Deep Learning based Plant Disease Diagnosis for Grape Plant

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Abstract—*Plant diseases are a major cause of food grain losses worldwide and a hazard to the overall agricultural production. Due to this, researchers, agronomists and subject matter experts are striving to investigate all possible solutions, in order to eradicate this threat and minimize the damages, to the economy as well the environment. In this extended abstract, the authors have evaluated two Convolutional Neural Network (CNN) architectures, namely, ResNet50 and VGG16, on PlantVillage dataset for Grape plant. Networks were trained and tested on 4062 healthy and diseased leaf images. Employing accuracy, loss and F1 score as performance measures, ResNet50 delivered better results.*

Keywords: *Deep Learning, Machine Learning, Plant Diseases, Grape Plant, Agriculture*

INTRODUCTION

With the steady growth of human population, there is an ever-increasing demand of food supply and therefore an urgent need to protect the crop yield from damages caused by the outbreak of diseases in plants [1]. Use of fungicides, pesticides and other chemicals have an adverse effect on the ecosystem; hence, there usage should be minimized. This can be achieved through constant monitoring of crops and early prediction of pathogen onslaught (namely virus, bacteria, fungi, nematodes, protozoa etc.), so that control measures can be exercised timely. Researchers in the fields of artificial intelligence, machine learning, image processing, deep learning, genetic algorithms etc. have applied and evaluated several computational techniques for identification, classification, quantification and prediction of diseases in various crops.

BACKGROUND

Deep learning was initially applied for detecting handwritten numerals in documents and since then it has been utilized in numerous areas viz. speech recognition, image classification, natural language processing etc, to name a few. It constitutes of four basic operations: Convolution, ReLu (Rectified Linear Unit), Pooling and Fully connected layer [2]. For image classification, as opposed to computing features beforehand and feeding them as input to the classifier, as in other machine learning approaches, deep learning models learn directly from the input images and generate feature maps. But for training purposes, a deep learning model requires thousands of images while other machine learning techniques can work with much less images. PlantVillage dataset [3] is an openly available collection of 54,306 images covering 14 crops and corresponding 26 diseases. This dataset has been used by various authors to evaluate different CNN architectures. Several models have been implemented and their performances compared, such as GoogleNet and AlexNet [4], AlexNet and SqueezeNet [5], AlexNetOWTBn and VGG16 [6] etc. Deep learning has also been trained and tested on this dataset for computing the disease severity levels in a plant [7].

MATERIALS AND METHODS

The Authors have implemented and evaluated the performances of pre-trained CNN architectures, ResNet50 [8] and VGG16 [9] on 4062 grape leaf images, both healthy and diseased, taken from the

PlantVillage dataset. The images constitute of grape leaves infected with black rot (1180), leaf blight (1076), black measles (1383), and healthy (423). The computed performance measures are model accuracy, model loss and mean F1 score. Table 1 lists a few details of both architectures. The dataset was split into 70-30 train-test ratio and images were downscaled to 256X256 pixel size for classification. Hyper-parameters for both were as follows:

For VGG16:

Learning Rate: 0.00001

Decay: 1e-6

Momentum: 0.9

For ResNet50:

Learning Rate: 0.001

Decay: 1e-6

Momentum: 0.9

Table 1: CNN Architectures Implemented

Model	Size (in MB)	Parameters	Depth
VGG16	528	138,357,544	23
ResNet50	99	25,636,712	168

RESULTS

Table 2 summarizes the resultant performance measures for both CNN architectures. While VGG16 delivered 100% accuracy for the training set, ResNet50 performed better for the test set. With greater mean F1 score, ResNet50 outperformed VGG16 and achieved higher success rate. Figures 1-2 demonstrate graphs with their comparative results for model accuracy and F1 score. These graphs are based on the figures 3-5, that depict the generated accuracy, loss and F1 score against epochs during implementation, for both models.

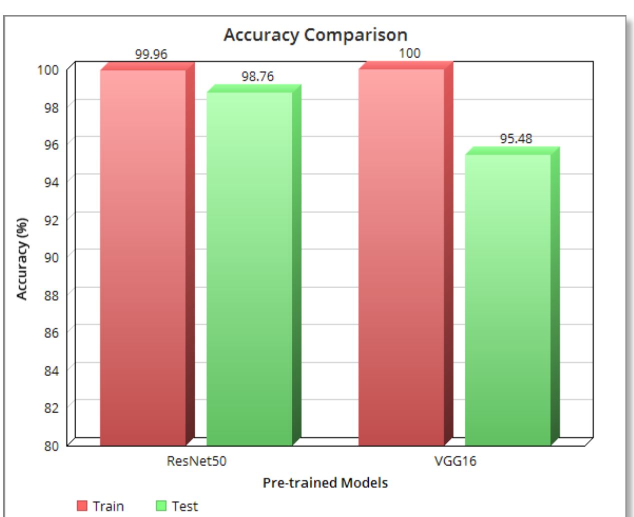

Fig. 1: Accuracy Comparison

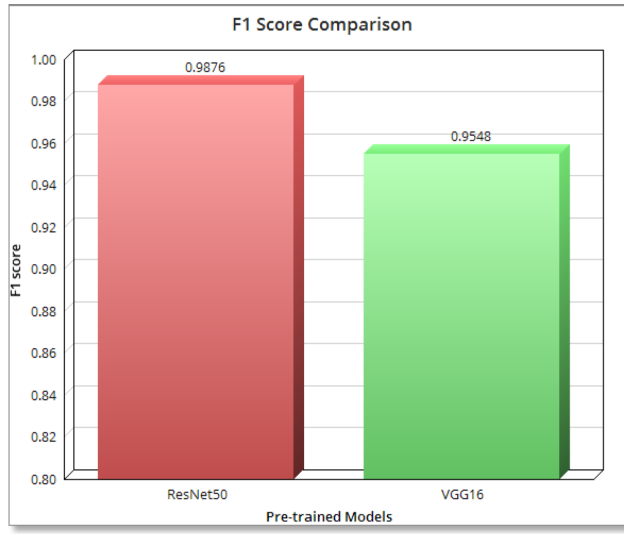

Fig. 2: F1 Score Comparison

Table 2: Performance Comparison

Model	Accuracy (%)		Loss		F1 Score
	Train	Test	Train	Test	
VGG16	**100**	95.48	**0.0017**	0.24	0.95
ResNet50	99.96	**98.76**	0.0056	**0.09**	**0.98**

CONCLUSION AND FUTURE ASPECTS

The authors implemented two popular CNN architectures, VGG16 and ResNet50. It is demonstrated that ResNet50 can be a good candidate for deep learning based image classification due to its less size, larger number of layers and better performance as compared to VGG16. This model can be easily implemented as a mobile application and used practically in real world conditions. As with the Grape plant, this model can be trained for several crops and utilized for disease diagnosis in plants. This approach needs to be implemented and tested on a much larger scale and most importantly, reach the farmers for actual deployment. As a mobile application, it would eliminate their dependency on heavy and expensive laboratory equipments as well as experts. But this approach is not suitable for early prediction of a disease, as it requires visual symptoms to appear on the plant leaf surface. These visual cues indicate a greater severity level of the disease. However, once the disease appears and is detected timely, its spread to the other parts of the field and adjoining areas can be controlled.

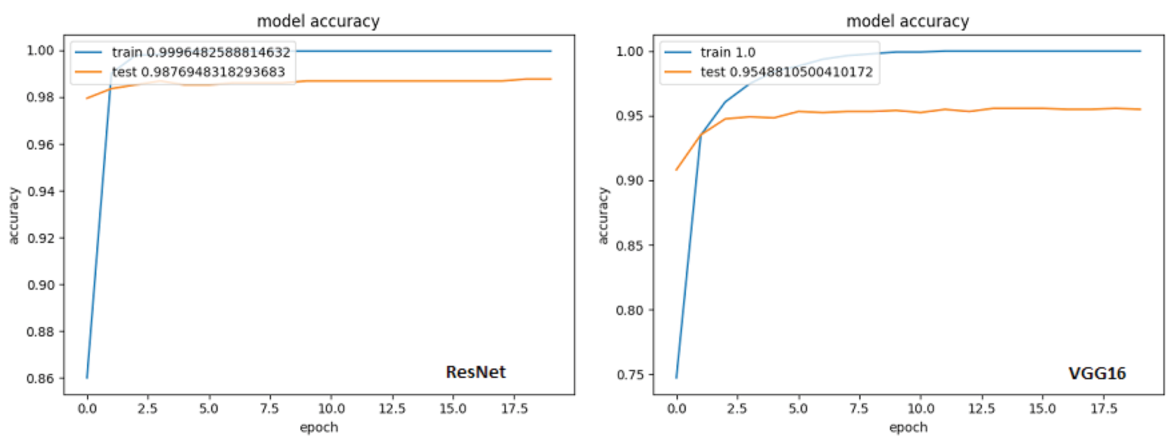

Fig. 3: Accuracy Graphs for both CNN Architectures

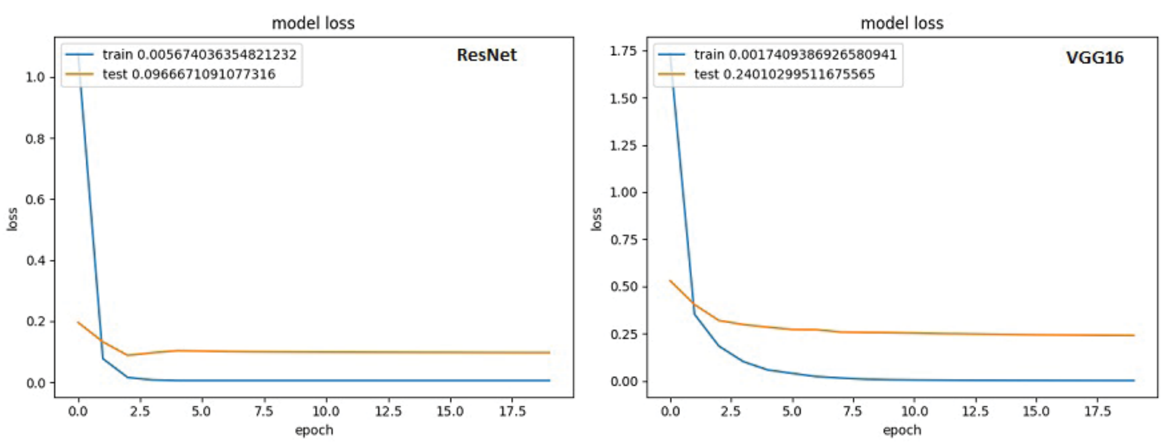

Fig. 4: Model Loss Graphs for both CNN Architectures

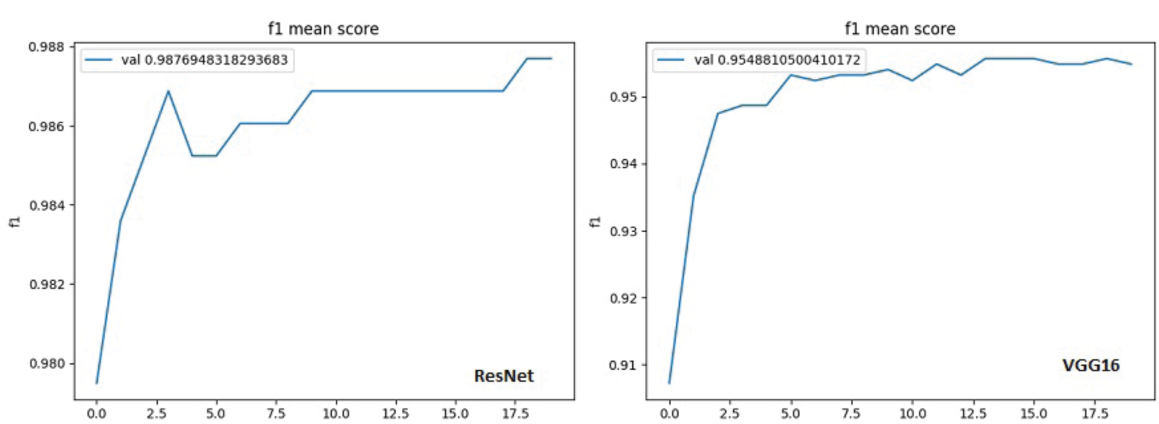

Fig. 5: Resultant F1 Score Graphs for both CNN Architectures

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