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Image-based Plant Diseases Detection using Deep Learning

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ABSTRACT

Agriculture plays a major role in developing countries like India, however the food security still remains a vital issue. Most of the crops get wasted due to lack of storage facility, transportation, and plant diseases. More than 15% of the crops get wasted in India due to diseases and hence it has become one of the major concern to be resolved. There is a need of automatic system that can identify these diseases and help farmers to take appropriate steps to get rid of crop loss. Farmers have followed the conventional method of identifying the plant disease with their naked eyes, and it not possible for all the farmers to identify these diseases the same way. With the advance in Artificial Intelligence, there is a need to incorporate the facilities of the computer vision in the field of agriculture. Deep Learning rich libraries and user as well as developer friendly environment to work with, all these qualities make Deep Learning as the favorable method to get started with this problem. In this paper we have used Deep Learning because of the advantages it offers to work with images especially in image classification to get improvised results. The methodology includes taking leaves of infected crops and label them as per the disease pattern. The images of infected leaves are processed pixel based operations are applied to improve the information from the image. As a next step feature extraction is done followed by image segmentation and at the last classification of crop diseases based on the patterns extracted from the diseased leaves. The CNN (Convolutional Neural Network) is used for the classification of diseases, for the demonstration purpose the public dataset is used consisting of around 87 K images (RGB type images) including healthy as well as diseased leaves.

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1. Introduction

Image based plant disease identification is the recently explored area by many researchers. As the crop waste is increasing due to diseases, it is becoming crucial to identify the diseases accurately and timely. In developing countries, especially in South Asia most of the population is dependent on agriculture directly or indirectly, in such countries it is becoming important to use the application

based plant disease identification which can help farmers to know the cause of diseases and get the precaution to treat them. Initial identification of the plant diseases on the basis of size of leaf, color of leaf, and growth of the pattern etc can be helpful to the farmers. With the boom in the usage of smart phones all over the world it is easy to get the picture image of the leaves, also many people around the globe have access to basic internet facility available to them. More than 300 million people access the internet for their convenience and use various applications. Governments have come across different facilities like 24*7 helpline numbers dedicated to farmers in order to solve their query but people residing in rural areas find it difficult to get the proper facilities and

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therefore struggle to get the solution to their problems. A basic application where farmers can simply work on self-paced image based disease identification would be helpful.

Crop disease is becoming the global threat and need attention from the researchers, using of pesticides and insecticides may give temporary solution but may not be helpful for longer run. Also, the chemicals have side effect on the crop which can ultimately have adverse effect on the health of citizens. In current scenario when the applications of Artificial Intelligence has spread in many cross domain areas, getting the help of AI to solve agricultural problem would be helpful. Although the number of crops and diseases are huge in number, getting started with identifying the diseases of common crops that are used in India would be a sensible start. The paper discuss the concept of image classification to identify the diseases with the help of features given by computer vision. A lot of related work [1,2] has been done on object identification using deep learning which claims to have improvised result in object identification, using such already existing model will help our system to get better accuracy and hence we have used deep learning for our implementation purpose. We have used deep neural network for processing the images which is taken as input (image of diseased plants) and get the output pair which maps crop with the disease present in the plant. Deep neural network consists of multiple neural networks that use mathematical model to process the input. The layers have different configuration in each level which is set according to the input data and the data passes through all these networks, modifying and clearing the data each layer and get the output from the last level. The main task is to decide on the feature of each layer and size of network along with the model that will be used. The tuning of network parameters are done during the training phase in order to improve the training process and to get the precise final results. The basic deep learning model used in this paper takes help of Convolution Neural Networks (CNNs), it is one of the powerful technique while working with huge amount of data and also turn out to be one of the most favored techniques for pattern recognition. As the work focus on image input, CNN is the preferred over other models.

To develop a better model for classifying the plant disease it is important to have rich data set for the purpose of training the model. In this paper we have used Plant Village dataset having $3 \times 224 \times 224$ with 50,000 images. Here we are addressing 38 number of diseases in 14 number of crops. As per the performance of the model the accuracy is 90.4%. The results are notable and provide the best one from the already existing systems using the image based approach for plant disease identification.

2. Related work/literature survey

The researchers have explored different ways to identify the plant diseases. However we are still far from the automated system that makes it easy to practice and to handle this problem. The use of computer technologies to identify the crop diseases have been researched at different levels. The authors in Lee et al. [3] have used unsupervised representation for as much as 44 plant species they have used CNN model and have utilized visualization technique based on deconvolutional networks (DN). As per [4], the methods based on machine learning techniques are relatively successful under some limitation and constraints and many of the problems are yet to be handled to reach to a successful implementation of method in real world. The paper also mentioned factors influencing the use of deep learning techniques for recognizing plant diseases, which includes the lack of annotated datasets, identification of symptoms, finding the accurate split of training and testing data in the model, the image quality, image capture conditions, multiple simultaneous disorder and disorder with similar

symptoms. Barbedo [5], worked on image segmentation method to identify plant diseases in black and white background and try to reduce the human error while taking less time in identifying these diseases. However it proposes to reduce the error caused due to pixel misclassification and to get the rich set of annotated datasets which helps to get the validation of the model precisely.

Many of the papers [6,7] on image based plant diseases identification follows some basic approach for preprocessing by removing the background and segmenting the lesion tissue of diseased plant. In the next step discriminative features are extracted to further analyze the plant disease and then a model is created for classification of diseases. In Al-Hiary et al. [6], the authors identified green colored pixels and then masked these pixels based on some specific threshold value. They have achieved an accuracy between 83% and 94%. Some researchers have worked on specific plants to identify the diseases, like in Mokhtar et al. [7], authors have worked on identifying two diseases namely Tomato yellow leaf curl virus (TYLCV) and tomato yellow leaf curl disease (TYLCD) in tomato plant using tomato leaves. They have used N-fold cross-validation technique as their model and an average of 90% accuracy. The earlier work on plant diseases classification have used some traditional machine learning approach to carry out their work in Arivazhagan et al. [8], the authors have discussed the detection of unhealthy region of plant leaves, they have used minimum distance criteria and SVM classifier on the plant leaf diseases using texture features.

Identifying the parameters for classification is a big challenge, in Tian et al. [9] genetic algorithm was used to select the parameters for Support Vector Machine (SVM). A combination of Kernel principal component analysis (KPCA)/GA-SVM model were used. They have classified the diseases in apple plants and claims to get the accuracy of more than 95% in three different diseases [10]. Focus on Oil palm leaves nutrient disease, in this paper the authors have relied upon Kernel- Based- Support Vector Machine for the purpose of classification and got accuracy of 95% with polynomial kernel with soft margin. In Krizhevsky et al. [11] the authors have trained deep convolution neural networks to classify diseases in 1000 different classes using LSVRC-2010 Image Net training set. They have used highly dense network with 60 million parameters and 500,000 neurons. In Ferentinos et al. [12] also convolution neural network model were developed for plant disease detection and results consisted of 58 distinct classes of [plant, disease] combination. The results for these classes were 99.53% and recommended for real time application to early detection of plant disease. Some researchers are proposed various techniques [13-22] for image disease detections and dealing with IoT devices for extracting the data. Moreover researchers are proposing various protocols in the field of healthcare [23-28] and vehicle communication [29-35] to protect the information exchanged among various devices to devices.

2.1. Implementation

As we have an image dataset and our problem is find defective images from that deep learning model is the best model to solve our model. Because deep learning is about structural learning keeping in mind that we have lesser number of train data.

We have couple of models, namely, building a naive network from very beginning and transfer learning by well-tuning the top-most layers of already trained deep neural network.

The naive networks consist only few number of convolution layers with few number of filters with each layer, then having couple of fully connected intermediate layers, and at the end normalization have been used. Then the training of naive networks having 2, 4, 6, 8, and 10 number of convolution layers. We have convolution layers with 32 filters of size 3×3 , activation like rectifier lin-

ear unit (ReLU), and each layers having max pooling layer of the size 2×2 , apart from final convolution layer, which have 64 filters. Initially, all the layers which are fully connected, has ReLU activation with 64 units in it and then it is proceeded by dropout ratio of 50% in dropout layer. In the correspondence of the 4 classes, last layer that is also fully connected, has exactly 4 outputs. Which become input to the next layer in order to calculate the probability output.

Since we have lesser number of training images to learn, transfer learning plays a vital role in order to make accurate network for the classification, using existing small amount of data, by having suitable parameters tuning of the network which is already trained on a large dataset, such as Image Net. Since the severity of the disease level classification targets to set a well suited image sets classification problem in comparison with Image Net, bottom layers only extracts the basic features, which can be extended to a bigger class of computer vision problems. Like in, the beginning layer that shows intensity of color and direction only, and in the Fig. 1, the first layer activation visualization of VGG16 model have been shown. As without training on our existing dataset, this architec-

ture activates by the spots of diseases, also in the leaf, and in the background.

For transfer learning, we have several comparisons like, VGGNet [36], ResNet50 [36], Inception-v3 [37] models of CNN. The VGGNet has 16 (VGG16) and 19 (VGG19) weight layers concluding a meaningful progress over existing models by using a model with slight variation with very few numbers of filters in convolution process. The basic Inception model GoogleNet joins the approach having nested networks and the plan of using different size filters isto manage many scales. The existing Inception-v3 model is a modified model with greater efficiency and can be improved with low count of parameter. ResNet is made up by putting one over other remaining basic building blocks. These basic building blocks consist of number of convolution layers by a loose connection or no connection in some of the blocks. This allows all piled layers to set in a remaining mapping, while skip connections has identity mapping. So our task become easier of minimizing the remaining filters rather than to minimize the main filter. This model breaks the breaking up problem: as putting many layers one over other, the efficiency stops at a point and then downs exponentially. ResNet50 is the 50-layer version of this network.

2.2. Material and experiment

DataSet: We are using Plant Village dataset that is an open access dataset available at Kaggle [38]. Plant Village dataset has about 50,000 images of fully healthy and unhealthy crops, having a range of 38 class already labeled. Our concern is in selecting the input images of fully healthy leaves of apples and input images having leaf black disease affected by the fungus named *Botryosphaeriaobtusa*. Every input image is kept into appropriate class by domain expert i.e. botanists: early healthy stage, middle healthy stage, healthy stage or in fully healthy stage. In fully healthy stage there are no spots in the leaves. The early stage healthy leaves have circular shape small spots with radius about 2.5 mm. The middle stage healthy leaves having more spots growing to random or shallow shape. The end stage healthy leaves infected by the tree in greater amount and cannot manage it to remain in the tree. All the input images are studied by the domain experts and classified with labeling into an appropriate disease. 180 images that were difficult to classify by experts were deleted from further consideration. In figure the example of every stages have been shown. At the end, we have 1650 input images of fully healthy leaves, 130 early stage healthy, 175 middle stage healthy, and 130 end stage disease healthy images.

As we have more number of healthy leaves than the diseased leaves, We have much variation in the number of samples for each class. To reduce the potential bias in our network in order to have more number of healthy stage class, Number of samples per class should be balanced. To make a good balance we have following strategy: In early stage healthy, middle stage healthy, and end stage healthy, We have 80–20 train test split strategy that means about 80% of the input images are kept for the training set and the reimagining's are the kept for test set. To healthy stage leaves, the images are classified into 12 classes, with 120 images in every class for training set, about 30 images are kept for testing. The resulting accuracy is calculated by averaging of 12 runs on the classes. As we know that Plant Village dataset has images captured from different angle and orientation of the same leaf, almost all images of the same leaf should be kept either in the training set or in the testing set.

Table 1 shows count of images used as training and testing for each classes.

Preprocessing: The samples of Plant Village datasets are different sized Red Green Blue images. By using basic deep learning, We need only 4 images in the first stage that is preprocessing stage.

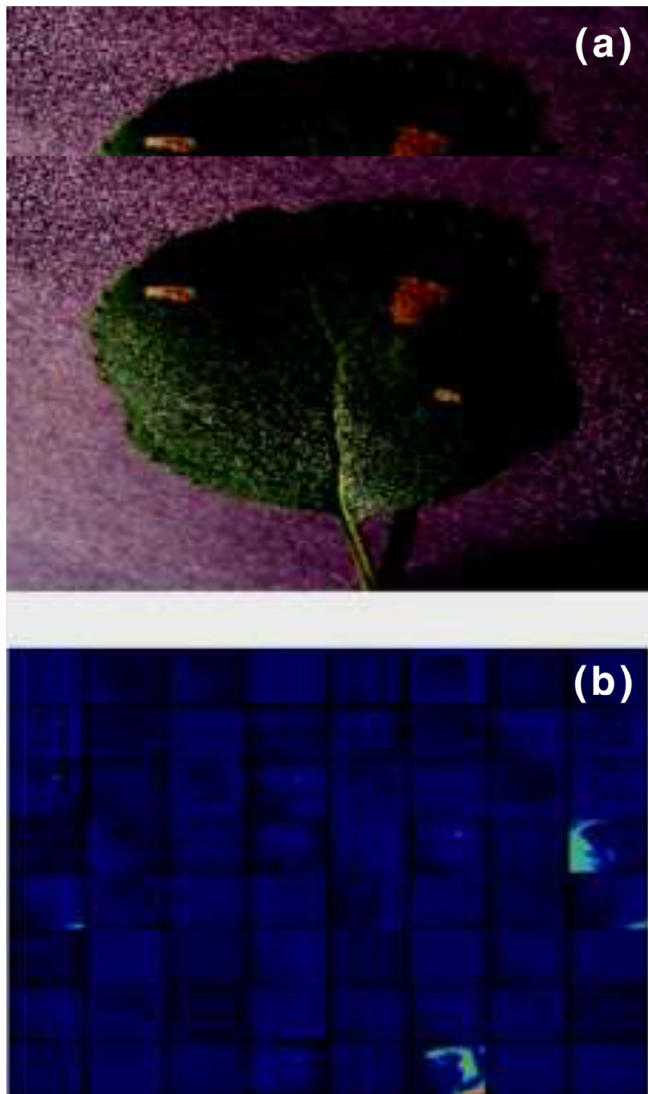


Fig. 1. In a model that is trained already, the visualization of starting convolution layers for a given input image. Source data; (b) Output of the starting convolution layer.

Table 1

Total samples of training and test dataset.

Class	Total images for training	Total images for testing
Healthy stage	110 × 12	27 × 12
Early healthy stage	108	29
Middle healthy stage	144	36
End healthy stage	102	23

This is done in different stages as follows: Initially, resizing of input image to 256×256 pixels for naive networks, 224×224 with all models we have used so far, in the Inception-V3 299×299 pixels. In the process of rescaling the images, suitable prediction and optimization have been applied. Then, division of 255 is performed to each pixel values that is computable to starting value of our network. Then, normalization performed to each of the samples. That actually increases the performance of the training notably. The process of normalization follows followings steps: for all training data, After calculating the mean and S.D., conversion of the training data to $X' = (X - M_x) / S_x$, have performed so that each features nearly look a normalized data distributed to 0 mean and 1 variance. At the end, some operations like rotation with varying angles, shearing, zooming, and flipping are used to the given inputs. This ensures over fitting and builds the model suitable to use.

Training Algorithm. The basic model of CNN (convolution neural network) consists of convolution layers, pooling layers, and at the end fully connected layers.

In convolution layer for each input image, computation of X_{ic} is performed as following

$$X_{ic} = RELU(W_i * X) \quad (1)$$

Here convolution operation have been denoted by $*$ and W_i stands for the kernels of the convolution layer. $W_i = [W_i^1, W_i^2, W_i^3, \dots, W_i^k]$ and K denotes the total number of convolution kernels. $M * M * N$ is a weight matrix with window size as M and number of input channels as N for each kernel.

As we have non linear saturation in our image best selection of activation function should be ReLu as it is much time faster than the other existing activation functions. ReLU is a rectified linear activation function as:

$$ReLU(x) = \max(0, x)$$

So in our model, We will be using ReLU.

As in the max pooling layer we have to calculate the largest value of the outputs of all convolution layers that do not intersect to each other. This technique sets varying rank on the existing surroundings and optimizes the size of our output.

The role of fully connected layer is to keep final layer on the top. Then all such c layers which are on the top compute the $ReLU(W_{fc}X)$, where X denotes the image to be given and fc denotes the weight matrix of the final layer.

The loss function calculates the variation of the result with the input, that is given by the domain expert, which is defined as the aggregation of cross entropy.

If our networks starts training with very high speed and gives very high accuracy in the beginning itself then we have to stop it as this is over fitting problem. For this purpose we use early stopping technique. In this after every epoch performance is evaluated with existing train data when loss of the test set data does not improve itself Early stopping just stop the training of the network. This way the over fitting is solved; we are conducting the transfer learning in following manner:

All final layers are swapped by the help of forming one more layer and keeping in mind that only well formed outer convolution layer of VGG19 with VGG16 with the go for finally connected lay-

ers. Delete the weights trained already to ensure the new gradient, now the existing network must start with appropriate values instead of setting any parameter. Now except the recent network, put all layers in the network. At the end training of fully connected layer is done by help of features produced in the final convolution layer. After the parameter tuning weight learning or adjustment is done. Then final convolution layer for all architectures used in our network are resumed with parallel training and slightly lower learning rate.

In Table 2 parameter tuning details of trained model have been shown. Apart from, learning rate schedule is employed. The variation in learning rate has been shown in the table.

3. Result and discussion

The accuracies of our naive network have been shown in the Fig. 2. By the depth of our model training and testing both accuracies improve slightly at in the beginning. The most suitable result, which is, a validation accuracy of 81.4%, is reached by our network with 10 convolution layers which we got in the parameter tuning. But this went down after depth of the network exceeds 10, since the data we have are not sufficient for models having this much amount of parameters. To resolve this, We have applied transfer learning in recently available deep models.

The outcome of parameter tuning of the Image Net models have been shown in Fig. 2. The final accuracy of existing validation set varies from 84.0% to 93.5%. The accuracy achieved after parameter tuning is better than the existing model which is already trained. The most relevant outcome is celebrated in the VGG16 model, having accuracy 93.5%. Our result conclude that even we have not sufficient data, the transfer learning can give better result.

In a comparative study, our artificial neural network model uses Stochastic gradient descent optimizer in the existing training data for all layers. Using random guessing 37 % accuracy reached in validation. As if we do not feature extractor in the convolution, the ANN is not able to locate correlations locally and also unable discriminate the features by utilizing available data.

The confusion matrix our models shown in the Table 2. The portion of validation accuracy predicted for all images of all the stages is shown with full details. Classification of all healthy stage leaves have been done precisely.

Initial and final stage accuracies are 93.5% and 87.2%, respectively. Intermediate stage accuracy is hoped not to be classified correctly, with the achieved accuracy 80.4%. But all those stages which have not classified correctly are having confusion with other subsequent stages. As, the Initial stage having confusion with the only intermediate stage and no one of initial stage is confused with the final stage.

Our findings depicts it is important to note that nearly 100% training accuracy is possible, that is undesirable and can be avoided by early stopping. But as we know that deep learning is data-driven, It is good if we have more training data to improve the validation accuracy further. Here we can note that VGGNet

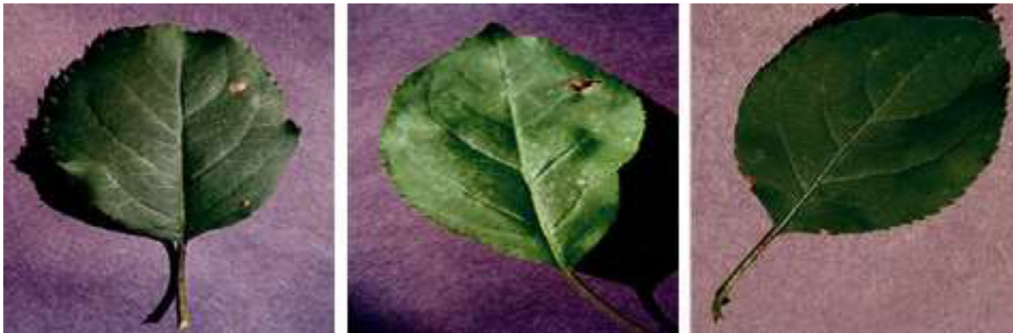
Table 2

Using transfer learning, the confusion matrix for the validation of VGG16 model.

	Validated			
	Healthy stage	Early Healthy stage	Middle Healthy stage	End Healthy stage
Healthy stage	27	0	0	0
Early stage	0	27	2	0
Middle stage	0	5	30	1
End stage	0	0	3	20



(a) healthy stage



(b) early healthy stage



(c) middle healthy stage



Fig. 2. For a black rot apple, Sample of leaf images of all the stages: (a) healthy stage, (b) early healthy stage, (c) middle healthy stage, and (d) end healthy stage.

model achieve the best performance which is also similar of [39,40], In which the plant identification task receives best performance by VGGNet model. The performance of other model like

ResNet is not as good as VGGNet in order to achieve our classification tasks although best result on the Image Net dataset has been recorded.

4. Conclusion & future scope

Our research build a deep learning model having ability to explore the meaningful features in the task of classification automatically, that actually prepare a complete roadmap in order to detect the seriousness of the disease. Having small number of input data, we trained a naïve network of slightly smaller size of varying number of layers in the beginning and completely tuned parameter four recent models: Inception-v3, and ResNet50, VGG19, VGG16. By making a comparative study of these existing networks. We concluded that well-tuning on already trained deep learning model has increased the efficiency of the model significantly. After parameter tuning of the VGG model, It reached its best, having the accuracy of 93.5% over existing validation data, concluding how our model is the new dominating technology for with greater extent of classification. In future, for several diseases data collection for all stages can be done by using variety of sensors, like available in infrared camera also in multi camera. The deep learning model will be added with cure proposal, Outcome validation, and so on.

CRedit authorship contribution statement

Adesh V. Panchal: Conceptualization, Data curation. **Subhash Chandra Patel:** Formal analysis, Funding acquisition. **K. Bagyalakshmi:** Investigation, Methodology, Project administration. **Pankaj Kumar:** Visualization, Validation, Resources, Software, Supervision. **Ihtiram Raza Khan:** Validation, Visualization. **Mukesh Soni:** Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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