Literature Review for Plant Disease Detection using AI

Plant disease has long been one of the major threats to food security because it dramatically reduces the crop yield and compromises its quality. Accurate and precise diagnosis of diseases has been a significant challenge. According to the Food and Agriculture organization of the United Nations (UN), transboundary plant pests and diseases affect food crops, causing significant losses to farmers and threatening food security.

Traditionally, identification of plant diseases has relied on human annotation by visual inspection. Nowadays, it is combined or substituted with various technologies such as immunoassays (e.g., enzyme-linked immunosorbent assay, ELISA) and PCR or RNA-seq to detect pathogen-specific antigens or oligonucleotides, respectively. Moreover, recent technical advances and dramatic cost reductions in the field of digital image acquisition have allowed the introduction of an array of image-based diagnosis methods at a practical level. However, as the acquired image encloses condensed information that is extremely difficult for the computer to process, it requires a preprocessing step to extract a certain feature (e.g., color and shape) that is manually predefined by experts. In such situations, deep learning is typically used because it allows the computer to autonomously learn the most suitable feature without human intervention. An initial attempt to use deep learning for image-based plant disease diagnosis was reported in 2016, where the trained model was able to classify 14 crops and 26 diseases with an accuracy of 99.35% against optical images. Since then, successive generations of deep-learning-based disease diagnosis in various crops have been reported.

Among various network architectures used in deep learning, convolutional neural networks (CNN) are widely used in image recognition. The first CNNs, the neocognitron and LeNet, were introduced in the 1980s, although the study of neural networks originally started in the 1940s. CNNs have been used for plant image analysis since the early days of their evolution. Thanks to the rapid development of hardware and the improvement of learning methods, large-scale deep CNNs became trainable in the 2010s. A major turning point for the CNNs was the introduction of AlexNet, which significantly outperformed the image classification accuracy of traditional machine learning approaches in ImageNet Large Scale Visual Recognition Challenge (LSVRC) 2012.

CNNs consist of convolutional layers, which are sets of image filters convoluted to images or feature maps, along with other (e.g., pooling) layers. In image classification, feature maps are extracted through convolution and other processing layers repetitively and the network eventually outputs a label indicating an estimated class. Given a training dataset, CNN, unlike traditional machine learning techniques that use *hand-crafted* features, optimizes the weights and filter parameters in the hidden layers to generate features suitable to solve the classification problem. In principle, the parameters in the network are optimized by back-propagation and gradient descent approaches to minimize the classification error.

After the invention of AlexNet, along with the advances in hardware, the CNN architecture became larger. VGG-19 consists of 19 layers, while GoogLeNet has 22 layers with junctions in its architecture. In LSVRC 2015, ResNet outperformed the classification accuracy of the human-level performance with a 152-layer network. However, complexity of the CNN architecture, which generally contributes to higher accuracy, has caused significant problems for interpretability and raised the following questions: What does CNN actually do in hidden layers? What feature in the input image contributes to inference and why the CNN diagnoses a specific disease? How can we validate the model if we do not know what type of data is processed inside? Deep learning was regarded as a *"black box"*, which prevented the use of CNNs in practical applications.

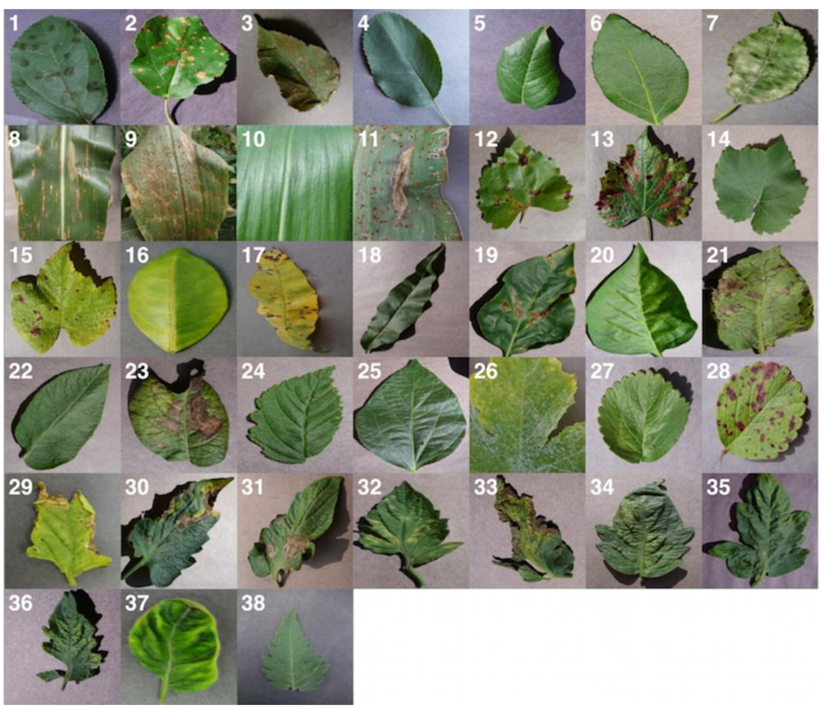
In this study, based on the findings of the previous studies, we provide a deeper evaluation of the visualization methods against the CNNs in plant science applications. Our results show that several visualization methods are usable in their original form, indicating that the CNN captures the lesion-specific features of respective diseases. However, several methods have to go through a process of targeted layer optimization to generate an optimum result owing to the differences in the CNN architecture and the datasets. Moreover, based on the layer-wise visualization, we identify an optimal number of feature extraction layers to simplify the CNNs by decreasing the number of network parameters by 75%.

Contributions. The following are the contributions of this study. First, this study is the first attempt of comprehensive analyses which studies what the CNNs learn during the plant disease diagnosis. This is a significant problem for the rapid development of deep learning techniques in the plant phenotyping tasks. It constructs a standard for selecting and interpreting CNN models for plant image analysis. Second, from the computer science perspective, this study provides novel results by the visualization of a CNN applied for plant image analysis. The trend of the visualizations is notably different from previous discussions in visualization analyses for general object recognition.

The spread of transboundary plant pests and diseases has increased dramatically in recent years. Globalization, trade and climate change, as well as reduced resilience in production systems due to decades of agricultural intensification, have all played a part. Considering spread of disease within India specifically, we can see how large number of farmers in India are losing their crops and are hence burdened by the loss, resulting in suicide. The lack of awareness among farmers regarding plant diseases is a key factor.

So, now it becomes important to find a cost effective solution for this massive problem. The solution that I found to be feasible in this case is Computer Vision. Deep learning with convolutional neural networks (CNNs) has achieved great success in the classification of various plant diseases. However, a limited number of studies have elucidated the process of inference, leaving it as an untouchable *black box*. Revealing the CNN to extract the learned feature as an interpretable form not only ensures its reliability but also enables the validation of the model authenticity and the training dataset by human intervention. In this study, a variety of neuron-wise and layer-wise visualization methods were applied using a CNN, trained with a publicly available plant disease image dataset. We showed that neural networks can capture the colors and textures of lesions specific to respective diseases upon diagnosis, which resembles human decision-making.

While several visualization methods were used as they are, others had to be optimized to target a specific layer that fully captures the features to generate consequential outputs. Moreover, by interpreting the generated attention maps, we identified several layers that were not contributing to inference and removed such layers inside the network, decreasing the number of parameters by 75% without affecting the classification accuracy. The results provide an impetus for the CNN *black box* users in the field of plant science to better understand the diagnosis process and lead to further efficient use of deep learning for plant disease diagnosis.



We came across the PlantVillage Disease Classification dataset on crowdAI platform. We have decided to choose this dataset to work on. For future work, we are still debating the model and architecture to use for our problem statement the development framework (TensorFlow or PyTorch).

Bibliography:

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