International Journal of Communication Networks and Information Security

ISSN: 2073-607X, 2076-0930

*Volume **14** Issue **1s** Year **2022** Page **114**:**120***

Leaf Disease Detection by Using Convolutional Pretrained Model

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Article History

Received: 13 July 2022
Revised: 20 September 2022
Accepted: 26 October 2022

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Abstract

Although agriculture plays an important role in developing countries such as India, food security remains a major concern. Due to a shortage of storage space, transportation, and plant diseases, the majority of crops are squandered. In India, infections cause more than 15% of crops to be wasted, making it one of the most pressing issues to be addressed. There is a need for an autonomous system that can detect these illnesses and assist farmers in taking the necessary procedures to avoid crop loss. Farmers have used the traditional approach of recognizing plant illnesses with their naked eyes. However, not all farmers can recognize these diseases in the same way. With the advancement of Artificial Intelligence, there is a need to apply computer vision capabilities to the agricultural area. Deep Learning's comprehensive libraries, as well as the user and developer-friendly environment in which to work, all combine to make Deep Learning the best way to get started with this topic. Taking leaves from diseased crops and identifying them according to the disease pattern is part of the process. Images of diseased leaves are processed using pixel-based procedures to improve the informational content of the images. The next step is feature extraction, image segmentation, and finally, classification of crop diseases based on patterns recovered from diseased leaves. Convolutional Neural Networks (CNNs) are used to classify diseases. Some of the deep learning pre-trained models have got more accuracy here. The comparison of two pre-trained models was shown.

Keywords: Machine Learning, CNN, Image Processing

1. Introduction

Agricultural lands are now converting into barren lands because of low yield and loss due to plant diseases and many other reasons such as weather etc. The latest technology can assemble as much food for 7 billion people for human society and increase more demand. However, several issues, particularly climate change, continue to threaten the food security of food. Food security is threatened by plant diseases globally, and it's disturbing for small-hold farmers whose livelihood is dependent on healthy crops. Small hold farmers produce more than 80% of crops in developing countries, and there is an estimated prediction of losses of more than 50% from pests and illnesses. Furthermore, almost 50% of the starving people reside in small hold farmer households, as small-hold farmers are very much vulnerable to the food supply intervention by parasites.

To prevent loss due to crop diseases, various strategies have been devised. Integrated pest management (IPM) tactics have progressively augmented historical approaches of broad pesticide use in the last decade.[17] Nevertheless, the method of accurately recognizing the disease when it hits the first time is essential in effective illness management. Disease identification should be supported, and it is done well by agricultural extension groups and other institutions such as local plant clinics. Lately, growing internet access has been advantageous to diagnosing disease information.[18] Mobile phone-based tools have emerged around the world that can benefit from the unprecedented and rapid adoption of mobile phone technology.[1]

As an example of end-to-end learning, deep neural networks are successfully deployed for various disciplines. Neural networks put in the image of a damaged plant and put out a diseased crop pair.[21]Nodes of a neural network are functions of mathematics that accept numerical inputs from incoming edges and put out numerical values as an output edge. A deep neural network consists of a stacked layer of nodes that maps an input layer to an output layer.[2] The goal here is to build a deep network in which network topology and the nodes and weights of edges accurately map the input to output.[3] Network parameters adjustment trains the deep neural networks so that the mapping improves with time. This computationally demanding process has greatly enhanced various conceptual and engineering innovations.[2]

If a disease can be quickly diagnosed, farmers can do the same, pick the ones they want, and go about farming with ease, resulting in a strong output. This benefits farmers with minimal costs and a simple process. They can simply heal those various diseases by using different pesticides that are dangerous.[1]

2. Methods Used For Predicting the Leaf Disease

It is easier to drive the residual water to zero or compare it with the stack of non-operated layers. In the meantime, the shortcut connection saves the previous layer's additional data. The increase in the number of layers in the network will cause degradation. This is solved by the ResNets thanks to the introduction of residual blocks. ResNets-(18, 34,50,101,152 the difference between the numbers is the number of network layers) outperformed other models of CNN in the dataset of ImageNet, indicating that features of images may be recovered by ResNets. After removing the fully connected layers, ResNets can be used as an encoder, and the fine-tuning is done with the pre-trained model, which was trained on the ImageNet dataset.

2.1 Resnet18

Another study found that having too many deep layers made dense image prediction redundant. Certain smaller layers associated with CNNs are more likely to understand low-scale features (such as object edge features, composition features, and design features). As the number of system layers increases as deeper layers understand higher-scale features (spatial context, global semantics, and local object features), lower-scale properties are definitely lost. The second convolution layer of ResNet-18 has visualization filters and outputs. Our study, on the other hand, necessitates segmenting the backdrop by performing an extensive picture prediction since the particular loss of low-scale characteristics will bring about erroneous image segmentation. ResNet-18's performance is definitely comparable to those of other ResNets, which could keep more low-scale functions due to the shallowness.[4]

As a result, we employ the ResNet-18 model as an encoder for our network model. Figure 3 shows the structure of the ResNet-18 network.ResNet-18 has 16 convolutional layers, two downsampling layers, and a few fully linked layers (FC). ResNet's input image is usually 224x224 pixels, the particular first convolution coating is 77 -pixels, the convolution kernel is 77 -pixels, and the following layers are 3x3 pixels.[5]

The intermediate pool is the feature map of the last convolutional layer, and the full join gives the eigenvectors and then is normalized by Softmax to get the categorical probabilities as pictured. As shown in figure 1, two convolutional layers of the same color output feature maps of the same size and form residual blocks with the same number of filters. A quick link (circular arrow in Figure 3) skips two layers. Dotted labels increase the size.[6]

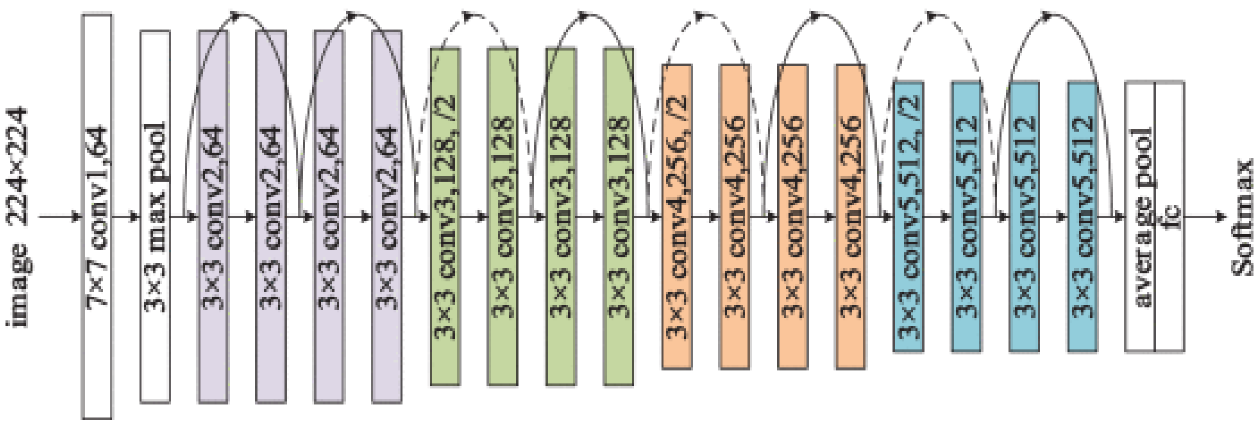


Figure 1. Resnet18 Architecture [7]

2.2 ResNet50 Architecture

ResNet50 is a variant of ResNet with 48 convolutional layers, 1 MaxPool layer, and one intermediate pool layer. There are 3.8 x 10^9 floating-point operations. This is a popular ResNet model, and we took a closer look at the ResNet50 design.[8]

layer name	output size	18-layer	34-layer	50-layer	101-layer	152-layer
conv1	112×112	7×7, 64, stride 2				
conv2_x	56×56	3×3 max pool, stride 2				
		$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times 2$	$\begin{bmatrix} 3\times3, 64 \\ 3\times3, 64 \end{bmatrix}\times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times 3$	$\begin{bmatrix} 1\times1, 64 \\ 3\times3, 64 \\ 1\times1, 256 \end{bmatrix}\times 3$
conv3_x	28×28	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times 2$	$\begin{bmatrix} 3\times3, 128 \\ 3\times3, 128 \end{bmatrix}\times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times 4$	$\begin{bmatrix} 1\times1, 128 \\ 3\times3, 128 \\ 1\times1, 512 \end{bmatrix}\times 8$
conv4_x	14×14	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times 2$	$\begin{bmatrix} 3\times3, 256 \\ 3\times3, 256 \end{bmatrix}\times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times 6$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times 23$	$\begin{bmatrix} 1\times1, 256 \\ 3\times3, 256 \\ 1\times1, 1024 \end{bmatrix}\times 36$
conv5_x	7×7	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times 2$	$\begin{bmatrix} 3\times3, 512 \\ 3\times3, 512 \end{bmatrix}\times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times 3$	$\begin{bmatrix} 1\times1, 512 \\ 3\times3, 512 \\ 1\times1, 2048 \end{bmatrix}\times 3$
	1×1	average pool, 1000-d fc, softmax				
FLOPs		1.8×10^9	3.6×10^9	3.8×10^9	7.6×10^9	11.3×10^9

Figure 2. Resnet50 Architecture [8]

3. Implementation of Plant Disease Detection Using Resnet50 Model

First, the required libraries should be installed.

- Torch
- Matplotlib
- Pillow
- Numpy

3.1 Download Dataset from Kaggle

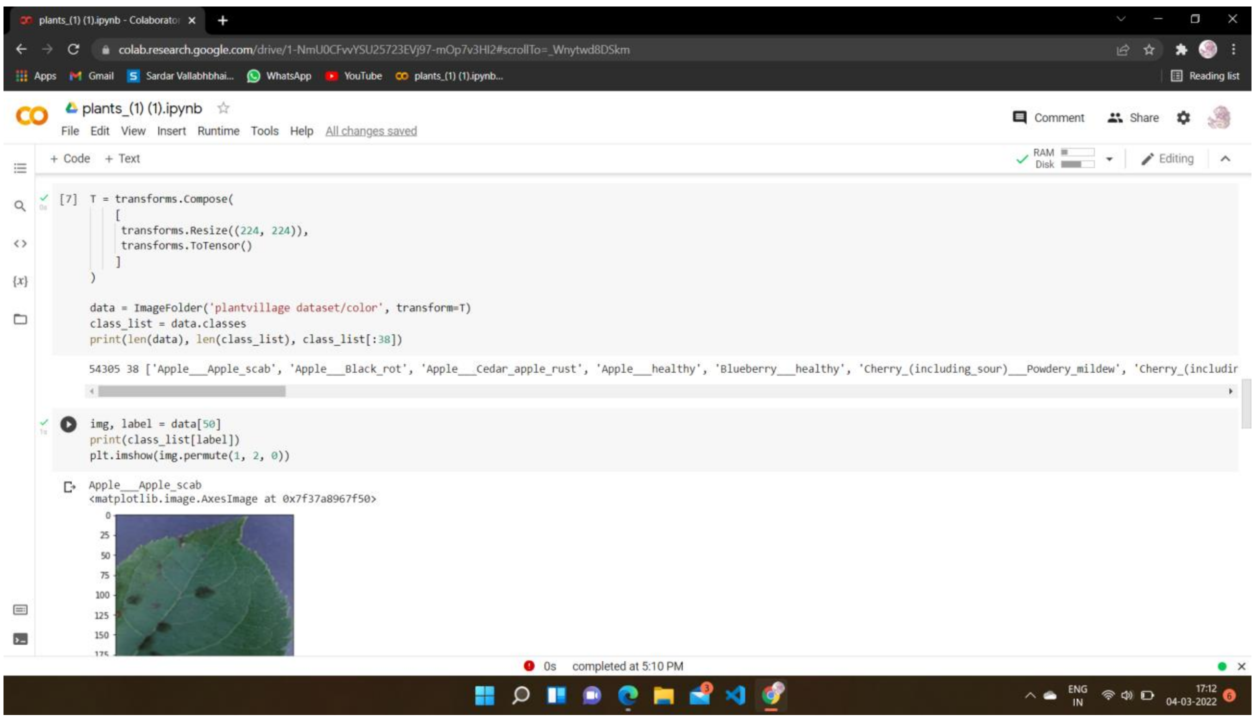
For downloading the dataset, some steps to be followed

- Create a kaggle account.
- Create a new API token in this account. A kaggle.json file will be downloaded.
- The downloaded file should upload in the workspace colab

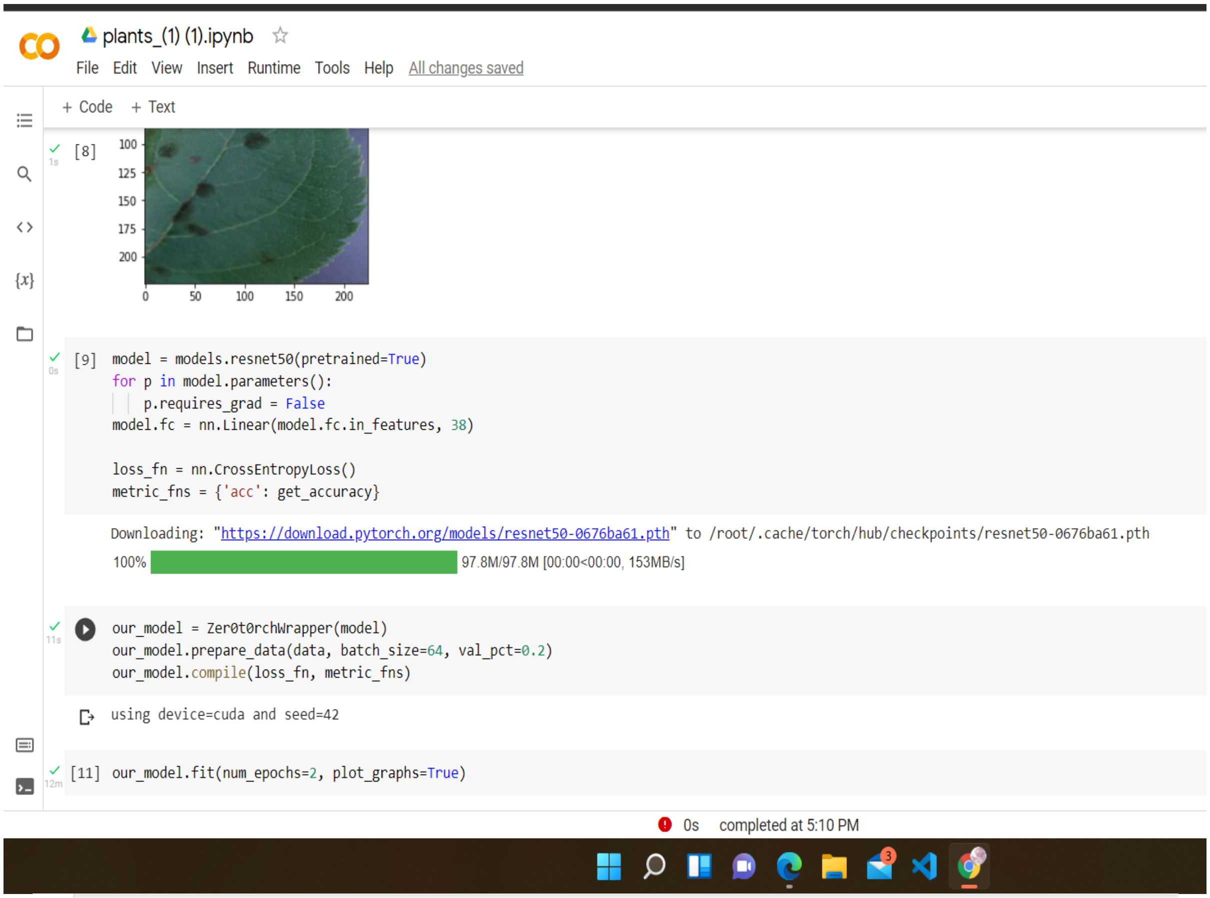
3.2 Importing Libraries

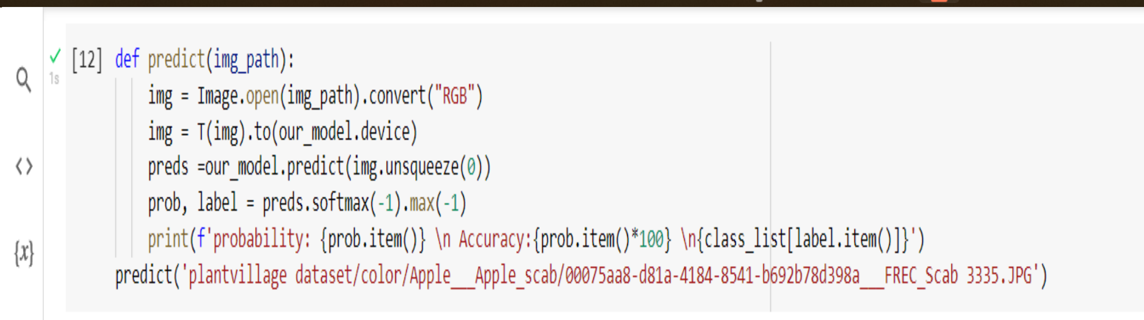
Libraries such as a torch,torchvision, NumPy, pillow(PIL) are imported.

```
import torch
import numpy as np
from torch import nn
import matplotlib.pyplot as plt
from torchvision import models, transforms
from torchvision.datasets import ImageFolder
from PIL import Image
```



Here a pretrained model resnet 50 is used and train the plant's dataset, and also Resnet18 is used to compare the model performance.





4. Results and Discussions

By using the Resnet50 model, the accuracy percentage of training data was 94.53%, and for the testing, data was 95.47%, and the results obtained after using the resnet18 are accuracy for the training data 92.05 %, test data accuracy 94.57 %. By training the same data with two Resnet models, the accuracy results are more for the Resnet50 model.

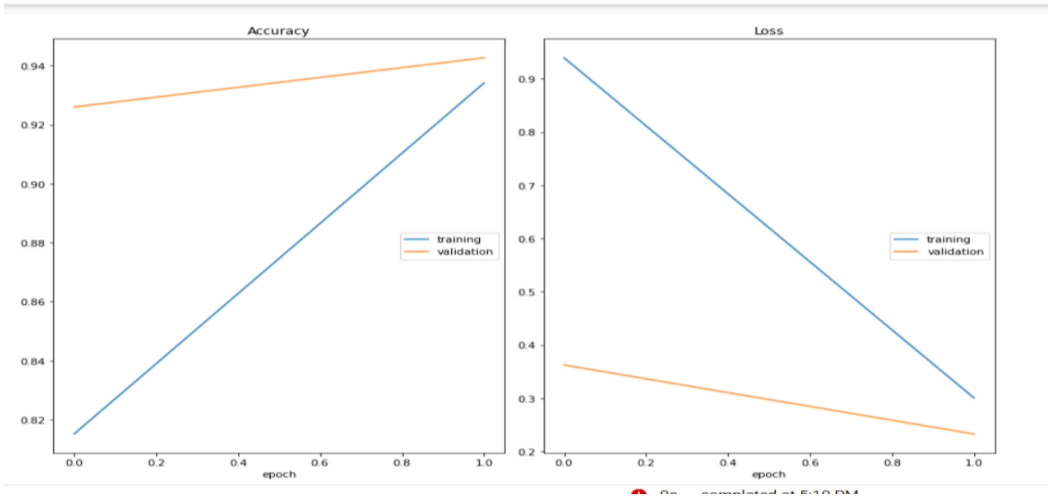


Figure 3. Accuracy Obtained For Resnet50 Model

Some of the predictions were taken, and the results showed the accurate one with more probability; hence the model works well, and this model can be used for the prediction of leaf disease.

```
predict('plantvillage dataset/color/Apple___Apple_scab/00075aa8-d81a-4184-8541-b692b78d398a___FREC_Scab 3335.JPG')

probability: 0.9817744493484497
 Accuracy:98.17744493484497
Apple___Apple_scab

[13] predict('/content/plantvillage dataset/color/Cherry_(including_sour)___Powdery_mildew/00705aa7-5ea2-4419-9440-8ba65e108eb9___FREC_Pwd.M 0267.JPG')

probability: 0.748978316783905
 Accuracy:74.8978316783905
Cherry_(including_sour)___Powdery_mildew

[14] predict('plantvillage dataset/color/Grape___healthy/00e00912-bf75-4cf8-8b7d-ad64b73bea5f___Mt.N.V_HL 6067.JPG')

probability: 0.9991317391395569
 Accuracy:99.91317391395569
Grape___healthy

[15] predict('/content/plantvillage dataset/color/Strawberry___healthy/00166615-5e7b-4318-8957-5e50df335ee8___RS_HL 1785.JPG')

probability: 0.8962686657905579
 Accuracy:89.62686657905579
Strawberry___healthy
```

5. Conclusion

Majorly Deep Learning concepts and techniques increased plant disease detection and categorization. It has solved, or at least substantially solved, traditional machine learning methodologies. Deep learning (DL), a branch of machine learning, is used for picture classification, target identification, and image segmentation. In this paper, a plant village dataset from kaggle is downloaded into the colab . We trained the plant diseases images with a large number of images with a pre-trained model. Images are predicted by using this trained model, and results are obtained in the front-end web pages or in the flask app. There are only 38 classes, and there are many plants and many datasets are required for detecting all plants, and the models should be improved for getting more accuracy. For detecting all plants, we need to train those datasets in TPUs to get accurate results. For now, we trained the image in GPU. Hence these kinds of improvements make the development in the agriculture sector and can stop the losses for farmers in the production. The accuracy obtained by using the Resnet18 model was less than the accuracy obtained for the ResNe50 model, so this model can be used rather than using the ResNet18 model.

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