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Investigation on Object Detection models for plant disease detection framework

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***Abstract*—Plant diseases are the most common and severe threat to precision agriculture. Therefore, identification and diagnosis of illnesses at a premature stage are vital. In addition, manual observation according to specific selection criteria is difficult and expensive. While various deep learning-based solutions have been proposed for this process, they usually suffer from lengthy training/testing times with massive datasets. In this paper, to address this problem, we explore the potential of computer vision-based object detection methods for early plant disease detection. A comparative study has been performed with three different benchmark object detection models YOLOv4, EfficientDet, Scaled-YOLOV4. The experimental results were evaluated with precision, recall, F1-score, and mean Average Precision (mAP) as performance metrics. All models are trained using the PlantVillage dataset. Empirical results show that the Scaled-YOLOv4 model is a well suitable object detection model providing a real-time solution in detecting even small infected regions of the plant leaves within less time duration.**

Therefore, detection and diagnosis of diseases at an early stage of infection are essential.

***Index Terms*—Biotic stress, Computer Vision, Object Detection, Plant disease**

I. Introduction

Plant diseases are the most severe threat to agriculture production, resulting in a high impact on developing countries economic growth. Traditional approaches for plant disease detection are time-consuming and labor-intensive. At present, Precision agriculture helps to detect and diagnose plant disease at an early stage, with less cost, time, and resources. In the past few years, image processing [1], machine learning [2], and computer vision [3] based applications are developed rapidly. Automatic disease detection techniques help to resolve agricultural issues successfully.

Initially, traditional approaches are used for plant disease classification. As referred in [4], symptoms are observed through a microscope by trained raters manually in a single shot. While performing this task, humans may lose keen observation within a short period. These difficulties are minimized to some extent by image processing techniques. In [5], the HSI color space method with segmentation to recognize the plant diseases is proposed. However, these approaches are more effective when the plants are at specific growth. Farmers need extensive subject expertise, finance, and resources to put these techniques into practice.

In addition, to reduce the degree of crop leaf injury, quantification is also considered a metric in different types of symptoms in diseased plant leaves. Through this viewpoint, [6], [7] are taken into consideration. Moreover, image acquisition also plays a vital role in better classification.

Recently, deep learning methods play a prominent role in plant disease detection. Specifically, Convolutional Neural Networks(CNN) are powerful to accomplish these tasks due to their advanced image processing capabilities [8]. In this work, we investigate various recent state-of-art object detection models for an effective automated plant leaf disease detection framework that overcome the drawbacks of the traditional systems.

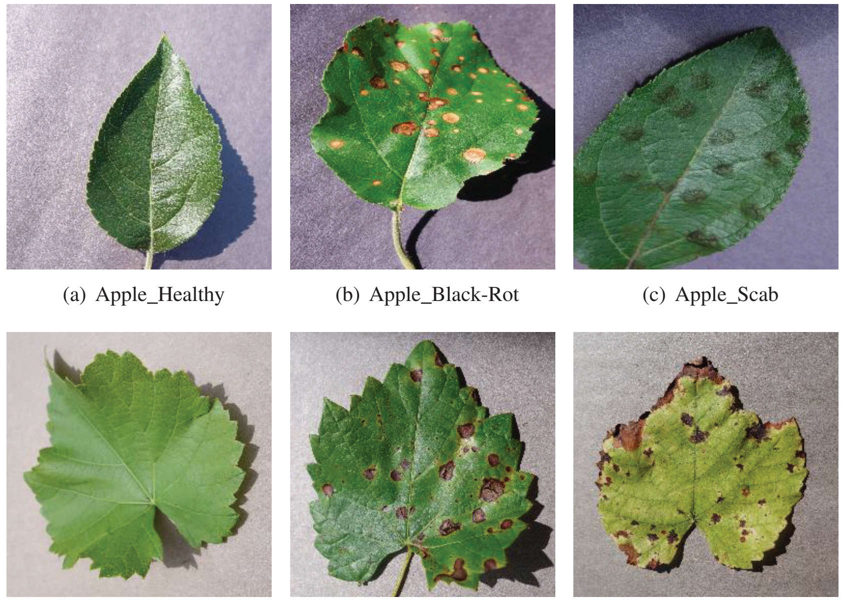
The paper is structured as follows: Section II presents the related works, and dataset details are described in section III. Section IV elaborates on the experimental result analysis and discussions. Finally, section V is dedicated to the conclusion along with the future scope.

II. Related Work

Object detection advancements in the field of deep learning open new solutions for precision agriculture. Object detection techniques are classified into one-step, and two-step approaches. One-step approach, predict the classification and localization of the whole image in only one instant. But in a two-step approach, first, the significant regions are generated, and then secondly, classification and localization are performed. One stage approach gives more speed compared to the two-step approach. The plant leaves datasets are well trained and fine-tuned to get precise results for accurate detection of the diseases.

In this line, initially, Convolutional Neural Network (CNN) are utilized for plant disease recognition tasks. This paper [9] employed five convolutional neural networks, namely AlexNet, AlexNetOWTBn, GoogleNet, Over feat, and VGG for plant disease classification using the plant village dataset. Liu et al. [10], AlexNet was used to diagnose four common apple leaf diseases: Mosaic, Rust, Brown, Spot, and Alternaria. With fine-tuning, the network was able to achieve an accuracy of 97.62%.

Zhang et al. [11] developed 3 channel Convolutional Neural Network (CNN) for cucumber disease recognition based on



(a) Apple_Healthy (b) Apple_Black-Rot (c) Apple_Scab

(d) Apple_Healthy (e) Apple_Black-Rot (f) Apple_Scab

Figure 1. Few sample instances of Healthy and Diseased leafy images

Table I
DATASET SUMMARY

Crop_Name	Disease_Category	Total_Samples	Label_Name
Apple	Apple_Scab	220	AAS
Apple	Apple _ Black-Rot	215	ABR
Apple	Apple_Healthy	150	AH
Grape	Grape_Leaf-blight	210	GLB
Grape	Grape_Black-Rot	225	GBR
Grape	Grape_Healthy	130	GH

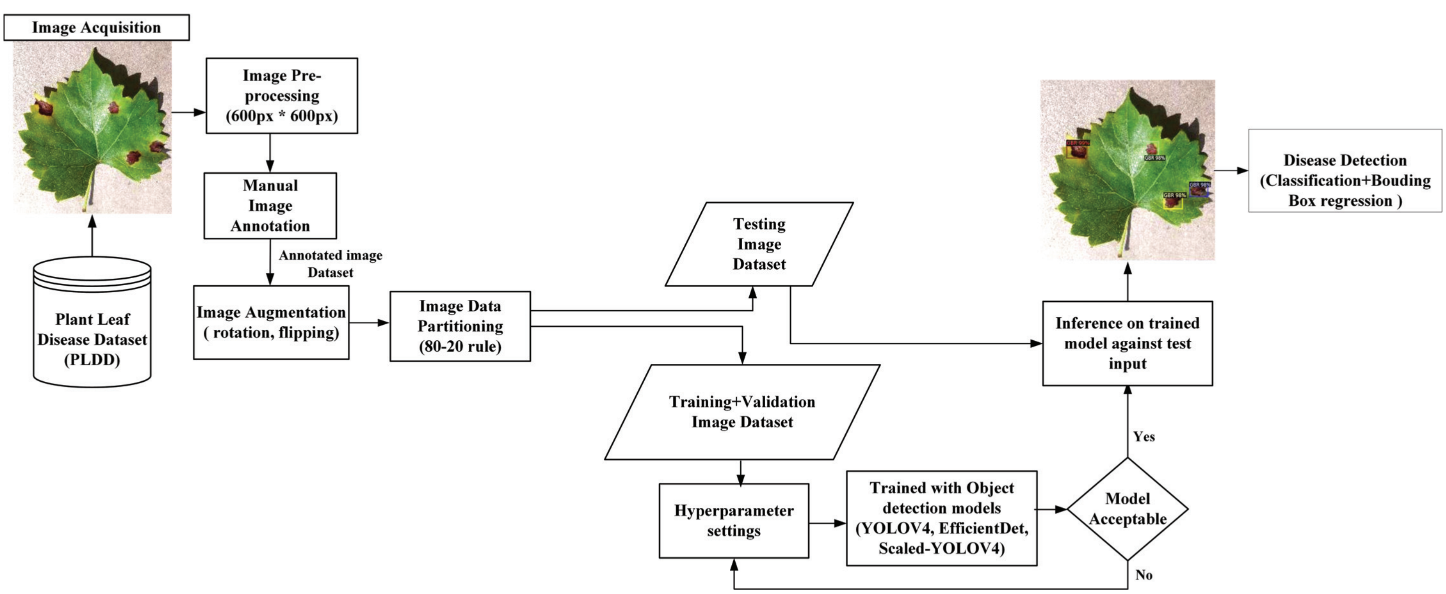


Figure 2. Visualization of Plant disease detection framework using Object detection models

color information on leaves images using the Plant village dataset and custom cucumber dataset. In [12], authors applied a transfer learning technique in CNN to detect mildew disease in pearl millet with an accuracy of 95%. Overall, extensive research has been conducted on deep learning algorithms for software-based agriculture products for plant disease classification. Existing approaches are focused on the classification of plant diseases. This article focus to see how well object detection algorithms are used as low-cost and accurate methods to design a framework for automatic plant disease detection.

III. Materials and Methods

A. Dataset Acquisition

The dataset used in our analysis is taken from the PlantVillage database available online [13]. The dataset contains 54,309 total images of fourteen distinct crop species with healthy and diseased labels. We consider two crop species from this archive, namely apple, guava. Few samples of plant disease combinations are shown in Fig. 1, and the details about the image dataset are given in Table I. Before training, all images are initially scaled to 256 x 256 dimensions and annotated, labeled manually. Image annotation is the technique of manually defining areas in an image and assigning labels to these regions. Several image annotation tools are available for this purpose. An open-source “LabelImg” tool is utilized by drawing the bounding box around the diseased portion of the image and labeled manually. These annotated leaf images are saved as XML files given as ground truth during the training process. The models are trained and tested using a total of 1,150 images of healthy and diseased leaves.

B. Overview of Object Detection Models

Object detection, which is a subset of computer vision, plays a significant role in this field of research. These techniques are currently the fastest approach to recognise and detect the disease lesions on the leaf effectively in real-time environments. It helps the farmers and agronomists to make timely decisions at an early stage of plant diseases. Therefore, highly accurate object detection models are required to accomplish these tasks. Fig. 2 shows the general pipeline of object detection models. This work compares three prominent object detection techniques, namely, YOLOv4, EfficientDet, Scaled-YOLOv4, in terms of speed and accuracy. A high-level description of each model is given below.

1) YOLOv4: YOLOv4 is a one-stage object detector from the You Only Look Once (YOLO) family. YOLOv4 is the recent object detection model introduced in the year 2020 [14]. Recently, various outstanding detection strategies based on the YOLOv3 have been integrated to enhance accuracy. In contrast to YOLOv3, which uses DarkNet53 as its backbone, YOLOv4 employs the cross-stage partial (CSP) structure as its backbone. CSPDarknet53 is a new backbone that can improve the convolution neural networks capability to extract in-depth features of the object. It also helps to reduce the calculations while boosting inference speed and accuracy. Over CSPDarknet53, the Spatial Pyramid Pooling (SPP) block enhances the receptive field and isolates the significant context features. Instead of the Feature Pyramid Networks (FPN), YOLOv4 utilized PANet for parameter accumulation at various detector levels. Another notable aspect of YOLOv4 is its ability to train on a single GPU. In addition, YOLOv4 used a novel activation self-regularised function called “mish”. It also introduced a new Mosaic data augmentation technique approach that combines four training images rather than just one image. Further, it uses a DropBlock regularization and CIoU loss for better convergence in speed and accuracy on Bounding box regression.

2) EfficientDet: EfficientDet follows one stage object detection paradigm. It is the most recent algorithm proposed by the Google research team [15]. It introduces the practical compound scaling approach that scales up the model width, depth, and resolution simultaneously in a systematic way. This technique helps to boost the accuracy of the model with limited computational resources. It is well suited to real-time image analysis with severe time and space restrictions. Based on compound scaling, seven versions of EfficientDet were obtained (D0-D7). Each version contains different EfficeintNet backbone versions (B0-B7). This architecture mainly contains three parts: Backbone network, BiFPN, Class/Box prediction network. In this work, the EfficientNet-B2 network act as a backbone network to extract the relevant features for EfficientDet-D2 Network. BiFPN network uses the optimal multi-scale feature fusion method results to improve the accuracy. It gives outstanding results compared to Feature Pyramid Network (FPN), PANNet, and NAS-FPN. Finally, all the fused features from the BiFPN network are passed to the Class/Box prediction network to make final predictions of the input plant diseased images, respectively.

3) Scaled-YOLOv4: This model is an efficient and advancement of one stage object detection network proposed by WongKinYiu and AlexyAB introduced in the year 2020 [16]. It is designed based on YOLOv4 architecture. Scaled-YOLOv4 authors used some scaling techniques to balance the model architecture in terms of image resolution, the number of channels, and the number of layers. These techniques help to increase the model performance and detection speed. The main difference in this architecture is YOLOv4; it follows CSPNet as the backbone network, also called YOLOv4-CSP. It is based on Cross stage partial method, which is suitable for small and large networks while ensuring the trade-off between speed and accuracy. Scaled-YOLOv4 follows a scaling approach, which changes the depth, width, and resolution and modifies the structure of the network. A few CSP-ized CNN backbones are considered, ResNet, ResNeXt, and the conventional Darknet backbone as part of the network design. CSP-ized means to use the concepts of Cross-Stage Partial Networks (CSP) propose by WongKinYiu [16]. The CSP is a novel method of designing convolutional neural networks that reduce the processing required for different CNN networks. Four distinct scaled versions are envisaged to train the YOLOV4 model, namely, YOLOv4-CSP, YOLOv4-P5, YOLOv4-P6, YOLOv4-P7. In this work, we choose the scale YOLOv4 model. i.e.,

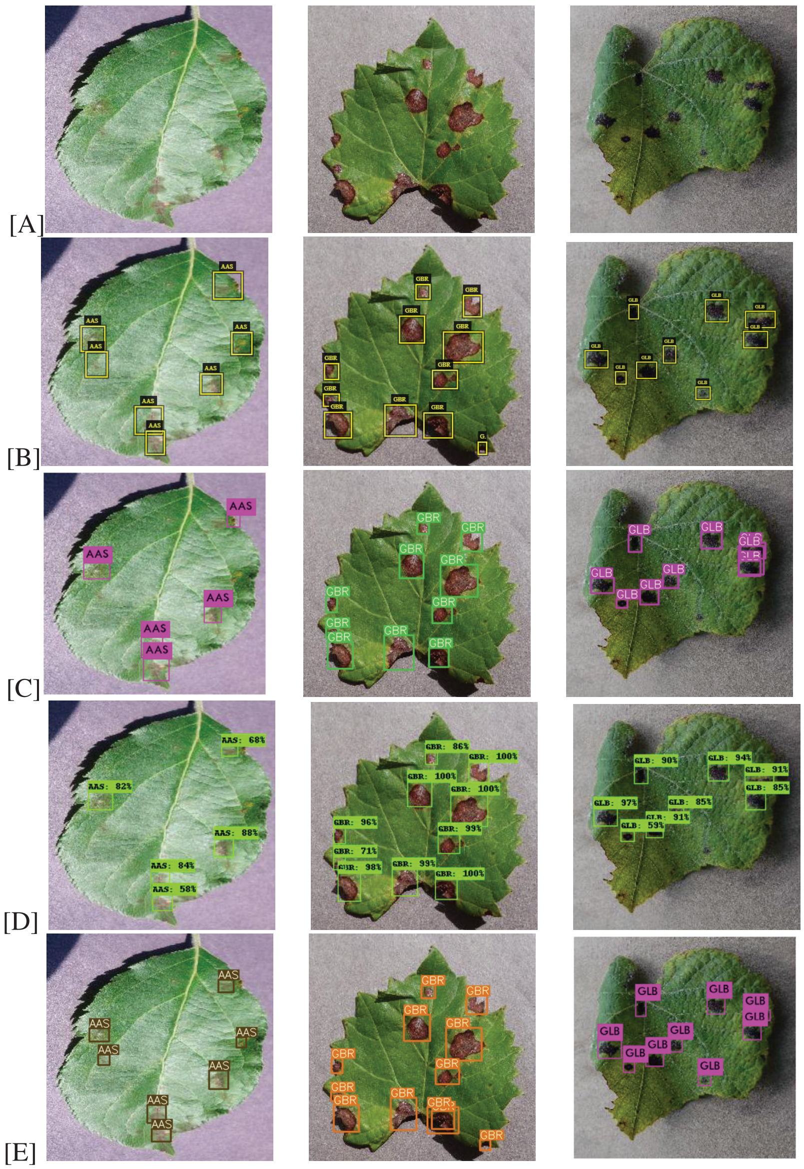


Figure 3. Comparison of state-of-art plant disease detection models: [A]- Original Image, [B]- Ground _Truth, [C]- YOLOv4, [D]- EfficientDet-D2, [E]- Scaled-YOLOv4

YOLOv4-CSP.

IV. Experimental results and analysis

All the frameworks are implemented using Pytorch 1.5.1, Python 3.7, and Open-cv 1.4.1 deep learning libraries. In this work, we consider the apple and grape crop diseases collected from the plant village dataset.

A. Performance measures

The following are the most frequent measures for evaluating model performance while dealing with object detection tasks:

$$IntersectionoverUnion(IoU) = \frac{Box_p \cap Box_g}{Box_p \cup Box_g} \quad (1)$$

where Box_p and Box_g as predicted bounding box and ground truth box respectively.

$$Precision = \frac{T_p}{T_p + F_p} \quad (2)$$

$$Recall = \frac{T_p}{T_p + F_n} \quad (3)$$

$$F1 - Score = 2 \times (\frac{Precision \times Recall}{Precision + Recall}) \quad (4)$$

where, T_p True Positive, T_n True Negative, F_p False-positive, F_n False Negative respectively.

The efficacy of the proposed automated plant disease detection model is quantified based on mean Average Precision (mAP). Average Precision (AP) is determined for detection problems that deals single class. Here, detection of leaf diseases is performed for 6 classes which is given by the Eq. 5.

$$MeanAveragePrecision(mAP) = \frac{1}{C}\sum_{i=1}^{C} AP_i \quad (5)$$

B. Detection results

A total of 1,150 images are considered to train three frameworks. For each framework, we utilize the pre-trained weights. For EfficientDet-D2, we used the pre-trained model on the Pascal VOC dataset. Adam Optimizer with learning rate 0.01, Swish activation function, and batch size of 8 are considered. In addition, the focal loss has been utilized for classification output, while smooth L1 loss is used for regression output. For yolov4 and scaled yolov4, we consider Adam optimizer with a learning rate of 0.01 and 0.001, respectively. Mish activation function is used for both frameworks. For loss function, focal loss and CIoU loss are used for classification and bounding box predictions. All three models are trained for 50 epochs, each with 10000 iterations.

Table II
EVALUATION OF BENCHMARK PLANT DISEASE DETECTION MODELS

Method	Precision	Recall	F1-score	$mAP_{@IoU=0.7}$
YOLOv4	0.7211	0.7231	0.7220	0.8098
EfficientDet- D2	0.7432	0.7512	0.7472	0.8191
Scaled-YOLOv4	0.7901	0.7814	0.7857	0.8306

Moreover, the model's weight value is saved for every 1000 steps. After training, the performance of three models is assessed in terms of Precision, Recall, F1-score, and mAP at IoU threshold 0.7, as shown in Table II. The empirical results show that scaled-YOLOv4 gives the best mAP with a good tradeoff between speed and accuracy. The few detection outcomes of the object detection models were shown in Fig. 3. It is observed, Scaled-YOLOv4 detect small infected portion on the leaf efficiently. EffcientDet-D2 also gives good detection accuracy but lag in inference speed compared to Scaled-YOLOv4.

V. CONCLUSION

This paper investigates the three benchmark one-stage object detection models for automatic plant leaf disease detection. We consider apple and grape crop species from the plant village dataset. All collected images are annotated manually and given as ground truth to train the models. Three models, YOLOv4, EffcientDet-D2, and Scaled-YOLOv4 are trained individually and achieved a mAp of 80.98%, 81.91%, and 83.06%. Empirical results state that Scaled-YOLOv4 achieves mAP, which is 1.15% and 2.08% more than EffcientDet-D2 and YOLOv4 models. Overall, the scaled-YOLOv4 exhibits a higher detection accuracy for small objects with limited computational constraints. Scaled-YOLOv4 is a suitable framework for real-time plant disease detection compared to the other two object detection models. We will focus on a cascaded object detection network in future work by expanding the dataset results to a more accurate detection framework.

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