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DETECTION AND CLASSIFICATION OF TOMATO LEAF DISEASE

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Abstract: Unpredictable climatic conditions can greatly affect the crops in terms of vulnerability towards various infections which may be fungal, bacterial, etc. Detection of plant diseases during the initial stages of its spread is crucial to stop its spread which can infect the healthy ones as well. Another major benefit of detecting the disease early is to safeguard farmers from huge losses. It is very difficult to identify leaf diseases with the naked eye. To overcome this problem farmers all over the world spray pesticides. This leads to the spoilage of plants if used in excess. Thus, a proper identification mechanism needs to be established to predict the diseases at an early stage. The existing approaches to this problem use various versions of Regional Convolutional Neural Network (R-CNN) for leaf disease detection. It is a two-stage detection algorithm which makes it expensive in terms of time. The proposed system uses You Only Look Once (YOLO) object detection algorithm for detecting the diseases. The YOLO algorithm is much faster when compared to other object detection algorithms like RCNN. It requires only one propagation through the neural network to detect objects and provides predictions with accuracy on par with comparatively slower algorithms mentioned earlier. This makes it capable of real-time prediction. Although the dataset used to train the YOLO model consists of images of healthy and diseased leaves of tomato plants, the proposed model can be trained for leaves of varieties of other plants for disease detection.

Keywords: YOLO, Detection, Leaf disease, Disease classification, crop yield, bounding box

I. Introduction:

Plant diseases are one of the major causes of lower crop yields and also have a significant impact on farmers whose earnings are totally dependent on their harvests. Plant diseases are becoming more and more common, as well as more sophisticated. As a result, research into detection and treatment of different plant diseases is critical.

Tomatoes are one of the most nutritious crops on the planet, and their cultivation and production

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have a significant impact on agricultural economic development. In 2020, tomato crop was the highest produced vegetable crop in the world [1], which indicates its high demand. Due to increasing demand, it has become a crucial part of people's daily life since it has high nutritional value. Like other plants and crops, tomato plants are also vulnerable to diseases and infections. Some of the diseases are bacterial spot, early blight, septoria leaf spot, etc.

The presence of tomato diseases in various parts of the plant can significantly reduce the production of tomatoes. If there is no proper control system for blocking the spread of disease, it may lead to the whole plant getting infected. This is the reason for using pesticides, to kill the pests' causing diseases and stop the spread. Although this is important, the increased usage of pesticides is not sufficient to control the spread of disease causing pests, resulting in excessive pesticide residues in vegetables, which is an undesirable result. Therefore, it is important to detect the diseases as early as possible and prevent its spread. Research on tomatoes shows how vulnerable a plant is to be affected by diseases [2]. In this case identification of diseases is necessary in reducing crop failures and ultimately improving crop yield.

The conventional way of detecting diseases is based on the farmer's observations and his knowledge. This procedure is not only slow, but also inefficient, subjective, low accuracy, and time-consuming. Researchers have been focusing on deep learning for efficient image recognition. Using deep learning for disease identification in crops greatly reduces the identification time.

Among various techniques in deep learning, the most widely used models for image recognition related tasks is Convolutional Neural Network (CNN). The main advantage of CNN over traditional machine learning techniques is the fact that CNN automatically extracts features from the input image as the image passes through the whole network. Almost all the object detection algorithms are based on CNN.

In this paper, images of tomato leaves with symptoms of various diseases are collected and accurate labelling is done for each image. The YOLO algorithm is chosen for training the model which detects and identifies tomato leaf disease in an image in real-time. Experimental results clearly show that the YOLO algorithm improves accuracy as well as the detection speed for tomato leaf disease detection.

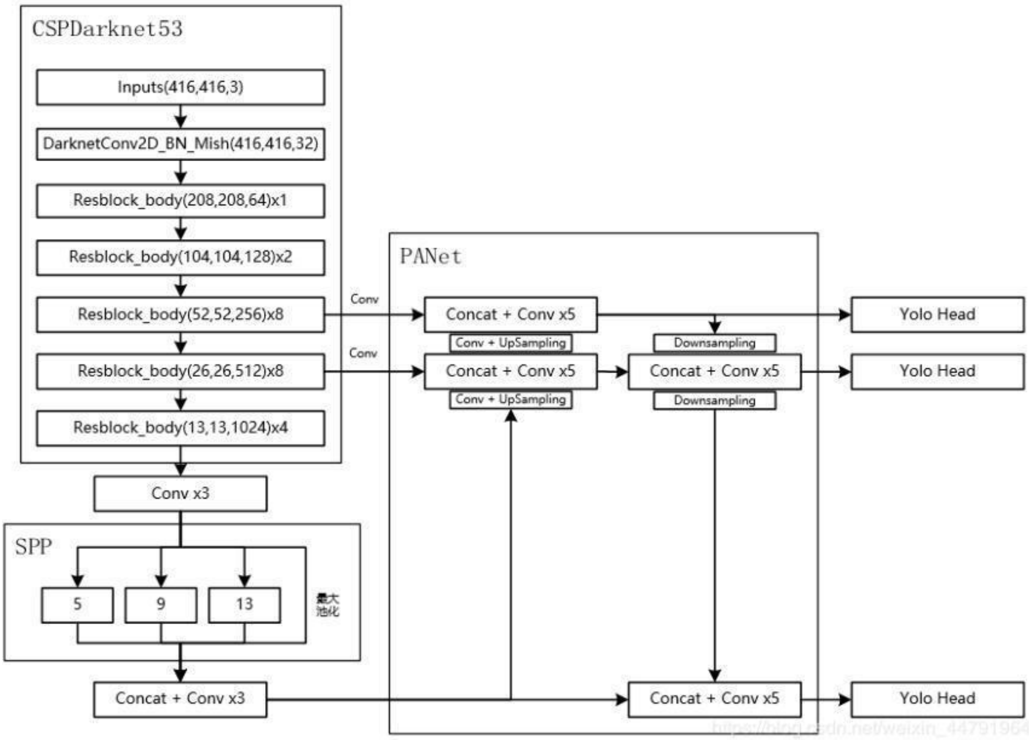
II. Research Background:

A) Observation 1

In recent times, neural networks are widely used for image recognition tasks. They can provide solutions for problems, which are generally characterized by non-linear ties which makes them more accurate for image recognition tasks. El. Helly et. al [3] opted for artificial neural networks (ANN) for detection of different cucumber disorders. A four-stage process was used for detection of cucumber disorders. The four stages are: enhancement, segmentation, feature extraction, classification. For the classification phase, an artificial neural network is implemented which consists of two hidden layers and five neurons per hidden layer and standard back propagation as the training algorithm. Although the model has good accuracy scores for predicting cucumber disorders, the fact that the feature extractor is a separate entity makes the total process of predicting a little more time consuming than the deep learning techniques available today.

B) Observation 2

The quality of image classification and object recognition has dramatically increased due to the advancements in deep learning. Deep learning techniques have the ability to extract features directly, which makes deep learning an obvious choice for researchers trying to solve objection detection related problems.



The model proposed by X. Sun et. al [4] is similar to the one mentioned above. It has a set of pre-processing steps which include image segmentation and enhancement before passing the image for prediction. Furthermore, CNN is used for prediction of the tea leaf disease. The CNN has the ability to directly extract features, therefore there is no need for a separate feature extraction step.

Figure 1. Structure of YOLOv4

Finally, the results of CNN for tea leaf detection were compared with other traditional machine learning algorithms. The results showed that CNN is much better than the traditional algorithms. Both the methods discussed above do not consider the positioning of the leaf in the image and are still slower due to the

presence of multiple separate steps before the actual classification task.

C) Observation 3

For the better real-time identification of insect pests and diseases on apple leaves, P. Jiang et. Al [5] have suggested an improved CNN-based model. The dataset used for training the model is a collection laboratory images with uniform background as well as natural images in the real-life conditions. This ensures that the trained model is more robust and generalized. An improvisation to the existing Single Shot Detector (SSD) [11] was done by adding GoogleNet inception structure and rainbow condition. The resultant model was trained to detect five different apple leaf diseases.

III. Existing Regime:

Faster Regional Convolutional Neural Networks(Faster R-CNN), is an object detection system that consists of two components [6]. A deep fully convolutional network serves as the first step, which produces proposed region proposals, while a fast R-CNN detector serves as the second step, that uses the proposed regions. It uses a depth residual network [7] for feature extraction to obtain deeper features. The gradient vanishing problem is solved by increasing the total layers in the network. In the overall setup of Faster R-CNN, the most crucial component is the Region Proposal Network. The RPN is responsible for the selection of the region proposals. Region proposals are those sections in the image where the chances of finding the intended objects is high. Then, the k-means clustering algorithm is used to cluster the bounding boxes. Next the anchoring gets improved based on the clustering results. Based on the mapping relationship between the feature maps and the original image, the bounding boxes are converted into regions of interest. A softmax classification is applied to the output feature vector obtained from the fully connected layer of the network which classifies the input tomato leaf image into one of the disease class or healthy. Furthermore, the object's experimentally created bounding box is adjusted by the regression operation so that it tends to the actual position of the object.

Faster RCNN is a type of two-stage object detector. Although the process of feature extraction and further detection and identification of the intended object is much faster compared to its predecessors R-CNN and Fast R-CNN, it still has two different steps for classification and bounding box regression.

IV. Proposed Methodology:

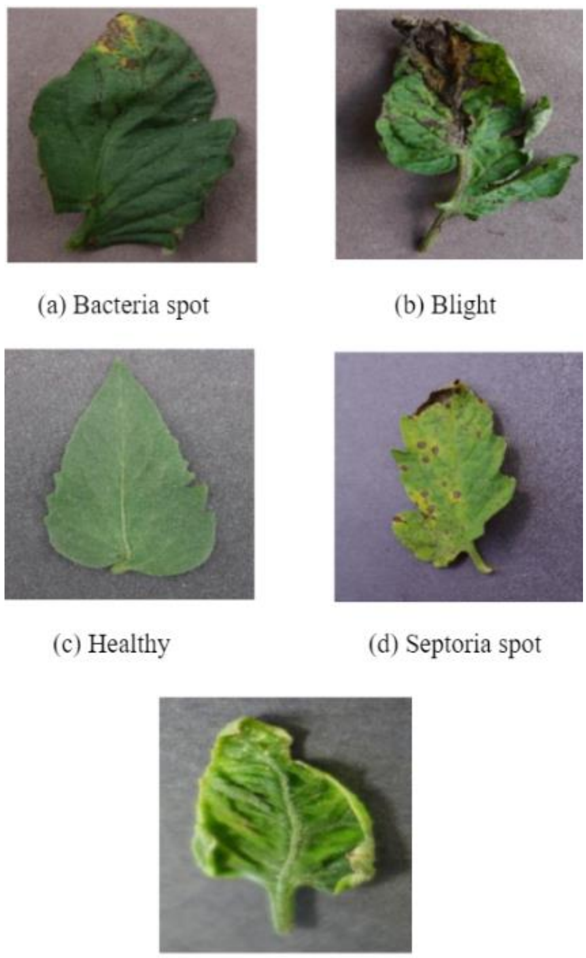
A. Datasaet

The dataset used for training the model in this project is from Kaggle. It contains 10 categories of different tomato leaf diseases. We selected four categories of tomato diseases and healthy categories for this project due to limitations of computation power for model training. After selection of five categories there are a total of 5500 images. The resolution of each image is 256 x 256. Each category of tomato disease has 1100 images individually. Images are annotated using an open-source platform called makesense.ai. The annotation files are in the YOLO format. Each annotation file contains a value for the class and the dimensions of the bounding box. Furthermore, the images are divided into test and train set. 1000 images for each category is put into a training set whereas the remaining 100 under the validation set. Fig. 1 shows a sample for each category in the dataset.

B. Algorithm

The algorithm of study for this paper is the You Only Look Once (YOLO) algorithm [8]. It performs the task of detection by mere conversion of the problem into a regression task.. Since it is an algorithm for object detection, the network of YOLO consists of Convolutional Neural Network (CNN) layers. The main aim of any object detection algorithm is to detect the presence of the intended object in the image and also locate its position by enclosing it in a bounding box. Same is the case with YOLO algorithm, the only difference compared to the Faster-RCNN being that YOLO performs both classification of the object as well as return the coordinates of the bounding box relative to the input image in a single pass through the network.

Using the same experimental setup, the object detector implemented using the YOLOv4 algorithm has lower detection time compared to the Faster-RCNN based object detector [9].



(a) Bacteria spot (b) Blight

(c) Healthy (d) Septoria spot

(e) Yellow leaf curl virus

Figure 2. Sample leaf images

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According to [8], an object detector consists of the following components: backbone, neck and a head. A backbone as its name suggests is one of the crucial parts of an object detector. It is responsible for extraction of features and producing feature maps. The backbone network implemented in YOLOv4 is CSPDarknet53 [10]. The neck links the backbone to the head. It mostly acts as a mediator that collects and combines the features obtained from the backbone and pass it to the head for detection. For the neck portion, it uses a Path Aggregation Network(PANet) [13] for the feature aggregation network. A Spatial Pyramid Pooling (SPP) [14] is fitted just after the backbone to highlight the important features. The head is the component where the actual prediction of the class and the bounding box happens. The head used in the YOLOv4 algorithm is the same as the head used in YOLOv3 [15]. The structure of the YOLOv4 algorithm is shown in Fig. 1. The network predicts 4 values for the bounding box denoted as b_x, b_y, b_w, b_h. The coordinates b_w represents the width of the box and b_h represents the height of the box. The coordinates b_x and by denote the centre of the bounding box where the values are calculated with top left corner of the of the image as (0,0). A multilabel classification is responsible for predicting the class contained within the bounding box.

V. Results Analysis:

A. Experimental Environment

The experimental hardware and the software environment are shown in table 1 and table 2 respectively.

Table 1. Experimental hardware environment

Hardware	Model	Number
CPU	Intel i7-7700HQ	1
Memory	SK Hynix 16GB	1
Graphics Card	Nvidia GeForce GTX 1050Ti	1
Solid state drive	Hynix 128GB	1
Hard drive	Western Digital 1TB	1

Table 2. Experimental software environment

Software name	Version
OS	Windows 10
Python	3.9.7
OpenCV	4.5.5
CUDA	11.2

B. Evaluation criteria

The evaluation criteria used to compare the results of the experiment is mean average precision (mAP).

For image processing and object detection, precision and recall are critical. The ratio of accurately identified and located classes in the output results to the total obtained results is its precision. Recall is the ratio of correctly identified and located classes in the output results to the number of classes.

C. Model Training

For training the YOLOv4 model we use the darknet framework [16]. Darknet has implementations of all the versions of YOLO readily available for training our custom object detector. The model is initialised using the default parameters as specified on the dark net website except a few which are dependent on the number of classes in the dataset.

Table 3. Model hyperparameter values

Name	Value

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Batch size	64
Learning rate	0.001
Momentum	0.9
Burn_in	1000
Decay	0.0005
Max_batches	10000
Channels	3

Table 4. Analysis of different models

Algorithm name	**Accuracy**	**Time (ms)**
Faster-RCNN	95.83	731
Faster-RCNN-res101	97.18	452
YOLOv4	99.7	280

D. Comparative analysis

A comparative analysis is performed with Faster-RCNN as well as improved Faster-RCNN as proposed in [17] to validate our proposed model. As mentioned earlier the evaluation criteria is mean average precision (mAP) and an additional criteria included is time taken for detection. The results of comparisons are mentioned in table 4. Although the improved version of Faster RCNN with residual network improves the mAP over the original one, YOLOv4 outperforms both the methods with accuracy of 99.7 as shown in table 5. In general, the YOLOv4 algorithm is better than Faster-RCNN in terms of detection and time.

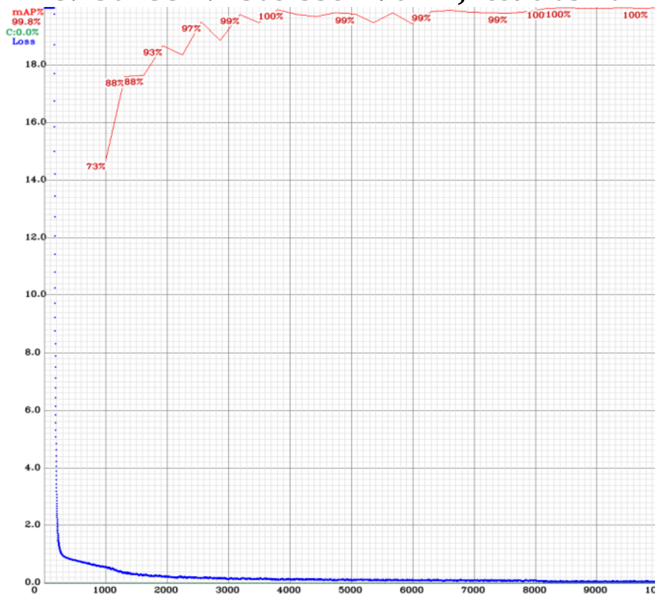

Figure 3. The graph of loss and mAP

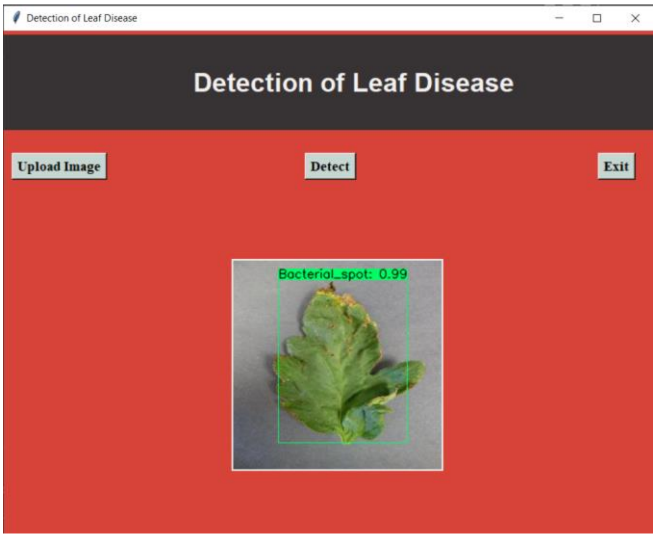

Figure 4. Prediction - Bacterial spot

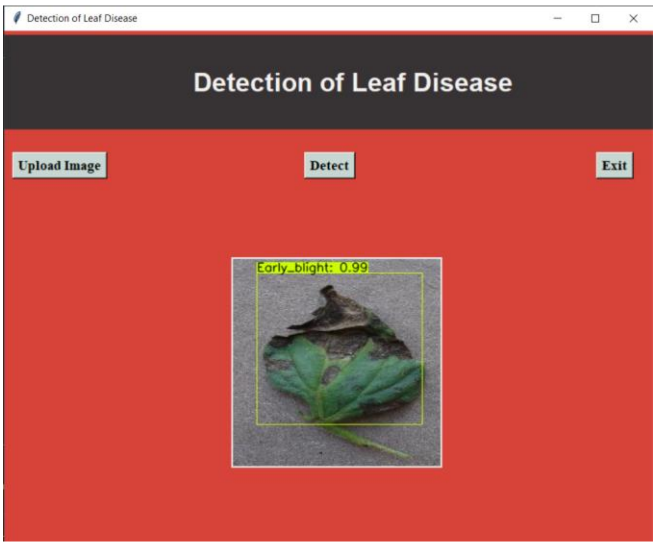

Figure 5. Prediction - Blight

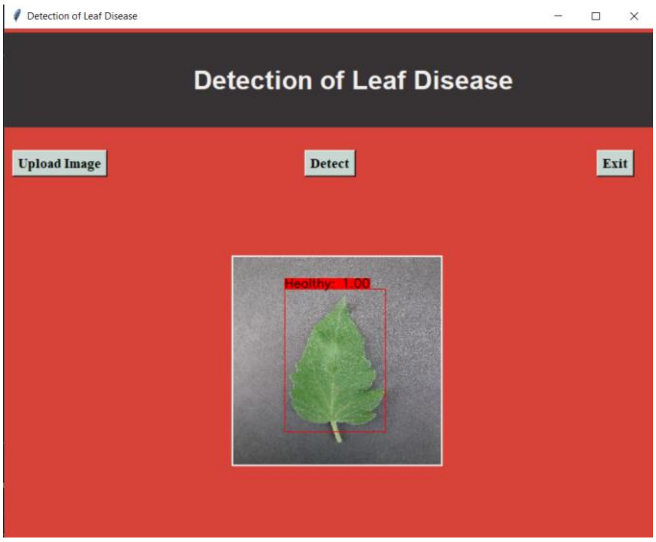

Figure 6. Prediction – Healthy

VI. Conclusion:

This research proposes the YOLOv4 algorithm for the detection and identification of tomato leaf diseases. As per testing results, the accuracy of detection provided by the algorithm is 99.7% and time taken for detection is around 280 ms using our local experimental environment. The experimental gains state that the proposed algorithm can precisely detect and identify the stated diseases. The comparative analysis states that the proposed algorithm has higher accuracy and shorter detection time compared to Faster-RCNN.

The dataset used for this paper has images containing a single leaf in controlled lighting conditions. Future works can include images of natural plants in real-life conditions. Currently the model trained to support this paper includes only 4 diseases and the healthy category. Future works will add more diseases for detection which will enhance the real time application usage. Furthermore, in order to make the model more generalized, future work will collect images of different types of diseases of a variety of plants for training.

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