__Original Research Article__

SOYBEAN DISEASE DETECTION AND SEGMENTATION BASED ON MASK-RCNN ALGORITHM

ABSTRACT

Anthracnose, frogeye leaf spot (FLS), rhizoctonia aerial blight (RAB), soybean mosaic virus (SMV), and yellow mosaic virus (YMV) of soybean are major common soybean leaf diseases that seriously affect soybean yield in India. However, the existing system needs a real-time detection method for soybean leaf diseases, which will help to take appropriate action for disease cure with minimum losses. This study studied a real-time detector for soybean leaf diseases based on deep convolutional neural networks. The 3,127 RGB images of disease-free leaves, anthracnose, FLS, RAB, SMV, and YMV-affected leaves of soybean were collected from the agriculture fields. The Mask R-CNN detection algorithm was used for the detection of soybean leaf diseases by introducing the ResNet50module. The pre-processed images (512×512 pixels) were used as input in Mask R-CNN. The model was trained at a number of epochs, training step per epoch training & validation, and learning rate were80, 500, 50, 8, and 0.001, respectively. The detection accuracy was calculated at three levels of minimum detection confidencei.e. 0.80, 0.85, and 0.90. Theresults indicate that the maximumdetection accuracy i.e. greater than 85% at 0.90 level of minimum detection confidence. This research indicates that the real-time detector based on deep learning provides a feasible solution for diagnosing soybean leaf diseases and provides guidance for the detection of other plant diseases. In addition to that the application of pesticide in the early stage reduce the use of pesticide resulting in less environmental pollution.

Keywords: Deep learning,leaf disease,Mask R-CNN,RGB images,Soybean.

INTRODUCTION

Soybean is a major oilseed crop produced and consumed worldwide and one of the most economically important crops in India. India is the world's fourth-largest soybean producer.India ranks fourth in the area with 11.34 million hectares (28.02 million acres) accounting for 9.41% of the world area and fifth in production with 11.22 million tonnes in 2019-20. The major soybean-growing states are Madhya Pradesh, Maharashtra, Rajasthan, Karnataka, and Telangana (Agricultural Market Intelligence Centre PJTSAU2020). According to an analysis of relevant investigation data, the yield loss of soybean caused by diseases accounts for about 10% every year and even more than 30% in serious cases (Chang *et al.*, 2018; Srivastava 1997). Today, it is affected by several diseases that worry a lot of farmers, and the fight against crop diseases remains a major problem for them, to control these diseases, a large number of chemicals or fungicides are used on the crop, which results in both economic loss and environmental pollution (Ali *et al*. 2017). Now new technologies based on artificial intelligence can develop precision agriculture, improve crops and manage and limit the misuse of chemicals in the beds (Milioto et al 2018,Paszke*et al*. 2017). Detection and classification of plant diseases are important tasks to increase plant productivity and economic growth. Computer vision, machine learning, and deep learning algorithms make it possible to develop tools for the control and analysis of plant diseases (Ali *et al*. 2017, Lauer *et al*.2011, Chapelle*et al*.1998).

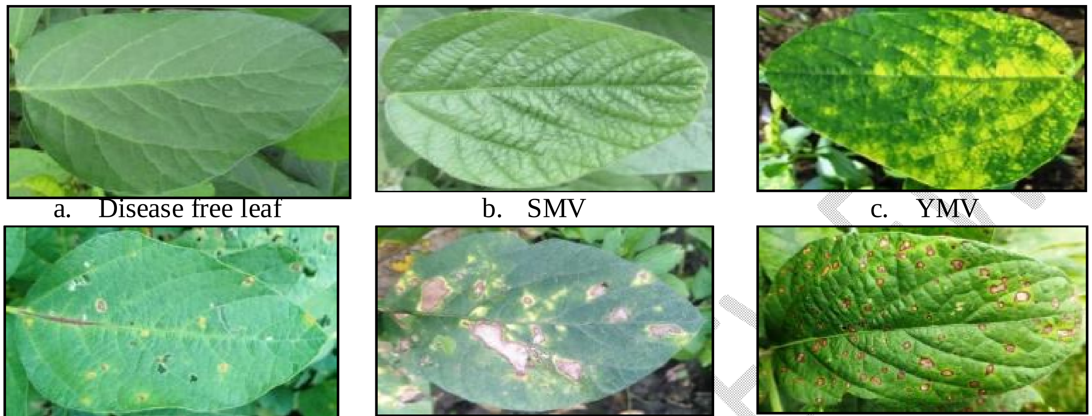
Especially in recent years, with the aggravation of environmental pollution, disease stress is more and more intense. Rapid recognition and monitoring of soybean diseases are key and core issues in the morphological-physiological phenotypic detection system of the soybean growth process, to achieve not only precise disease control and variable application but also a reduction in pesticide residues according to the situation and, ultimately, improvement in crop quality and yield. With the rapid development of deep learning in smart agriculture, it has been widely applied in the detection of diseases and pests, recognition of flowers and fruits, classification of plant species, and other fields (Singh *et al.*, 2016).There are a number of deep learning models were used for the detection of the foliar disease in different crops with an accuracy of up to 99 % (Jawade*et al.* 2020, Gurle*et al.*, 2019, Baranwal, *et al.*, 2019, Wallelign*et al.*, 2018 and Wu *et al.*, 2019).

The Mask R-CNN, is evolved from R-CNNs (R-CNNs, Fast and Faster R-CNNs).Region Based Convolution Neural Networks (R-CNNs) are used for Object Detection through a two-step process - Region Extraction and Performing Classification. With ~2000 regions selected for each image for feature extraction and subsequent classification run over them using Linear SVM, it made training costs extensive and slower. To improve on this further, Fast-RCNN was proposed. It uses a single deep ConvNet instead of individual ConvNets for each region, Softmax was introduced for SVM, and Region of Interests (ROIs) were proposed using selective search which again was slower when dealing with large datasets (Girshick, 2015).Faster-RCNNs on the other hand use Region Proposal Network (RPN), a deep Convolutional Network to propose regions. These regions are then fed to a detector that is similar to Fast-RCNN which implements classification on the RoIPool. The idea behind Mask R-CNN was to improve upon the results of Faster-RCNN. The main motivation was to go beyond just bounding an object in an image but looking at an object class in an image with pixel-level granularity. Furthermore, creating a fair trade-off between increasing training and inference speed versus the Average Precision was also a keenly observed trait (Renu, 2019).Mask R-CNN performs pixel-level instance segmentation using a binary mask for each object class. Furthermore, the RoIAlign layer is introduced to remove harsh quantization and reduce misalignment. Thus, improving AP by ~3 points (Hui, 2018). Also, when it comes to algorithm frameworks like Fully Convolutional Instance Segmentation (FCIS or FCIS++) that work on the principle of finding spatial-sensitive channels using convolution, it causes problems when it comes to object instances that are overlapping and thus it cannot segment them properly. Having individual binary masks for each class solves the problem.The mask-rcnn was used in this study for disease detection in different crop leaf with 71.9-100% accuracy (Yingshu and Yi, 2022, and Udawant and Srinath,). The mask-rcnn was used in this study for disease detection in soybean leaf for timely prevention/remedial action taken by farmers and same time saving of pesticides for preventing environmental pollution.

MATERIALS AND METHODS

In this study, a dataset of soybean leaf imageswas collected and annotations of diseased regions and corresponding segmentation masks were fed into the detection algorithm. The dataset contains images of various types of soybean diseases. A pre-trained Mask R-CNN model on the COCO dataset was used to initialize the model and fine-tune it on the collected soybean disease dataset. The developed model was evaluated on a separate test dataset containing soybean leaf images with known diseases. The details are given below:

Data collection and pre-processing: ARGB dataset of soybean leaf images was collected from MP(Bhopal and Indore), and Uttarakhand (Almora) states of India. The dataset contains images with five types of soybean diseases such as SMV, YMVAnthracnose, RAB,FLS,and disease-free leaves (Fig. 1). The identification of different diseases in the soybean leaveswas done with the help of plant pathologist. The RGB images were collected by using a Canon camera, mobile phones of pixel size ranging 1500-2000×1500-2000.



a. Disease free leaf b. SMV c. YMV

d. Anthracnose e. RAB f. FLS

Fig. 1: Soybean leaves with different disease and disease-free leaf

The details of the soybean leaf disease dataset are given in Table 1.

Table 1: Soybean leaf dataset

Disease/disease-free leaves	Train/validation/test	Total quantity
Anthracnose	343/ 144 / 81	568
Disease free leaf	134/ 56 / 34	224
FLS	236 / 98 / 59	393
RAB	253 / 105 / 63	421
SMV	360 / 150 / 90	600
YMV	553 / 230 / 138	921
Total	**1,887 / 783 / 465**	**3,127**

In the experiment, 60% of the dataset was used for training, and the other 25% was used for validation. 15%of images were used for testing the model. The ratio size of the training dataset and validation dataset is 2.4:1.

Annotation: The features of diseases were identified withthe help of anexpert plant pathologist. Then the disease feature were annotated and segmentation maskswere generated. The annotations of diseased regions were done with the help of the VIA 2.0.11 tool by usingthe circle andthe polygon option.

Training: Mask R-CNN (Regional Convolutional Neural Network) is a popular deep learning algorithm that is used for object detection, instance segmentation, and object tracking in images and videos(Kaiming, 2017).Mask R-CNN is an extension of the Faster R-CNN algorithm, which is a two-stage object detection algorithm that uses a region proposal network (RPN) to generate candidate object regions and then classifies and refines those regions using a separate network. Mask R-CNN adds a third branch to the Faster R-CNN architecture to generate a binary mask for each instance of an object in addition to its bounding box and class label. This allows the algorithm to perform instance segmentation, which involves identifying the pixels that belong to each instance of an object in an image.

The main components of the Mask R-CNN algorithm are:

Backbone network: This is typically a convolutional neural network (CNN) such as ResNet, VGG, etc. that is used to extract feature maps from the input image.The disease detection category trained in this paper is relatively simple, and the requirements for the network layer are lower; thus, to further improve the running speed of the algorithm, this paper uses ResNet50. This structure has strong robustness and adaptability, and requires fewer parameters.

Region Proposal Network (RPN): This network generates candidate object regions (bounding boxes) from the feature maps produced by the backbone network.

RoI (Region of Interest) Pooling layer: This layer extracts a fixed-size feature map from each candidate region that is produced by the RPN.

Object detection branch: This branch classifies the candidate regions and refines their bounding boxes using the RoI feature maps.

Mask prediction branch: This branch generates a binary mask for each candidate region that indicates which pixels belong to the object and which pixels do not.

The network structure block diagram of the Mask RCNN algorithm is shown in Figure 2.

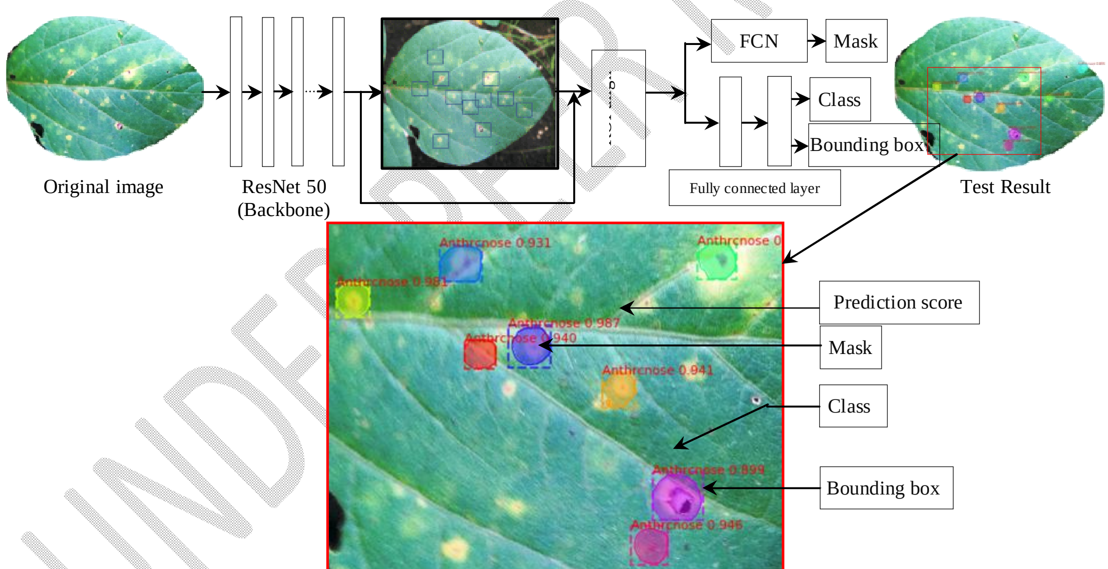


Fig.2. Mask RCNN network framework model

The hardware i.e. processor, RAM and graphics card were Inter(R) Core(TM)i5-4590, CPU@3.30GHz, 12GB and NVIDIA GeForce GT 730, respectively used in this study.The software i.e. Tensor Flow, Python and operating system version were 2.2.0, 3.7.4 and Windows 10 Pro, 64-bit were used, respectively. The model training was done in two stages. In first phase only the heads layers were trained. In this all the backbone layers were freezedand only the randomly initialized layers (i.e. the ones that we didn't use pre-trained weights from MS COCO) were trained. Then in second stage fine tuning of all the layers was done. The model was tested on the ResNet50 backbone with two parameter settings i.e. training epoch 67, 500, 50(model-1) and ResNet50, 100, 10, 2 (model-1). After comparison of these models finally,a ResNet50 model with the parameters a batch size, learningrate, learningmomentum, weightdecay of 2, 0.001, 0.9, 0.0001, 80 epoch for training Steps per epoch 500 and validation steps per training 50 (model-3) was trained.

Testing: The model-1 and model-2 were evaluated by comparing train loss (train_loss), validation loss (val_loss), RPN class loss (rpn_class_loss), RPN bounding box loss (rpn_bbox_loss), validation RPN class loss (val_rpn_class_loss), validation RPN bounding box loss (val_rpn_bbox_loss), MRCNN class loss (mrcnn_class_loss), MRCNN bounding box loss (mrcnn_bbox_loss), validation MRCNN class loss (val_mrcnn_class_loss) and validation mrcnn bounding box loss (val_mrcnn_bbox_loss). Whereas model-3 was tested for detection accuracy and IoU.In Mask R-CNN, IoU stands for intersection over the union. It is a metric used to evaluate the accuracy of object detection and segmentation algorithms.When an object is detected and segmented, the algorithm draws a bounding box around the object and generates a binary mask that represents the exact pixels that belong to the object. The IOU metric measures the overlap between the predicted mask and the ground truth object's actual shape the actual shape of the object).To compute the IOU, the area of intersection between the predicted and ground truth masks is divided by the area of union between the two masks. The IOU ranges from 0 to 1, where 0 indicates no overlap between the masks, and 1 indicates perfect overlap. A higher IOU score indicates a better segmentation performance of the algorithm.Whereas the maximum detection accuracy was evaluated at three minimum confidence level i.e. 0.8, 0.85 and 0.9.

RESULT AND DISCUSSION

The comparison of different parameters of models with different parameter settingi.e. model-1 and model-2 is shown inFig. 3. The detection minimum confidence was kept at 0.7.

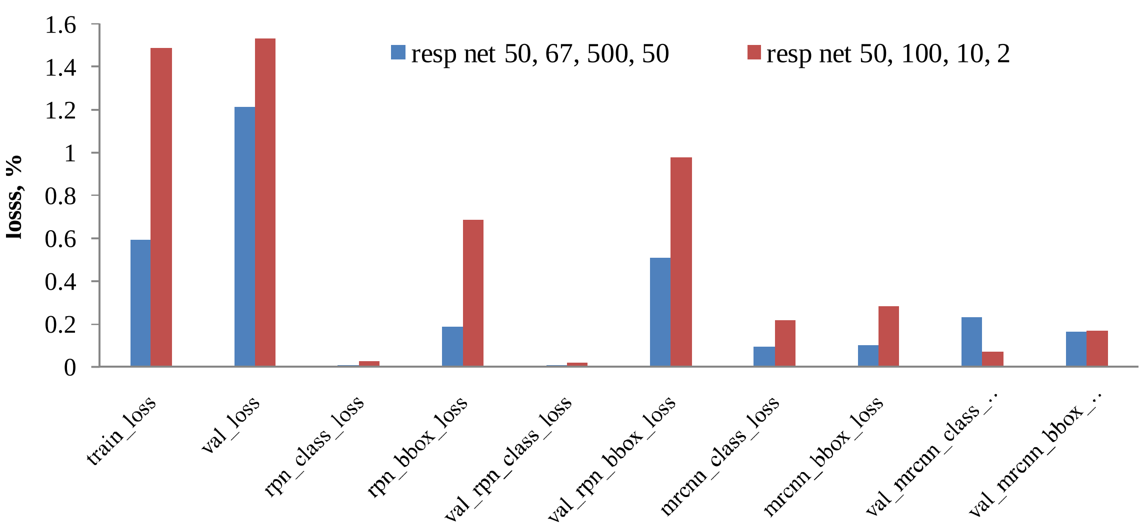


Fig.3: Train and validatiy losses at different stages of training of MASK-RCNN model

The different loss observed in model-1 and model-2 was higher in case of model-2 except val_mrcnn_class_loss. The different losses in model-1 i.e. train loss, validation loss, rpn class loss, rpn bounding box loss, validation rpn class loss, validation rpn bounding box loss, mrcnn class loss, mrcnn bounding box loss, validation mrcnn class loss and validation mrcnnbounding box loss were found 0.59, 1.21, 0.009, 0.18, 0.008, 0.509, 0.092, 0.102, 0.231 and 0.164, respectively. The different losses for model-1 i.e. train loss, validation loss, rpn class loss, rpn bounding box loss, validation rpn class loss, validation rpn bounding box loss, mrcnn class loss, mrcnn bounding box loss, and validation mrcnn bounding box losswas observed 0.896, 0.32**,** 0.016**,** 0.5**,** 0.014**,** 0.468**,** 0.124**,** 0.178and 0.005 respectively**.** Whereas invalidation mrcnn class loss was found 0.1614 higher in model-1 than in model-2. The higher epoch and training and validation steps are giving less losses so model-3 with higher training epoch and higher steps were used for the training of the model and testing of the test dataset.

The result of the detection accuracy ofdifferent disease classes at different minimum levels of confidence score is shown in Fig.4. In this the maximum detection accuracy was found at a 90% minimum level of confidence score.

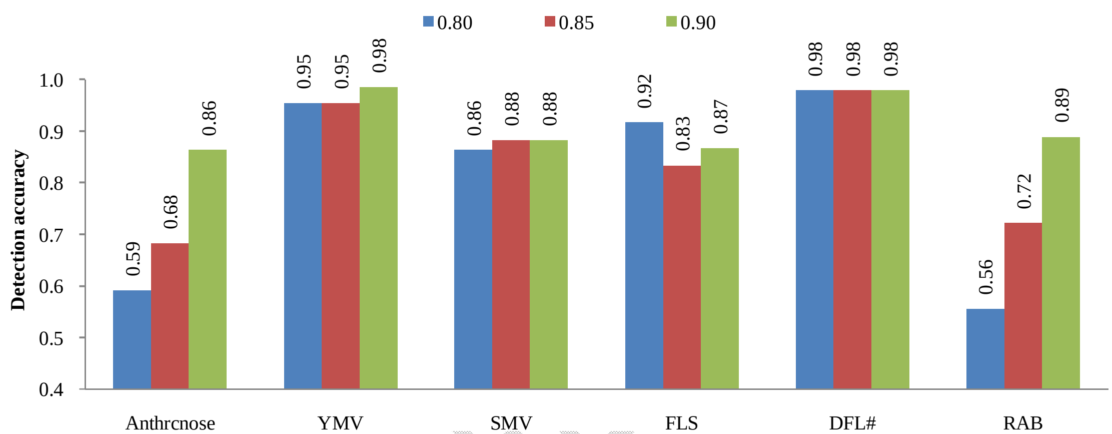
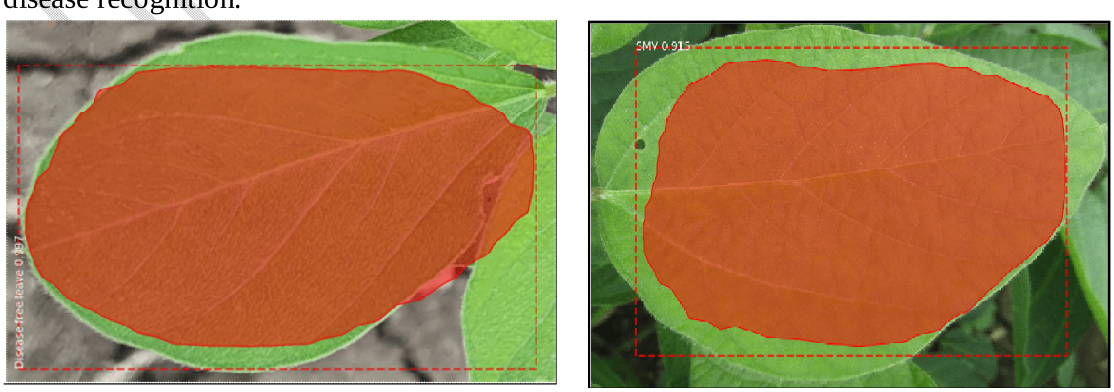


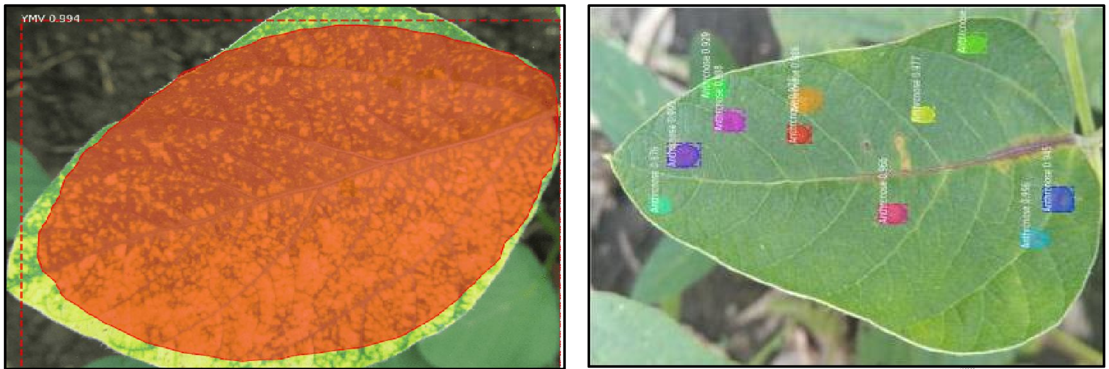
Fig. 4: The detection accuracy of different disease types at different minimum levels of confidence score([#]*DFL-Disease free leaf***)**

The experiment results of the detection of disease-free leave and different disease in one soybean leaf are shown in Fig.5. Soybean leaf disease and disease-free leaf detection results on a single leaf with detection accuracy are shown in Figure 5. The detection minimum confidence was kept at 0.8. The disease-free and disease-detection accuracy in the leaves shown in Fig. 5for disease-free leaf, SMV, YMV, anthracnose, FLS, and RAB were found 99.7, 91.5, 99.4, 92.9-99.6, 91.2-97.2 and 99.2-99.7,respectively. In the case of anthracnose, RAB, and FLS multiple spots detected above an accuracy level of 90% are sufficient for disease recognition.

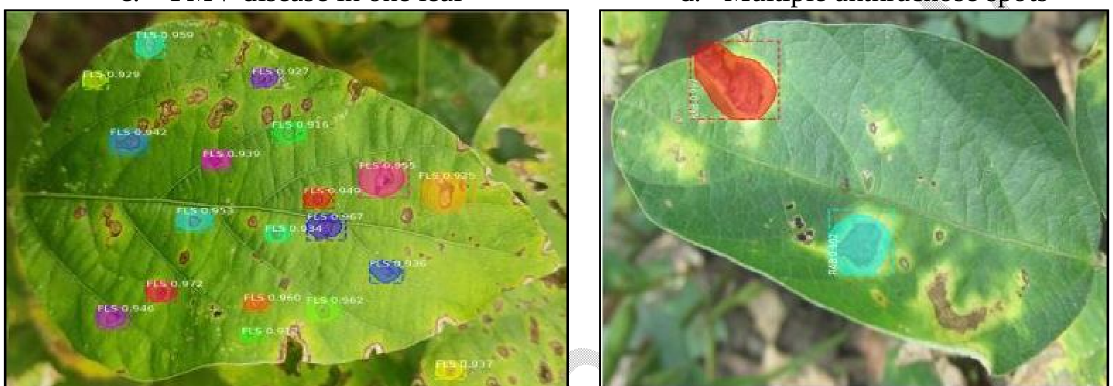


a. Disease-free leaf

b. SMV disease in one leaf



c. YMV disease in one leaf d. Multiple anthracnose spots

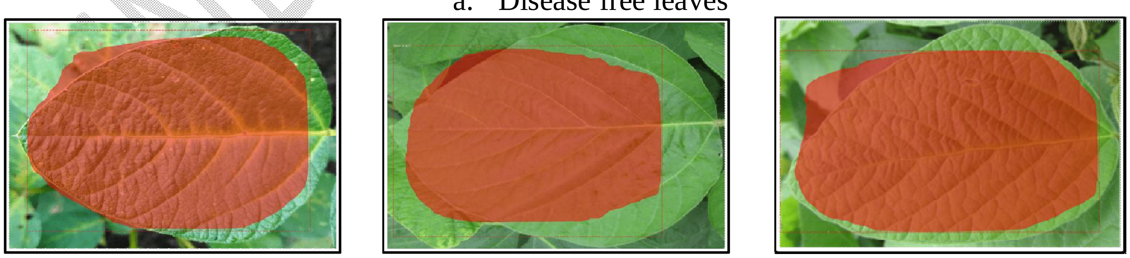


e. Multiple FLS spots in one leaf f. Multiple RAB patches in one leaf

Fig.5: Soybean leaf disease and disease-free leaves detection results on a single leaf

Afew more test results of the detection of disease-free leaves and different diseases in three different soybean leaves are shown in Fig.6.

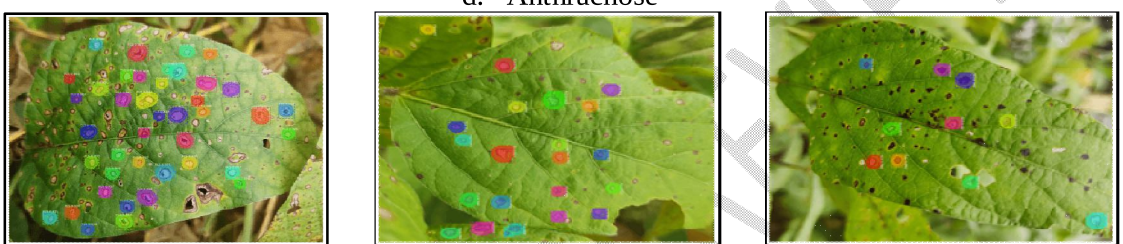
a. Disease free leaves



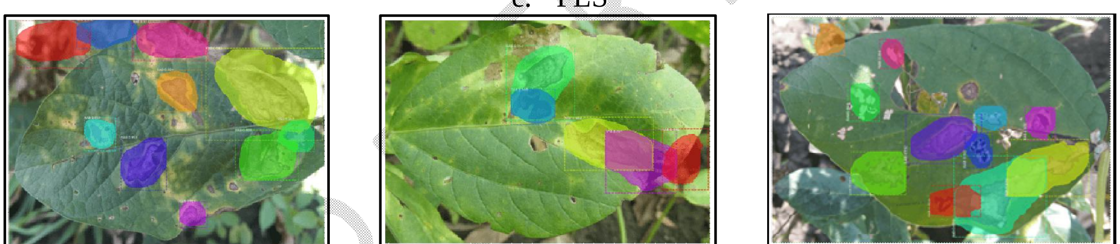
b. SMV

c. YMV

d. Anthracnose



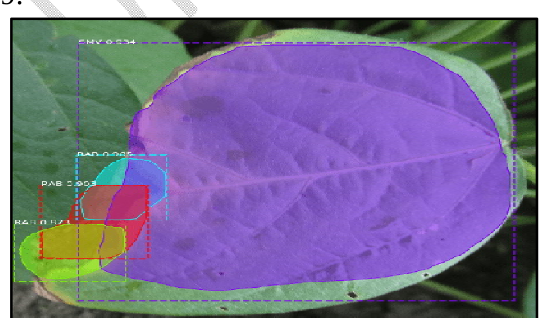
e. FLS



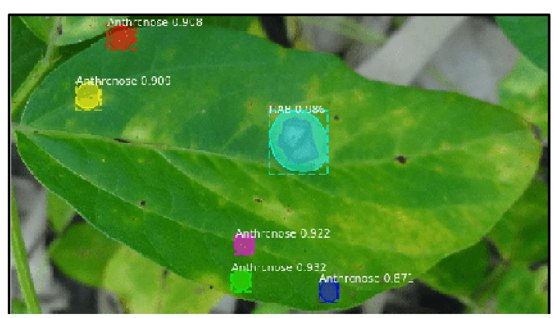
f. RAB

Fig.6: Soybean leaf disease and disease-free leaves detection results shown in three different leaves

Multiple disease detection: The model is able to detect more than one disease in soybean leaf as shown in Fig.7. The confidence score was found 90.3-98.5% for RAB and 93% for SMV and 90.8-93% for anthracnose and 98% for RAB when level of confidence is more than 0.9.



a. Detection of RAB (90.3-98.5%) and SMV(93%)



b. Detection of Anthracnose (90.8-93%) and RAB (98%)

Figure 7: Multiple disease detection

However, it is important to note that the accuracy of the Mask R-CNN algorithm depends heavily on the quality and diversity of the training dataset. The addition of a dataset will increase variability and improve the accuracy of testing field data. Further, it may be necessary to use other techniques such as data augmentation and model assembling to further improve the accuracy of the model.

CONCLUSION

In this paper, the selected soybean disease detection and segmentation was done based on the Mask R-CNN algorithm with the backbone ResNet50. Image Acquisition is performed by collecting a data set of 3,127 soybean leaves from primary sources. The results demonstrate that our model can accurately detect and segment selected diseased soybean plants from healthy ones, with high accuracy i.e. more than 85% at 0.9 level of minimum confidence level. This approach has the potential to improve the efficiency and effectiveness of soybean disease management, which can benefit the agriculture industry and food security. Future work can focus on scaling up the model with larger datasets and more types of diseases of the soybean crop, as well as integrating the model into a real-time monitoring system.

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