Deep Learning based Model for Plant Disease Detection

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Abstract : Diseases in Crops are one of the major reasons that affects the crops output. Crops play a very significant role for survival of beings including but not limited to us (human beings), as they are one of the significant sources of daily life needs including food. Identification of the diseases in a rapid way so that a cure can be take in time, is still a cumbersome process. Fortunately, in this era where smartphones are picking up rapidly and recent advances in machine learning, it is now possible to build smartphone assisted disease diagnosis. Using an open source database of around 54,306 images of crops with and without disease, we trained a Deep (CNN) Convolutional neural network to identify 14 distinct species with 26 diseases or their absence thereof. The trained model is observed to show approximately 99.35 % accuracy on the held out test set, illustrating that the approach is viable.

***IndexTerms* - Neural Network, TensorFlow, Image Classification, Diseases in Crops.**

I. INTRODUCTION

Plant Diseases are a major crop threat for farmers. In agriculture based country such as India, plant diseases account as a major factor and often lead to a considerable amount of losses in almost every agriculture based place in country. These losses not only affect the farmers but the country too. Agriculture is of an utmost importance for any country not just for economy but for survival.

There are several ways to detect plant pathologies. Some diseases cannot be visibly detected as they do not have any symptoms that can be identified by naked eye, or these symptoms are identified after the time for prevention is already over. In these cases, generally a very sophisticated analysis is done by using a powerful microscope, if necessary. In other cases, the symptoms can only be identified in parts of the (EMS) electromagnetic spectrum that doesn't lie in the visible range of Human eye. A very common path to detect symptoms in this case is by taking advantage of remote sensing techniques which explores more than one hyper spectral images. The methods that adopts this approach often deploy digital processing of tools to achieve their goals. Generally, diseases result in some variation of manifestation in visible spectrum. In the majority of cases, the diagnosis is performed by the humans while actually creating the dataset. This activity was performed by experts of Plant-Village organisation which has no direct affiliation with our research. Trained people may be efficient enough to categorize the plants as per their state of health although there is always a possibility of human error.

Object recognition using computer vision and computer vision itself in specific, has made enormous improvements in the previous few years. The PASCAL-VOC Test [1] and lately the Large Scale Pictorial Recognition Test (ILSVRT) [2] centred on the Image-Net dataset [2] has been widely used as standards for many visualization associated complications in computer vision, with object classification. In 2012, a large, Deep (CNN) Convolution Neural Network achieved a top-5 error of 16.4% for the classification of images into 1000 possible categories [3]. In the following 3 years, various advances in Deep (CNN) Convolutional Neural Networks lowered the error rate to 3.57% [3] [4] [5]. Although training the models for classifying images can be a tough task, but when we talk about performance, the trained models can turn out to be time saving method. This makes it more suitable for mobile applications.

II. METHODS FOR DETECTING PLANT DISEASE

A. DATASET

We have analyzed a dataset consisting of a total 54,306 images spanning over 14 species and covering 26 kinds of diseases or there lack. The dataset is provided by PlantVillage publicly. Dataset contains 38 labels with a combination of each crop's name and the disease that it is suffering from. Also a healthy state is recorded in each one of them. Images were resized to 225 x 225 pixels for the approach we followed. Fig 1 shows a sample of images from PlantVillage dataset.

Through all our trials, we used three diverse forms of the entire Plant-Village dataset. We started with the Plant-Village dataset as it is, in colour; then we experimented with a grey-scaled version of the Plant-Village dataset, and lastly we ran all the trials on a version of the Plant-Village dataset where the leaves were sectioned, hence eliminating all the extra background info which might have the potential to present some characteristic bias in the dataset due to the standardised process of data collection in case of Plant-Village dataset. Separation was programmed by the means of a script tweaked to execute well on our specific dataset.

B. PREVIOUS KNOWN APPROACHES

A heavy load of approaches that try to detect disease using method of classification to determine whether a plant is affected by a disease or not is observed. Previously, only visualization was used to detect diseases in plants but with modern methods like DNA tests and serological methods results are far more accurate. But these methods usually take 1-2 days and are expensive so only practiced when necessary.

Classification methods can be thought of as an extension of detection methods for disease in plants. Instead for attempting to detect single specific disease, this method tries to quantify and identify among all the possibilities. Methods for classification generally includes a separation step that is generally followed by extraction of characteristics that will be fed to the classifier. This subsection discusses the various methods that were proposed and experimented by some of the scientist before our work.

One of the very first attempts with this method were made by Hetzroni et al. [6]. The system developed by them tried to identify zinc, iron and nitrogen deficiency. Analog videotape camera hardware was chosen in capturing the images, then the images were digitized. Firstly the images were segmented. Then characteristics such as size and color were extracted from both HSI and RGB illustrations of image. These parameters were then fed to the neural networks and statistical classifier.

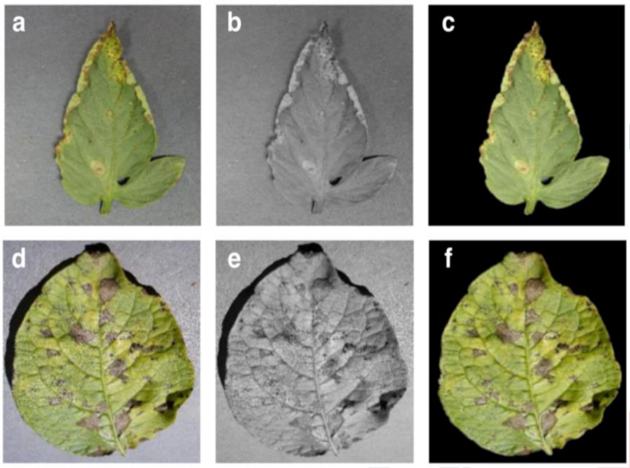

Fig 1 Smaple Image Dataset from PlantVillage showing three different forms of images. ***(a) and (d) are coloured images, (b) and (e) are grayscaled and (c) & (f) are segmented coloured versions.***

Pydipati et al [7] compared two methods to identify and categorize three kinds of citrus diseases. A total of 39 features were collected, which were separated into four subsets. Then they were tested with the two different approaches. The first one was based on Mahalanobis minimum distance classifier. The second one was based on radial basis functions neural network classifier.

Authors concluded that both the methods performed well.

Meunkaewjinda et al [8] proposed a method which used numerous colour representations (UVL, YCbCr and HIS etc.) through its carrying out. The method was to detect and categorize diseases in grapevines. An MLP network was used to separate leaves and background, which was then coupled with color library. The colour of leaves are then grouped by an unsupervised self-organizing plot. An inherent algorithm was used to determine cluster count to be adopted for each case. SVM is then supposed to determine and separate healthy and diseased regions.

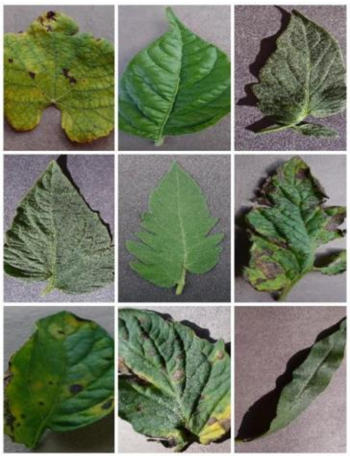

Fig 2 Dataset Images Used in Training the Model Based on Deep Neural Networks

C. OUR APPROACH

We measure the applicability of the deep neural network for the identification of diseases in the plant. Utilizing the dataset comprising of leaves of various plants we trained a deep neural network on top of two widely popular and advanced trained models – Inception V3 and Mobile Net. Mobile Net is a very small but well-organized convolutional neural network [9].

Training over an already trained model utilises a technique called transfer learning meaning thereby, only improvements are found and the advances are observed as the training is just improved and results get more and more accurate with time that we provide to train the model. Thus, a highly trained model is observed in the end result which is capable of giving some serious results. We used transfer learning to train the model with the dataset by Plant-Village. There is a research difficulty in transfer learning that emphases on keeping knowledge acquired when solving a difficulty and applying it to a different or connected problem. For example, when trying to identify trucks, knowledge acquired while learning to recognize cars can apply. This area of research deals with the long history of psychological literature on the transfer of learning, although formal relations between the two areas are limited. So, in order to reduce this redundancy of using different knowledge than what is required to be used we used Deep CNNs so that accuracy can be highly improved. This doesn't mean that there won't be any mistakes or redundancy but this can ensure that redundancy is negligible and end results would be highly accurate.

We have trained the mobile net [6] with deep convection neural networks, which is in Plant Village for its default maximum efficiency training in 4000 steps. Training was done in three ways. Firstly we trained the model with coloured image datasets, in second iteration of testing we trained the model with segmented, coloured dataset. Finally we tested a version with a grayscale version of dataset too.

D. PERFORMANCE MEASURE

To assess our approaches for each method we split the dataset into test and train dataset for each training iteration. For each kind of dataset i.e. colored unsegmented, colored segmented and grayscale version we split the dataset into train set and test set. This allowed for assessing how the model would perform on different conditions including when exposed to an unseen image.

Train dataset comprised of 80% of dataset whereas 20% was reserved for test purpose. Images were selected randomly for classification as test or train image by a custom script we wrote. Only these 20% images were used to test the model in order to check the performance of model on random images but performance of the model was quite accurate as compared to other models

III. SMARTPHONE INTEGRATION

After successfully training the deep convolution neural network, we integrated the model for access via smartphone which was our main goal. We developed a backend using Django Framework which binds the model with a set of APIs and also serve a web based interface for the same. The APIs were later used to develop front-ends for Android and iOS platforms.

A diagram showing how the model will work with smartphone integration is shown below to check the procedure of model. This smartphone integration will enable farmers to detect plant diseases right there on the field and this model is all about saving time and efforts of farmers.

A real time offline detection of diseases and crop species can be done with this model as well as online detection is also possible. This model not only detect diseases using smartphone but also with the web applications and furthermore web browsers can also be used to take advantage of the model.

Since Android also supported integration of model directly into the application, we developed another version of same so that offline diagnosis would be possible as well.

The final results were pleasing as it resulted in very convenient interface or method which allowed to access power of machine learning in a simple but intuitive manner.

The model that was trained on deep neural networks has its own application and works fine. The accuracy of the model is very high and developing an application for this model is just another advantage to the model as it will help in easier implementation of the model. Currently, only an android application is available for this model and no ios application is available as ios doesn't allow open source integration directly.

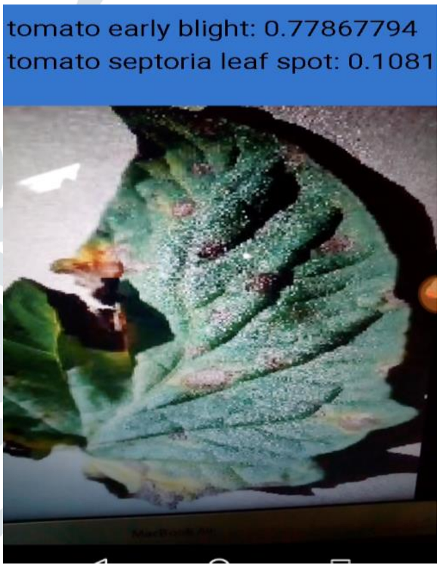

Fig 3 Screenshot of real time offline detection of disease and crop species for a given leaf image

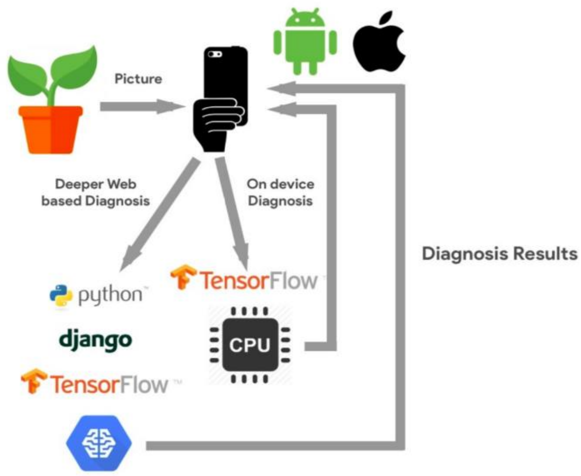

Fig 4 Schematic Diagram depicting flow of a general use case for the developed smartphone assisted diagnosis system

IV. RESULTS

The models performed well in each scenario. Although with this varying dataset, the model was expected not to deliver a higher accuracy, but it performed quite well ranging from 82% to 99% accuracy for different test cases.

Three versions of datasets (colour, grey-scale, and fragmented) show a specific difference in performance during all experiments when we keep the remaining experimental configuration stable. In the case of the colourful version of the dataset the models perform best. While designing the experiments, we were concerned that neural networks can learn to take only the lighting conditions, the method of collection of data and the underlying biases associated with the device. Therefore, we experimented with the gray-scale version of the same dataset to test the adaptability of the model in the absence of colour information, and its ability to learn high level structural patterns especially for crops and diseases. As expected, the colourful version of the dataset reduced performance compared to experiments.

Accuracy of the Trained Model on Dataset When	
Images used were altered from training time	***Images used were the ones used during training***
Accuracy was around 39 %	Accuracy was around 82 % - 99 %

Table 1 – Tabular Representation of results comparing the accuracy of model using Deep Neural Networks and Traditional Neural Networks

While these models yields really nice results when tested on Plant Village dataset, however for any image which is sourced from an arbitrary location, say a random image search on internet, the accuracy decreased drastically. But this would not affect the model as the model should be trained on the dataset that include the testing images because this is what this model is about i.e first train and then use. Still An accuracy of approximately 39% was observed when tested against the random sources other than PlantVillage dataset and this means that model can be extended to train on an entirely different dataset in order to improve the accuracy of model on random images.

V. Discussion

The advances in convolution neural network has been drastic in previous few years. This is evident from the experiments we conducted for the image classification using Plant-Village dataset. Before the introduction of neural networks and then the convolution neural network, the traditional approaches were very limited. Deep CNN increases the number of hidden layers in the processing of images. Traditional approaches were more dependent on the predefined features that were programmed in the script already.

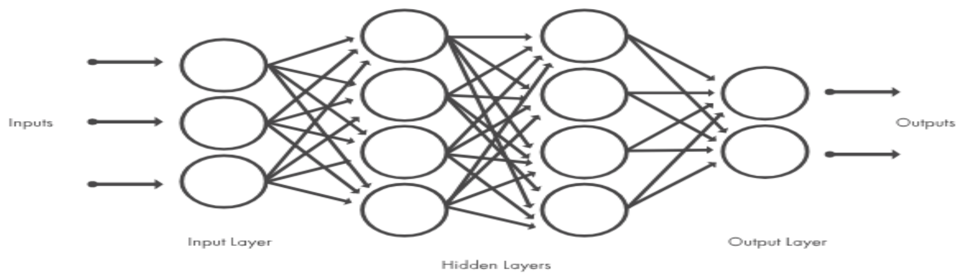

Fig 5 Diagram Showing the Working of Deep CNNs with Multiple Hidden Layers

The above diagram shows that the number of layers used in the deep CNNs are very large as compared to traditional Neural Networks. Images are taken and broken into multiple pieces and these pieces are further divided into multiple layers and these layers are used to identify the images and perform operations on them.

Deep CNNs take much time to train but due to the multiple layers, their accuracy is far more than traditional Neural Networks.

Using the deep convolutional neural network design, we trained a model based on pictures of plant leaves keeping an objective of categorising both crop species and the occurrence and identity of diseases on images that the model had not seen before. Within the Plant-Village dataset of 54,306 pictures comprising of 38 classes of 14 crop classes and 26 diseases, the objective is attained as verified by the top correctness of 99.35%. Thus, without any characteristic engineering, the model properly categorizes crop and disease from 38 potential classes in 993 out of 1000 images. Importantly, although the exercise of the prototype took a lot of time, the categorization itself is very fast, and can thus effortlessly be executed even on a smartphone. This grants a vibrant path towards smartphone-assisted crop disease identification on an enormous global scale.

However, there are a lot of boundaries at the present period that are required to be addressed in upcoming work. First, when examined on a dataset of images captured under circumstances altered from the images used during the training time, the model's correctness is condensed considerably, to just above 39%. It's significant to note that 39% correctness is much greater than the one that was centred on random choice of 38 classes (2.6%), but nonetheless, a much different set of training data is required to advance the correctness. Our present outcomes specify that more (and more variable) data alone will be adequate to considerably boost the correctness, and matching data gathering efforts are in progress. Results would also have been better if there was a bigger dataset and training time was also increased but that would again be time consuming and results in this model were satisfying even with this dataset. Plant-Village can provide a larger dataset which can be used to train our model and improve the accuracy of this model.

VI. Conclusion

Image classification using neural networks proved to be a better approach in diagnosing the disease in a crop. However, a better knowledgebase is still required to equip the Trained AI to tackle known and unknown diseases. The work discussed in this paper demonstrates that a real time offline disease detection is possible and can provide a really powerful means to common man. This model can be used to save time and efforts in a big way and not only farmers but this model can be used to on an entirely different dataset and the working of this model will be completely different then. The development of this project also demonstrates that training an AI on cloud is possible and allows working on the go without having to carry a heavy machine along all the time. Cloud computing and can provide powerful hardware on the go and this model is trained on cloud computing so user need not to worry about the performance of hardware thereby saving time and money. To conclude, it will be safe to say that we have successfully tested the capabilities of AI and its usefulness while providing a reliable solution for a big problem at the same time. Together, Deep Learning and Cloud Computing have an endless future and a lot to improve in both the fields and so much more to be developed. This model is just an example that things can be done in a manner that will help common people with their problems by providing a solution which everyone can use and advances in the field of Deep Learning and Cloud Computing are yet to be developed. Clubbed with additional dataset, knowledgebase, and proper hardware for training AI and other needs, this approach will blossom to full glory and reach to help millions.

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