Detection and Classification of Plant Leaf Diseases by using Deep Learning Algorithm

M. Akila
PG Student
Department of CSE
Arasu Engineering College,
Kumbakonam, India

P. Deepan
Assistant Professor,
Department of CSE
Arasu Engineering College
Kumbakonam, India

Abstract—**Plant leaf diseases and destructive insects are a major challenge in the agriculture sector. Faster and an accurate prediction of leaf diseases in crops could help to develop an early treatment technique while considerably reducing economic losses. Modern advanced developments in Deep Learning have allowed researchers to extremely improve the performance and accuracy of object detection and recognition systems. In this paper, we proposed a deep-learning-based approach to detect leaf diseases in many different plants using images of plant leaves. Our goal is to find and develop the more suitable deep-learning methodologies for our task. Therefore, we consider three main families of detectors: Faster Region-based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Network (R-FCN), and Single Shot Multibox Detector (SSD), which was used for the purpose of this work. The proposed system can effectively identified different types of diseases with the ability to deal with complex scenarios from a plant's area.**

Keywords— Plant Leaf Diseaases, Deep Learning, faster R-CNN, R-FCN, SSD

I. INTRODUCTION

Agriculture is the mainstay of the Indian economy. Immense commercialisation of an agriculture has creates a very negative effect on our environment. The use of chemical pesticides has led to enormous levels of chemical buildup in our environment, in soil, water, air, in animals and even in our own bodies. Artificial fertilisers gives on a short-term effect on productivity but a longer-term negative effect on the environment, where they remain for years after leaching and running off, contaminating ground water. Another negative effect of this trend has been on the fortunes of the farming communities worldwide. Despite this so-called increased productivity, farmers in practically every country around the world have seen a downturn in their fortunes. This is where organic farming comes in. Organic farming has the capability to take care of each of these problems. The central activity of organic farming relies on fertilization, pest and disease control.

Plant disease detection through naked eye observation of the symptoms on plant leaves, incorporate rapidly increasing of complexity. Due to this complexity and to the large number of cultivated Crops and their existing phytopathological problems, even experienced agricultural experts and plant pathologists may often fail to successfully diagnose specific diseases, and are consequently led to mistaken conclusions and concern solutions. An automated system designed to help identify plant diseases by the plant's appearance and visual symptoms could be of great help to amateurs in the agricultural process. This will be prove as useful technique for farmers and will alert them at the right time before spreading of the disease over large area.

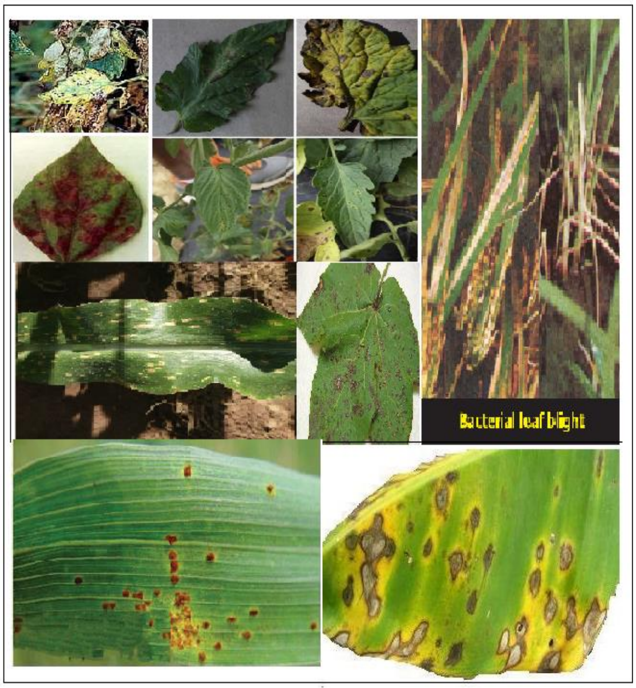

Fig.1 Diseases affected leaf images

Deep learning constitutes a recent, modern technique for image processing and data analysis, with accurate results and large potential. As deep learning has been successfully applied in various domains, it has recently entered also the domain of agriculture. So we will apply deep learning to create an algorithm for automated detection and classification of plant leaf diseases. Nowadays, Convolutional Neural Networks are considered as the leading method for object detection. In this paper, we considered detectors namely Faster Region-Based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Networks (R-FCN) and Single Shot Multibox Detector (SSD). Each of the architecture should be able to be merged with any feature extractor depending on the application or need. We consider some of the commercial/cash crops, cereal crops, and vegetable crops and fruit plants such as sugarcane, cotton, potato, carrot, chilly, brinjal, rice, wheat, banana and guava, these leaves images are selected for our purpose. Fig. 1 shows images of the diseased affected leaves on various crops. The early detection of plant leaf diseases could be a valuable source of information for executing proper diseases detection, plant growth management strategies and disease control measures to prevent the development and the spread of diseases.

II. RELATED WORK

Here, we take some of the papers related to Plant leaf diseases detection using various advanced techniques and some of them shown below,

In paper[1], author described as an in-field automatic wheat disease diagnosis system based on a weekly supervised deep learning framework, i.e. deep multiple instance learning, which achieves an integration of identification for wheat diseases and localization for disease areas with only image-level annotation for training images in wild conditions. Furthermore, a new in-field image dataset for wheat disease, Wheat Disease Database 2017 (WDD2017), is collected to verify the effectiveness of our system. Under two different architectures, i.e. VGG-FCN-VD16 and VGG-FCN-S, our system achieves the mean recognition accuracies of 97.95% and 95.12% respectively over 5-fold cross validation on WDD2017, exceeding the results of 93.27% and 73.00% by two conventional CNN frameworks, i.e. VGG-CNN-VD16 and VGG-CNN-S. Experimental results demonstrate that the proposed system outperforms conventional CNN architectures on recognition accuracy under the same amount of parameters, meanwhile maintaining accurate localization for corresponding disease areas. Moreover, the proposed system has been packed into a real-time mobile app to provide support for agricultural disease diagnosis.

In paper [2], author discussed and to perform a survey of 40 research efforts that employ deep learning techniques, applied to various agricultural and food production challenges. Examine the particular agricultural problems under study, the specific models and frameworks employed the sources, nature and pre-processing of data used, and the overall performance achieved according to the metrics used at each work under study. Moreover, study comparisons of deep learning with other existing popular techniques, in respect to differences in classification or regression performance. Findings indicate that deep learning provides high accuracy, outperforming existing commonly used image processing techniques.

In paper [3], author discussed about convolutional neural network models were developed to perform plant disease detection and diagnosis using simple leaves images of healthy and diseased plants, through deep learning methodologies. Training of the models was performed with the use of an open database of 87,848 images, containing 25 different plants in a set of 58 distinct classes of [plant, disease] combinations, including healthy plants. Several model architectures were trained, with the best performance reaching a 99.53% success rate in identifying the corresponding [plant, disease] combination (or healthy plant). The significantly high success rate makes the model a very useful advisory or early warning tool, and an approach that could be further expanded to support an integrated plant disease identification system to operate in real cultivation conditions.

In paper [4] author describes a methodology for early and accurately plant diseases detection, using artificial neural network (ANN) and diverse image processing techniques. As the proposed approach is based on ANN classifier for classification and Gabor filter for feature extraction, it gives better results with a recognition rate of up to 91%. An ANN based classifier classifies different plant diseases and uses the combination of textures, color and features to recognize those diseases.

In paper [5] authors presented disease detection in Malus domestica through an effective method like K-mean clustering, texture and color analysis. To classify and recognize different agriculture, it uses the texture and color features those generally appear in normal and affected areas.

In paper [6] authors compared the performance of conventional multiple regression, artificial neural network (back propagation neural network, generalized regression neural network) and support vector machine (SVM). It was concluded that SVM based regression approach has led to a better description of the relationship between the environmental conditions and disease level which could be useful for disease management

III. PROPOSED METHODOLOGY

Plants are susceptible to several disorders and attacks caused by diseases. There are several reasons that can be characterizable to the effects on the plants, disorders due to the environmental conditions, such as temperature, humidity, nutritional excess or losses, light and the most common diseases that include bacterial, virus, and fungal diseases. Those diseases along with the plants may shows different physical characteristics on the leaves, such as a changes in shapes, colors etc. Due to similar patterns, those above changes are difficult to be distinguished, which makes their recognition a challenge, and an earlier detection and treatment can avoid several losses in the whole plant. In this paper, we are discussed to use recent detectors such as Faster Region-Based Convolutional Neural Network (Faster R-CNN), Region-based Fully Convolutional Networks (R-FCN) and Single Shot Multibox Detector (SSD) to detection and classification of plant leaf diseases that affect in various plants. The challenging part of our approach is not only deal with disease detection, and also known the infection status of the disease in leaves and tries to give solution (i.e., name of the suitable organic fertilizers) for those concern diseases.

A. *Faster Region-Based Convolutional Neural Network (Faster R-Cnn)*

Faster R-CNN is one of the Object detection systems, which is composed of two modules. The first module is a deep fully convolutional network that proposes regions. For training the RPNs, the system considers anchors containing an object or not, based on the Intersection-over-Union (IoU) between the object proposals and the ground-truth. Then the second module is the Fast R-CNN detector [13], [14] that uses the proposed regions. Box proposals are used to crop features from the same intermediate feature map which are subsequently fed to the remainder of the feature extractor in order to predict a class and class-specific box refinement for each proposal. Fig. 2 shows the basic architecture of Faster R-CNN. The entire process happens on a single unified network, which allows the system to share full-image convolutional features with the detection network, thus enabling nearly cost-free region proposals.

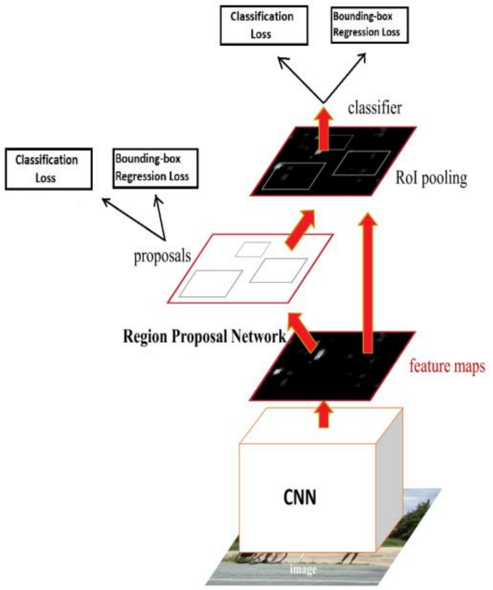

Fig. 2. Basic architecture of Faster R-CNN

B. *REGION-BASED FULLY CONVOLUTIONAL NETWORK (R-FCN)*

We develop a framework called Region-based Fully Convolutional Network (R-FCN) for object detection. While Faster R-CNN is an order of magnitude faster than Fast R-CNN, the fact that the region-specific component must be applied several hundred times per image led [12], [13], [16], [19] to propose the R-FCN (Region-based Fully Convolutional Networks) method which is like Faster R-CNN, but instead of cropping features from the same layer where region proposals are predicted, crops are taken from the last layer of features prior to prediction. R-FCN object detection strategy consists of: (i) region proposal, and (ii) region classification. This approach of pushing cropping to the last layer minimizes the amount of per-region computation that must be done. The object detection task needs localization representations that respect translation variance and thus propose a position-sensitive cropping mechanism that is used instead of the more standard ROI pooling operations used in object detection [13], [20]. They show that the R FCN model could achieve comparable accuracy to Faster R-CNN often at faster running times.

C. *Single Shot Detector (Ssd)*

The SSD approach is based on a feed-forward convolutional network that produces a fixed-size collection of bounding boxes and scores for the presence of object class instances in those boxes, followed by a non-maximum suppression step to produce the final detections. This network is able to deal with objects of various sizes by combining predictions from multiple feature maps with different resolutions [13], [15]. Furthermore, SSD encapsulates the process into a single network, avoiding proposal generation and thus saving computational time.

IV. EXPERIMENTAL RESULT

In our system processing starts with Data collection, through some the pre-processing, feature extractor steps to be allowed and then finally detect the diseases from image. Fig. 3 shows the overview of our proposed system.

OVERVIEW OF THE SYSTEM

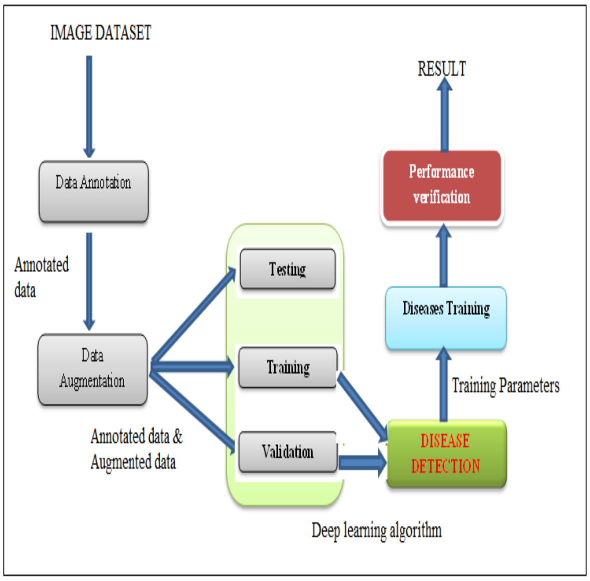

Fig. 3. System design

D. *DATA COLLECTION*

Dataset contains images with several diseases in many different plants. In this System we consider some of the commercial/cash crops, cereal crops, and vegetable crops and fruit plants such as sugarcane, cotton, potato, carrot, chilly, brinjal, rice, wheat, banana and guava. Diseased leaves, healthy leaves all of them were collected for those above crops from different sources like images download from Internet, or simply taking pictures using any camera devices or any else.

E. *IMAGE PRE-PROCESSING*

Image annotation and augmentation

Image annotation, the task of automatically generating description words for a picture, is a key component in various image search and retrieval applications. But in this system, we manually annotate the areas of every image containing the disease with a bounding box and class. Some diseases might look similar depending on its infection status.

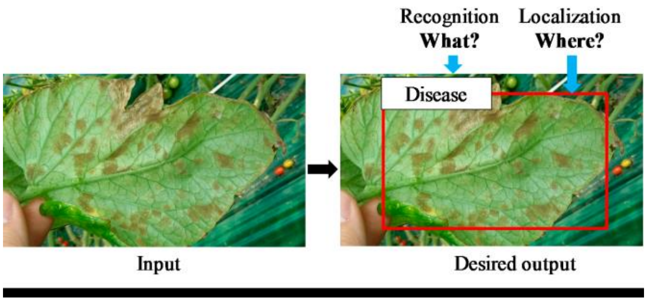

Fig. 4. Annotated Image

Annotation process might able to label the class and location of the infected areas in the leaf image. The outputs of this step are the coordinates of the bounding boxes of different sizes with their corresponding class of disease, which consequently will be evaluated as the Intersection over-Union (IoU) with the predicted results during testing. Fig. 4 shows the annotated image.

Images are collected from various sources were in various formats along with different resolutions and quality. In order to get better feature extraction, images are intended to be used as dataset for deep neural network were pre-processed in order to gain consistency. Images used for the dataset were image resized to 256×256 to reduce the time of training, which was automatically computed by written script in Python, using the OpenCV framework [7], [8].

In machine learning, as well as in statistics, overfitting appears when a statistical model describes random noise or error rather than underlying relationship [9]. The image augmentation contained one of several transformation techniques including affine transformation, perspective transformation, image rotations [10] and intensity transformations (contrast and brightness enhancement, color, noise). Fig 5 and Fig 6 shows an example for affine transformations and simple rotations.

Fig. 5. Affine transformations

Fig. 6. Rotations

F. IMAGE ANALYSIS

Our system main goal is to detect and recognize the class disease in the image. We need to accurately detect the object, as well as identify the class to which it belongs. We extend the idea of object detection framework to adapt it with different feature extractors that detect diseases in the image.

Faster R-CNN

Faster R-CNN [13], [14] for object recognition and its Region Proposal Network (RPN) to estimate the class and location of object that may contain a target candidate. The RPN is used to generate the object a proposal, including their class and box coordinates.

R-FCN

Similar to Faster R-CNN,[13], [16], [20] R-FCN uses a Region Proposal Network to generate object proposals, but instead of cropping features using the RoI pooling layer it crops them from the last layer prior to prediction.

SSD

SSD generates anchors that select the top most convolutional feature maps and a higher resolution feature map at a lower resolution. Then, a sequence of the convolutional layer containing each of the detection per class is added with spatial resolution used for prediction [13], [15]. Thus, SSD is able to deal with objects of various sizes contained in the images. A Non-Maximum Suppression method is used to compare the estimated results with the ground-truth.

G. Feature Extraction

There are some conditions that should be taken into consideration when choosing a Feature Extractor, such as the type of layers, as a higher number of parameters increases the complexity of the system and directly influences the speed, and results of the system. Although each network has been designed with specific characteristics, all share the same goal, which is to increase accuracy while reducing computational complexity. In this system each object detector to be merged with some of the feature extractor. [13]The system performance is evaluated first of all in terms of the Intersection-over-Union (IoU), and the Average Precision (AP) that is introduced in the Pascal VOC Challenge [17]

$$\mathrm{IoU}(A,B) = \left|\frac{A\cap B}{A\cup B}\right| \qquad (1)$$

where A represents the ground-truth box collected in the annotation, and B represents the predicted result of the network. If the estimated IoU outperforms a threshold value, the predicted result is considered as a true positive, TP, or if not as a false positive, FP. TP is the number of true positives generated by the network, and FP corresponds to the number of false positives. Ideally, the number of FP should be small and determines how accurate the network to deal with each case is. The IoU is a widely used method for evaluating the accuracy of an object detector. [13][17]The Average Precision is the area under the Precision-Recall curve for the detection task. As in the Pascal VOC Challenge, the AP is computed by averaging the precision over a set of spaced recall levels [0, 0.1, . . . , 1], and the mAP is the AP computed over all classes in our task.

$$AP = \frac{1}{11}\sum_{r\epsilon\{0,0.1,\dots,1\}} p_{inter\,p}\ (r) \qquad (2)$$

$$p_{\mathrm{interp}}\,(r) = \max_{\tilde{r}:\tilde{r}\geq r} p(\tilde{r}) \qquad (3)$$

where $p(\tilde{r})$ is the measure precision at recall $\tilde{r}$.

Faster R-CNN for each object proposal, [14]we extract the features with a RoI Pooling layer and perform object classification and bounding-box regression to obtain the estimated targets. We used batch normalization for each feature extractor, and train end-to-end using an Image Net Pre trained Network.

To perform the experiments, our dataset has been divided into training set, validation set and testing set. Evaluation is performed on the Validation set after that training is process is performed on the training set and then final evaluation done in testing phase. As in the Pascal Visual Object Classes (VOC) Challenge [17], the validation set is a technique used for minimizing over fitting and is a typical way to stop the network from learning. We use the training and validation sets to perform the training process and parameter selection, respectively, and the testing set for evaluating the results on unknown data.

V. CONCLUSION

Crop protection in organic agriculture is not a simple matter. It depends on a thorough knowledge of the crops grown and their likely pests, pathogens and weeds. In our system specialized deep learning models were developed, based on specific convolutional neural networks architectures, for the detection of plant diseases through leaves images of healthy or diseased plants. Our detector applied images captured in-place by various camera devices and also collected from various resources. Our experimental results and comparisons between various deep-architectures with feature extractors demonstrated how our deep-learning-based detector is able to successfully recognize different categories of diseases in various plants and also give solution for concern diseases. Pests/diseases are generally not a significant problem in organic systems, since healthy plants living in good soil with balanced nutrition are better able to resist pest/disease attack. We hope our proposed system will make a suggestive contribution to the agriculture research.

REFERENCES

[1] Jiang Lu, Jie Hu, Guannan Zhao, Fenghua Mei, Changshui Zhang, An in-field automatic wheat disease diagnosis system, Computers and Electronics in Agriculture 142 (2017) 369–379.

[2] Andreas Kamilaris, Francesc X. Prenafeta-Boldu Deep learning in agriculture: A survey, Computers and Electronics in Agriculture 147 (2018) 70–90.

[3] Konstantinos P. Ferentinos, Deep learning models for plant disease detection and diagnosis Computers and Electronics in Agriculture 145 (2018) 311–318.

[4] Kulkarni Anand H, Ashwin Patil RK. Applying image processing technique to detect plant diseases. Int J Mod Eng Res 2012;2(5):3661–4.

[5] Bashir Sabah, Sharma Navdeep. Remote area plant disease detection using image processing. IOSR J Electron Commun Eng 2012;2(6):31–4. ISSN: 2278-2834.

[6] Rakesh Kaundal, Amar S Kapoor and Gajendra PS Raghava "Machine learning technique in disease forecasting: a case study on rice blast prediction," BMC Bioinformatics, 2006.

[7] Srdjan Sladojevic, Marko Arsenovic, Andras Anderla, Dubravko Culibrk, and Darko Stefanovic, Deep Neural Networks Based Recognition of Plant Diseases by Leaf Image Classification, Hindawi Publishing Corporation, Computational Intelligence and Neuroscience Volume 2016, Article ID 3289801, 11 pages http://dx.doi.org/10.1155/2016/3289801.

[8] J.Howse,OpenCV ComputerVision with Python, PacktPublishing, Birmingham, UK, 2013.

[9] D. M. Hawkins, "The problem of over-fitting," Journal of Chemical information and Computer Sciences, vol. 44, no. 1, pp. 1–12, 2004.

[10] C. C. Stearns and K. Kannappan, "Method for 2-D affine transformation of images," US Patent No. 5,475,803, 1995.

[11] Sankaran, S. Mishra, A.; Ehsani, R. A review of advanced techniques for detecting plant diseases. Comput. Electron. Agric. 2010, 72, 1–13.

[12] Huang, J., Rathod, V., Sun, C.; Zhu, M., Korattikara, A., Fathi, A., Fischer, I., Wojna, Z.,Song, Y., Guadarrama, S., et al. Speed/accuracy trade-offs for modern convolutional object detectors. In Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Honolulu, HI, USA, 22–25 July 2017.

[13] Alvaro Fuentes , Sook Yoon , Sang Cheol Kim and Dong Sun Park A Robust Deep Learning-Based Detector for Real-Time Tomato Plant Diseases and Pests Recognition, Sensors 2017, 17, 2022; doi:10.3390/s17092022.

[14] Ren, S., He, K., Girshick, R., Sun, J. Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks. IEEE Trans. Pattern Anal. Mach. Intell. 2016, 39, 1137–1149.

[15] Liu, W., Anguelov, D, Erhan, D., Szegedy, C., Reed, S.; Fu, C.; Berg, A.C. SSD: Single Shot MultiBox Detector. In Proceedings of the European Conference on Computer Vision ECCV, Amsterdam, The Netherlands, 8–16 October 2016; pp. 21–37.

[16] Dai, J., Li, Y., He, K., Sun, J. R-FCN: Object Detection via Region-based Fully Convolutional Networks. arXiv 2016, arXiv:1605.06409v2.

[17] Everingham, M., Van Gool, L., Williams, C., Winn, J., Zisserman, A. The Pascal Visual Object Classes (VOC) Challenge. Int. Comput. Vis. 2010, 88, 303–338.

[18] R. Girshick. Fast r-cnn. In Proceedings of the IEEE International Conference on Computer Vision, pages 1440–1448, 2015.

[19] J. Dai, K. He, and J. Sun. Instance-aware semantic segmentation via multi-task network cascades. arXiv preprint arXiv:1512.04412, 2015.

[20] R. Girshick. Fast r-cnn. In Proceedings of the IEEE International Conference on Computer Vision, pages 1440–1448, 201