Undergraduate Honor Research Project Proposal

Topic: Deep convolutional neural networks for plant disease detection and severity prediction

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Abstract

Plant disease is a major threat to the food security, impacting both agricultural yield quantity and quality in unpredictable ways. The Food and Agriculture Organization estimates that approximately 25% of global crop losses are caused by diseases, insects, and weeds. In the United States, approximately $40 billion in crop yield losses are caused by plant diseases annually. Therefore, an accurate and affordable plant disease diagnosis system is critical for identifying plant disease at an early stage, allowing for mitigation efforts to control disease propagation. Recent developments in Machine Learning and Computer Vision technologies offer exciting new pathways to develop such diagnosis systems that allow for rapid detection of disease across large spatial areas, with minimal human intervention. This proposed project will allow for a broad survey of Machine / Deep Learning methodologies, extensive testing of these approaches against an open-source database of agricultural plant disease images, and a final application of the appropriate methodology to a field / greenhouse dataset collected here. The final goal of this effort is to develop and validate a deep learning approach for plant disease diagnosis, which will provide a robust, real-time capability to: (a) recognize disease; (b) identify specific diseases; and (c) quantify disease severity.

Background and Motivation:

Plant diseases are caused by a variety of plant pathogens, including viruses, bacteria, oomycete, fungi, nematodes, and parasitic plants. Plant diseases can be an issue for any plant system, but those affecting agricultural systems can have a particularly detrimental impact on human livelihoods and health. For example, the Late blight of potatoes, a disease caused by Phytophthora infestans -- a fungus-like oomycete pathogen, was first discovered in the early 1840s in Ireland. After the epidemic outbreak, about 1 million people died from starvation, and about 2 million people immigrated to other countries to escape starvation. This example points to the tremendous human impacts that major agricultural disease outbreaks can cause. More common are less massive outbreaks that result in loss of yield, detrimental impacts to economies, and particularly devasting effects on small farm holders or subsistence farmers.

According to the Food and Agriculture Organization (FAO), about 25% of crop losses are caused by diseases, insects, and weeds. In the United States, $40 billion in losses are caused by plant diseases annually [1], making it a problem that needs technological solutions for effective, reliable, and early identification of disease when it can be treated or remediated. Plant disease occurrence typically involves physical symptoms that can be seen by the human eye, and therefore offers the potential for applications of current machine vision and machine learning technologies to potentially automate disease detection over extensive spatial domains.

Significance:

Most of traditional strategies in plant disease monitoring and tracking depend on visual inspection. In some cases disease detection is aided by microscopic observation at the molecular level [2]. These approaches tend to be accurate, but are limited in the spatial extent to which they can be applied, and can be biased by the previous experiences of the person making the visual inspections [2]. These methods are likewise costly and not practical for the broad agricultural community. What is required is an accurate and affordable plant disease diagnosis system that will help farmers detect plant diseases at early stages, across extensive fields, and with the ability to be deployed many times throughout a growing season.

A major consideration for agriculture in the coming decades is the need to increase agricultural productivity to feed a growing population and mitigating hunger [2]. A major factor in this effort could be plant disease detection, which would prevent significant economic losses and enhance the resilience of smallholder agriculture. The development of accurate and affordable plant disease diagnosis systems is therefore an urgent priority.

Research goal

Motivated by the recent advances of machine learning and computer vision systems, numerous achievements have been made in deep learning since the success of ImageNet Large Scale Visual Recognition Challenge (ILSVRC) [3]. It has been demonstrated that the deep learning approach can achieve more accurate results than the traditional approach for some plant disease recognition problems ([4, 5]). These initial studies merit further research, and extension to addition diseases, cropping systems, and geographic contexts. As well, much less progress has been made in the more complicated problem of diagnosing disease severity level, and in differentiating the type of disease that is occurring – critical for properly managing or mitigating a disease outbreak situation. Our goal here is to design a real-time plant disease diagnosis system based on the neural networks (NNs) presented in two recent papers ([4, 5]), and extend these NN methodologies to disease severity prediction.

Key aspects of such a system are affordability, robustness, accuracy, and ease-of-use. An initial list of expected challenges that will be faced as we proceed with this work are:

- Can an automated approach to diagnosis of plant disease be more accurate than human experts?
- Can the application be made affordable and effective to use, so that it could be widely

distributed to small stakeholder farmers, who are disproportionately impacted by plant disease outbreaks?

- What is the most suitable architecture for this problem?
- How to deal with images that have mixtures of different types of diseases?
- How to train our model to distinguish the different types of disease?
- How to predict the severity of disease?
- How to make our model more robust in real-time image-acquisition / field survey scenarios (i.e. when acquiring imagery by hand or by drone)?

Methodology

Image requisition

In the first step of this research, we will conduct an experiment to verify the performance of the models described in these papers [4] [5]. The Plant Village Project [4] tested a Convolutional Neural Network (CNN) model based on two architectures: AlexNet and GoogleNet. They achieved 99.35% accuracy at recognizing 14 crops and 26 diseases by using GoogleNet. The authors [5] tested their CNN model based on three architectures (Faster R-CNN, R-FCN, and SSD) and two feature extractors (VGG-16 ad ResNet-50), and a mean AP over 85% had achieved at recognizing 9 different types of tomato leaf diseases with R-FCN architecture and ResNet-50 feature extractor. Given the success of this work, we will use these models / architectures as the starting point for our work here, and will broaden our examination of algorithms / architectures as opportunities emerge, or as research is published that indicates advances that should be considered here.

The Plant Village Project released their dataset to the public. This is a tremendous open-source resource for our testing purposes. Here we will limit our focus to four types of corn leaf diseases (Corn Gray Leaf Spot, Corn Common Rust, Corn healthy, and Corn Northern

Leaf Blight) to allow us to focus on developing and validating models for these critical diseases of a primary Midwest U.S. commodity crop.

Image Processing:

Data annotation and data augmentation techniques will be used for the image processing step, which proved to have better performance in the previous recognition project in [5]. Data annotation is the approach of manually annotating diseased leaf area with bounding boxes and classes in each image. Data augmentation is a technique for overcoming the overfitting problem when the training dataset is too small.

Severity Prediction

The severity level will be calculated based on two factors, the diseased area and the color depth. To compute the diseased area, we will define a healthy index that can give a range to determine the healthy condition from a pixel value. Thus, any pixel value that falls into this range will be counted as a health pixel (1), otherwise it is a diseased pixel (0). By counting the number of diseased pixels, we will obtain the proportion of diseased area in an image. To compute the color depth of a diseased region, we will convert the image to grayscale. The result of grayscale image conversion is a description of the brightness of each pixel, which has range from 0 to 255, 0 for white, and 255 for black. The level of severity will be divided into 3 levels: mild, moderate, and severe. Based on the corresponding pixel value, all the diseased pixels will be categorized into one of three containers: mild, moderate, and severe. The container with the highest number of diseased pixels will be displayed as an output. An anticipated result is displayed in Figure 1.

We anticipate challenges in: (1) defining the specific range of the health index; (2) defining the boundary between each severity level. We will consult with plant disease experts at OSU, for which there are several with expertise in corn diseases, given the importance of this problem to Ohio.

Meta-architecture

The following classification architectures and feature extractors will be used for benchmark testing, and the mean AP (Average Precision) value and Bounding Box evaluation method [3] will be used to evaluate model predictive performance:

- Architectures: Faster Region-Based Convolutional Neural Network (Faster R-CNN), Single ShotMultibox Detector (SSD), and Region-based Fully Convolutional Networks (R-FCN)
- Feature extractor: VGG net (VGG-16), Residual Network(ResNet-50, ResNet-101), and GoogLeNet.

System overview

Our project aims to develop a robust and accurate plant leaf disease diagnosis system. We envision the technical approach developed here to be tested in a real-time application deployment, in either field or greenhouse settings. The flow chart of CNN framework architecture shows in Figure 2.

Timeline of Future Semester:

Sep, 2019 -- Nov, 2019	Using public dataset to explore the best Meta-architecture and create a benchmark testing report
Nov, 2019 -- Dec, 2019	Select the best meta-architecture and use it to implement disease leaves diagnosis program.
Jan, 2020 -- May, 2020	Implement the disease severity prediction module and integrate into the diagnosis system, take a 3 credit hour research course 4999H in Spring 2020, start to write the draft paper for research thesis, and present at an external research meeting (e.g. IEEE SAC's paper competition—April 6^{th}-7^{th})
May, 2020 -- Aug, 2020	Collecting sample data (Diseased corn leaves images) from the field and verify its performance, take a 3 credit hour research course 4999H in Fall 2020, optimize the research thesis.
Aug, 2020 -- Nov, 2020	Finalized the research thesis, submit paper to the knowledge bank, prepare for the oral defense, and present at an OSU sponsored event (e.g.Fall Undergraduate Research Festival – Nov, 2020).

Personal Statement:

I am a senior Computer Science and Engineering major, with a minor in Statistics. I plan to graduate in the Autumn 2020. I have had many experiences with robotics projects and competitions, such as FIRST competition, IEEE SAC's Micromouse, RoboMaster, and EcoCar. These experiences have motivated me to pursue an Honors Thesis research project that utilizes my skills in robotics and machine learning to solve a practical problem of great importance to humanity. After my graduation, I intend to pursue a Master's degree and Ph.D. to continue my research career. My current research interests are focused on the practical applications of Machine Learning and Computer Vision, and my future vision for my research is to use these techniques to provide solutions that help people, and to make contributions to the development of these technologies.

Figures:

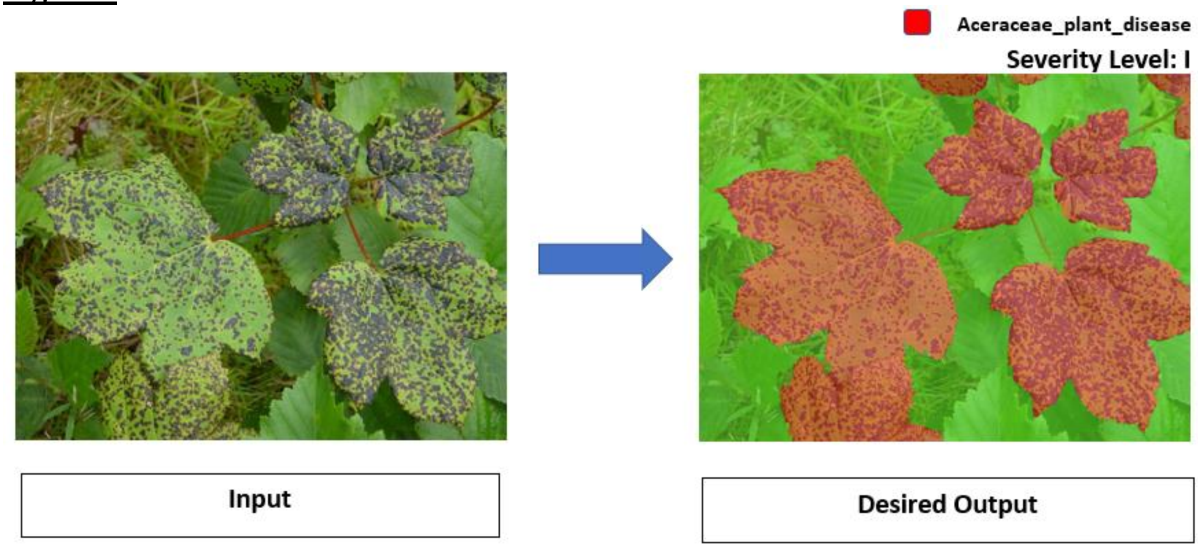

Figure 1. Image segmentation of Plant diseased leaves. Severity level (I: mild, II: moderate, III: severe)

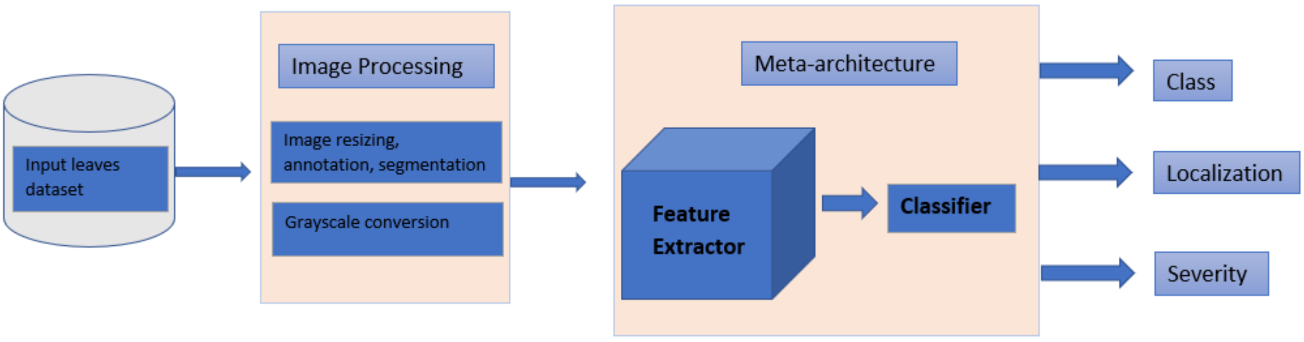

Figure 2: Proposed CNN Framework architecture

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