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Automated identification of plant disease using deep learning

Kazi Riad UDDIN[1,*], Md Habib KHAN[1], Mohammad Mizanur RAHMAN[2], Arafath Al FAHIM[1]

[1]Chittagong University of Engineering & Technology, Faculty of Mechanical, Department of Mechatronics & Industrial Engineering, Chattogram/BANGLADESH
[2]Chittagong University of Engineering & Technology, Faculty of Mechanical, Department of Mechanical Engineering, Chattogram/BANGLADESH

[*]Corresponding author: u1509011@student.cuet.ac.bd
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Abstract

The preliminary identification of plant diseases plays a predominant role in preventing loss of production. The laboratory identification process of plant diseases is time-consuming and could not be conducted in the countryside, where experiment facilities are rarely found. This paper shows a deep learning approach to confine the infection area and identify the diseases by using images of their leaves. Deep learning works well with large amounts of data. So we can increase the accuracy and reduce the loss by engrossing a plethora of data. However, it will not increase the efficiency of the models. In this paper, we use several cutting-edge deep learning models, such as MobileNet, ResNet, and EfficientNet, along with Faster R-CNN and SSD on a small dataset. The dataset contains 2366 images of 27 types. The dataset was taken in a real environment. The data augmentation technique cannot be used with a small dataset. All state-of-the-art deep learning model are trained as a baseline to work on the efficiency of the models. We experiment with the best performer for computation cost. So, to increase the efficiency of the model we implement cyclic learning rate which performs 53.81% map@.50 on best performer EfficientDet. It also lessens the variance, which suggests that cyclic learning not only works as a learning rate but also functions as a data augmentation. In the future, we will apply this learning rate to a dataset containing a large number of plant disease collection images, where different types of data augmentation can be used to not only increase the images but also decrease the generalization loss. Farmers can predict plant diseases more accurately using this system.

Keywords: PlantDoc, Deep learning, Convolution neural network, Cyclic learning rate

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1. Introduction

The main strength of our country's economy is coming from the agricultural sector. The farm sector share is 12.68 percent in 2019-20 and employment in the farming sector is 37.75 percent in 2020 (The Global Economy,2019). Every year, the loss of plant production occurs. It is estimated that 4-14% of rice yield in Bangladesh is lost every year to different insect pests (The Global Economy, 2021). Farmers do not have adequate knowledge to detect the early stages of the disease of the plant. Experts in this field are required for this, which is a rare occurrence. For detection, experiments are carried out in the laboratory, which is prolonged. Alternatively, the plant's disease symptoms can be seen by visualization which is more feasible and not as prolonged. Deep learning is the most effective approach for this. Deep learning is a sort of machine learning and artificial intelligence that is essentially a deep neural network with three or more layers that mimics how people acquire information. Neural networks are layers of nodes, similar to how neurons make up the human brain. Individual layer nodes are linked to nodes in neighboring layers. Depending on how many layers the network contains, it is said to be deeper. The information that neural networks carry could be texts or images. Images are divided into pixels, where pixels contain information about the images. A deep learning technique known as a convolutional neural network (CNN) is used to deal with images, extracting valuable information from these pixels. CNN is the best approach (Russakovsky et al., 2015) for finding valuable information from the images without any human involvement, which can be used for identification as this information are labeled by human according to the respective class. Since plant diseases can be identified by symptoms on the leaf, images of plant disease's leaf can be used for identification in the CNN technique. Deep learning research and applications in plant disease diagnosis (Amara et al., 2017; Cañizares et al., 2015; Jiang et al., 2019; Lu et al., 2017; Ramcharan et al., 2017; Rangarajan et al., 2018; Sibiya & Sumbwanyambe, 2019; Too et al., 2019; Türkoğlu & Hanbay, 2019) have become prevalent as a response to the object detection breakthrough facilitated by deep learning. The authors employed various types of state-of-the-art deep learning model on a vast amount of data. However, deep learning has a downside because it does not perform well in limited dataset. Furthermore, the data augmentation technique cannot be used when there are insufficient datasets. Accuracy and training loss are limited to a certain range.

To overcome these challenges, this study employs a recent deep learning approach to improve accuracy and reduce training loss using sparse data, as well as a new learning method known as cyclic learning rate (Smith, 2015). This study proves a method for determining the dynamic learning rates for neural network training that does not require doing a large number of tests to get the optimum values without further computation. It also helps reduce the difference between training loss and evaluation loss. In our approach, there are two stages. In the first stage, the models extract information from the image by using a convolutional neural network, and in the second stage, utilizing this information, the algorithm localizes the disease area by applying the Region Proposal Network. Employing all state-of-the-art deep learning model as a baseline, EfficientDet (Tan et al., 2020) outperforms them. We experiment two EfficientDet variants where EfficientD1 gives best results because of its high width and resolution. By applying cyclic learning rate to EfficientD0, it surpasses EfficientD0 and EfficientD1 without a cyclic learning rate by 5.39% and 1.21%, based on map@.50. It also performs second-lowest variance value for its ability of data augmentation characteristics. The main contribution of this study is that:

- Proposing a method for recognizing of plant diseases based on deep learning,
- Experimenting the state-of-art deep learning model i.e. ResNet, MobileNet, EfficientNet and their different versions with the small dataset for obtaining better architecture,
- Develop a more efficient system over small dataset without extra cost, and can be improved in future by using more dataset and different data augmentation techniques.

2. Material and Methods

2.1. Dataset

The datasets we use are obtained from PlantDoc (Singh et al., 2020) with real images. It has a total of 2366 images of 27 different types of plant diseases. The distribution of images according to class can be seen in Figure 1. Dividing the dataset into two parts: the training part and the testing part. The sample images are given in Figure 2. In this study, 90% of the whole dataset is used for training on around 2134 images, and 10% of the whole dataset is used for testing on around 232 images. The method of making test datasets is based on the k-fold. The class ratio of the diseases in the training and testing datasets is taken to be the same. There were no data augmentation techniques used because of the small dataset.

2.2. Methods

We divided our work into two parts. The method is showned in the Figure 3. In this figure, feature extractor and feature network are working as an extraction of image as well as serving the images into mult-scale. While in the detection head all information from the feature network is used in the deep neural network for prediction.

(i) To extract feature information:

The CNN (Convolutional Neural Network) is the best because it pulls features from the images without any human supervision and is computationally efficient to extract the image features. It learns the feature maps from the training, which are used to predict the test data. Some famous architectures, for instance, MobileNets (Howard et al., 2017), ResNet (He et al., 2015), and EfficientNet (Tan & Le, 2019), were used to detect the diseased plant's features. While implementing this architecture, we used TensorFlow Object Detection (TFOD). The images must go through pre-processing steps before they can be used in feature extraction. First of all, images have to be the same shape. So, we have used 416x416 shaped images. CNN handles the rest of the image processing. Any manual work is not done. This is the best part of the CNN, which improves the accuracy to extract more information from the images and also leads us to implement a more efficient deep learning model.

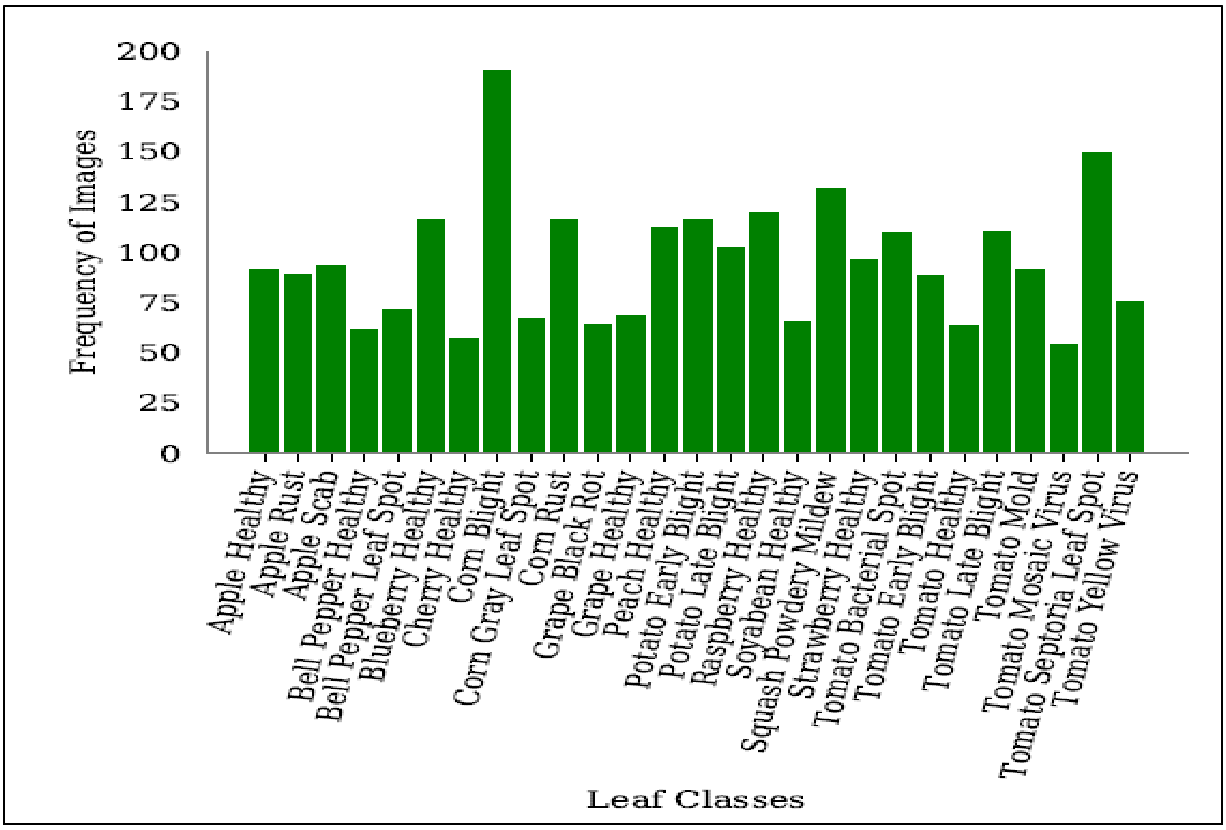


Figure 1. Distribution of the dataset

Figure 2. Sample images of the dataset

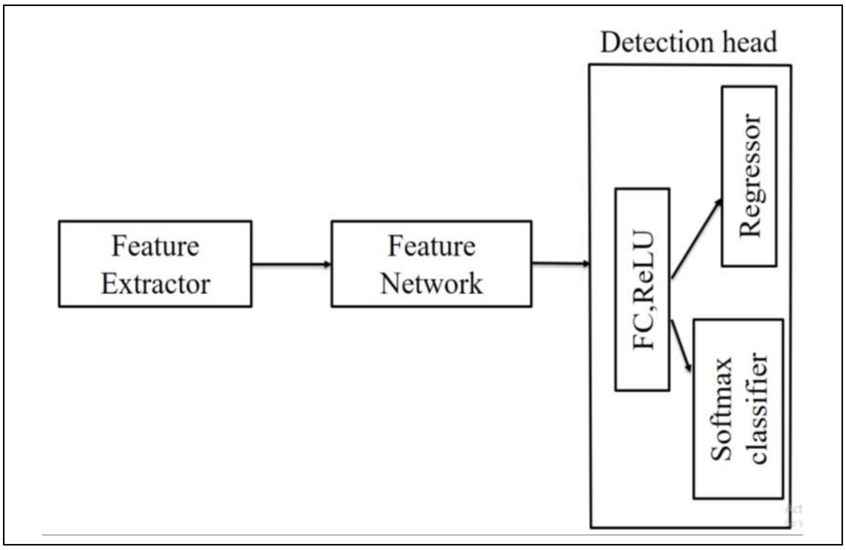


Figure 3. The basic model

(ii) To localize the diseased area:

We used these extraction features to localize the plants' diseased areas, and to make the features in the same scale, we used Faster R-CNN, SSD, and BiFPN. The Region Proposal Network (RPN) is used to estimate the class and location of object proposals that may contain a target candidate. The results from the feature extraction are multi-scale, where different types of information are acquired using feature maps. The RPN is used to generate the object proposals, including their level and recommendation. We extract the features from the object proposal with the RoI (region of interest) pooling layer and perform object classification and bounding box regression to obtain the estimated targets. By training the entire model as a baseline with the above dataset, we applied our proposed cyclic learning rate to the best deep learning model.

2.3. System configurations

Deep learning models require extensively using Graphics Processing Units (GPU) with CUDA threads activated. This work was done with 16 GB of GPU p100 and 32 GB of Random Access Memory performed on google platform.

3. Results

3.1. Training dataset with state-of-art deep learning model

The objective of this analysis is to compare the state-of-the-art deep learning model with this limited dataset to determine which model gives better performance. The metric for comparing the model's performance is mAP(mean Average Precision) and loss is used. For training the different types of state-of-the-art models, pretrained weights are used for initial training from the Coco dataset, which is taken from Google researchers. Due to a lack of resources, this practice weight is used to train the fast. Otherwise, it will take days, weeks, or more time to train the single model. In the previous studies (Singh et al., 2020), the authors used MobileNet and Inception-ResNet, whose mAP values are 32.8 and 38.9, respectively. Inception-ResNet performs well, but its drawback is that it takes a huge amount of time and a huge number of parameters.

In our approach, other deep learning models like ResNet50, ResNet101, EfficientDet and their different versions are used as an extraction of details from the images, while Faster RCNN is used in all of these models as a localization of the objects in the images. YOLO (You Look Only Once) is an effective real-time object recognition algorithm and is able to attain excellent precision. But we do not use it because it is only applicable to the training dataset, where the dataset should be more than 1000 per class. Comparing these state-of-the-art models, the EfficientD1 gives the best performance based on the mAP value.

Using other EfficientDet variants (EfficientD0-EfficientD7), accuracy can be increased, at the expense of memory size and computation cost. For localizing the objects, the SSD is used in the EfficientDet. The deep learning models SSD_MobileNet_v2 and Faster RCNN ResNet_50 are saturated in 50k steps, whereas other models are overfitted after their given steps in Table 1. EfficientDet outperforms all other models because of its architecture for dealing with the image information in Figure 4(a) and the cosine learning rate which is used is shown in Figure 4(b). It works on image features based on three parts. The parts are depth, width, and resolution. Going deeper in the neural network increases accuracy. We see that in Table 1, ResNet_101 transcends ResNet_50. It discovers more information in the image as a result of a deeper network. However, increasing the network's depth will not provide the required accuracy, and its progress will be halted at a certain point. By expanding the width and resolution along with the depth of the network, the predictions are improved. That's how EfficientDet works. So by increasing the depth, width, and resolution ratio, we can further escalate its improvement. For this reason, EfficientD1 exceeds EfficientD0's accuracy and has a lower loss value. But it engenders higher computation costs and memory loss because of the increased width, depth, and resolution. Without increasing computation costs or memory size, the focus was on improving accuracy and decreasing loss.

Table 1. Different model performances

Model	mAP@.50 IOU(%)	mAP@.75 IOU(%)	Training_loss	Evaluation_loss	Step
SSD_MobileNet_v2	28.39	18.40	0.9754	1.1140	50k
Faster_R-CNN_Resnet_50	43.40	33.72	0.4674	1.0250	50k
SSD_ResNet_101_v1	40.71	31.35	0.4020	1.0180	40k
SSD_ResNet_50_v1	42.37	33.31	0.3642	0.9314	36k
Faster_R-CNN_ResNet_101	45.18	35.52	0.2934	0.8303	34k
EfficientD0	48.42	35.19	0.4309	0.8148	43k
EfficientD1	52.60	37.25	0.3734	0.5752	35k
EfficientD0 (Cyclic learning rate)	53.81	37.62	0.2753	0.5004	35.5k

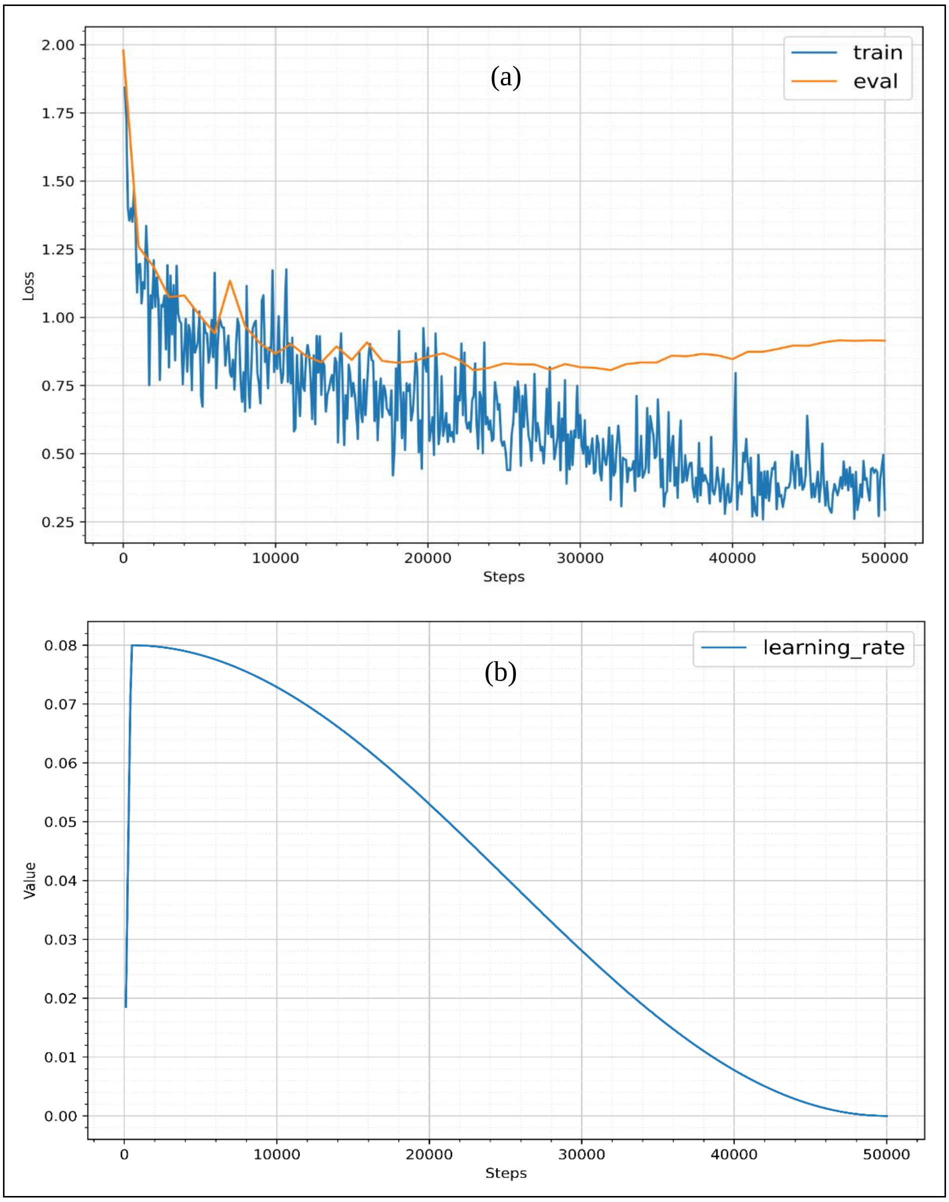


Figure 4. EfficientD0 (a) Training & evaluation loss, (b) Cosine learning rate

3.2. Modify the parameter to increase the efficiency of the deep learning model

Without increasing the memory size, computation cost, or parameters (weights and biases), the model accuracy can be increased by using data augmentation and increasing the training dataset. If the dataset does not meet the minimum dataset for data augmentation, it can not be used because it will overfit our model. A new strategy is used to increase the accuracy and efficiency of the model by introducing a new learning rate called the "cyclical learning rate" rather than using the traditional learning rate like the cosine decay learning rate (used as a base for comparing the model). In the cosine learning rate, the model training learning rate is small at first and then gradually increases to optimize the model's performance.

The cyclic learning rate in Figure 5(b) not only works as a gradient descent to reach to the optimum point of the loss but also works like data augmentation. Data augmentation jobs are to reduce the generalization loss (variance), which is the difference between the training and evaluation losses and this reflexes on the performance of the EfficientDet when the cyclic learning rate is used in Figure 5(a). In Table 2, the variance of the model can be seen where SSD_MobileNetV2 has a minimum variance but a huge loss value and a minimum mAP value in Table 1. Except the EfficientD0 with cyclic learning rate has minimum variance regarding all other deep learning model. The prediction of the images from the EfficientD0 with cyclic learning rate model are shown in the Figure 6.

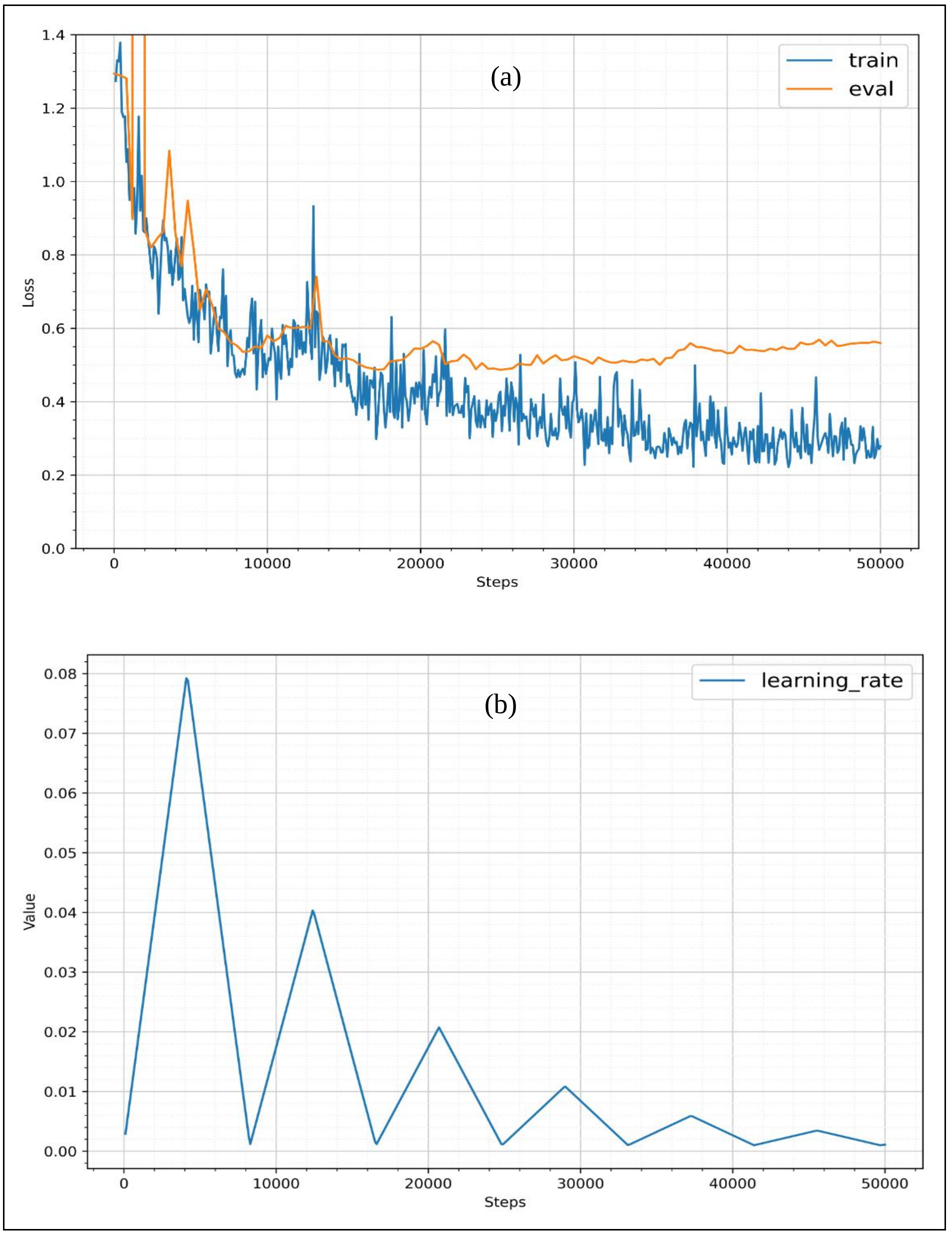
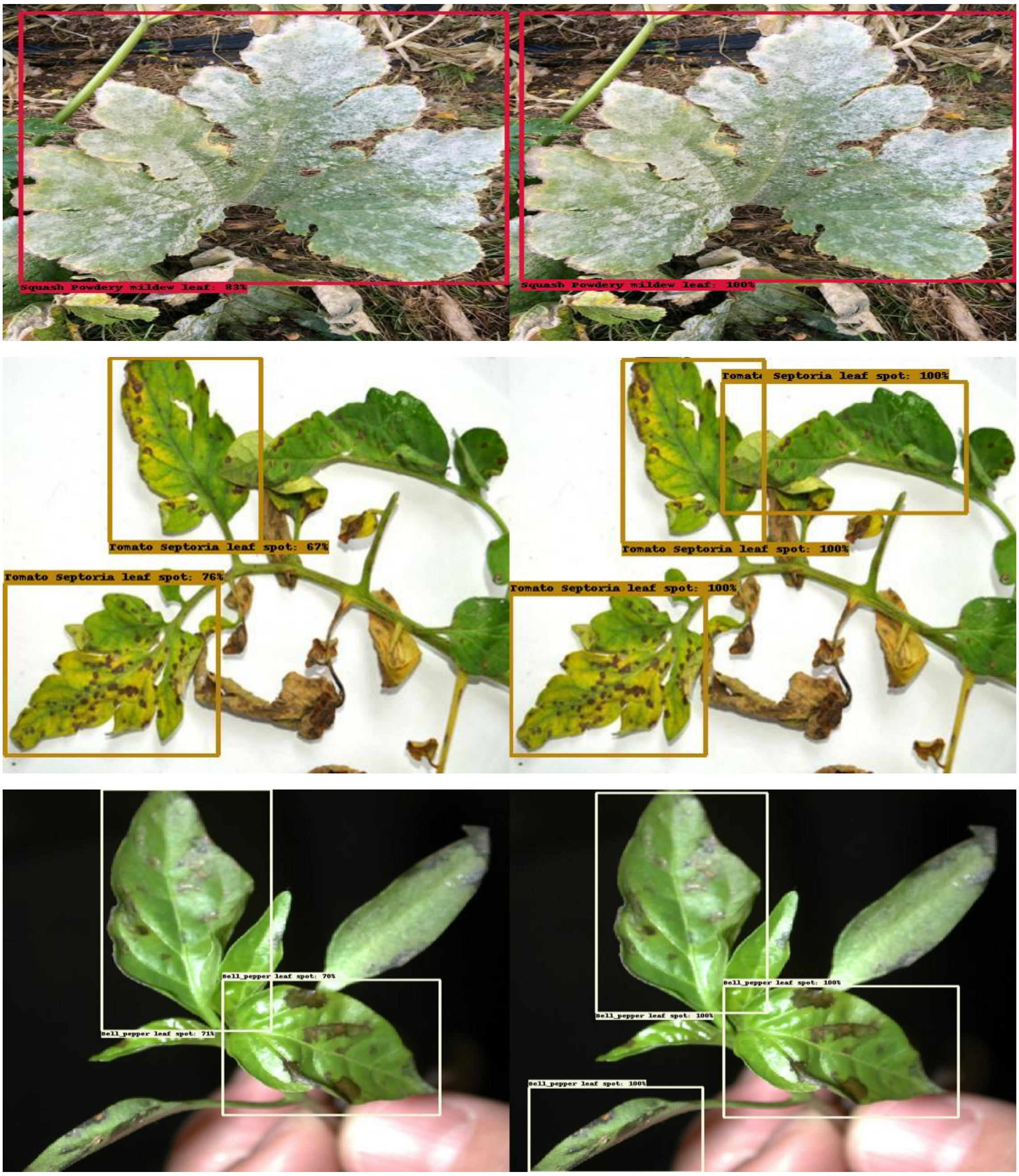


Figure 5. EfficientD0 with cyclic learning rate (a) Training & evaluation loss, (b) Learning rate



(a) Prediction (b) Original

Figure 6. Images from prediction of test data

Table 2. Comparison of models' variance

Model	Variance
SSD_MobileNet_v2	0.6160
Faster_R-CNN_Resnet_50	0.5672
SSD_ResNet_101_v1	0.5576
SSD_ResNet_50_v1	0.5369
Faster_R-CNN_ResNet_101	0.4309
EfficientD0	0.3839
EfficientD1	0.2251
SSD_MobileNet_v2	0.1386

4. Conclusion

In this study, we aim to detect plant diseases automatically based on improved CNN. This study utilizes some robust CNN architectures for extracting features that will be used to localize the areas with bounding boxes and classify them into different classes. Our plant dataset limited additional task involvement such as size, background alteration, and brightness enhancement-our ideas for our country's farmers to detect diseased areas in real-time under a variety of conditions. So we used real images. Our goal is to perceive a more appropriate and precise deep-learning architecture for recognizing various disease and pest categories, including multiplex situations, without using more computation. For that reason, we implement a cyclic learning rate on EfficientD0, which not only improves the loss and accuracy but also lessens the generalization loss without any computation costs. It also surpasses the updated EfficientD1, which should be better in terms of accuracy and loss. So in the future, we can enhance the model's efficiency by collecting more images per class. We did not use any data augmentation techniques. By applying data augmentation and accessing more images, the accuracy will be increased. We anticipate that our thesis work will make a remarkable contribution to the agriculture sector by providing more efficient automated disease detection in plants by localizing the infection area to the users with little knowledge of the plants they are farming.

5. Future Scope

The whole model is implemented on a limited dataset. Using a cyclic learning rate, we hope to improve the model's efficiency without incurring high computational costs. In the future, we could use this technique on a huge dataset and also employ data augmentation techniques to improve the accuracy of the model, which is not applicable to a limited dataset.

Conflict of interest

The authors declare that there is no conflict of interest.

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