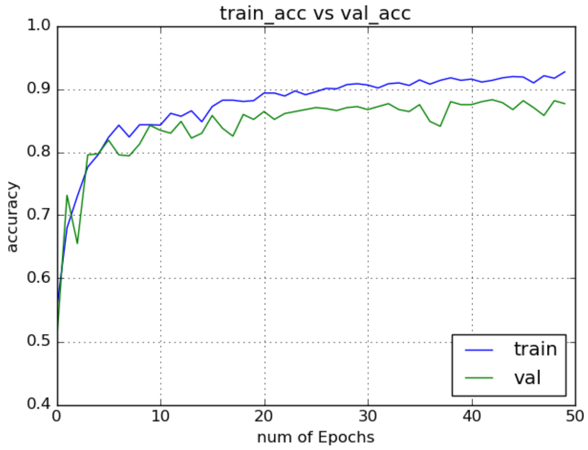

Fig. 2. Training and validation accuracies for tomato plant species.

Tomato plant species achieves an highest accuracy of 88.6% for validation data.Table 2 represents potato leaf samples from plantvillage dataset of different diseases namely, early blight, late blight and healthy.

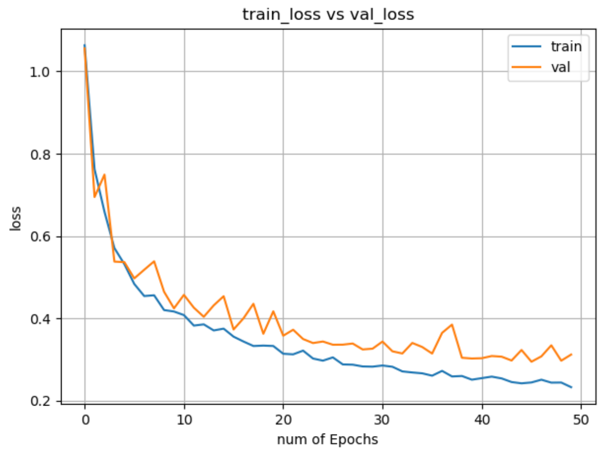

Fig. 3. Training and validation loss graphs for tomato plant species.

Table 2: Images representing diseases of potato plant species from plantvillage dataset.

		
Early blight	Healthy	Late blight

Figure 3 represents training and validation accuracies for potato dataset. It achieves an highest accuracy of 94.6 %. Figure 4 represents loss graphs for potato plant species. Loss gradually decreases as number of epochs increases. Confusion matrix of three classes is represented by figure 5.

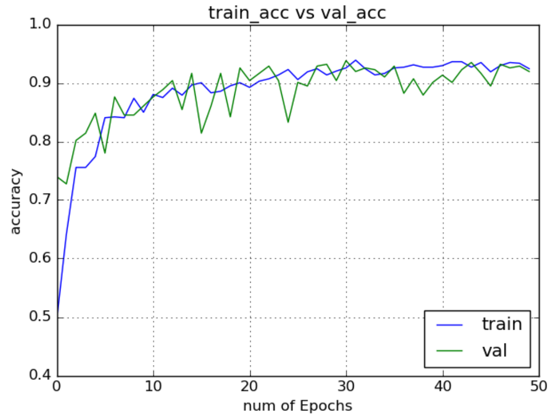

Fig. 3. Training and validation accuracies for potato plant species.

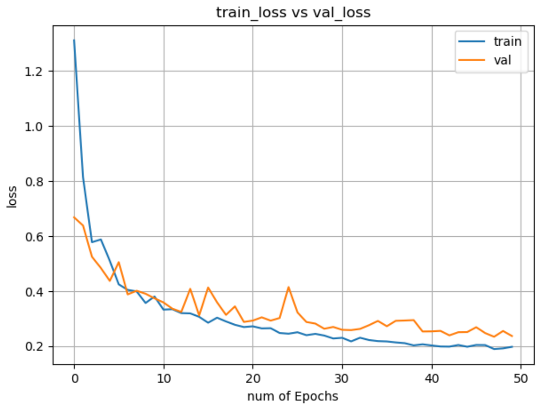

Fig. 4. Training and validation loss for potato plant species.

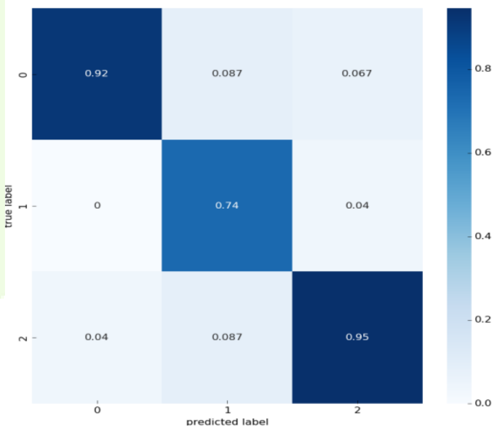

Fig. 5. Confusion matrix for potato plant species.

V. CONCLUSION

The proposed tries to build a plant disease detection system using convolutional neural network architecture. VGG 16 is used as classifier and feature extractor. Experiments are performed on potato and tomato plant species. Deep learning based architecture achieves significant results which can be further improved by adding more data and experimenting wwith different optimizers.

REFERENCES

[1] Simonyan, Karen and Zisserman, Andrew, “Very Deep Convolutional Networks for Large-Scale Image Recognition”, arXiv 2014

[2] S. R. Dubey and A. S. Jalal, "Adapted approach for fruit disease identification using images", Int. J. Comput. Vis. Image Process., vol. 2, no. 3, pp. 44-58, Jul. 2012.

[3] J. G. A. Barbedo, "Plant disease identification from individual lesions and spots using deep learning", Biosyst. Eng., vol. 180, pp. 96-107, Apr. 2019.

[4] S. H. Lee, H. Goëau, P. Bonnet and A. Joly, "New perspectives on plant disease characterization based on deep learning", Comput. Electron. Agricult., vol. 170, Mar. 2020.

[5] C. Bi, J. Wang, Y. Duan, B. Fu, J.-R. Kang and Y. Shi, "MobileNet based apple leaf diseases identification", Mobile Netw. Appl., vol. 10, pp. 1-9, Aug. 2020.

[6] X. Zhang, L. Han, Y. Dong, Y. Shi, W. Huang, L. Han, et al., "A deep learning-based approach for automated yellow rust disease detection from high-resolution hyperspectral UAV images", Remote Sens., vol. 11, no. 13, Jun. 2019.

[7] D. Chad, W. H. Tyr, S. Chen et al., “Automated identification of northern leaf blight-infected maize plants from field imagery using deep learning,” Phytopathology, vol. 107, pp. 1426–1432, 2017.

[8] C. Ni, D. Wang, R. Vinson, M. Holmes, and Y. Tao, “Automatic inspection machine for maize kernels based on deep convolutional neural networks,” Biosystems Engineering, vol. 178, pp. 131–144, 2019.

[9] Y. Lu, S. Yi, N. Zeng, Y. Liu, and Y. Zhang, “Identification of rice diseases using deep convolutional neural networks,” Neurocomputing, vol. 267, pp. 378–384, 2017.

[10] Z. Zhang, H. Liu, Z. Meng, and J. Chen, “Deep learning-based automatic recognition network of agricultural machinery images,” Computers and Electronics in Agriculture, vol. 166, p. 104978, 2019.

[11] X. Zhang, Y. Qiao, F. Meng, C. Fan, and M. Zhang, “Identification of maize leaf diseases using improved deep convolutional neural networks,” IEEE Access, vol. 6, pp. 30370–30377, 2018.

[12] R. A. Krishnaswamy, P. Raja, and R. Aniirudh, “Tomato crop disease classification using pre-trained deep learning algorithm,” Procedia Computer Science, vol. 133, pp. 1040–1047, 2018.

[13] S. Coulibaly, B. Kamsu-Foguem, D. Kamissoko, and D. Traore, “Deep neural networks with transfer learning in millet crop images,” Computers in Industry, vol. 108, pp. 115–120, 2019.

[14] Ahmad W, Shah S, Irtaza A (2020) Plants disease phenotyping using quinary patterns as texture descriptor. KSII Trans Internet Inf Syst 14(8):3312–3322.

[15] Zhang, Keke & Wu, Qiufeng & Liu, Anwang & Meng, Xiangyan. (2018). Can Deep Learning Identify Tomato Leaf Disease?. Advances in Multimedia. 2018. 1-10. 10.1155/2018/6710865.

[16] Saleem, Muhammad Hammad, Johan Potgieter, and Khalid Mahmood Arif. 2020. "Plant Disease Classification: A Comparative Evaluation of Convolutional Neural Networks and Deep Learning Optimizers" Plants 9, no. 10: 1319.

[17] Ökten, İ., Yüzgeç, U. (2022). Rice Plant Disease Detection Using Image Processing and Probabilistic Neural Network. In: Seyman, M.N. (eds) Electrical and Computer Engineering. ICECENG 2022. Lecture Notes of the Institute for Computer Sciences, Social Informatics and Telecommunications Engineering, vol 436. Springer,

[18] Thanjai Vadivel & R. Suguna (2022) Automatic recognition of tomato leaf disease using fast enhanced learning with image processing, Acta Agriculturae Scandinavica, Section B — Soil & Plant Science, 72:1, 312-324,

[19] M. Vaidhehi & C. Malathy (2022) An unique model for weed and paddy detection using regional convolutional neural networks, Acta Agriculturae Scandinavica, Section B — Soil & Plant Science, 72:1, 463-475,

[20] Wahabzada, M., Mahlein, AK., Bauckhage, C. et al. Plant Phenotyping using Probabilistic Topic Models: Uncovering the Hyperspectral Language of Plants. Sci Rep. 2016; 6:22482.

[21] Hongyan Zhu, Haiyan Cen, Chu Zhang, Yong He. Early detection and classification of tobacoo mosaic virus based on hyperspectral imaging.American Society of Agricultural and Biological Engineers. 2016:162460422.

[22] Dimitrios Moshou, Cédric Bravo, Jonathan West, Stijn Wahlen, Alastair McCartney, Herman Ramon. Automatic detection of ‘yellow rust’ in wheat using reflectance measurements and neural networks. Computers and Electronics in Agriculture. 2004; 44(3):173-188.

[23] Alfadhl Yahya Khaled, Samsuzana Abd Aziz, Siti Khairunniza Bejo, Nazmi Mat Nawi, Idris Abu Seman & Daniel Iroemeha Onwude. Early detection of diseases in plant tissue using spectroscopy – applications and limitations. Applied Spectroscopy Reviews. 2018; 53(1):36-64.

[24] Lowe, A., Harrison, N. & French, A.P. Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. Plant Methods. 2017; 13(80):56-74.

[25] Poornima Singh Thakur, Pritee Khanna, Tanuja Sheorey, Aparajita Ojha. Trends in vision-based machine learning techniques for plant disease identification: A systematic review. Expert Systems with Applications. 2022; 208: 11117.