Crop Disease Detection Using Deep Learning

Omkar Kulkarni
Dept. of Information Technology,
Pune Institute of Computer Technology, Savitribai Phule Pune University,
Pune, India.
Email: omkar.omkar.135@gmail.com

***Abstract*—In recent times, drastic climate changes and lack of immunity in crops has caused substantial increase in growth of crop diseases. This causes large scale demolition of crops, decreases cultivation and eventually leads to financial loss of farmers. Due to rapid growth in variety of diseases and adequate knowledge of farmer, identification and treatment of the disease has become a major challenge. The leaves have texture and visual similarities which attributes for identification of disease type. Hence, computer vision employed with deep learning provides the way to solve this problem. This paper proposes a deep learning-based model which is trained using public dataset containing images of healthy and diseased crop leaves. The model serves its objective by classifying images of leaves into diseased category based on the pattern of defect**

Keywords—Crop disease, Deep learning, Transfer Learning, MobileNet, InceptionV3, Image classification.

I. Introduction

Agriculture is the main source of food, raw material and fuel which contributes to the economic development of a nation. Nearly 66% of the population depends on agriculture directly or indirectly. As there is a rapid growth in global population, agriculture is struggling to fulfill its necessity. The food security remains threatened by various circumstances including climate change, the decline in pollinators, crop diseases, lack of irrigation, etc. Crop disease alleviates the production and also the quality of food. Crop diseases not only affect the food security at the global level, but it also has adverse consequences for small scale farmers whose income depends on healthy cultivation. There is an advantage that the crop diseases can be controlled by identifying the diseases as soon as it develops on crops. Due to advancement of internet, field of computer vision it has been possible to provide impactful solution to this problem.

The objective of this paper is to provide an application which predicts the type of crop disease based on textural similarity of leaves. Publicly available dataset containing healthy and diseased crop leaves is used to train the model. The early diagnosis of crop disease can be used to prevent further damage that can be done to the crops which is helpful for sustaining the cultivation.

The remaining part of the paper is organized as follows. Section II includes the related work done in this particular area. Section III deals with the proposed model and the methodology that has been used to solve the problem. Section IV deals with experiments performed to on the given problem and results obtained for the same. Finally, the results are concluded which includes comparison between different models and future scope.

II. Related Work

The identification of the crop species is the basic requirement before we identify the class of disease. Abdul Kadir in his research work has used color features like mean, standard deviation, skewness and kurtosis are made on the pixel values of the leaves. He has consolidated features coming through grey level co-occurrence matrix (GLCM) functions which identifies the texture of an image. It generates a GLCM that produce statistical measures by calculating how frequently pairs of pixel with specific values and in a specified spatial relation occur in an image [1].

In paper [2], neural network is used to detect the disease. If leaf is infected, further processing is done to identify the disease. Genetic algorithm is used along with SVM to optimize loss and identify the type of disease. This paper states method for optimization of loss function using genetic algorithm, which is similar to theory of natural selection where only strong parameters survive.

In paper [3], semi-supervise learning is used in the form of Generative Adversarial Networks to classify images. In such type of learning discriminator is transformed into a multi-class classifier and generator is used only for training of discriminator. In paper [4], transfer learning is used for content based image recommendation and Inception-V3 model is used for building of neural

III. Methodology

In this paper the implementation is done in different phases in the following manner: collecting the dataset, pre-processing the dataset, training the Convolutional Neural Network (CNN) model to identify the type of crop, training CNN model to detect the disease, validation of model through obtained results.

A. Dataset

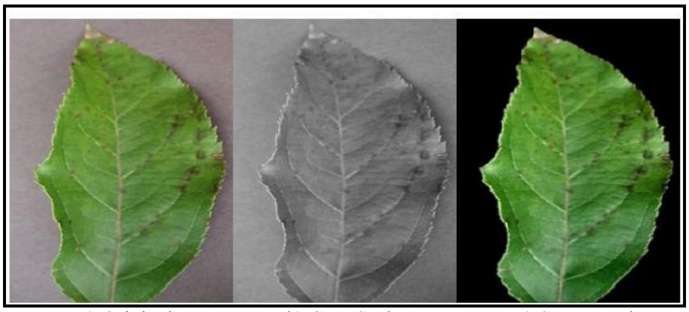
Plantvilla which is an open source dataset is used which contains 54,306 images of crop leaves classified in 38 different classes. The dataset covers 13 type crop species and 26 types of diseases. Each class has pair of fields containing the name of crop and the name of disease. All these images are segmented and resized to 224 x 224 size and are converted into grayscale images before further processing.

B. Preprocessing of image

The images present in the dataset have varying background and non-uniform lighting which affects accuracy of the application. The pre-processing of image is essential for removing noise and segmentation of the image which helps in improving the accuracy of CNN model. Hence, to handle the

978-1-5386-5257-2/18/$31.00 ©2018 IEEE

varying background problem, segmentation is performed that extracts only relevant part of the image. So, after performing the segmentation all the leaf images with black background are obtained. Further, to handle the non-uniform lighting conditions segmented images are converted to grey scale images and are passed on for further processing. Images obtained after preprocessing are shown in fig 1.



a.) Original b) Grey Scale c) Segmented

Fig 1. Preprocessing of leaf

C. Crop disease detection and classification

Classification of the disease is performed in two steps where the first step is to detect the type of crop and seconds step is to detect the type of disease. To perform these task deep convolutional neural networks is used. Transfer learning is used to build the deep learning model and is trained using the ImageNet dataset. Transfer learning is a machine learning technique in which a model is trained on one task is re-purposed on another related task. It is a technique in which pre-trained neural networks are used to build the neural network for similar kind of task to implant rapid and sustainable progress for solving the problem. These pre-trained networks are developed by training on large datasets which contains enormous number of diversified images.

Several research organizations build such kind of models which take weeks to train on latest high-end hardware. These are released under a permissive license for reuse that are directly incorporated to build new model for solving similar type of problems. These pre-trained models can be fine-tuned by using new dataset, if its nature is similar to the dataset on which network is trained. In such type of cases only last layer of network is trained, then tuned network can be directly used to solve problem. If the size of dataset is large enough then the pre-trained model can be retrained using new data and, in such case, the neural network is initialized with weights of the pre-trained model.

Among the various pre-trained models such as Xception, VGG16, VGG19, MobileNet, ResNet50, InceptionV3, etc. InceptionV3 and MobileNet are used for implementation through transfer learning. The InceptionV3 architecture as shown in Fig 2 has 23,851,784 parameters and depth of 159 layers and MobileNet architecture as shown in Fig 3 has 4,253,864 parameters and depth of 88 layers.

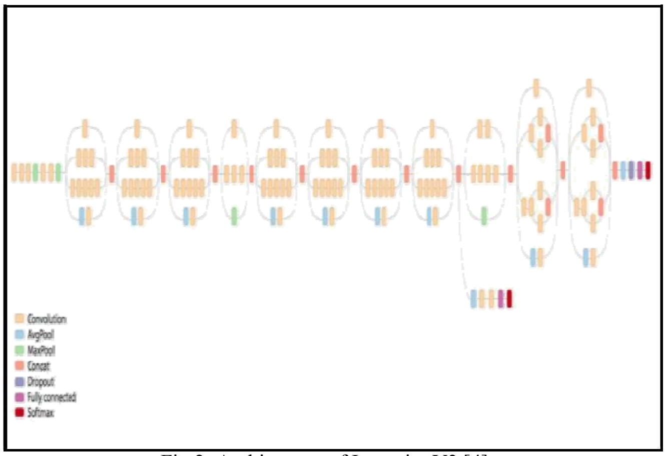


Fig 2. Architecture of InceptionV3 [4].

Type / Stride	Filter Shape	Input Size
Conv / s2	$3 \times 3 \times 3 \times 32$	$224 \times 224 \times 3$
Conv dw / s1	$3 \times 3 \times 32$ dw	$112 \times 112 \times 32$
Conv / s1	$1 \times 1 \times 32 \times 64$	$112 \times 112 \times 32$
Conv dw / s2	$3 \times 3 \times 64$ dw	$112 \times 112 \times 64$
Conv / s1	$1 \times 1 \times 64 \times 128$	$56 \times 56 \times 64$
Conv dw / s1	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 128$	$56 \times 56 \times 128$
Conv dw / s2	$3 \times 3 \times 128$ dw	$56 \times 56 \times 128$
Conv / s1	$1 \times 1 \times 128 \times 256$	$28 \times 28 \times 128$
Conv dw / s1	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 256$	$28 \times 28 \times 256$
Conv dw / s2	$3 \times 3 \times 256$ dw	$28 \times 28 \times 256$
Conv / s1	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
5× Conv dw / s1	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
5× Conv / s1	$1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$
Conv dw / s2	$3 \times 3 \times 512$ dw	$14 \times 14 \times 512$
Conv / s1	$1 \times 1 \times 512 \times 1024$	$7 \times 7 \times 512$
Conv dw / s2	$3 \times 3 \times 1024$ dw	$7 \times 7 \times 1024$
Conv / s1	$1 \times 1 \times 1024 \times 1024$	$7 \times 7 \times 1024$
Avg Pool / s1	Pool 7×7	$7 \times 7 \times 1024$
FC / s1	1024×1000	$1 \times 1 \times 1024$
Softmax / s1	Classifier	$1 \times 1 \times 1000$

Fig 3. Architecture of MobileNet [5].

Transfer learning is used to build deep learning model using MobileNet and InceptionV3 pre-trained models. These models are fine-tuned by using image dataset of 5 different types of crops with 5277 images. These models are initialized with the weights of the pre-trained model. Dataset is preprocessed and divided into 80%-20% training and testing data. Label encoding is used for conversion of output to categorical type. Image data generator is used to introduce variation in the input images. A dense layer is appended with the softmax activation function to extract the result from model. Adam optimizer is used with the categorical cross entropy as loss function. These pre-trained models are then re-trained for 10 epochs with batch size of 8 by using new training dataset to create required model. Dropout of 1e-3 is added to overcome the problem of overfitting. Generated model is tested using testing dataset to find out validation accuracy. Performance of both the models is measured on the basis of training accuracy, training loss and validation accuracy, validation loss per epoch.

A dedicated deep convolutional neural network is used to detect disease related to individual crop which incorporates similar methodology of plant detection. There are multiple models generated for disease detection each corresponding to a particular type of crop. The type of plant is detected using previously mentioned model which determines to which disease detection model the image should be passed on for detection of the type of disease. The models build for identification of disease are evaluated using testing dataset on the basis of training accuracy, training loss and validation accuracy, validation loss per epoch.

IV. RESULTS

In this section results and observations of the experimentation performed on both the models are mentioned. After the experimentation on trained model it is found that model trained using segmented images perform better than model trained using color and gray-scale images. In case of experimentation for detection of crop type, as per Fig 4-7 both MobileNet and InceptionV3 models perform well with 99.62% and 99.74% accuracy respectively. Significant growth in accuracy is observed in initial stages which get converged later on. Exponential drop in loss function signifies faster learning in the initial stage. It is observed that InceptionV3 model performs better than MobileNet in the task of crop detection

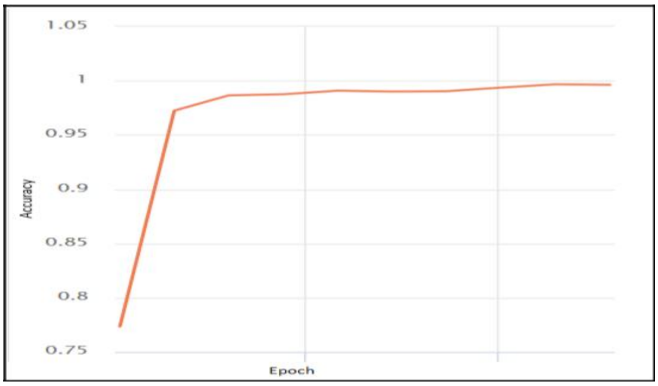


Fig 4. Accuracy Vs Epoch for crop detection for MobileNet

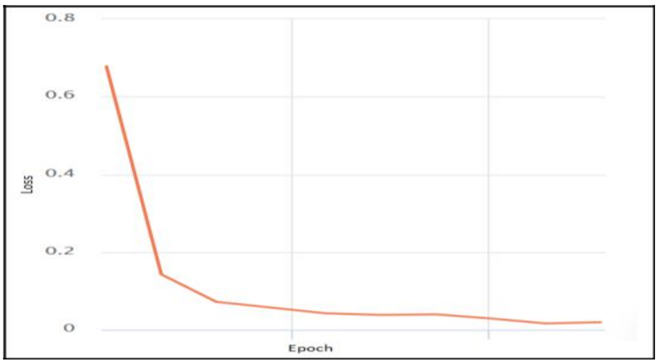


Fig 5. Loss Vs Epoch for crop detection for MobileNet

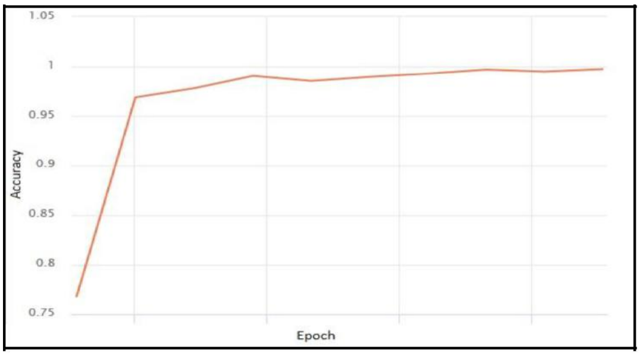


Fig 6. Accuracy Vs Epoch for crop detection for InceptionV3

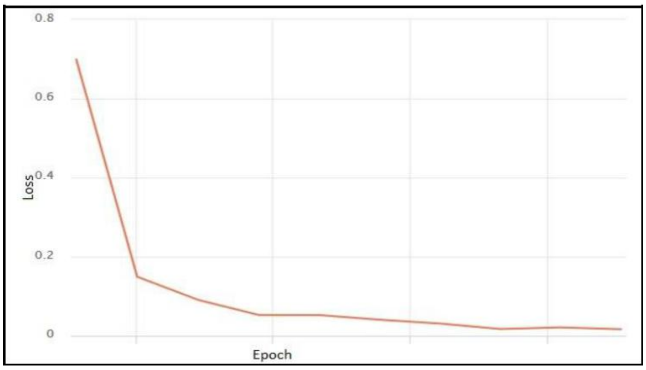


Fig 7. Loss Vs Epoch for crop detection for InceptionV3

In similar way for crop disease detection as per Fig 8-11 both MobileNet and InceptionV3 models shows steady growth with 99.04% and 99.45% accuracy respectively. Slight decrement can be observer in the accuracy from 6th epoch to 7th epoch in case of InceptionV3 model. Value of loss function at the end of 10th epoch supports the better performance of InceptionV3 in the task of disease detection.

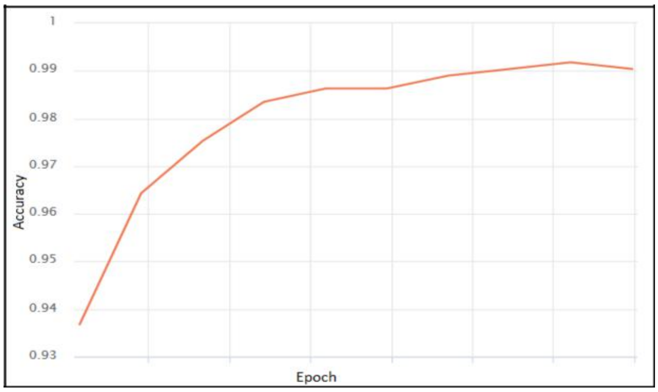


Fig 8. Accuracy Vs Epoch for disease detection for MobileNet

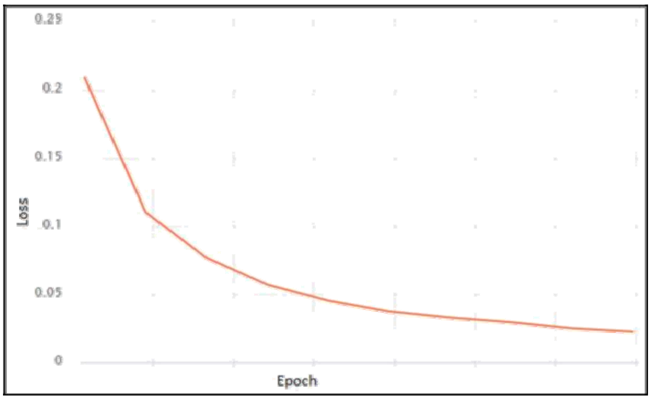


Fig 9. Loss Vs Epoch for disease detection for MobileNet

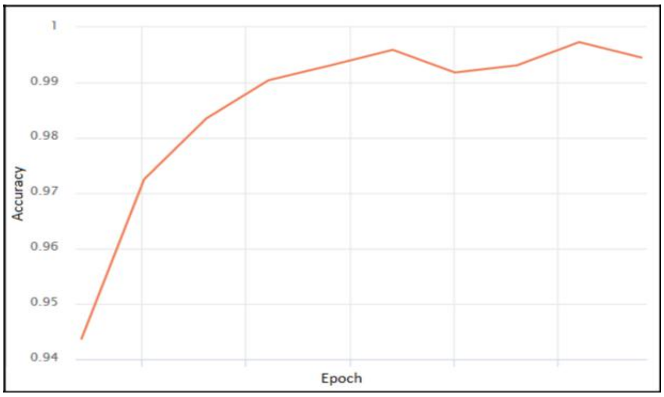


Fig 10. Accuracy Vs Epoch for disease detection for InceptionV3

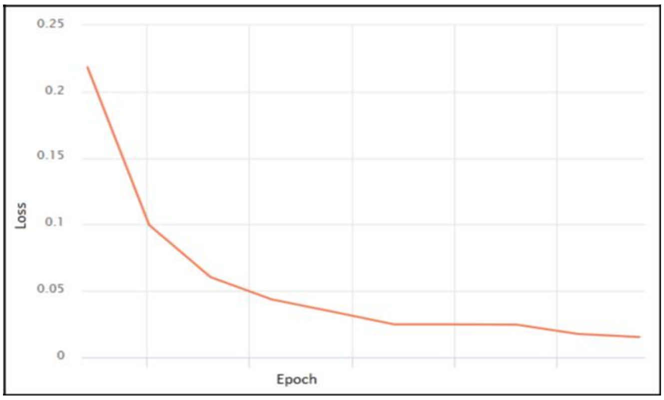


Fig 11. Loss Vs Epoch for disease detection for InceptionV3

V. CONCLUSION

In this paper, respectively, the applications of Deep Convolutional Neural Networks have been formulated with the goal of classifying both crop species and identity of disease on images. The proposed methodology was tested on five classes of crops and three types of crop diseases for each class. The experimental results show that the InceptionV3 model performs better than the MobileNet model in terms of accuracy and validation loss.

An extension of this work will include the classification of images that are not captured in a controlled environment and images that have multiple orientation. Also, the number of classes of crops and its diseases can be further increased. This methodology can be integrated with smart phone applications that would provide user friendly GUI and simplicity for its usage.

REFERENCES

[1] Kadir, A., "A Model of Plant Identification System Using GLCM, Lacunarity and Shen Features," Research Journal of Pharmaceutical, Biological, and Chemical Sciences Vol.5(2) 2014.

[2] Naik, M.R., Sivappagari, C., "Plant Leaf and Disease Detection by Using HSV Features and SVM," IJESC, Volume 6 Issue No.12, 2016

[3] Greg Olmschenk, Hao Tang, Zhigang Zhu, "Crowd Counting with Minimal Data Using Generative Adversarial Networks for Multiple Target Regression, Applications of Computer Vision (WACV), 2018 IEEE Winter Conference on Computer Vision (WACV), 2018.

[4] Surbhi Jain, Joydip Dhar, "Image based search engine using deep learning", 2017 Tenth International Conference on Contemporary Computing (IC3), August 2017

[5] Andrew G. Howard, Menglong Zhu, Bo Chen, Dmitry Kalenichenko, Weijun Wang, Tobias Weyand, Marco Andreetto, Hartwig Adam, "MobileNets: Efficient Convolutional Neural Networks for Mobile Vision Applications", arXiv preprint arXiv:1704.04861v1, 2017.