

Plant Disease Detection and Localization using GRADCAM

Ninad Shukla, Sushila Palwe, Shubham, Mohit Rajani, Aaryan Suri

Abstract: Plant diseases are diseases that change or disrupt its important functions. The reduction in the age at which a plant dies is the main danger of plant diseases. And farmers around the world have to face the challenge of identifying and classifying these diseases and changing their treatments for each disease. This task becomes more difficult when they have to rely on naked eyes to identify diseases due to the lack of proper financial resources. But with the widespread use of smartphones by farmers and advances made in the field of deep learning, researchers around the world are trying to find a solution to this problem. Similarly, the purpose of this paper is to classify these diseases using deep learning and localize them on their respective leaves. We have considered two main models for classification called resnet and efficientnet and for localizing these diseases we have used GRADCAM and CAM. GRADCAM was able to localize diseases better than CAM

Keyword: Plant Leaf Diseases , Deep Learning, Efficientnet , GRADCAM.

I. INTRODUCTION

Agriculture is the backbone of most developing economies in the world . However, the massive commercialization has created negative effects on the environment. The accumulation of harmful chemicals in soil, water, air, and even in our bodies have already started showing negative effects in the form of deadly and incurable diseases like cancer. While the fertilizers give short term relief to farmers in terms of increased production but has catastrophic effects on environment in longer term, where they remain for a long time after being washed away by rains and contaminates the ground water . Other negative effects of this type of farming is faced by plants and further by the farmers who are dependent on the production of these farms for their livelihood .This is because chemical fertilizers are salt. Excess concentration of salts can cause a salt burn which is the condition of dehydration and destruction of plant tissue. The abundant nutrients reacts with the scarce nutrients which makes them absent for plants . In fact these so called increased productivity has instead led to a downfall in the incomes of farmers all around the world. There are various ways in which farmers can deal with this problem like by applying nutrients in right amounts at the right time of the year. Farmers can plant cover crops or perennial species to avoid periods of empty ground on farm fields when the soil (and the nutrients it contain) are most susceptible to erosion

Revised Manuscript Received on February 01, 2020.

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and loss into waterways. Organic farming is able to take care of this problem as the main purpose of this kind of farming is based on fertilizing the plants and controlling the diseases. The management of crops require careful watch on diseases that can decrease the production. While most of the plant disease detection is done by the naked eyes, it is not the most efficient method .This is because of the fact that this method incorporate increasing complexity, which make them difficult to be detected by even the experts with long experiences. And the result of this is the wrong conclusions about the diseases and further the wrong treatments. Modern technology with the help of deep learning can automate this task in such a way that it is also affordable to the farmers. Deep learning can classify and localize the diseases based on visual symptoms like leaf of the plants .This can be integrated with smartphones ,as almost everyone today has a smartphone where they can take an image of a plant leaf and upload it and can get notified about the diseases of the plant.

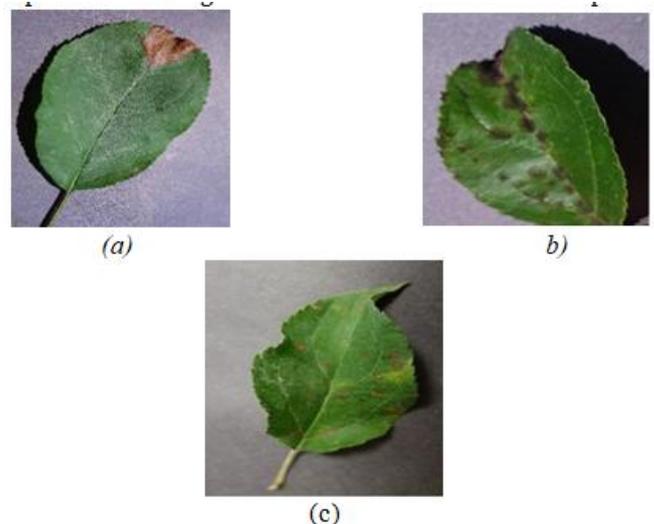


Fig 1. Images of Leaf affected by diseases (a) Black Scab (b) Black Rot (c) Cedar Rust

Deep learning is a subset of machine learning that tries to copy the human brain for processing data and making decisions. After a massive success in various domains like disease detection from medical images, self driving cars etc.it has entered the agricultural field. So we will use Deep Learning to localize and classify diseases on plant leaves . And convolutional neural networks are the best way to classify images in deep Learning. For the purpose of localization of diseases we have considered two methods namely CAM(Class Activation Maps)[7],Grad-Cam[8] .We have considered 3 diseases of apple namely apple scab, cedar rust and black rot. Figure 1 shows one image each of a plant disease of apple . The early prediction of diseases can help in collecting information for detecting diseases properly ,

and making strategies for proper plant growth

II. RELATED WORKS

Here we have taken studied some research papers that have also detected and classified plant diseases. Paper[1] uses deep multiple instance learning which is based on a comparatively weak supervised deep learning model. This framework was used to build an in-field automatic wheat disease diagnosis system. It used only image level annotations to classify and localize disease areas. The training images were obtained from wild conditions. Moreover, to check the accuracy of their system they also used Wheat Disease Database 2017(WDD2017) which contains the images of wheat diseases. They used two models called VGG-FCN-VD16 and VGG-FCN-S and were able to get accuracies of 97.95% and 95.12% respectively. In paper[2] the authors have used deep-learning based approaches with the aim of developing more suitable methodologies to detect diseases in plants using the images of the leaf of that plant.

They used three kinds of detectors for this purpose: Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD), which was used for this work. Identification of diseases even in very diverse and complex environment around the plant was the main advantage of this system

They used disease infected plant leaves in large amounts from Africa and Southern India for the purpose of training that were first screened by experts. They used transfer learning to retrain 3 models of CNN. Six models using images collected from various parts of banana were used to make six models. The robustness and ease of deployability for banana disease detection were shown by the results using Deep Convolutional Neural Network. Pre-trained disease recognition model was used . To develop a network that can make better predictions in terms of accuracy Deep transfer learning (DTL) was used.

In Paper [4] model was developed to identify 13 categories of plant diseases among healthy leaves , with the added ability to separate them from their environment. This method of disease recognition had never been proposed before according to author. The paper fully describes all the steps to implement this disease recognition model, beginning from collecting data , prescreened by experts .Using framework, Caffe (which was made by Berkley Vision and Learning center)the CNN models were trained. 91% and 98% were the respective precision they obtained and on average 96.3% on separate class tests were the experimental results. The technique which is applied to process the digital information from the images is called image processing

While the technique used to detect a disease from the input images is called plant disease detection. In paper [5] methods based on text based features extracted from the images were used. Extraction of these text based features was done by GLCM algorithm. Input images were segmented using clustering techniques like k-mean clustering. Classification of input image into two classes was done by using SVM classifiers on already present

algorithms. KNN classification is used instead of SVM classifier to get better performance.

The result was improved accuracy and classifying the data into multiple classes.

This paper[6] presents an improved method for leaf disease detection using an adaptive approach. The algorithm presented used to preprocess, segment and extract information from the preprocessed image. K-Means algorithm is used for segmentation to achieve different clusters. The shape feature and color texture features are obtained from the affected regions and sent to the SVM classifier.

III. PROPOSED METHODOLOGY

Plants are very vulnerable to all the harms and abnormalities caused by the diseases. There are two types of factors that cause diseases to plants which are biotic and abiotic factors. Living things like fungi ,bacteria ,viruses ,nematodes ,insects ,mites and animals are responsible for Biotic plant diseases. On the other hand, nonliving factors like drought stress , sunscald, freeze injury, wind injury, chemical injury ,nutrient deficiency are the main reasons behind abiotic problems. Moreover, improper methods like watering too much also contributes to abiotic disorders . Abiotic diseases do not show many disease signs while biotic diseases show physical symptoms of these pathogens like fungal growth, bacterial ooze, or nematode cysts, or the presence of mites or insects. Sadly the destruction done by both biotic and abiotic factors appear like each other. Despite of properly looking for the signs, correctly detecting can be hard. For instance, changing leaf color to brown of a leaf of oak tree is caused by drought stress is similar to browning of leaf due to oak wilt ,a vascular problem, or browning due to anthracnose, a not very serious plant disease.. In this paper we have discussed the use of visual explanation techniques to localize diseases through leaves. These include CAM and Grad-Cam .And for classifying we have used Efficientnet[10].

A).CAM

They help in the understanding that which part or region of the image have how much influence on the prediction of the class of that image. Heat maps are used to highlight the pixels which have greater effect on the class of that image. The layers of CNN behave like unsupervised model in this case. And we are saved from the tedious work of annotating the huge dataset with bounding boxes manually . The implementation of the class activation map technique depends on the global average pooling layers which are augmented after the final convolutional layer to spatially diminish the image dimensions and reduce parameters hence minimizing over-fitting. The flow through CAM based architecture can be described in the following ways. Before the last CNN layer in a normal neural network, let us assume an N dimensional image with N number of filters; If the input image is $m*m$, the shape of the output of final layer will be $N*a*a$ where a is the number of filters in the previous layer. The global pooling layer takes the N channels and returns their spatial average where channels with higher activations have higher signals.

A weight is then given to each output per class by either attaching dense linear layers with softmax or by putting linear classifiers on the top of GAP. A heat-map is then created for each class as output images from the previous layer are employed in calculating their weighted sum.

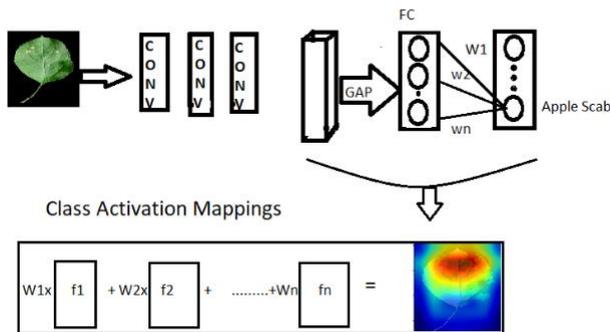
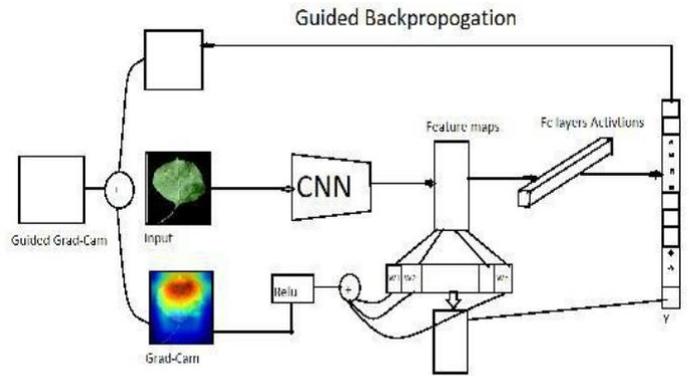


Fig.2 Architecture of CAM[7]

Fig.3 Architecture of Grad-Cam[8]

In any neural network vectors which are the partial derivative of the function $f(x)$ and are directed towards the greatest rate of increase of that function are called gradients. Based on this information flowing through a generic convolutional network, Grad-CAM uses class specific to produce localization maps of the significant regions of the image, making black box models more transparent, by displaying visualizations that support output predictions. In other words, Grad-CAM combines pixel space gradient visualization with class discriminative property. Here assumption are made that the final score as described below can always be calculated as a generalized linear combination of pooled average feature maps which depends on the following parameters: weights for a particular feature map, number of pixels in the activation map etc. Final feature map is a heat map for various channels with relation to the category. So it weighs every channel in the feature with the class gradient with respect to that channel and finds out its importance for that category. The average pooling over the two dimensions of the gradient of that particular class output with respect to one particular feature map tells us the importance of that feature map for that class which is then further multiplied with the feature map and its results are then pooled along the channel dimensions. Then a non linear ReLU transformation is used to normalize it to positive region predictions. And these spatial score defines the importance of that feature map to that class. The current pixel space visualization are combined with Grad-CAM to obtain high resolution class discriminative visualization called Guided Grad-CAM. In this backward RELU pass is modified to pass only positive gradients which improves backpropagation's ability to localize even the smaller objects. This makes it perfect for this project as the guided backpropagation algorithm helps obtain coarse localization of the diseases on plant leaves. But it does have some drawbacks like it cannot localize the multiple instances of same class. This means that if there is more than one region where same disease is present then Grad-Cam will not be able to localize it. Other disadvantage is that continuously upsampling and downsampling might lead to loss in signal



B) Grad-Cam

C). Grad-Cam++

Improvement over the disadvantages of Grad-Cam were made in Grad-Cam++ as it can perform a better localization multiple instances of same class in a single frame. Its ability to localize scattered instances is especially helpful for multi label classification. Unlike Grad-cam, Grad-Cam++ gives different weightage to each pixel according to their importance in the gradient feature map. Grad-Cam++ is a generalization of Grad-Cam. The weights of Grad-Cam++ is shown as follows[9]

$$w_c^k = \left(\sum_i \sum_j \frac{\partial^2 Y^c}{(\partial A_{i,j}^k)^2} \right) / \left(2 \left(\frac{\partial^2 Y^c}{(\partial A_{i,j}^k)^2} \right) + \sum_a \sum_b A_{a,b}^{k,c} \left(\frac{\partial^3 Y^c}{(\partial A_{i,j}^k)^3} \right) \right) \left(\text{relu} \left(\frac{\partial Y^c}{\partial A_{i,j}^k} \right) \right)$$

But there is an assumption made that score of particular class must be a smooth function and so, the differentiable exponential function is passed through the penultimate layer. The higher order derivatives are ignored and saliency maps act as a linear combination with RELU forward activations. Saliency maps after up-sampling are multiplied point-wise with pixel visualization which is produced by guided back propagation which further leads to the generation of class-discriminative saliency maps. Using weighted combination of gradients Grad-CAM++ generates the best salience map. All these advantages of Grad-Cam++ makes it the best approach to localize different diseases and even the same diseases but at different places in the same frame. So to overview these three methods with their computing expressions

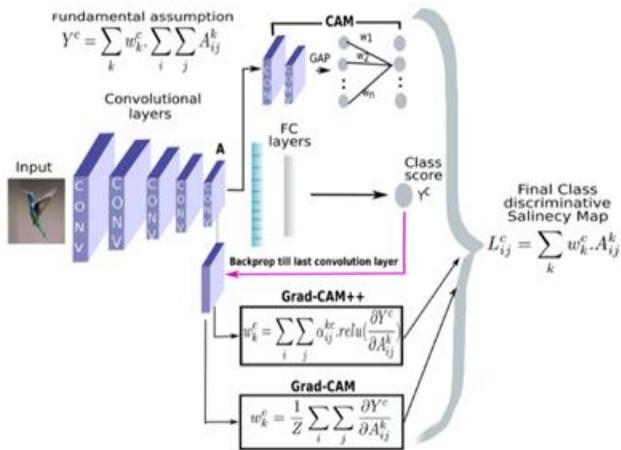


Fig.4 An overview of CAM, Grad-CAM and Grad-CAM++[9]

IV. EXPERIMENT RESULTS

The first step of our project is data collection. After collecting the data we used some preprocessing techniques then the data was trained on various deep learning models and the results were compared after that we used various localization techniques called CAM and Grad-Cam .

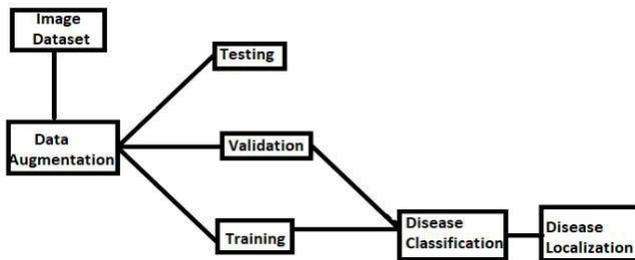


Fig.5 Overview of the system

D) Data Collection

We have used the Plantvillage for training our models. We used one plant category of apple .Within the plant village dataset there are a total of 1902 images of apple in each of the three formats called color, segmented, grayscale. And a total of 5706 images.Three diseases of apple were considered called as apple scab , cedar rust and back rot. Here 987 images of healthy plant leaves,378 of scab ,372 of black rot and 165 of apple cedar rust were available .So it can be seen that the dataset was imbalanced. In order to avoid using all the unnecessary information which could lead to model getting some bias in data segmented image parts of the leaves are used. Plantvillage dataset was collected using regularized technique. A script was used for automatically obtaining the Segented images. Colors, Saturation components (in various color spaces) from various sections of the image and lightness were analyzed to produce a group of masks. These masks were then used for segmentation. We were also able to fix the color casts which was very strong in some of the images of the collection and this helped us to remove a potential bias. We have used the Plantvillage for training our models. We used one plant

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Fig.6 Images of Applescab in three forms called color,grayscale and segmented

E Image Preprocessing.

The Plantvillage dataset contains images of different diseases in varying amounts. This makes it imbalanced. This imbalanced dataset leads to overfitting in any model. According to machine learning whenever a model explains random noise instead of underlying relationship it introduces overfitting. [12].There are many solutions to overcome this problem like upsampling , undersampling. We have used image augmentation technique to deal with this problem [13].Here we first compared the number of images available for each class and then we generated more images by applying 3 kinds of transformations on the images of the minority class. Here the image on which transformation was to be applied was selected randomly and the transformation to be applied was also selected randomly. The transformations applied were random noise, horizontal flip and random rotation .

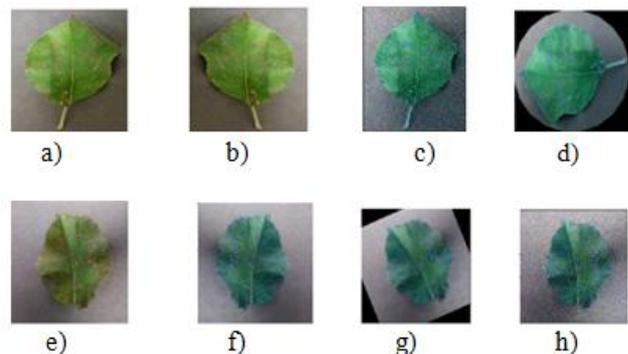


Fig.7 Image with different augmented techniques applied on it and its result a)Leaf1:- Original image

b)Leaf1:Flipped image c)Leaf1:- Rotated image
d)Leaf1:-imagewith noise e)Leaf2:-Original
image f)Leaf2:-Flippedimage g)Leaf2:-Rotated
image h)Leaf2:-image with
noise

In recent years CNNs have been able to get massive success in recognising and classifying images [14] [15] [16] [17] [18]. Before CNN, features were obtained using hand engineering and then these features were used to classify images using learning algorithms. Some examples of these feature extractors are SIFT[19],HoG[20]. Then came, AlexNet[14] which was able to perform supervised learning using DCNN structure for classification of images with more than one classes, and left behind other approaches of using hand-engineering to obtain features by a large measure. And due to the removal of the tedious work of extracting features and their generalization they have

become the best method for computationally inferring disease on plant.

So we used DCNN called Efficientnet [10] for classification task The main advantage of Efficient Net is that it is smaller as compared to other models which gave same accuracy on image net data. For insatnce, the ResNet50 underperforms the EfficientNet even though ResNet50 has 23,534,592 parameters .On the other hand EfficientNet has only 5,330,564 parameters. Its main building block is mobile , combined with inverted bottleneck MBConv. By directly using connections between bottlenecks that joins a less number of channels than expanding layer depth wise seperated convolution that efficiently decreases calculations by a factor of k^2 , than the earlier models.Here kernel size is represented by k, which tells the height and width of the 2D window.

Table 1:- Mean F1 score across various experimentconfigurations . Each cell in the table represents the Mean F1 score,mean precision, mean recall for the corresponding experimental configuration.

		Efficientnet			Reset		
		F1-Score	precision	Recall	F1-Score	Precision	Recall
Train:-20%	Grayscale	0.745	0.78	0.74	0.67	0.7875	0.6975
	Color	0.8675	0.89	0.8	0.72	0.807	0.72
Test:-80%	Segmented	0.8225	0.86	0.83	0.74	0.8275	0.7675
Train :-40%	Grayscale	0.79	0.81	0.8	0.63	0.7625	0.69
	Color	0.8025	0.87	0.805	0.68	0.7125	0.685
Test:-60%	Segmented	0.835	0.865	0.84	0.46	0.7075	0.5375
Train:-50%	Grayscale	0.7525	0.76	0.765	0.7	0.827	0.7175
	Color	0.8225	0.8725	0.8375	0.75	0.8	0.76
Test:-50%	Segmented	0.84	0.8875	0.84	0.64	0.665	0.665
Train:-60%	Grayscale	0.8	0.815	0.8125	0.81	0.8275	0.8275
	Color	0.795	0.825	0.82	0.77	0.865	0.7725
Test:-40%	Segmented	0.74	0.845	0.75	0.705	0.7675	0.735
Train:-80%	Grayscale	0.7	0.725	0.725	0.705	0.7675	0.735
	Color	0.835	0.875	0.8375	0.78	0.8175	0.8
Test:-20%	Segmented	0.8475	0.88	0.8525	0.74	0.805	0.74

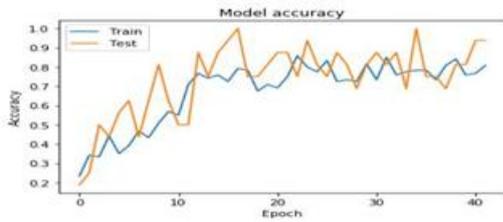


Fig.8 History of training Efficientnet with 60% training data and 40% testing data contains colored images accuracy

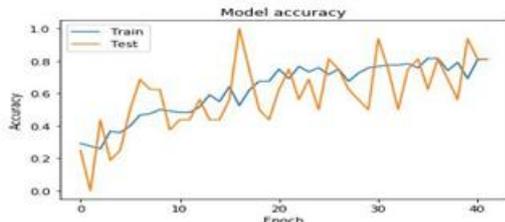


Fig.9 History of training Resnet with 60% training data and 40% testing data contains colored image Model accuracy

g)DISEASE LOCALIZATION

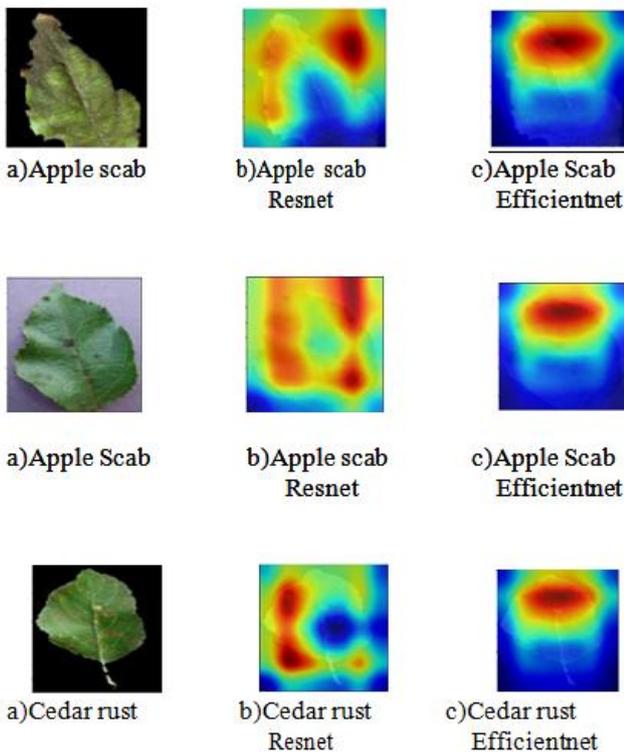


Fig.10 Shows the image of the leaf with plant and the othertwo images show how Grad-Cam was able to localize them after being attached to Resnet and Efficientnet

V. CONCLUSION

Protecting a crop from diseases is not a simple task. And knowledge of the pests, pathogens and detecting them plays an important part in protecting them from diseases. We have tried to make a specialized deep learning model to classify and localize diseases. The classification of different type of plant diseases by our proposed method is shown by our experimental results and comparisons. And our comparison

between Grad-CAMs of two separate models show how both of them are able to localize these diseases. And the main advantage of this model is that the huge dataset did not have to be separately annotated with bounding boxes to localize the diseases. And this is the main reason that this approach in future can also be used for annotating huge datasets using categorical data. By making the visualizing techniques these activation maps might also be used as segmented masks for computer vision tasks like Semantic segmentation. As it can make the process of masking automatic rather than manual. We hope that our proposed system will be able to contribute to the field of agriculture

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