DISEASED PLANT DETECTION USING NEURAL NETWORK

Project Report

Machine learning ITCS6156

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Introduction:

Problem Statement:

Agriculture is the major source of economy for most of the countries around the world. This sector contributes to the maximum GDP of a nation's economy. Developed nations have proven results from being benefited using agricultural sector. Developing nations need to consider agriculture as their benefactor and walk in the paths led by developed nations. That being said a nation as a whole has to focus on agricultural health aspects too. Domestic plants that provide us with essential resources like fruits and vegetables are prone to various diseases. These diseases if detected in earlier stages can help prevent the plants from early loss. Thus maintaining plant nutrition is one of the main challenges for any country which intends to promote agriculture.

Many factors influence disease development in plants including hybrid/variety genetics, age of the plant at the time of infection, environment (e.g., soil, climate), weather (e.g., temperature, rain, wind, hail, etc.), single versus mixed infections, and genetics of the pathogen populations like fungal, bacterial, viral or nematodes which can damage plant parts above or below the ground. Due to variation inherent in these factors, diagnosis of plant diseases can be difficult at the early stages of disease on individual plants as well as at the early stages of an epidemic. This is one of the main reasons that we have decided to take up this project which helps in detecting the diseases in plants. Proper care if not taken can have devastating effects on the plants and in turn on the whole ecosystem.

This project focuses on detecting the diseases that spoil the growth of the plants for example, 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 if detected at earlier stages can help in taking appropriate actions to cure them. This detection of diseases is done using Convolutional Neural Networks and Saliency Map[6] Visualization.

Motivation:

The current research in the field of plant diseases was the basis of our motivation. It is known that most of these diseases go undetected during their early stages of prevention. This motivated us to create a machine learning model that detects the plant diseases with higher accuracy.

Review from other researchers:

Sanjay et al. in their work “Agricultural plant Leaf Disease Detection Using Image Processing” speak about detecting these diseases in plant leaves using texture statistics. The RGB values obtained from the image are converted to HSV values and masking is done to remove the green pixels. They use the remaining portion of the image for texture analysis using Color co-occurrence matrix. The authors of this paper use Random Forest for classification. Random forest classifier is helpful for classifying small number of samples and does not work effectively with larger number of samples.

Sachin et al. also worked on similar grounds to detect plant diseases using feature extraction in their work “Plant diseases detection using Image Processing”. The authors use feature extraction which involves steps like pre-processing, image acquisition and image segmentation. They use SVMs, back propagation algorithms to identify and classify various plant diseases using image processing techniques. The drawback in this model was similar to the previous one as SVMs would work great with smaller datasets but the complexity increased along with the size of the dataset. This would eventually lead to increase in the support vectors as they are proportional to the number of samples. A possible solution to that issue would be using multi-class SVMs where the SVM will be trained for each class.

Mohanty et al. used a varying approach in the work “Using Deep Learning for Image-based Plant Disease Detection”. The authors introduced the concept of using Deep Neural Networks for detecting plant diseases. Deep Neural Networks revolve around the concept of using more than one hidden layer in their neural network model. The authors used two major CNN architectures - AlexNet and GoogleNet because they are pre trained against Color, Gray-scaled and segmented image dataset. The deep neural network implemented in their work has been trained by tuning the network parameters like bringing alterations to the activation, batch normalization, pooling and dropout. The main challenge the authors of this paper face is the size of the dataset because image classifiers require relatively large labelled dataset in order to train the network

Summary of proposed approach:

Our convolutional neural network model used a dataset [5] that contains 7552 labelled images. These are given as the training input to the network. In the initial stage, the images are preprocessed i.e. they are loaded and resizing is done to maintain uniformity among images. The dataset [5] contains raw colored, segmented and gray scaled images. The approach that we followed was to create saliency mapped images. This is done by computing the gradient of output category with respect to the input image. This process tells us how the output category values could change with respect to a small change in input image pixels. Thus, visualizing these gradients will highlight salient image regions that contribute efficiently towards the output. The image gradients corresponding to the original image are provided as input to the CNN model for training and testing. The process of tuning the architecture is carried out by changing the parameters like activation function, number of layers, dropout and pooling. Lastly, the model's performance is evaluated by using binary cross entropy since the predicted output is a crop disease pair with 38 possible classes.

Data Description:

Source: https://github.com/spMohanty/PlantVillage-Dataset
The dataset contains three different versions:

- Color
- Greyscaled
- Segmented

Each of these versions has 54,306 Images, 38 classes.

Some of the classes are Pepper bell Bacterial spot, Pepper bell healthy, Potato Early blight, Potato Late blight, Potato healthy, Tomato Bacterial spot, Tomato Early blight, Tomato Late, Tomato Leaf, Tomato Septoria leaf spot, Tomato Spider mites Two spotted spider mite, Tomato Target Spot, Tomato Yellow Leaf Curl Virus, Tomato mosaic virus, Tomato healthy.

Background:

1. **Sanjay, B. Dhaygude & et al [1]** Application of texture statistics for detecting the disease in leaf of the plants is the main approach in this paper. Firstly, the RGB images are converted into Hue Saturation Value (HSV) color space representation because RGB is ideal for color generation whereas HSV model is a good color descriptor. Next is Masking i.e., removing the green pixels using a precomputed threshold level because the green colored pixels mostly represent the healthy (unaffected) areas of the leaf and they do not add any valuable weight during disease identification. The left-over part is the infected area which is segmented using 32X32 patch size. These 32X32 segments are then further used for texture analysis by Color Co-occurrence matrix. In this paper Random Forest is used classification. It is good and simpler approach, but its

complexity increases as the number of samples increases. The more trees we have the more difficult to build a random forest. And if you have a dataset with lots of noisy images in it then Random Forest’s may overfit the data (It depends on how well you pre-process your dataset).

2. **Sachin D. Khirade & et al [2]** Feature Extraction is the major technical difference in this paper that is used to fragment the disease part of the plant**.** It involves the steps like image pre-processing, image acquisition and image segmentation for the detection of plant diseases. This paper also discussed about feature extraction techniques to extract the features of the infected leaf and for classification of disease in plants. For the feature extraction, color co-occurrence method is used. SVM’s, back propagation algorithms can be efficiently used. From these methods, we can identify and classify the various plant diseases using image processing technique. The problem with the SVM is, it works great with small dataset and since it is a non-parametric model the complexity increases proportionally with the size of the dataset. We can end up with lot of support vectors in the worst- case because the more samples in the training set the more support vectors we would require. They could have used multi- class SVM’s where the SVM has to be trained for each class.

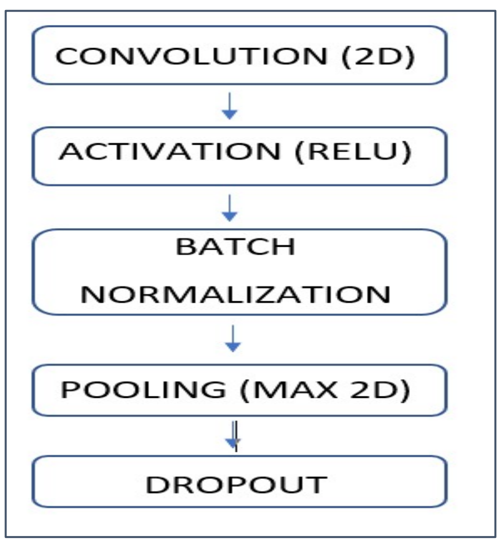
3. **Mohanty SP & et al [3]** The concept of Deep Neural Networks has been implemented in this paper. Deep neural networks are nothing but having more than one hidden layers. This paper mainly uses two major CNN architectures namely AlexNet and GoogLeNet which has been trained against Color, Grey scaled, segmented image dataset and their accuracies are determined. Deep neural network has been trained by tuning the network parameters, such as bringing in alterations to the activation, batch normalization, pooling and dropout. To improve the training process. A challenging task faced in this paper is the size of the dataset, since image classifiers required relatively larger labelled dataset in order to train the network.

Method:

The dataset [5] 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[6] 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.

Experiment:

Keras (v.2.2.4) is used 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[6] visualization is done where the image gradients corresponding to the original image is fed as input to classify the healthy and diseased plant.

Parameters that were used are # of filters, # of stride, padding size, activation function, dimension, pool size, dropout threshold.

Model: "sequential_1"

Layer (type)	Output Shape	Param #
conv2d_1 (Conv2D)	(None, 256, 256, 32)	320
activation_1 (Activation)	(None, 256, 256, 32)	0
batch_normalization_1 (Batch	(None, 256, 256, 32)	128
max_pooling2d_1 (MaxPooling2	(None, 85, 85, 32)	0
dropout_1 (Dropout)	(None, 85, 85, 32)	0
conv2d_2 (Conv2D)	(None, 85, 85, 64)	18496
activation_2 (Activation)	(None, 85, 85, 64)	0
batch_normalization_2 (Batch	(None, 85, 85, 64)	256
conv2d_3 (Conv2D)	(None, 85, 85, 64)	36928
activation_3 (Activation)	(None, 85, 85, 64)	0
batch_normalization_3 (Batch	(None, 85, 85, 64)	256
max_pooling2d_2 (MaxPooling2	(None, 42, 42, 64)	0
dropout_2 (Dropout)	(None, 42, 42, 64)	0
conv2d_4 (Conv2D)	(None, 42, 42, 128)	73856
activation_4 (Activation)	(None, 42, 42, 128)	0
batch_normalization_4 (Batch	(None, 42, 42, 128)	512
conv2d_5 (Conv2D)	(None, 42, 42, 128)	147584
activation_5 (Activation)	(None, 42, 42, 128)	0
batch_normalization_5 (Batch	(None, 42, 42, 128)	512
max_pooling2d_3 (MaxPooling2	(None, 21, 21, 128)	0
dropout_3 (Dropout)	(None, 21, 21, 128)	0
flatten_1 (Flatten)	(None, 56448)	0
dense_1 (Dense)	(None, 1024)	57803776
activation_6 (Activation)	(None, 1024)	0
batch_normalization_6 (Batch	(None, 1024)	4096
dropout_4 (Dropout)	(None, 1024)	0
dense_2 (Dense)	(None, 4)	4100
activation_7 (Activation)	(None, 4)	0

Total params: 58,090,820
Trainable params: 58,087,940
Non-trainable params: 2,880

Fig. Model summary

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 uses saliency map[6] visualization where the image gradients corresponding to the original image are fed to the sequential model to classify the plants as healthy or diseased. 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.

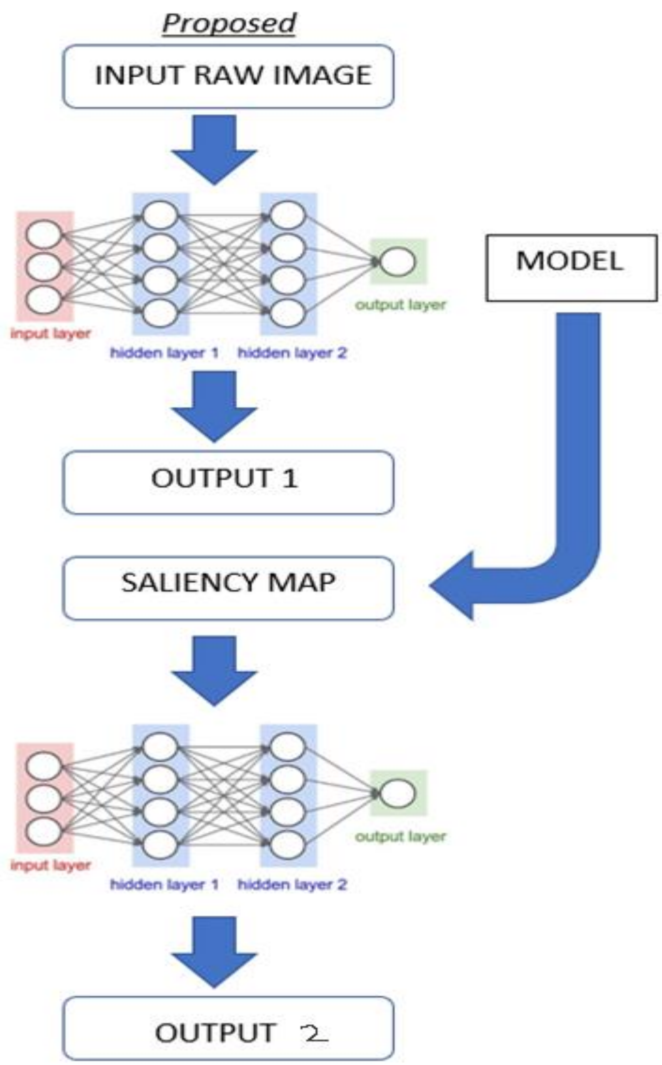


Fig. Proposed approach

Fig. Raw colored leaf

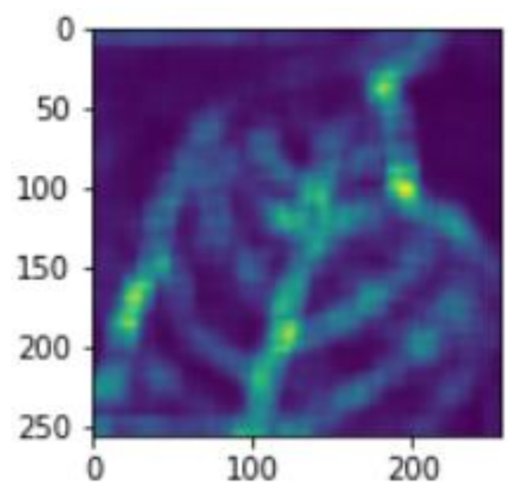


Fig. Salient Image of the leaf

Figure on the left side is the raw colored image of the leaf and the image of the right side is the saliency image of the colored image found of the left side. Both these are images of healthy leaf.

Proposed approach explanation:

The raw colored images are given as input to the CNN. The architecture that is used here is Alexnet and it consist of five hidden layers. The raw colored image is preprocessed by resizing the image to 256 x 256 pixels. Using these raw colored images, the model is trained. Saliency map [6] is a visualization technique that reveals how the model is trained, i.e. it shows which portion of the leaf is used for training the model. This model contains the gradient details that can be used to produce the saliency image. So once the model is trained, it can be used to create saliency image dataset [5]. This dataset [5] is then used to train a new model the same way it was trained which is then used for prediction.

The prediction results are shown below.

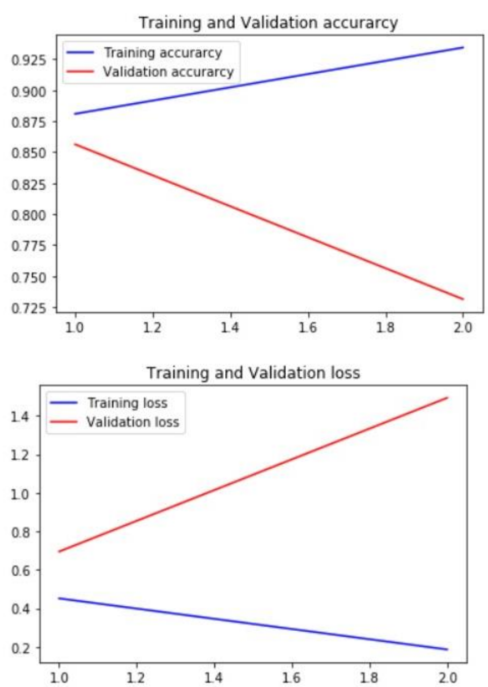


Fig. Raw colored image – Accuracy and Loss

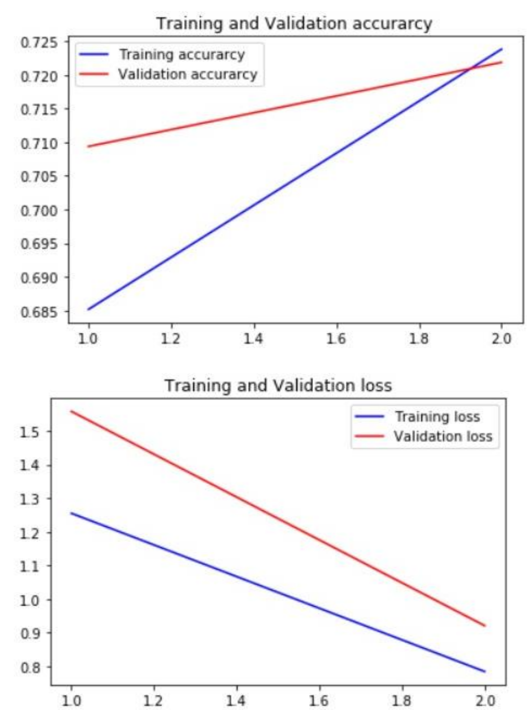


Fig. Saliency image – Accuracy and Loss

```
[INFO] Calculating model accuracy
160/160 [==============================] - 20s 122ms/step
Test Accuracy: 72.1875
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It can be seen from the graph above that it is converging faster for the saliency image when compared to the raw colored images. Two epochs were used to train and test the model which gave us 72.18 % accuracy.

Response to feedback (Mid progress report):

Feedback: We were asked to include a separate section for data description.
Response: We created a new section for data description in our final report.

Feedback: We were asked to cite the reference for our dataset and saliency map.
Response: We have cited the sources for our dataset and saliency map.

Feedback: We were asked to make our approach section brief with more detailed explanations.
Response: We modified our approach section by explaining few concepts in detail and thus making our description brief.

Feedback: We were asked to explain how critical saliency images would be to make a difference.
Response: The necessary explanations have been included in the method section clearly.

Conclusion:

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.

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.

Reference:

- [1] Prof. Sanjay B. Dhaygude, Mr.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", 2015.
- [3] Mohanty SP, Hughes DP and Salathé M (2016) Using Deep Learning for Image-Based Plant Disease Detection. *Front. Plant Sci.* 7:1419. doi: 10.3389/fpls.2016.01419
- [4] https://github.com/spMohanty/PlantVillage-Dataset/tree/master/raw/color
- [5] https://www.kaggle.com/emmarex/plantdisease
- [6] https://arxiv.org/pdf/1312.6034.pdf