

DISEASED PLANT DETECTION USING DEEP NEURAL NETWORK

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INTRODUCTION

Agriculture is one of the major backbone for any economy throughout the world. Plants provide us with many resources that fit into the everyday life of human beings. These plants have now been undergoing a lot of diseases as a side effect from different pesticides or chemicals that are used to grow them. This is one of the main reasons that we have decided to take up this project to detect the diseases in plants. If proper care is not taken over this issue, it can have tremendous effects on the plants and in turn on the whole ecosystem in which every organism lives.

This project focuses on detecting the diseases that spoil the growth of the plants e.g. Tomato is one such plant that gets affected by many diseases like bacterial spot, early and late blight, leaf mold, mosaic virus etc. These diseases must be detected at earlier stages so that appropriate actions can be taken to cure them. This project is implemented using Convolutional Neural Networks and Saliency Map Visualization to detect such disease efficiently.

APPROACH

The dataset contains images of healthy and diseased plants. Our approach is to obtain salient images from the colored raw images that have been trained using the model. These Salient images are given as the input to our CNN. We introduced the concept of Saliency Map Gradient of the model with respect to the input image.

Saliency map is an analytical method that allows estimating the importance of each pixel, using only one forward and backward propagation through the network. While using colored images, we first extract the leaf portion from the noisy image and then process it to determine the important region that is needed for the model to determine and classify the leaf. But here we use saliency of the image from the trained model to generate salient images which is then used to train a model and use it for classification because these images extracts only the portion of the leaf that are diseased. So such images tend to classify better than the colored images.

Modifying the CNN architecture by changing the parameters like activation function, number of layers, dropout and pooling helped in achieving better accuracy. Finally the performance of the model was evaluated by using binary cross entropy.

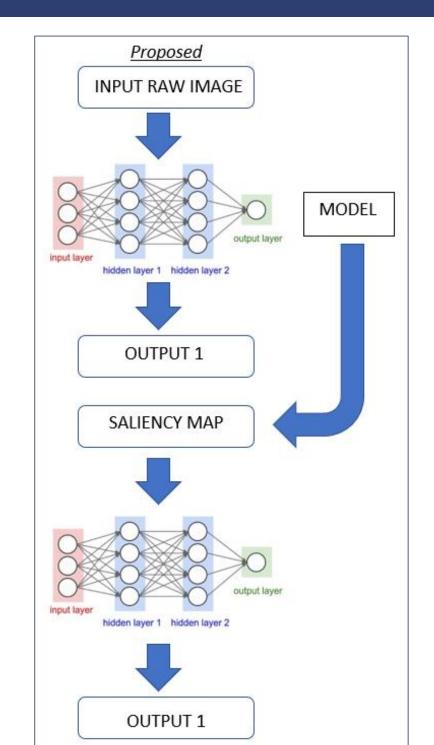
IMPLEMENTATION

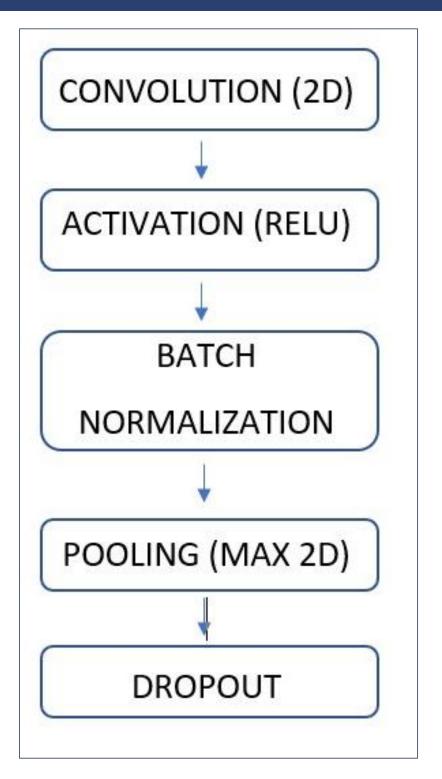
- Keras (v.2.2.4) with Tensorflow as the backend.
- Prior to building the model, the input image was preprocessed by resizing the image to 256 x 256 pixels and also the images were converted to 2D array.
- Sequential model was implemented with 5 hidden layers, where each layer performs the following operations - Convolution, Batch Normalization, Max Pooling, Activation and Dropout.
- Initially the images were fed as input to the model to classify them as healthy or diseased plants.
- Later Saliency Map visualization is done where the image gradients corresponding to the original image is fed as input to classify the healthy and diseased plant.
- Parameters: # of filters, # of stride, padding size, activation function, dimension, pool size, dropout threshold.
- Parameter evaluation: using 20 epochs

EXPERIMENT

The current technique uses preprocessed image as input, passes that to the sequential model and classifies the images as healthy or diseased plants. Our proposed technique saliency visualization the where gradients image corresponding to original image are fed to the sequential model to classify plants as healthy diseased.

Fig: Proposed model.





Also the sequential model presented here consists of five hidden layers as a part of its architecture namely Convolution, Activation Function (Relu), Batch Normalization, Pooling(Max2D), and Dropout.

Fig: Sequential Model

Although there are state of the art techniques currently which help in classifying plant diseases with an accuracy of 97.6%, they use raw colored, gray scaled, segmented images. Collecting labeled images is very expensive because it is done manually. This difficulty of data collection has forced the previous studies to use small datasets to train and test classifiers and the time taken to train the model was high.

CONCLUSION

Hence in our approach, the Salient images are used which help in not just reducing the training time for the model but also converge faster.

FUTURE WORK

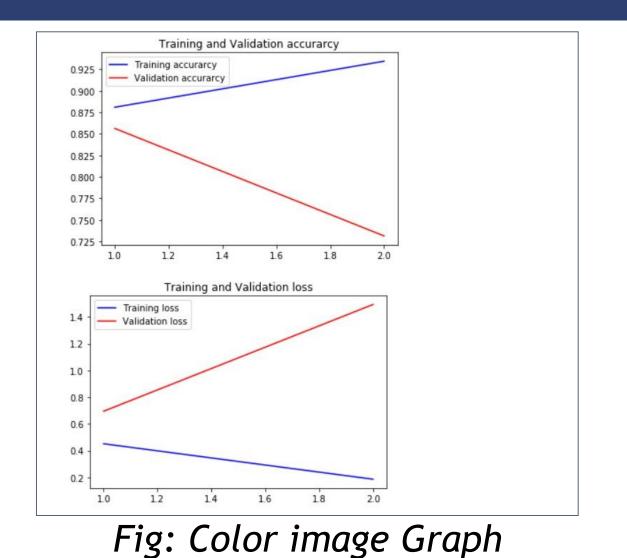
We would like to extend this project to detect which chemicals are harmful for the growth of the plant and how the nutrients in the soil would impact the future of plant growth for agriculture. With advancements in machine learning classifiers and techniques we would be able to detect intricate problems in plants at ease before they affect other plants and also try to improve the efficiency and performance of the model.

REFERENCE

- [1] Sanjay B. Dhaygude, Nitin P.Kumbhar, "Agricultural plant Leaf Disease Detection Using Image Processing", International Journal of Advanced Research in Electrical, Electronics and Instrumentation Engineering Vol. 2, Issue 1, January 2013
- [2] Sachin D. Khirade, A.B Patil, "Plant Disease Detection Using Image Processing", International Conference on Computing Communication Control and Automation", February 2015.
- [3] Sharada P. Mohanty, David P. Hughes and Marcel Salathe, "Using Deep Learning for Image-Based Plant Disease Detection", Frontiers in Plant Science, September 2016
- [4]https://github.com/spMohanty/PlantVillage-Dataset/tree/master/raw/color
- [5]https://www.kaggle.com/emmarex/plantdiseas

RESULT

Training accurarcy



0.715
0.700
0.695
0.690
0.685
10
12
14
16
18
20

Training and Validation loss

Validation loss

Validation loss

15
14
13
12
11
10
0.9
0.8

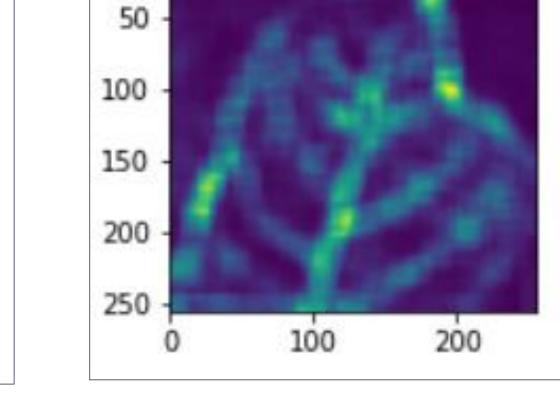


Fig: saliency map as input

Fig: Saliency Image

The training accuracy loss and validation accuracy loss values are plotted for the existing technique where the colored images are given as input. The same values are plotted for our proposed architecture when the saliency mapped images are given as input. This comparison shows that results are more accurate when the image gradients from the saliency images corresponding to the original image are given as input to the model.