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An Improved Deep Learning Model for Plant Disease Detection

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***Abstract:** In current era, Deep Convolution Neural Networks (DCNNs) are desperately improved localization, identification and detection of objects. Recent days, Big data is evolved which leads huge data generation through modern tools like surveillance video cameras. In this paper, we have focused on plant data images in agricultural field. Agriculture is one of major living source in India. To increase the yield by preventing diseases and detection of diseases place major role in agriculture domain. By using Improved and customized DCNN model (improved-detect), We trained plantdoc and plant village datasets. Mainly we used Tomato, Corn and potato plant for model training and testing. we have experimented on plant image data set-tomato leaves both healthy and diseased ones. Experimental results are compared with state of the architectures like Mobile Net, Dark Net-19, ResNet-101and proposed model out PERFORMS in location and detection of plant diseases. obtains best results in computation and accuracy. In the below results sections, we have presented the results with suitable models.*

***Index Terms:** Deep Learning, Single shot detection, Residual blocks, Improved-yolo, object localization, object detection*

I. INTRODUCTION

Plants act as an important resource for everyone in terms of food. So it is very important to notice that the plants are not affected by any diseases. If disease occurs, then it is very necessary to detect plant diseases in the early stage. There exist many models that help in detecting and classifying plant diseases.

In Recent days, Machine learning is a great way to detect diseases. It is nothing but it will give the computers the ability to learn without explicitly programmed. There exist many models in machine learning to detect plant diseases. Some of them are K-means, KNN for classifying the leaves are healthy or diseased. Later on, there is advancement in the field of machine learning which results in the evolution of deep learning. Deep learning algorithms are learning the features from input images during training stage and exhibit results with suitable metrics. The working of deep learning is as follows. Actually, in deep learning the information is passed through some layers. The output of the previous layer is given as input to the next layer. It passes the learned features from one layer to next layers using activation functions till the output layer produces the desired outcomes.

The following sections describes recent works on plant disease classification and detection with advantages and disadvantages.

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II. PROPOSED METHODOLOGY

Basically, the proposed network is trained for object classification which is used for monitoring working condition of pin insulators [1] [1] Uses convolution neural network with plant village dataset. The overall accuracy obtained here is 85.3 percent. The drawback of this method is taking more training time. And also currently constrained to the classification of single leaves, facing up, on a homogeneous background. When tested on a set of images taken under conditions different from the images used for training, the model's accuracy is reduced substantially.[2] They combined meta-architectures like R-CNN and SSD with deep feature extractors and the challenging part of their approach is due to the lacking number of samples, some classes with high pattern variation tend to be confused with others which resulting in false positives or lower average precision.[3] Uses CNN approach; the main drawback was that the entire photographic material included solely images in experimental setups but not in real conditions in the cultivation field. Another important issue that should be noted and should be resolved is that the testing dataset used for the assessment of the models and part of the same database that constituted the training set.[4] The images used to train and evaluate the models are with different resolutions like quality, focus and brightness as they are captured with mobile phones having different cameras through a participatory sensing approach. They used the application of single shot detection in tea leaves that helps in reducing the disease and pest detection time through automation. From the results, it can also be realized that only classification cannot reliably help when there are occurrences of multiple pest and also disease conditions in a single image.[5] Uses deep learning CNN Approach with dataset images of apple leaf disease which consists of the images taken under field conditions and also it consists of laboratory images. Accuracy performance limited to 78.80. [6]

Uses a method to improve the accuracy and to reduce the parameters on googlenet and cifar-10 models are proposed to detect the diseases in plant. The activation function used over here is ReLU. The googlenet achieves accuracy of 98.9 and the cifar model achieves an average accuracy of 98.9. They used the data set with less existing images and augmented data set with rotation and flip operations. In total their dataset consists of 3060 images in that 80 percent were used for training and 20 percent is used for testing.

Used more pooling operations which leads to the increasing of accuracy. [7] Uses deep learning model to detect diseases. Data set Images from plant village dataset was used. Two different deep learning architectures are used namely AlexNet and SqueezeNet. Ten different classes along with the healthy images are used for training. In their work, AlexNet performed with accuracy 0.9722 when training from scratch, segmented images, and 80 training and 20 testing. Using GPU, the trained models are tested. Based on the results the conclusion is that AlexNet performed slightly better than SqueezeNet because the SqueezeNet is smaller than the AlexNet.[8]Uses single neural network for detecting the objects. During predictions their network will generate the scores. In SSD the size of the images is 300x300 and 512x512.

For the image 300x300 the SSD achieves 74.3 Map and for 512x512 it achieves 76.9 mAP. The method produces good accuracy than other one stage detectors.[9] Uses deep learning-based approach that helps in classifying the tomato leaf diseases. The diseases are early blight, downy mildew and powdery mildew. The dataset consists of the images taken from the nursery, plant village and farm. The training and testing were implemented in Torch7 machine learning framework. They have proven that the model will provide accuracy with minimum computational effort. [10] Uses deep convolutional neural network. They have used dataset consists of 30880 images for training and 2589 for validation taken from various internet resources. After the 100th training of iteration they have achieved the accuracy of 96.3. The drawback of this methodology is taken more time for training.[11] Uses a method for rice disease identification method based on deep convolutional neural network technique. They have used the dataset which consists of both healthy and diseased leaves. The total number of images present in that dataset is 500. CNN is trained to identify the diseases. The CNN has achieved an accuracy of 95.48. Used model has high convcalergence rate along with better recognition of diseases. But only the drawback they have encountered is that the images in the dataset are very less.

A. DATASET

Two data sets are used in this model, one is Plantdoc dataset has 2569 images with 13 plant species and 30 classes which are both healthy and diseased categories. Data set is published by IIT which contains 8851 labels are experimented. Second one is Plant village dataset. It contains 54309 labelled images for 14 different crops. Images of tomato leaves are used in this work. Along with healthy leaves there exist 10 different classes. We experimented with three variant diseases.

B. Recent advancements in object detection

YOLO(You Only Look Once) is an algorithm which is used for detecting objects of various sizes. This model takes image as an input and it will be passed in neural network and then we will get the bounding boxes in the output. Here, the bounding box helps in locating the objects. In the advancements of YOLO we will have versions like v1,v2,v3. Mainly, darknet is used to train the neural networks.

In the past years, the object detection was done by the process is called sliding window. In this, sliding window over the image in step-wise until it reaches last portion of image, once the process is completes again the size of the window was increased and then again sliding process will be taken place for better detection. Also, there are various methods which are used for object detection like R-CNN and Fast R-CNN. The process involved in this is, firstly by using regional proposal method we will generate bounding boxes after that the second step is to use the classifier on those boxes. Finally, the third step is to remove the duplicates. The drawback of this method is taking more processing time and chances of occurring false positives are more so that to overcome all these problems YOLO was coming into existence. YOLO treats the problem of detection as regression problem and not as classification problem. And it uses convolutional layers for all the tasks which are done in Fast R-CNN and R-CNN. **YOLO Version1 (YOLO V1)** is evaluated on the Pascal voc dataset. It consists of 2 fully connected layers along with the 24 convolutional layers. To produce the probabilities of each label. The first 20 convolutional layers followed by pooling layer and a fully connected layer is trained on the ImageNet of 1000 class classification dataset. The resolution of each image is 224x224. And 2 fully connected layers along with the 4 convolutional layers which are present in the last are used for object detection. The resolution of the dataset was changed to 448x448 for better detection of the objects. The drawbacks of yolo v1 is encounter the background errors (false positives) and also it finds difficult to localize small objects.**YOLO Version 2 (yolo v2)** is faster and better. The variation in this model is, firstly, Batch normalization is done which is used to decrease the problem of over-fitting and also helps in improving the stability of the neural network. Secondly, high resolution classifier it means that the input size of the image is increased from 224x224 to 448x448 which helps in increasing the mean average precision.Anchor boxes is another thing which makes v1 differ from the v2. YOLO v2 uses dark net-19 architecture. It contains 19 convolutional layers, 5 max pooling layers and a softmax layer. Even though it has many improvements which makes separate from YOLO V1. Still the yolo v2 is producing less accuracy. To improve the accuracy, not only in salient object detection, this model focusing on smaller object detection in plant images.

III. PROPOSED APPROACH

In this model. we consider an input image 416X416 with seventy-five layers design of Improved-detect with three residual blocks. Mainly it uses the features from yolo v2 and extending to residual units for up sampling process. Improved-Detect model results in good accuracy. The features which made Improved-detect is different from other models is improved bounding box score. One special feature in Improved-detect is it uses darknet-53 network which is having 53 convolutional layers. Darknet-53 composes of 3x3 and 1x1 filters. YOLO V2 lacks in incorporating important features like residual blocks and skip connections.

So these all are presented in the Improved-detect (Improved

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YOLO). It uses 9 anchor boxes generated by using the K-means clustering algorithm. There are many layers added to the base network thus making Improved-YOLO as a 75 layered architecture. The process performed in three levels. At first level, the image is down sampled by the network till 81 layers with a stride 32. Then the image size becomes 13x13x255 from 416x416. One detection is made at this level.

After this the feature map from one layer is connected to the another convolutional layer and then it is up sampled resulting into 26x26 feature map. Then this feature map is concatenated with the feature map from layer 61. This concatenated feature map is passed through the 1x1 convolutional layer and at this layer the feature map which is obtained is used for detection. In this process the detection at different scales are performed.

Mainly, it uses Residual blocks carry the flow of information from the initial layer to last layer. Skip connections are presented over here. In Improved yolo has more layers and it is going deeper and deeper. So to avoid this complexity using skip connections in layered architecture. The advantages in Improved yolo are the localization errors are decreased. Detection at different scales are improved as well as it has very good accuracy and complexity is also very less. Detail process showed in figure1.

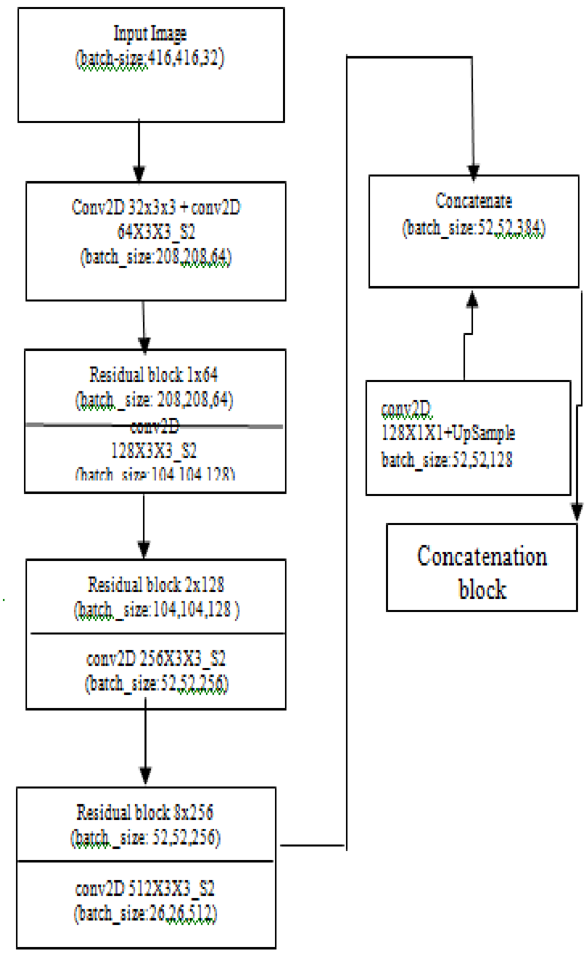


Figure1: Proposed Architecture

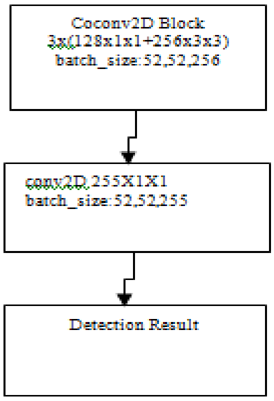
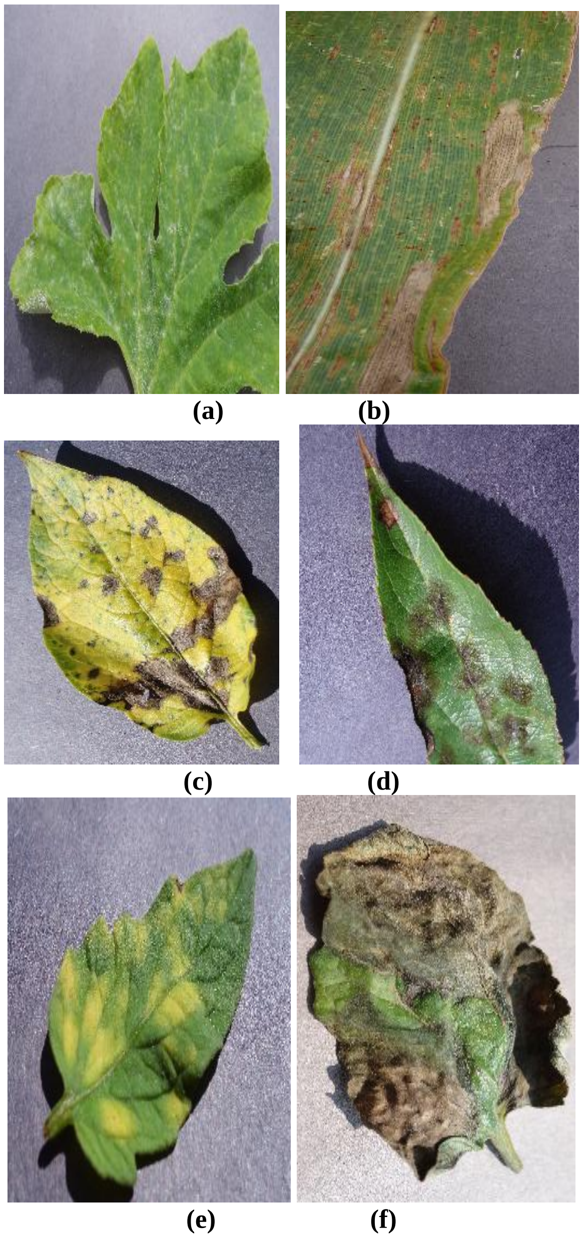


Figure 2: Concatenation block to Figure1

IV. SAMPLE IMAGES OF DATA SET

In this model, we trained the plant images of tomato,potato,corn with diseases.



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(g) (h)

Figure2(a)-(c)SquashMildew,corn_blight,PotatoEarly figure2(d)-(f)Apple_Scab,TomatoMold and TomatoLate, Figure2(g)-(h)TtomatoEarly and tomato mosaic

V. EXPERIMENTAL RESULTS AND DISCUSSION

A. Feature Extraction And Classification

To perform image classification there exists various deep learning architectures. These classification models are evaluated in terms of accuracy and parameters. We have chosen MobileNet, Inception v2 and ResNet -101 for feature extraction as they are having different architectures. In this they have evaluated the accuracy of backbone networks for classification of different health conditions of a plant.The proposed model uses darknet-53 produces high accuracy in various conditions.

Table1: Feature extraction and classification metrics

DarkNet-19	74.1	15.7
MobileNet	71.1	3.3
Inception v2	73.9	10.17
ResNet-101	76.4	4.60
Proposed model	99.10	61.5

The metrics which are used to evaluate classification and localization performance are mAP and IOU. IOU is used to measure the accuracy of the object detector on dataset. Intersection Over Union (IOU) can be defined as,

$$\text{IOU} = \frac{\mathit{Area\ of\ overlap}}{\mathit{Area\ of\ union}}$$

In the above equation area of overlap is defined as the intersection between the ground truth bounding box and the predicted bounding box. Area of union is defined as the area which is enclosed by both the ground truth bounding box and the predicting bounding box.

Mean Average Precision (mAP) is used to decide whether the predicted object is correct or not. It is also a most common evaluation metric. After computing the threshold for IOU between the ground truth and anchor for that result the detection will be marked as correct or incorrect. The precision recall curve is computed after getting the true positive and false positive values.

$$\text{mAP} = \frac{1}{N}\sum_{r=0}^{1}(\max(p(\bar{r})))\ \textit{such that,}\ \bar{r} \geq r$$

where p is precision and r is recall.

Table2: Acuracy and inference time for detection

Model	mAP	mAP 50	mAP 75	Time (ms)
DarkNet-19	46.6	68.4	46.4	102
MobileNet	48.9	68.4	45.6	87
Inception v2	56.7	81.6	58.3	230
ResNet-101	58.4	82.7	61.1	310
Proposed Model	69.3	84.1	98.5	110

From the above table1 and 2 shows the comparison of existing models with the proposed model and proved the proposed model is more accurate in localization as well as classification. It is very fastest compared to YOLOV2. The proposed model can detect the diseases in various conditions. This study can also be extended to find the diseases occur in other plants.

VI. CONCLUSION

There are many deep learning models that were developed in this project based on CNN for detection of diseases. The database used over here is an open database which consists of 56878 images which are taken under in both laboratory and real conditions. The dataset comprises of 13 plant species with 30 distinct classes. Darknet-53 is the most successful architecture which was achieved 99.10 of success rate in the classification. Based on this performance we can clearly state that the CNN is highly suitable for detection and diagnosis of plant diseases.

Mainly, in tomato, corn and potato plants the detection rate very high compared to other architectures. Despite the success rate of the model there are some drawbacks like when the database is expanding the time taken to train the images with variant disease type of images. Further, expanding the model to improve accuracy, data augmentation is required for huge expansion of data set of images.

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