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A Review on Crop Disease Detection using Deep Learning

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Abstract: Lately, extreme atmosphere changes and absence of invulnerability in yields has caused a significant increment in the development of harvest infections. This causes enormous scale devastation of harvests, diminishes development and inevitably prompts money related loss of ranchers. Because of quick development in an assortment of maladies and sufficient information of rancher, distinguishing proof and treatment of the sickness has turned into a noteworthy test. The leaves have surface and visual likenesses which characteristics for an ID of illness type. Henceforth, PC vision utilized with profound learning gives the best approach to tackle this issue. This paper proposes a profound learning-based model which is prepared utilizing open dataset containing pictures of solid and infected harvest leaves. The model serves its target by arranging pictures of leaves into infected classification dependent on the example of imperfection.

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

I. Introduction

Agribusiness is the principle wellspring of nourishment, crude material and fuel which adds to the financial improvement of a country. Almost 66% of the populace relies upon farming legitimately or in a roundabout way. As there is fast development in the worldwide populace, horticulture is attempting to satisfy its need. The sustenance security stays undermined by different conditions including environmental change, the decrease in pollinators, crop maladies, absence of water system, and so on. Yield malady lightens the creation and furthermore the nature of nourishment. Harvest ailments do not just influence the nourishment security at the worldwide level, yet it likewise has unfriendly ramifications for little scale ranchers whose salary relies upon sound development [1, 2]. There is a bit of leeway that the yield sicknesses can be constrained by distinguishing the maladies when it creates on harvests. Because of the headway of web, a field of PC vision it has been conceivable to give a significant answer for this issue. The target of this paper is to give an application which predicts the kind of yield ailment dependent on textural closeness of leaves. A freely accessible dataset containing solid and ailing harvest leaves is utilized to prepare the model. The early determination of yield malady can be utilized to anticipate further harm that should be possible to the harvests which are useful for continuing the development.

II. 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 [3].

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 types of crop species and 26 types of diseases. Each class has a pair of fields containing the name of the crop and the name of the 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 the accuracy of the application [4]. The pre-processing of the image is essential for removing noise and segmentation of the image which helps in improving the accuracy of CNN model. Hence, to handle the varying background problem, segmentation is performed that extracts only relevant part of the image. So, after performing the segmentation all the leaf images with a 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.

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 [5]. 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 an enormous number of diversified images.

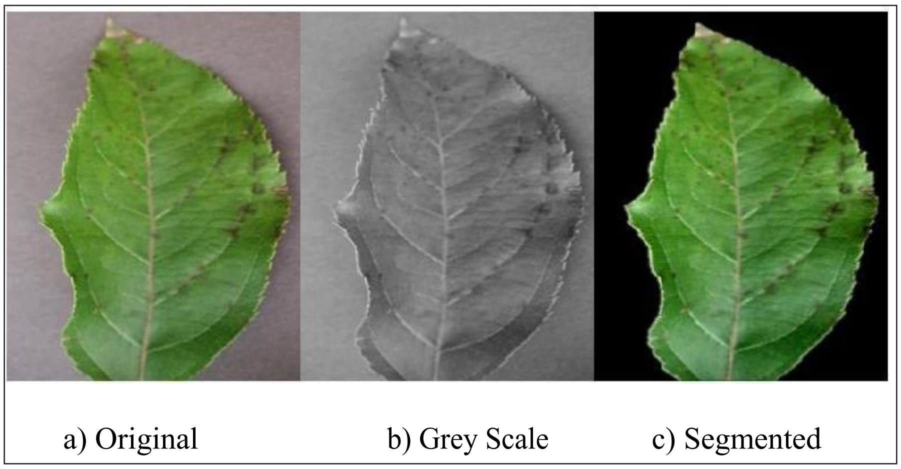

Fig. 1: Preprocessing of Leaf

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

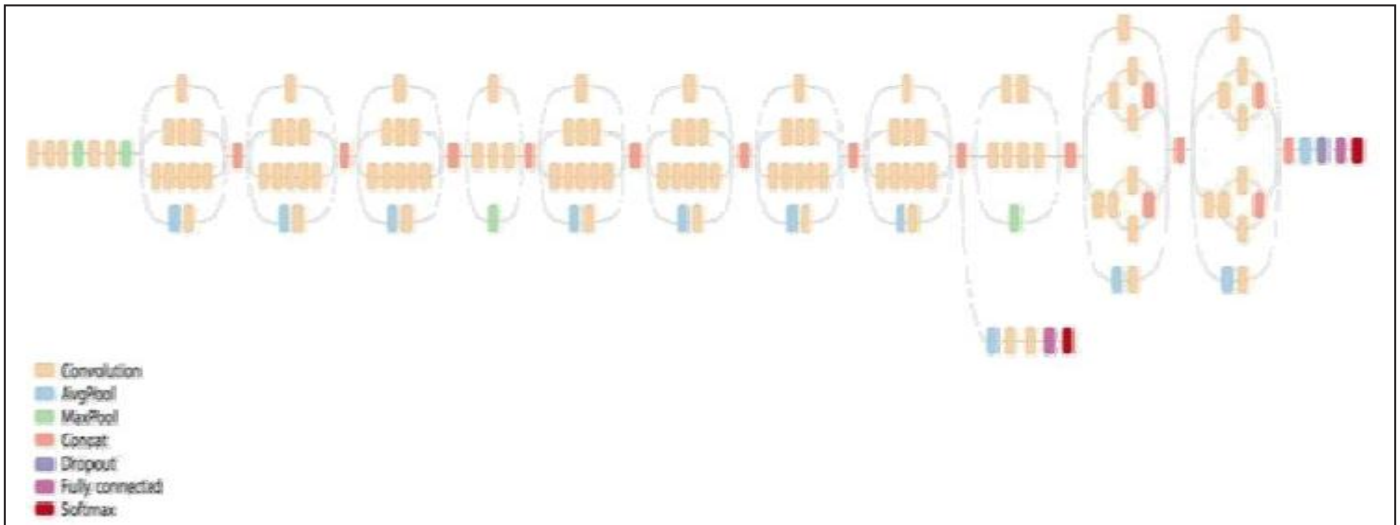

Fig. 2: Architecture of InceptionV3 [4]

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	$1 \times 1 \times 256 \times 512$	$14 \times 14 \times 256$
$5\times$ Conv dw / s1 Conv / s1	$3 \times 3 \times 512$ dw $1 \times 1 \times 512 \times 512$	$14 \times 14 \times 512$ $14 \times 14 \times 512$
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 the model. Adam optimizer is used with the categorical cross-entropy as a loss function. These pre-trained models are then re-trained for 10 epochs with a batch size of 8 by using new training dataset to create the required model. Dropout of 1e-3 is added to overcome the problem of overfitting. The generated model is tested using the 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.

III. Results

In this section results and observations of the experimentation performed on both the models are mentioned. After the experimentation on the trained model, it is found that model trained using segmented images perform better than model trained using colour and grey-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.

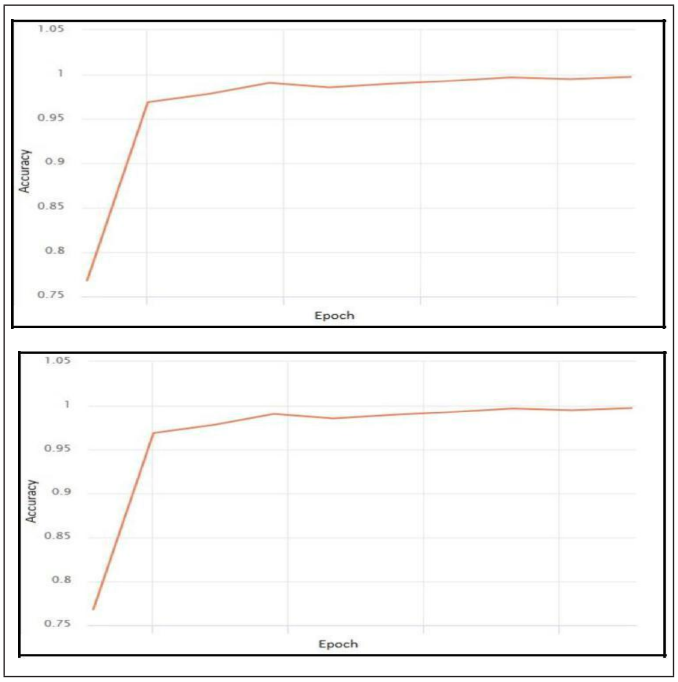

Fig. 4: Accuracy Vs Epoch for Crop Detection for MobileNet

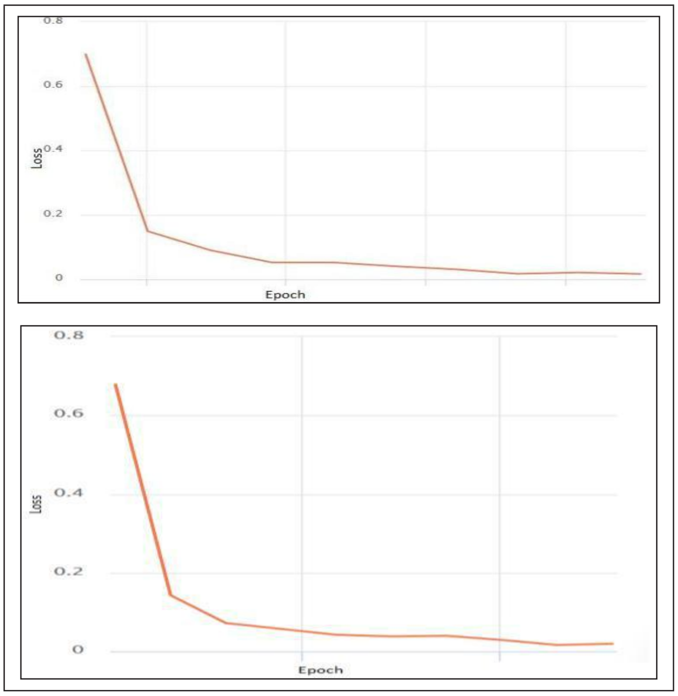

Fig. 5: Loss Vs Epoch for Crop Detection for MobileNet

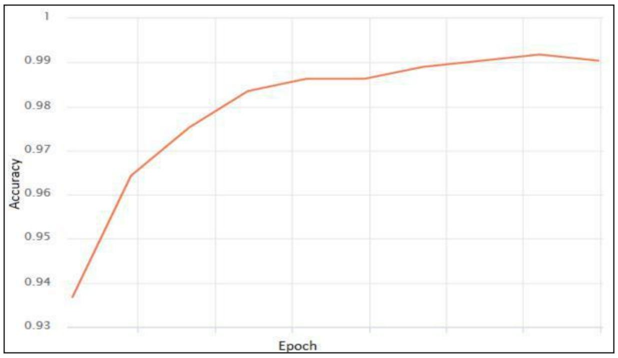

Fig. 6: Accuracy Vs Epoch for Crop Detection for InceptionV3

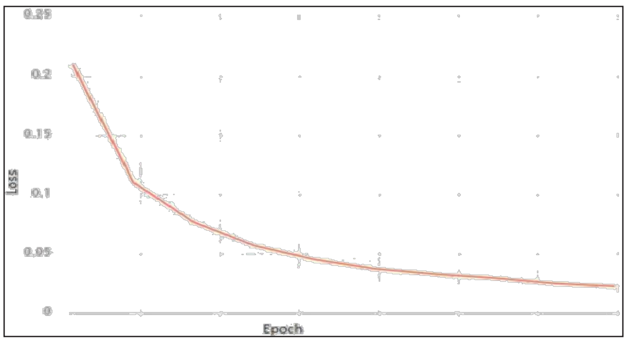

Fig. 7: Loss Vs Epoch for Crop Detection for InceptionV3

In a similar way for crop disease detection as per Fig. 8-11 both MobileNet and InceptionV3 models show steady growth with 99.04% and 99.45% accuracy respectively. Slight decrement can be an 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.

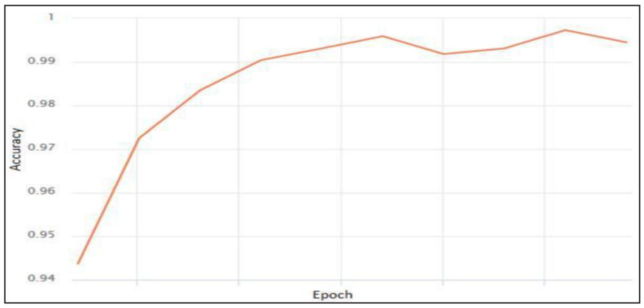

Fig. 8: Accuracy Vs Epoch for Disease Detection for MobileNet

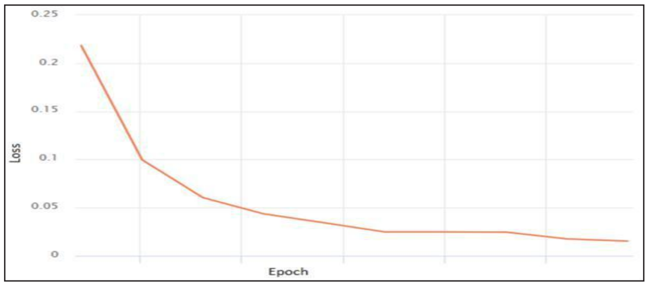

Fig. 9: Loss Vs Epoch for Disease Detection for MobileNet

IV. 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 orientations. Also, the number of classes of crops and its diseases can be further increased. This methodology can be integrated with the applications that would provide user-friendly GUI and simplicity for its usage.

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