**Using Deep Learning for Image-Based Crop Disease Detection in Nigeria**

**ABSTRACT**

Crop diseases are a major threat to food security, but their rapid identification remains difficult in many parts of sub-Sahara Africa due to the lack of the necessary infrastructure. The increased number of smartphones and recent advances in computer vision made possible by deep learning has paved the way for smartphone-assisted disease diagnosis. Using a locally collected dataset of 1640 (268 actually) images of diseased and healthy plant leaves collected under controlled conditions, we trained a deep convolutional neural network to identify 5 arable crop diseases. The trained model achieved an accuracy of 72.22 – 81.03% on a held-out test set, demonstrating the feasibility of this approach. Overall, the approach of training deep learning models on increasingly large and publicly available image datasets presents a clear path toward smartphone-assisted crop disease diagnosis on a massive global scale.

**Keywords:** crop diseases, machine learning, deep learning, computer vision.

**INTRODUCTION**

Modern technologies have given human society the ability to produce enough food to meet the demand of more than 7 billion people. However, food security remains threatened by a number of factors including plant diseases (Strange and Scott, 2005), climate change (Tai et al., 2014), the decline in pollinators (Report of the Plenary of the Intergovernmental Science-Policy Platform on Biodiversity Ecosystem and Services on the work of its fourth session, 2016), and others. Plant diseases are not only a threat to food security at the global scale, but can also have disastrous consequences for smallholder farmers whose livelihoods depend on healthy crops. In the developing world, more than 80 percent of the agricultural production is generated by smallholder farmers (UNEP, 2013), and reports of yield loss of more than 50% due to pests and diseases are common (Harvey et al., 2014). Furthermore, the largest fraction of hungry people (50%) lives in smallholder farming households (Sanchez and Swaminathan, 2005), making smallholder farmers a group that’s particularly vulnerable to pathogen-derived disruptions in food supply.

Various efforts have been developed to prevent crop loss due to diseases. Historical approaches of widespread application of pesticides have in the past decade increasingly been supplemented by integrated pest management (IPM) approaches (Ehler, 2006). Independent of the approach, identifying a disease correctly when it first appears is a crucial step for efficient disease management.

Historically, disease identification has been supported by agricultural extension organizations or other institutions, such as local plant clinics. In more recent times, such efforts have additionally been supported by providing information for disease diagnosis online, leveraging the increasing Internet resources worldwide. Even more recently, tools based on mobile phones have grown rapidly, taking advantage of the historically unparalleled rapid uptake of mobile phone technology in all parts of the world (ITU, 2015).

Smartphones in particular offer very novel approaches to help identify diseases because of their computing power, high resolution displays, and extensive built-in sets of accessories, such as advanced HD cameras. As of April 2022, there were 5 billion internet users worldwide, which is 63% of the global population (WDP, 2022). The combined factors of increased smartphone, HD cameras, and high-performance processors in mobile devices lead to a situation where disease diagnosis based on automated image recognition, can be made available at an unprecedented scale. In this paper, we demonstrate the technical feasibility using a deep learning approach utilizing locally sourced 1640 (268 actually) images of 5 crop species with 5 diseases (or healthy). An example of each crop-disease pair can be seen in **Figure 1.**

Hello, there’s an image here

Computer vision, and object recognition in particular, has made tremendous advances in the past few years. The PASCAL VOC Challenge (Everingham et al., 2010), and more recently the Large Scale Visual Recognition Challenge (ILSVRC) (Russakovsky et al., 2015) based on the ImageNet dataset (Deng et al., 2009) have been widely used as benchmarks for numerous visualization-related problems in computer vision, including object classification. In 2012, a large, deep convolutional neural network achieved a top-5 error of 16.4% for the classification of images into 1000 possible categories (Krizhevsky et al., 2012). In the following 3 years, various advances in deep convolutional neural networks lowered the error rate to 3.57% (Krizhevsky et al., 2012; Simonyan and Zisserman, 2014; Zeiler and Fergus, 2014; He et al., 2015; Szegedy et al., 2015). While training large neural networks can be very time-consuming, the trained models can classify images very quickly, which makes them also suitable for consumer applications on smartphones.

Deep neural networks have recently been successfully applied in many diverse. Neural networks provide a mapping between an input-such as an image of a diseased plant-to an output-such as a crop disease pair. The nodes in a neural network are mathematical functions that take numerical inputs from the incoming edges, and provide a numerical output as an outgoing edge. Deep neural networks are simply mapping the input layer to the output layer over a series of stacked layers of nodes. The challenge is to create a deep network in such a way that both the structure of the network as well as the functions (nodes) and edge weights correctly map the input to the output. Deep neural networks are trained by tuning the network parameters in such a way that the mapping improves during the training process. This process is computationally challenging and has in recent times been improved dramatically by a number of both conceptual and engineering breakthroughs (LeCun et al., 2015; Schmidhuber, 2015). In this paper, we report on the classification of 5 diseases in 5 crop species using 268 images with a convolutional neural network approach. We measure the performance of our models based on their ability to predict the correct crop-diseases pair, given 38 possible classes. The best performing model achieves an overall accuracy of 81.03%, hence demonstrating the technical feasibility of our approach.

**METHODS**

**Dataset Description**

We analyze 268 images of plant leaves, which have a spread of 5 class labels assigned to them. Each class label is a crop disease pair, and we make an attempt to predict the crop-disease pair given just the image of the plant leaf. **Figure 1** shows one example each from every crop-disease pair from the dataset. In all the approaches described in this paper, we resize the images to 224 × 224 pixels, and we perform both the model optimization and predictions on these downscaled images.

In our experiments, we use the whole dataset. We start with the locally sourced dataset as it is, in color. This experiment was designed to understand if the neural network actually learns the “notion” of plant diseases, and not just the inherent biases in the dataset.

**Measurement of Performance**

To get a sense of how our approaches will perform or generalize on new unseen data, and also to keep a track of if any of our approaches are overfitting, we run all our experiments across a range of train-test set splits, namely 80–20 (80% of the whole dataset used for training, and 20% for testing). It must be noted that in many cases, the collected dataset has multiple images of the same leaf (taken from different orientations), and during all these test-train splits, we make sure all the images of the same leaf go either in the training set or the testing set. Further, for every experiment, we compute the mean precision, mean recall, mean F1 score, along with the overall accuracy over the whole period of training at regular intervals (at the end of every epoch).