Düzce University Journal of Science & Technology, 8 (2020) 1110-1117

Düzce University
Journal of Science & Technology

Research Article

Detection of Apple Leaf Diseases using Faster R-CNN

Melike SARDOGAN [a], Yunus OZEN [b,*], Adem TUNCER [b]

[a] *Institute of Science, Yalova University, Yalova, TURKEY*
[b] *Department of Computer Engineering, Faculty of Engineering, Yalova University, Yalova, TURKEY*
* *Corresponding author's: yunus.ozen@yalova.edu.tr*
DOI: 10.29130/dubited.648387

ABSTRACT

Image recognition-based automated disease detection systems play an important role in the early detection of plant leaf diseases. In this study, an apple leaf disease detection system was proposed using Faster Region-Based Convolutional Neural Network (Faster R-CNN) with Inception v2 architecture. Applications for the detection of diseases were carried out in apple orchards in Yalova, Turkey. Leaf images were obtained from different apple orchards for two years. In our observations, it was determined that apple trees of Yalova had black spot (venturia inaequalis) disease. The proposed system in the study detects a large number of leaves in an image, then successfully classifies diseased and healthy ones. The disease detection system trained has achieved an average of 84.5% accuracy.

Keywords: *Convolutional neural network (CNN), Faster R-CNN, Leaf disease detection*

Faster R-CNN Kullanarak Elma Yaprağı Hastalıklarının Tespiti

ÖZET

Görüntü tanıma tabanlı otomatik hastalık algılama sistemleri, bitkilerde görülen yaprak hastalıklarının erken tespitinde önemli bir rol oynamaktadır. Bu çalışmada, Inception v2 mimarisi ile Daha Hızlı Bölgesel Evrişimsel Sinir Ağı (Faster R-CNN) kullanılarak bir elma yaprağı hastalığı tespit sistemi önerilmiştir. Hastalıkların tespiti için uygulamalar Türkiye'nin Yalova ilindeki elma bahçelerinde gerçekleştirilmiştir. Yaprak görüntüleri iki yıl boyunca farklı elma bahçelerinden elde edilmiştir. Yaptığımız gözlemlerde Yalova'nın elma ağaçlarında özellikle kara leke hastalığının olduğu tespit edilmiştir. Çalışmada önerilen sistem bir görüntü içerisindeki çok fazla sayıda bulunan yaprakları tespit etmekte, ardından hastalıklı ve sağlıklı olanları başarılı bir şekilde sınıflandırmaktadır. Eğitilen hastalık tespit sistemi ortalama %84.5 doğruluk elde etmiştir.

Anahtar Kelimeler: *Evrişimsel sinir ağı (ESA), Daha hızlı bölgesel-ESA, Yaprak hastalığı tespiti*

Received: 18/11/2019, Revised: 06/01/2020, Accepted: 26/01/2020

I. INTRODUCTION

Agriculture is one of the major sources of economy for most of the countries. Fighting with diseases in a smart way results in an efficient and competitive agriculture-based economy. Automatic plant identification and disease detection are possible due to the improvements in artificial intelligence studies. Automating identification and detection processes lead to the development of advanced early-warning systems. In order to prevent plant diseases, it is important to intervene on time. Early plant disease detection minimizes yield losses and increases the effectiveness and efficiency of treatments.

Currently, the detection of plant diseases is mainly based on human experts to conduct on-site research and evaluate experience-based disease categories. Modern agriculture requires techniques to replace human experience-based solutions with machine intelligence-based solutions [1]. A human can identify plant diseases by eyes, but the machine is capable of vision-based automatic identification.

The literature includes several approaches including automatic analysis of fruits, vegetables, leaves or flowers [2]. Recently, machine learning algorithms and image processing methods have been used frequently for plant disease detection [3]. Deep Learning is a set of techniques in the machine learning domain that consists of multiple processing layers that enable learning to represent multiple level data abstractions. It has the capacity to extract the features automatically from the raw input data, without explicitly defining which features to use and how to extract them [4]. The studies show that deep learning is effective in identifying and classifying diseases under different conditions such as lighting, resolution, background, size, and orientation.

Improvements have been made to image classification through Convolutional Neural Networks (CNNs). Recently, modifications of the CNN architecture involving different layer sequences have been proposed such as AlexNet [5], ResNet [6], DenseNet [7], Inception [8], and VGGNet [9]. The state-of-the-art agricultural studies that are conducted based on these models have acceptable results on common datasets such as the PlantVillage dataset. Standard CNN models are particularly designed for extracting generic descriptions from a dataset and categorizing the input data, but they are insufficient to locate desired objects on an image in object detection networks. Region proposal algorithms such as Region-Based CNN (R-CNN) [10] are developed to address this problem. Faster Region-Based Convolutional Neural Network (Faster R-CNN) [11] is an improved version of R-CNN to locate objects on an image. The proposed system in the study employs Faster R-CNN with Inception v2 architecture to detect and classify healthy/diseased apple leaves.

The system in the study has been developed on top of TensorFlow framework. TensorFlow is a framework that helps building several kinds of artificial neural network (ANN) models for automatically recognizing images. TensorFlow includes two approaches for image recognition as classification and object detection. Classification models recognize categories like leaves, fruits, trees, or any other objects. The classification system classifies the image into a category as a whole. Object detection is the process of detecting multiple objects in the same image. Object detection models annotate the objects and indicate their location in the image. The TensorFlow Object Detection API performs building, training and deploying object detection models. It identifies objects employing models such as ResNet-50 and ResNet-101. These models were trained with the iNaturalist Species Detection Dataset and they are ready to use for application development.

The rest of the paper is organized as follows: In Section II, the literature review and state-of-the-art studies on plant leaf disease detection based on deep learning models is discussed. In Section III, the architecture and technical details of Faster R-CNN are introduced. A plant leaf disease detection system based on Faster R-CNN with Inception v2 architecture has been proposed. The experimental results are detailed in Section IV. Section V concludes the paper.

II. LITERATURE REVIEW

The CNN is employed in many studies as a deep learning method to classify leaves for identifying or detecting the diseased ones. Ferentinos [12] compared the performance of pre-trained AlexNet, AlexNetOWTB, GoogLeNet, Overfeat, and VGGNet architectures on an open database containing 87848 leaf photos of healthy and infected plants. The VGGNet achieved a success rate of 99.53% accuracy on that dataset. Gensheng et al. [13] implemented a pre-trained CIFAR10-quick CNN model for tea leaf disease identification. Their experimental results indicate that identification accuracy is 92.5%. Geetharamani et al. [14] trained a CNN model on plant leaves including 39 classes. They achieved a 96.46% classification accuracy rate. Rangarajan et al. [15] classified 7 classes of tomato leaf images obtained from the PlantVillage open dataset using pre-trained AlexNet and VGG16 Net. They achieved a 97.4% accuracy rate with AlexNet. Sardogan et al. [16] detected and classified tomato leaf diseases obtained from the PlantVillage database with a CNN model, and they used the learning vector quantization algorithm for the learning phase. As seen in the examined papers, agricultural studies in the literature are generally carried out on pre-recorded and pre-processed image datasets with pre-trained CNN models. These studies were also carried out on a single leaf on image datasets. Their models are insufficient, and it is hard to apply in real-world scenarios [17]. On the other hand, it is intended from a plant leaf disease detection system to identify many leaves in an image.

Faster R-CNN is capable of finding and marking multiple objects and regions on images. Ozguven et al. [18] utilized a Faster R-CNN model to automatically detect diseased areas in sugar beet leaves. They achieved an accuracy of 95.48% on 155 images. In a study by Huang et al. [19], Faster R-CNN was applied to a marine organism recognition task and they achieved 59.93% accuracy. Quane et al. [20] presented an improved Faster R-CNN model for a field robot platform to extract features from images at different growth stages and detect corn seedlings. It is seen that the Faster R-CNN is suitable for developing a plant leaf disease detection system.

In the literature, the majority of the studies on the classification of leaf diseases are performed by collecting leaves and taking images in a laboratory environment. Real-world leaf photos have some challenges that are not contained at the ones obtained from good quality public datasets. The common public datasets contain single leaf photos that are taken in a laboratory. However, in real field conditions, the detection becomes more complex and leaf photos include many leaves and multiple regions containing the disease. The proposed system in this paper employs Faster R-CNN for detecting diseased and healthy leaves and their locations on apple images. Unlike other studies, the application in this study was carried out on real-world data by taking images containing many leaves from apple trees.

III. MATERIAL AND METHOD

A. FASTER R-CNN

Standard CNN learns features of the image and classify the whole image [21]. However, it cannot identify different objects and locations in images. Because the output layer is of variable length, i.e., the number of objects in the image is not constant, the standard CNN is not used. To address this problem, the standard CNN can be used to take different regions in the image and classify the object in that region. However, this approach does not seem appropriate because the objects have different dimensions and locations within the image. Therefore, a large number of region selections may be required, and this may increase the cost of computation.

Faster R-CNN is a kind of CNN developed based on R-CNN. It is consisting of the Region Proposal Network (RPN) and the Fast R-CNN [22]. The selective search method is used to find the region proposals in R-CNN and Fast R-CNN algorithms. But this method is a slow and time-consuming process [23]. Faster R-CNN uses a separate network, referred to as RPN, which is used to predict the region proposals instead of using a selective search algorithm. The RPN is used after last convolution layer of

CNN. More recently, the Faster R-CNN has been a tremendous success in object detection and recognition.

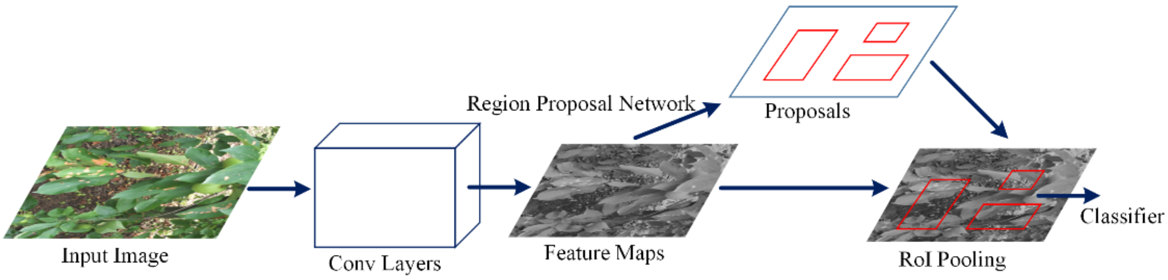


Figure 1. *The structure of Faster R-CNN*

As shown in Figure 1, convolution layers are used to obtain feature maps from the tree images given as input. Then, feature maps are fed to RPN and Region of Interest (RoI) pooling layer. The outputs of the RPN proposals are not fixed while the input of the object detection network is fixed. For each proposal, RoI pooling process is applied to extract fixed-length features from the feature maps, then these maps are sent to fully connected layers to predict class and bounding box.

B. THE APPLE LEAF DISEASE DETECTION SYSTEM

The proposed deep learning model in this study is based on Faster R-CNN with Inception v2 architecture. Inception v2 [8] is one of the pre-trained CNN models. It modifies the feature extraction process in standard CNN [24]. One of the objectives of this model is to reduce the complexity of the convolution network. The proposed model was constructed by collecting healthy and diseased images from apple orchards in Yalova province. Then, the dataset annotation was performed manually and, was increased employing data augmentation. The collected images were divided into two sets, 80% as training and 20% as testing: The model was trained using the training dataset, and the performance of the model was evaluated using the testing dataset. The results contain both the classes of the diseased/healthy leaves and their locations on the images. Figure 2 illustrates the block diagram of the whole detection system. At the end of the training of the model, detection is made for two classes; diseased and healthy leaves. In bounding boxes, the position information of each detected leaf is given.

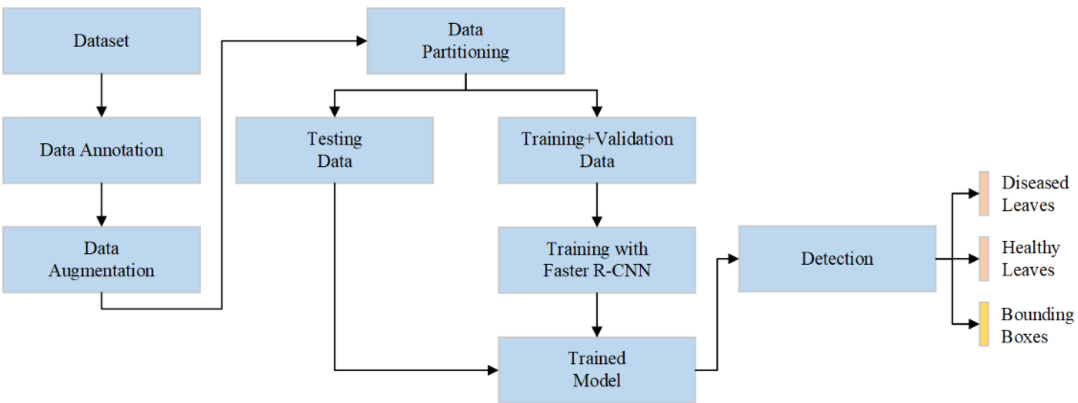
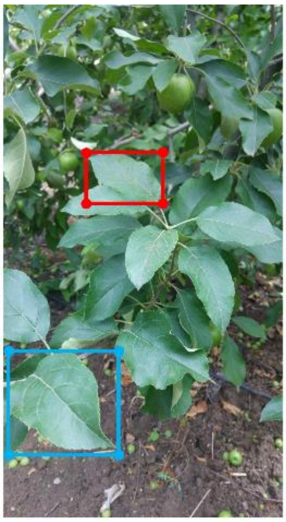


Figure 2. *The diagram of the detection disease system*

The plant observation periods vary with the season and depend on factors such as temperature, illuminance, and humidity. For instance, sudden and frequent change in air temperature is suitable for the emergence of apple black spot disease. Therefore, leaf samples were collected in various weather conditions during the autumn season when apple black spot disease was observed. Totally 700 diseased and healthy apple leaf images were collected. The most common disease of apple leaves is apple black spot disease in Yalova province, thus the diseased images include apple black spot disease infected regions.



(a)


```xml
<object>
      <name>diseased</name>
      <pose>Unspecified</pose>
      <truncated>0</truncated>
      <difficult>0</difficult>
      <bndbox>
         <xmin>1526</xmin>
         <ymin>1283</ymin>
         <xmax>2064</xmax>
         <ymax>2090</ymax>
      </bndbox>
   </object>
   <object>
      <name>healthy</name>
      <pose>Unspecified</pose>
      <truncated>0</truncated>
      <difficult>0</difficult>
      <bndbox>
         <xmin>3564</xmin>
         <ymin>1773</ymin>
         <xmax>4609</xmax>
         <ymax>2924</ymax>
      </bndbox>
   </object>
```


(b)

Figure 3. (a) *Image of annotated leaves* ***(b)*** *XML document*

Every image has many leaves containing both healthy and diseased ones. Most of the images have complex backgrounds, which affect the generalization performance of the model. Before feeding the model, the images in the dataset were annotated manually in the study. An XML file was generated for each annotated image that contains the classes, and the coordinate values of each lesion's bounding boxes. A sample annotated image is shown in Figure 3. The image contains a healthy region annotated with a blue rectangle and a diseased region annotated with a red rectangle.

The over-fitting problem of CNNs in the training phase can be overcome by increasing the number of images in the dataset employing data augmentation. A set of techniques have been applied for data augmentation, including horizontal flips, vertical flips, and rotation. Thus, the model avoids over-fitting and achieves high performance by learning more patterns in the training phase.

IV. EXPERIMENTAL RESULTS

The experiments were conducted on images of both healthy and diseased apple leaves to evaluate the performance of the Faster R-CNN with Inception v2 architecture. Figure 4 shows the detection of diseased and healthy leaves for two different tree views. The leaves detected in the yellow rectangle indicate healthy leaves and the leaves detected in the green rectangle indicate diseased leaves.

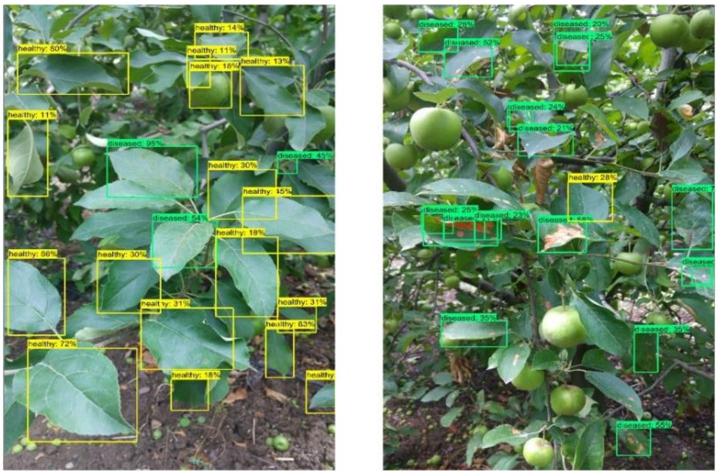


Figure 4. *Detection results*

In this study, accuracy, precision, recall and f1 score metrics were used to measure the success of the model. The calculations of these metrics are shown in the following equations;

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

$$Precision = \frac{TP}{TP + FP} \tag{2}$$

$$Recall = \frac{TP}{TP + FN} \tag{3}$$

$$F1\ Score = 2 \times \frac{Precision\ \times Recall}{Precision + Recall} \tag{4}$$

where *TP* is true positive, *TN* is true negative, *FP* is false positive, and *FN* is false negative. When the results in the Table 1 are taken into consideration, it is seen that the disease detection system performed with Faster R-CNN has achieved average of 84.5% accuracy rate.

Table 1. *Performance results of the model*

Classes	Accuracy	Precision	Recall	F1 Score
Diseased	0.84	0.92	0.80	0.86
Healthy	0.85	0.88	0.77	0.82

V. CONCLUSION

In recent years, deep learning algorithms have been used frequently for plant leaves disease detection systems. CNNs, a type of deep neural networks, are one of the most widely used models in deep learning architectures. In this study, an apple leaf disease detection system was proposed using Faster R-CNN with Inception v2 architecture, which is one of the pre-trained CNNs. The dataset used in the study were obtained by collecting diseased and healthy images from apple orchards in Yalova province. Studies in the literature have generally been performed on pre-processed images including a single leaf. In contrast, the application was performed on real-world data by using complex images including many leaves in this study. The results contain both the classes of the diseased/healthy leaves and their locations on the images. According to experimental results, the proposed system detects healthy and diseased leaves successfully with average of 84.5% accuracy rate.

ACKNOWLEDGMENT: This study was supported by the Research Fund of Yalova University (Project Number: 2018/AP/0001).

VI. REFERENCES

[1] E. Kiani and T. Mamedov, “Identification of Plant Disease Infection using Soft-Computing: Application to modern botany,” *Procedia Computer Science*, vol. 120, pp. 893-900, 2017.

[2] V. Singh and A.K. Misra, “Detection of Plant Leaf Diseases using Image Segmentation and Soft Computing Techniques,” *Information Processing in Agriculture*, vol. 4, no. 1, pp. 41-49, 2017.

[3] K. Golhani, S.K. Balasundram, G. Vadamalai, and B. Pradhan, “A Review of Neural Networks in Plant Disease Detection using Hyperspectral Data,” *Information Processing in Agriculture*, vol. 5, no. 3, pp. 354-371, 2018.

[4] A. Kamilaris, and F.X. Prenafeta-Boldú, “Deep Learning in Agriculture: A Survey,” *Computers and Electronics in Agriculture*, vol. 147, pp. 70-90, 2018.

[5] A. Krizhevsky, I. Sutskever, and G.E. Hinton, “Imagenet Classification with Deep Convolutional Neural Networks,” *In Advances in neural information processing systems*, pp. 1097-1105, 2012.

[6] K. He, X. Zhang, S. Ren, and J. Sun, “Identity Mappings in Deep Residual Networks,” *In European conference on computer vision*, pp. 630-645, 2016.

[7] G. Huang, K.Q. Weinberger, and L. Van Der Maaten, “Densely Connected Convolutional Networks,” *In Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 4700-4708, 2017.

[8] C. Szegedy, V. Vanhoucke, S. Ioffe, J. Shlens, and Z. Wojna, “Rethinking the inception architecture for computer vision,” *In Proceedings of the IEEE conference on computer vision and pattern recognition*, pp. 2818-2826, 2016.

[9] K. Simonyan, and A. Zisserman, “Very Deep Convolutional Networks for Large-Scale Image Recognition,” *Int. Conf. Learn. Represent*, pp. 1-14, 2015.

[10] R. Girshick, J. Donahue, T. Darrell, and J. Malik, “Region-Based Convolutional Networks for Accurate Object Detection and Segmentation,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 38, no. 1, pp. 142-158, 2015.

[11] S. Ren, K. He, R. Girshick, and J. Sun, “Faster R-CNN: Towards Realtime Object Detection with Region Proposal Networks,” *IEEE Trans. Pattern Anal. Mach. Intell.*, vol. 39, no. 6, pp. 1137-1149, 2017.

[12] K.P. Ferentinos, “Deep Learning Models for Plant Disease Detection and Diagnosis,” *Computers and Electronics in Agriculture*, vol. 145, pp. 311-318, 2018.

[13] G. Hu, X. Yang, Y. Zhang, and M. Wan, “Identification of Tea Leaf Diseases by using an Improved Deep Convolutional Neural Network,” *Sustainable Computing: Informatics and Systems*, 100353, 2019.

[14] G. Geetharamani, and A. Pandian, “Identification of Plant Leaf Diseases using a Nine-layer Deep Convolutional Neural Network,” *Computers & Electrical Engineering*, vol. 76, pp. 323-338, 2019.

[15] A.K. Rangarajan, R. Purushothaman, and A. Ramesh, “Tomato Crop Disease Classification using Pre-trained Deep Learning Algorithm,” *Procedia Computer Science*, vol. 133, pp. 1040-1047, 2018.

[16] M. Sardogan, A. Tuncer, and Y. Ozen, “Plant Leaf Disease Detection and Classification Based on CNN with LVQ Algorithm,” *In 2018 3rd International Conference on Computer Science and Engineering (UBMK), IEEE*, pp. 382-385, 2018.

[17] E.C. Too, L. Yujian, S. Njuki, and L. Yingchun, “A Comparative Study of Fine-tuning Deep Learning Models for Plant Disease Identification,” *Computers and Electronics in Agriculture*, vol. 161, pp. 272-279, 2019.

[18] M.M. Ozguven, and K. Adem, “Automatic Detection and Classification of Leaf Spot Disease in Sugar Beet using Deep Learning Algorithms,” *Physica A: Statistical Mechanics and its Applications*, vol. 535, 122537, 2019.

[19] H. Huang, et al., “Faster R-CNN for Marine Organisms Detection and Recognition using Data Augmentation,” Neurocomputing, vol. 337, pp. 372-384, 2019.

[20] L. Quan, et al. “Maize Seedling Detection under Different Growth Stages and Complex Field Environments Based on an Improved Faster R–CNN,” *Biosystems Engineering*, vol. 184, pp. 1-23, 2019.

[21] X. Lei, and Z. Sui, “Intelligent Fault Detection of High Voltage Line Based on the Faster R-CNN,” *Measurement*, vol. 138, pp. 379-385, 2019.

[22] R. Girshick, “Fast r-cnn,” *In Proceedings of the IEEE international conference on computer vision*, pp. 1440-1448, 2015.

[23] V. Kafedziski, S. Pecov, and D. Tanevski, “Detection and Classification of Land Mines from Ground Penetrating Radar Data Using Faster R-CNN,” *In 2018 26th Telecommunications Forum (TELFOR), IEEE*, pp. 1-4, 2018.

[24] A. Alamsyah, M.A.A. Saputra, and R.A. Masrury, “Object Detection Using Convolutional Neural Network To Identify Popular Fashion Product,” *In Journal of Physics: Conference Series*, vol. 1192, no. 1, pp. 012040, 2019.