Cotton leaf disease detection using Faster R-CNN with Region Proposal Network

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Abstract: Indian agriculture consists of cultivating many crops and 70% of Indian population depend on it either for food or for commercial purpose. India is one among the largest producers of cotton in the world. But the production gets affected due to various reasons like attacks in different parts of the plant by pests, insects, nutritional deficiencies, climatic conditions etc. Detection of leaf diseases is a major problem which needs to be addressed during all stages of plant growth using computational intelligent techniques. After detection, remedy for the diseases need to be identified and suggested so that farmers can take appropriate actions.This paper provides a solution to this problem by detecting and analyzing the diseases in cotton plant and suggests suitable remedies for that disease through deep learning. Training of models was performed with the database of over 4,000 images. It uses Faster R-CNN with Region Proposal Network (RPN)which is an extension of Fast R-CNN for detection of diseases.Integrating RPN with faster R-CNN reduces the running time and enable cost-free region proposals. It has an average accuracy of 96% in identifying the disease.

Keywords: Deep Learning, Cotton leaf diseases, Faster R-CNN, Region Proposal Network

1. Introduction

India is an agricultural country and about 70% of the population depends on it. As agriculture is backbone for the country, there are wide variety of options for choosing the agricultural crops and the pesticides to be used. Among them, cotton (Gossypisum) is an important crop as India is one of the largest producers of cotton. Cotton is originated in India and scientists believe that it was initially cultivated in Indus delta. Cotton has good medicinal uses and is used to cure nausea, fever, headache, diarrhoea, dysentery, nerve pain and bleeding.

Cotton grows well in warm and humid climate. It is grown from mid of March to June. It requires a minimum rainfall of 1200 mm. For germination period, the minimum temperature needed is 16°C. The temperature required for proper vegetative growth is 21°-27°C. The temperature above 37°C is not suitable for the cotton plant growth. The air temperature for the suitable growth is 21°-37°C. The water needed for the cotton plant between germination and boll formation is 500 mm. The cotton cultivation is most suitable in loamy sand soils. In India, it is grown well in alluvial soils, red soils and laterite soils of peninsular regions.The cotton plant is affected with many diseases leading toreduction in productivity and quality. The diseases are caused by various bacteria, virus and fungus. From many studies, it is found that plant disease show their patterns on the plants which are visually observable (Parikh et al 2016). Monitoring the plant health and protection from diseases play an important role in successful cultivation of crops. Initially, monitoring and analysis of plant diseases were done manually. This process needs a large amount of manual work and more time for management. Image processing techniques available in deep learning can be used in plant disease detection. Mostly, symptoms for the diseases are visible in the leaves, stem or fruits. Hence, this paper focuses on the symptoms that are seen in leaves in order to identify the diseases.

In this paper, three leaf diseases are detected and analysed. The major disease of cotton is bacterial blight caused by the infection ofXanthomonasaxonopodispathovarmalvacear um (Xcm) a Gram negative, motile rod-shaped, non spore–forming bacterium with a single polar flagellum. The bacterium infects the plant at all stages from seed to cultivation of the plant. There are five common phrases of symptoms. This bacterium survives on infected, dried plant debris in soil for several years. It is also seed-borne. The secondary spread is much faster as it occurs through wind and hence it is necessary to identify this disease as early as possible.Another major disease in cotton plant is yellow leaf curl virus which is of viral origin caused by the whitefly Bemisiatabaci. This disease is otherwise known as Cotton leaf curl disease (CLCuD). It affects the plant in almost in all the stages including seeding, fruiting and in flowering stages. The other major disease is late blight disease. The symptoms for this disease is that the leave appear brown in colour with grey centres or leaf blight with concentric rings.

Among many methods that are used for detection of leaf diseases, deep learning methods have gained much attention nowadays andthe proposed methodology uses one such deep learning method called Faster R-CNN with Regional Proposal Network, an improved version of fast R-CNN. In addition to that, remedies for the diseases are also stored in the knowledge base and this will be suggested to the analysts for further actions. Performance of the proposed method is better than other methods which are compared.

2. Literature Review

Different machine learning methods were introduced by researchers to detect diseases in various plants and the details are given below.

Methods like Artificial Neural Network (ANN) Vakilianet al (2013), feed forward back propagation neural network (Sannakki et al (2013),ANN (Kutty et al 2013), Convolutional Neural Network (Lee et al 2015), K-means clustering and ANN (Khirade and Patil 2015), One Class Support Vector Machines Pantazi et al (2016), image processing techniques (Johannes et al 2017) are used for detecting diseases in various plants like cucumber, grapes, watermelon etc.

The performance of disease detection has greatly improved when researchers started usingdeep learning methods in this regard. Some initial examples that used deep learning are Grinblatet al (2016),Mohanty et al (2016), Sladojevic et al (2016) for identifying diseases in different types of plants. Fuentes et al (2017) detected the disease in the tomato plant and also recognized the pesticide used on the plant using deep learning. In this system, the model was tested and trained to the large tomato disease and pesticide dataset. Three families of detectors were used including Faster R-CNN, R-FCN and SSD. These methods were combined with the meta architectures such as VGG net and Residual Network. This model was proved to be efficient and it can identify nine types of diseases.

Pawaraet al (2017) compared two methods in deep learning for identification of plant diseases using the image of the leaves. The comparisons are between local descriptors and bags of visual words. They were used to identify the diseases of the datasets such as AgrilPlant, LeafSnap and Folio. The support vector machine and multi-layer perceptron classifiers are compared with AlexNet and GoogLeNet. This yield an accuracy of 97%.Amara et al (2017) used deep learning related approach to identify the diseases in leaves of the banana plant using their images. To automate this system,LeNet architecture is used in convolutional neural network for identifying and classifying the datasets which was proved to be efficient. The process consists of two frameworks namely image preprocessing and deep-learning based classification. The banana leaf datasets are resized and converted into grayscale image. The significant featuresare extracted and classified and the results are analysed. The two diseases that are identified in this approach are banana sigatoka and banana speckle.Lu et al (2017) identified diseases in rice plants using deep convolutional neural networks. In this model, ten diseases in rice plants were identified. The datasets were collected by capturing the images from the field. The models were trained after the extraction of the features from the imagetested by giving inputs and checking for the desired outputs. Through this model, it was proved that the deep convolutional neural networks are more efficient than the convolutional neural networks. This model yielded an efficiency of 95.48%.

Liu et al (2018) identified diseases in the leaves of an apple tree using deep convolutional neural networks. The datasets of these diseases are collected and trained with the model. The pathological images of these apple diseases are generated. The trained model is evaluated by testing it with the captured image from the field. This model yielded an accuracy of 97%.Fernentinos (2018) proposed a methodology in which plant leaf disease detection and diagnosis are performed using an open database of 87,848 images containing 25 different plants in a set of 58 distinct classes including healthy leaves. Several model architectures were trained for achieving high efficiency. Five basic CNN architectures namely (i) AlexNet, (ii) AlexNetOWTBn, (iii) GoogleLeNet, (iv) Overfeat and (v) VGG were tested in this work for identifying the diseases from the images of the plant. These architectures along with their trained and tested processes were implemented using Torch7 machine learning framework with programming language LuaJIT. The paper approached a method to train and test the dataset in which the dataset is trained in the laboratory conditions and tested in field conditions and then vice versa. In both cases, the testing and training ratio were far wider. Although the architecture VGG resulted in a high efficiency, it had an issue in which the testing dataset were a part of the training dataset.

Kamilariset al (2018) had surveyed 40 research efforts that uses deep learning techniques. The author also compared the deep learning techniques with other available popular techniques in order to determine which technique is the best one to approach. Deep learning has an advantage of feature learning in which it extracts the feature from higher level to lower level data. It can also solve complex problems which can increase the accuracy level and can reduce error. The convolutional neural network consists of deep and feed forward artificial neural network. The first layer has general ones of the dataset and becomes more specific at the deeper levels. The most advantage of using deep learning in image processing is that it well supports feature engineering. It also has a disadvantage that the training time is much longer when compared with other methods but the testing time is faster than other methods. The author discussed about various techniques including data variation, data pre-processing, data augmentation and technical details and performance metrics. From this survey paper, it is proved that the deep learning provides superior results when compared with other methods.

Barbedo (2019) collected the dataset of various plants by using different sensors with resolution ranging from 1 to 24 MPixels. Instead of collecting various images for the same plant, data augmentation is used to explore the use of individual spots and lesions for detection of the disease without considering whole part of the leaf. The whole process is divided into two parts. The first part focused on the classification problem to identify the origin of the symptom which was already found. The second part focused on detecting the disease among the healthy tissues. By this experiment, results were gradually improved while considering individual lesions and spots instead of the whole leaf. The accuracy obtained with data augmentation in this approach is 12% higher than the original images.

To the best of our knowledge, it is identified that only very few standard research works had already been carried out for detecting diseases in leaves of cotton plant separately and are explained here.Ghaiwat and Arora (2016) have extracted 12 different features from the images of cotton leaves and diseases in cotton leaves are identified using Back Propagation Neural Networks (BPNN). The method identifies three types of diseases namely Powdery mildew, Downy mildew and leafminer. Adhao and Pawar (2018) have developed an android application capable of identifying 5 types of diseases in cotton leaves. It also monitors the soil quality and provides appropriate remedies for the farmers. It has automatic switch on/off mechanism to control motor and sprinkle pesticides to the farms based on needs of plants. The classification of diseases is done with the help of Support Vector Machine (SVM). But, its results show only 83.26% of detection accuracy. Zhang et al (2018) have proposed an automatic disease segmentation method for cotton leaves using Gradient and Local Information (GLI). A segmented monotone decreasing edge composite function speeds up setting up of level set curve in gradient smooth region. Then, canny edge detection operator gradient is passed as the global information. The energy function value guides the curve evolution in order to obtain the smooth curve.

Khairnar and Goje (2020) have introduced a methodologycalled K means clustering based Support Vector Machine (KM-SVM) to accurately identify visually observable diseases in cotton leaves using their symptoms. First, K-means clustering is used to segment the infected cotton leaves. Color and texture features are then segmented and significant features are extracted and samples are classified using SVM. It also suggests fertilizers for the affected diseases.

From the literatures, it is clearly inferred that there are many difficulties in manual observation of all plant diseases and the best solution is making the process automated. It is also stated that by making the process automated, the pesticides usage can be reduced thereby making the human lives much healthier.

Basic description about Fast R-CNN

CNN is the type of Deep Neural Networks which are suitable for image processing problems especially in plant disease detection as noted in the above literatures. CNN have architectures like LeNet, AlexNet, VGG-16, Resnet etc. Instead of working on a massive number of regions, R-CNN proposes a bunch of boxes in the image and check each and every box that containsobjects. It uses selective search for extracting these boxes form an imagecalled as regions. The entire process of object detection using R-CNN has 3 models.

i. CNN for feature extraction
ii. Linear SVM classifier for identifying objects
iii. Regression model for tightening the bounding boxes

All this process makes RCNN very slow where 40 to 50 seconds are needed to identify an image on average.Fast R-CNN is used to overcome the drawbacks of R-CNN andperformedusing the following steps:

i. An image is taken as an input and this image is passed to the ConvNet
ii. This gives the feature map of the image which generates the region of interest (RoI)
iii. This RoI pooling layer is used to reshape the images according to the ConvNet
iv. The fixed size regional proposal feature map is flattened and now this is a feature vector
v. After this, each and every region is passed to the fully connected network and the feature vector is the input to those layers
vi. The softmax layer is used at the beginning of the fully connected network to obtain the output. The linear regression layer is also used along with the fully connected network to set the bounding box coordinates for predicted classes.

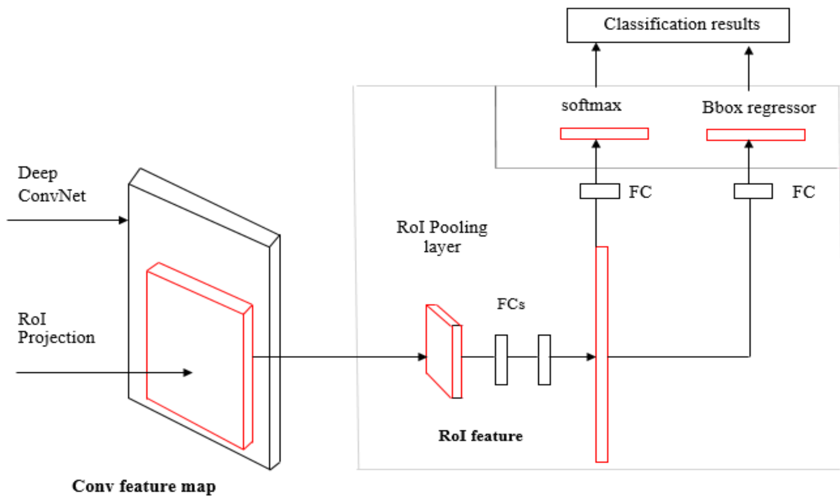

Fig.1 Working model of Fast R-CNN

3. Proposed Method

The proposed work uses Faster R-CNN with RPN method which is an extension of Fast R-CNN method for detecting diseases in cotton leaves to improve the classificationperformance.The steps involved in the proposed methodology are as follows:

i. Image acquisition
ii. Image Preprocessing
iii. Feature extraction
iv. Disease classification

Image acquisition

Image acquisition refers to capturing an image of a cotton leaf with the help of camera from real fields. The most common method is to acquire photo by using digital camera among many other methods. For this methodology, photos are taken from plant village dataset which are trained and tested.

Image preprocessing

Further processing and analysis is carried out by image preprocessing to increase the quality of image. Image smoothing and image enhancement are performed. Image smoothing is the process of removing undesired distortion from the image to improve quality of the input image and smoothing filter is used in this experiment to smooth out the image. Image enhancement is used to increase the contrast of image. Image clipping is done to get interested region.Image segmentation is performed by HSV and Grayscale method in order to extract the required objects from the unnecessary ones in the image being processed. The segmented results are binary images with extracted object represented as 1 and others as 0.

Feature extraction

To predict the infected regionstactfully, feature extraction is used. Feature extraction involves reducing the amount of features needed to describe the large dataset. It is a method of identifying set of characteristics and image characteristics that meaningfully represents analysis data and significant classification. It is expected that the extracted features contain appropriate information from the input data and using this decreased representation for doing the required job.In the existing methods, feature extraction methods like Texture content counting, Gray Level Co-occurrence Matrix (GLCM) are used. In the proposed methodology, feature extraction is done by CNN architectureitself and the resultant feature subsets are stored in feature dataset.Inception v2 model is used for this purpose in convolutional layers of CNN. It shows less computational complexity than other CNN models and can be effectively used in big data environments. Processing large datasets and sizeable convolutions incur high computational cost. When there are more number of dimensions in input frames are reduced, it results in loss of information and is called as "Representational bottleneck". But, in inception v2 model convolutions, smart factorization approach is used to reduce the number of dimensions. The model uses three convolutional layers with dimensionality reduction filter bank, five layers of deeper filter bank and then two layers of wider filter bank as given in figure 2. The result obtained from wider filter bank is then passed onto RPN layer. The main advantage noted here is that wider filter banks removes the representational bottleneck problem completely.

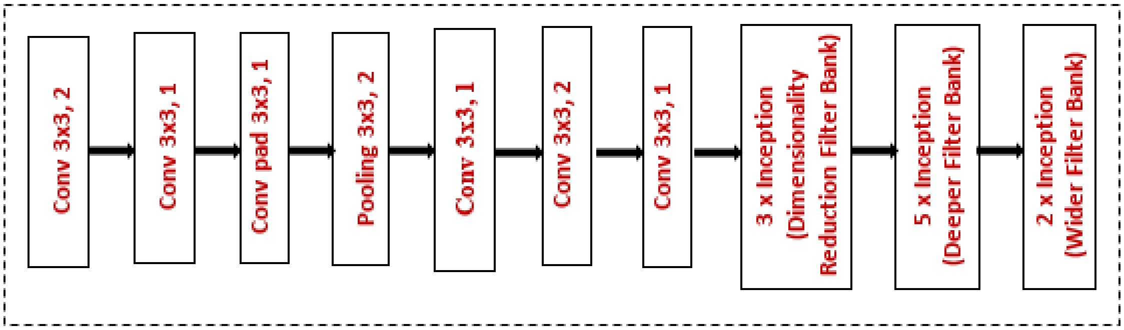

Figure 2. Inception v2 model

Disease classification

In the classification phase, co-occurrence feature values of the leaves that are stored in feature dataset are used. For classification of the image, Faster R-CNN with RPN is implemented.The modified version of Fast RCNN is Faster R-CNN which uses selective search for generating Regions of Interest, and Region Proposal Network. RPN takes features of image,maps them as input and generates a set of object proposals which produce score as the output. Figure3 represents the working model of Faster R-CNN with RPN with the below steps:

- Image is sent to ConvNet as input which returns the feature map for that image
- RPN is applied on the result which returns the object proposals along with their objectness score
- For bringing down all the proposals to the same size, RoIpooling layer is applied
- Finally, the proposals are passed to a fully connected layer which has a softmax layer and a linear regression layer at its top to classify and output the bounding boxes for objects

RPN reduces the computational complexity of faster R-CNN by scanning and analyzing all image locations such that the point to process is identified easily in less duration. It has a specialized and unique architecture within itself. As given in figure 3, RPN uses a sliding window over the feature maps from ConvNet. At each window, it generates k anchor boxes of different shapes and sizes. Anchor boxes are fixed sized boundary boxes that are placed all over the image and have different shapes and sizes. Scale and aspect ratio are two primary factors for image processing where scale indicates size of the image and aspect ratio refers to the ratio of image width (W) to image height (H). Hence for the entire image, W*H* k anchors are being generated. RPN usually performs both classification and regression. For each anchor, RPN predicts two factors. First one is the probability that an anchor object is present or not inside the anchor box (generated by classification) and second is the bounding box for adjusting the anchors to fit the object (generated by regression).

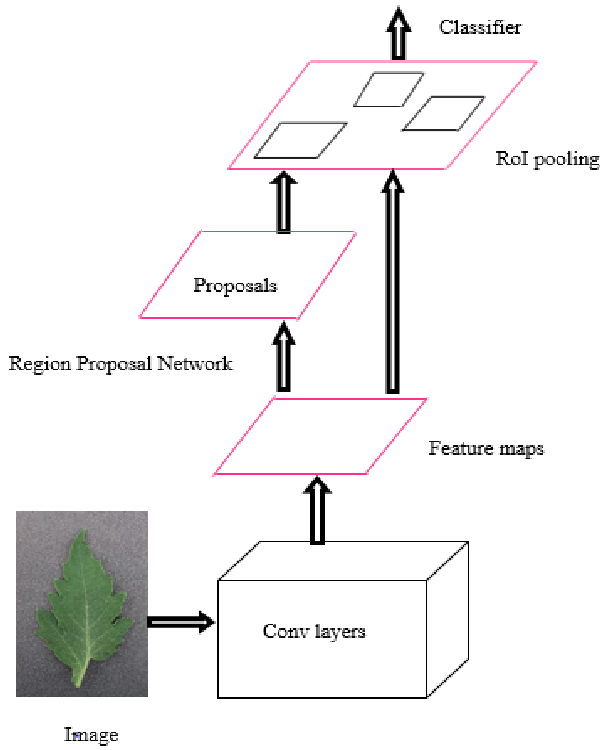

Figure3. Working model of Faster R-CNN with Region Proposal Network

An example case is given in figure 4where RPN has a 3x3 window sliding over a high level conv feature map. It is then resampled to 256 dimensional vector before feeding into fully connected classification and regression layers. 2k confidence scores are generated by classification and 4k bounding box offsets are produced by regression layer totally adding to 4k +2k outputs for the given RPN. RPN exhibits translational invariant property by being robust to translations and makes it suitable for a variety of applications. These bounding boxes are passed on to the RoI pooling layer. This layer crops each proposal that contains an object. It extracts fixed sized feature maps for each anchor. These feature maps are passed to a fully connected layer which has a linear regression layer and a softmaxfunction which classifies the object.

It has multi-scale anchors creating 'Pyramid of Anchors' which reduces execution time and cost involved than other multi-box algorithms. RPN algorithm is trained to create a model and evaluates loss function. It assigns labels to anchors which have highest intersection-over-union overlap with a ground truth box and intersection-over-union overlap value greater than 0.7.

$$L(\{p_i\},\{t_i\}) = \frac{1}{N_{cls}}\sum_i L_{cls}(p_i, p_i^*) + \lambda \frac{1}{N_{reg}}\sum_t p_i^* L_{reg}(t_i, t_i^*)$$

Wherei - the index of anchor in the mini-batch
p_i- estimated probability that the anchor i is an object (from classification layer)
t_i - vector of 4 parametrized coordinates of predicted bounding box (from regression layer)
p_i^* - ground truth label and is 1 if anchor is positive and 0 if it is negative
t_i^* - ground truth box associated with positive anchor
L_{cls} – log loss over two classes (object and not object) – classification loss
$L_{reg}(t_i, t_i^*) = R(t_i - t_i^*)$ where R is the robust loss function
N_{cls}, - Normalized cls value (mini batch size usually taken as 256)
N_{reg} - Normalized reg value (number of anchor locations approximately 2400)

λ- balancing parameter (default value is 10) – scale classifier and regressor to the samelevel

The entire term $p_i^* L_{reg}(t_i, t_i^*)$ have regression loss value included only for positive anchors whose ground truth label is 1 (ie.,p_i^*=1) and is not activated if p_i^*=0.

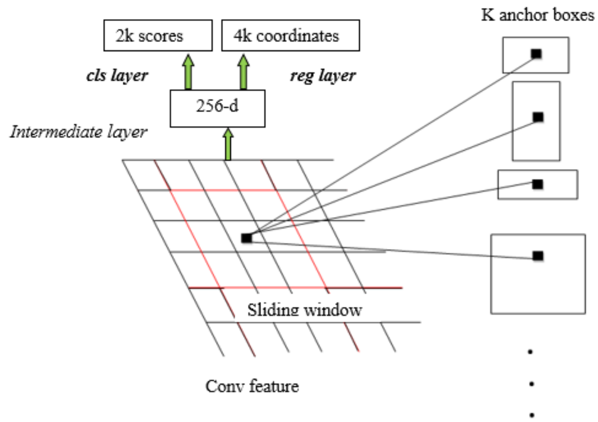

Figure4. Working model of RPN

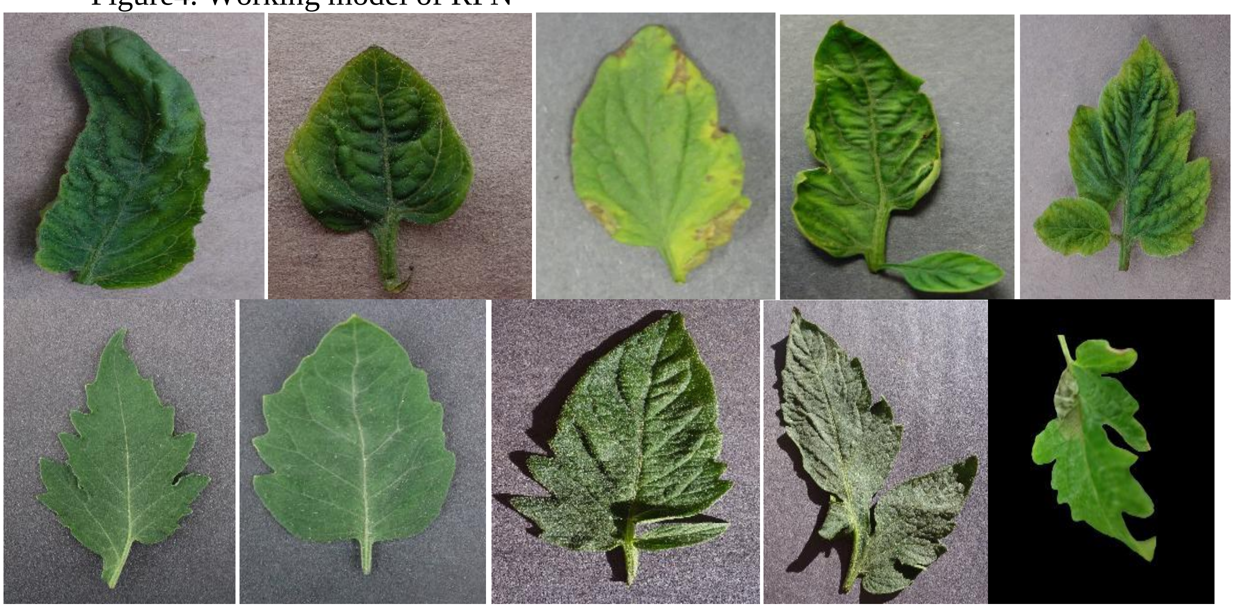

Figure 4. Images of Diseased cotton plant leaves

Figure 5. Images of healthy leaves of cotton plant leaves

The inception v2 model is optimized

4. Results and Discussion

The images for input dataset are taken from publicly available PlantVillage dataset. The input dataset for our experiments contain 4000 cotton leaves images which contain 4 classes of healthy leaves, Bacterial blight diseases, yellow leaf curl virus and late blight diseases. Figures 4 and 5 show the sample images of diseased and healthy cotton plant leaves respectively.

using gradient descent method called Adam optimization.The accuracy of object recognition algorithm is evaluated using Intersection over Union (IoU). The models are trained for 40,000 steps with learning rate of 0.0002 for Adam optimizer.Minibatch size is fixed to 20 and IoU is set to 0.5:0.95. The ratio of training to testing datasets is 70:30. As given in figure 6, detection of diseases in cotton plants is successfully completed using Faster R-CNN with RPN.

Table 1 shows average precision and average recall values with the given IoU. The experiments are performed with 2000 anchor boxes for training but with varying number of proposals like 500, 1000 and 2000 during testing. Average Precision and Recall values are appreciable with all sizes of proposals. When number of proposals increases, the precision and recall values get improved which convey that more number of proposals increase the probability of significant features getting included in the process. Hence for further evaluations, 2000 proposals are utilized.

Table 1. Performance of Faster R-cNN with RPN

Number of anchor boxes for training	Number of proposals for testing	Average Precision	Average Recall
2000	500	0.92	0.93
2000	1000	0.95	0.96
2000	2000	0.98	0.97

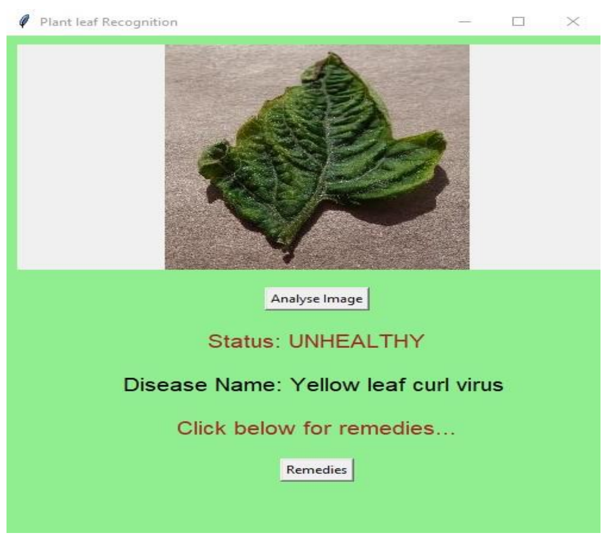

Figure 6. Diseases detection result and remedies

This model classified almost 95.57% of all the testing images correctly. As shown in figure 7, this model was able to classify a high percentage of images correctly from total testing images. It classifies 94% of bacterial blight, 95% of yellow leaf curl virus, 95% of late blight and 96% of healthy leaves accurately.

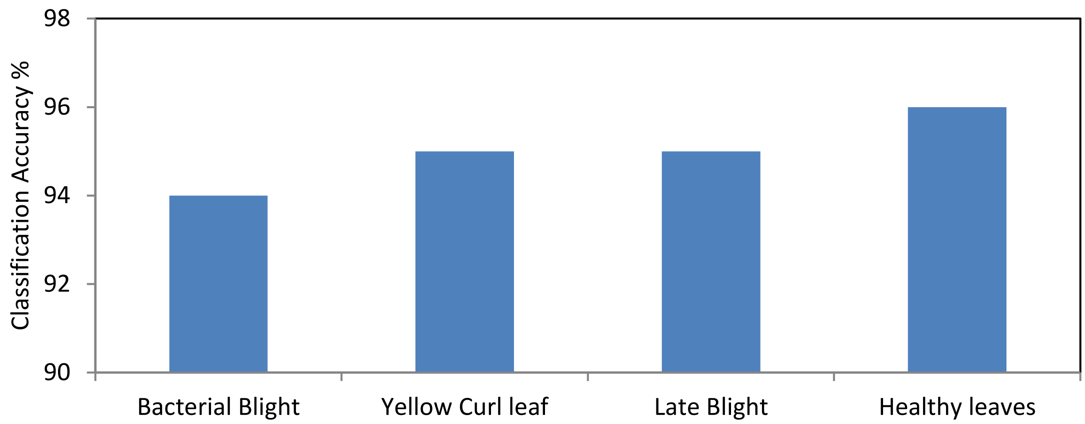

Figure 7. Faster R-CNN Inception v2 model results

The performance of proposed Faster R-CNN with RPN is compared with that of BPNN (Ghaiwat and Arora 2016), SVM (Adhao and Pawar 2018), GLI (Zhang et al 2018), KM-SVM (Khairnar and Goje 2020), and Fast R-CNN. As shown in figures 8 and 9, the training and testing time for Faster R-CNN is less when compared with other models. Except fast R-CNN and faster R-CNN, other models consume quite long time. The execution time is very much reduced in these two methods since they include all novel strategies which intend to complete the process quicker. When compared with training time, testing time is very much reduced in CNN models than other models. This is possible due to the fact that convolution layers are efficiently designed in such a way that optimized set features are selected and pooling helps in further improving the classification performance. Similarly, the classification accuracy rate is also higher in Faster R-CNN than other methods as shown in Figure10.

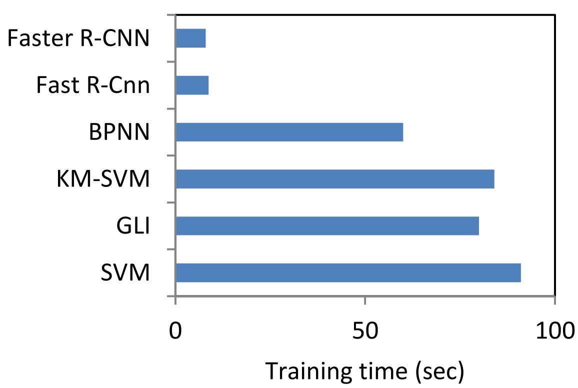

Figure 8. Time taken to train the model

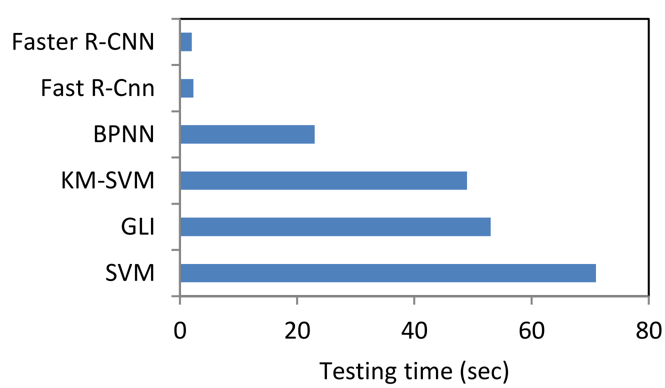

Figure 9. Time taken to test the model

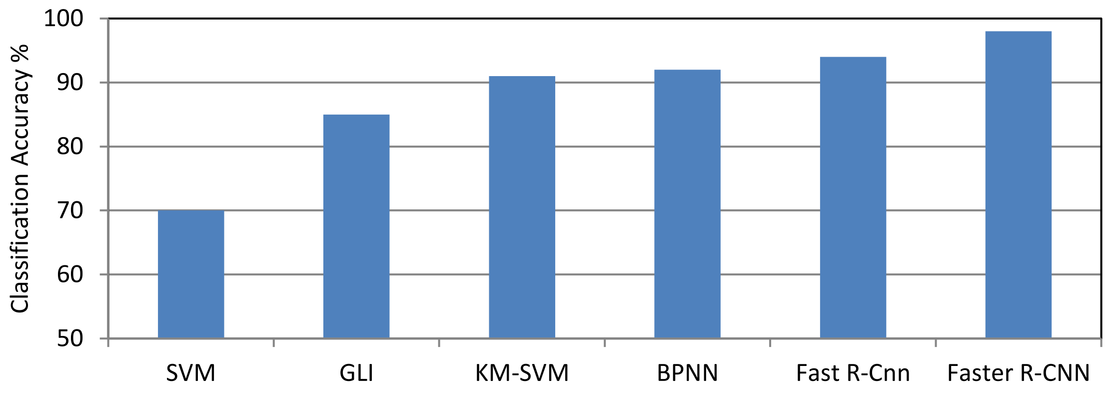

Figure 10.Comparison of accuracy by machine learning methods

Figure 10 is further split to show the classification accuracy of different models disease wise. Identification of each and every disease leaf is more accurate in faster R-CNN when compared with other convolutional models and traditional models as in Figure 11.

This implementation is created as an application and used in mobile phones. Using phones, disease names can be displayed to the users and remedies for the classified diseases are also suggested. Remedies for the diseases which are detected in this model are suggested in table 2.

Table 2. Remedies for the diseases

Name of the disease	**Remedy**
Bacterial blight	Mixture of Agrimycin-100 (0.01%) + Blitox-50 (Copper oxychloride)- 0.2%
Yellow leaf curl virus	Using sticky yellow traps and the insecticide organophosphates
Late blight	Mixture of Cymoxanil 8% + Mancozeb 64%

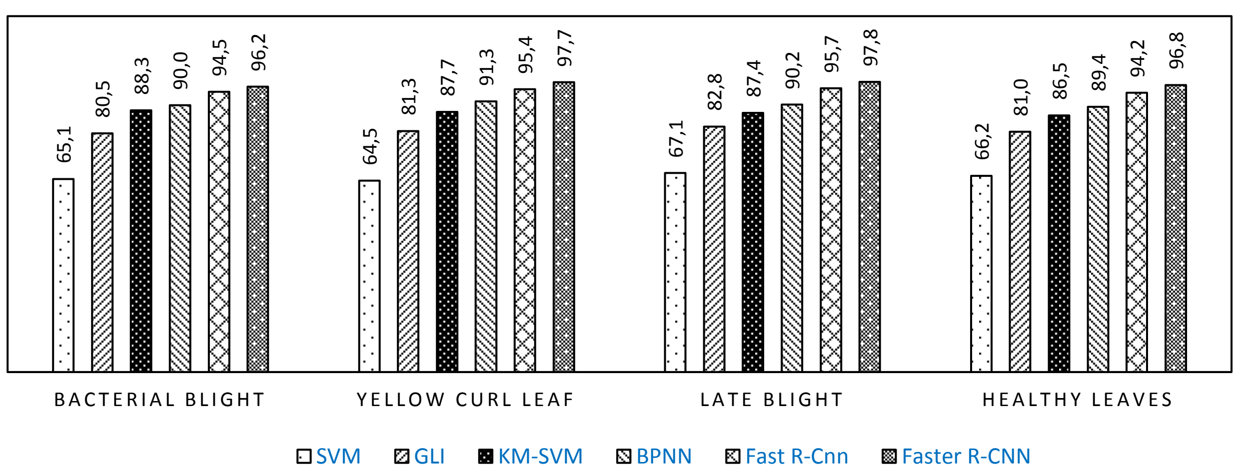

Figure 11. Classification accuracy % of diseasedand healthy leaves

6. Conclusion

In this paper, Faster R-CNN, a deep learningmethod together with RPN is used for detecting and classifying images which are combination of both the healthy and diseased leaves of cotton plant. The dataset contains diversifiedimage data and they are properly pre-processed and further processed. The faster R-CNN speeds up the classification process and RPN further enhances the process by generating proposals capable of capturing highly significant features. On comparison with other machine learning and deep learning models,fasterR-CNN is proved to be much faster with better classification accuracy, average precision and average recall. Remedies of the identified diseases are also suggested in the proposed system for analysts and farmers to take appropriate actions. In future, this project can be enhanced by implementing as a real time detection system using other deep learning models for the farmers in the agricultural field by placing sensors in the field.

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