Automated image-based diagnosis of cowpea diseases

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Abstract

Cowpea is the third most important legume food crop in Uganda with the eastern and northern regions accounting for most of the production in the country. However, it is vulnerable to virus and fungal diseases, which threaten to destabilize food security in sub-Saharan Africa. Unique methods of cowpea disease detection are needed to support improved control which will prevent this crisis. In this paper, we discuss automated disease detection model for cowpea based on deep neural network computational techniques that can be used by non-experts and smallholder farmers to do the field-based diagnosis of cowpea diseases. Image recognition offers both a cost-effective and scalable technology for disease detection. New transfer learning methods offer an avenue for this technology to be easily deployed on mobile devices. Using a dataset of cowpea disease images taken in the field in Uganda, we applied transfer learning to train a deep convolutional neural network to identify three cowpea diseases and to identify healthy plants as well. The best-trained model accuracies were 98% for healthy, 95% for powdery mildew, 98% for cercospora, and 96% for the mosaic virus. The best model achieved an overall accuracy of 93% for data not used in the training process. Our results show that the transfer learning approach for image recognition of field images offers a fast, affordable, and easily deployable strategy for digital plant disease detection.
Keywords: Transfer learning, mobile epidemiology, Inception v3 model, MobileNet V1 model

1 Introduction

The yield of cowpea has significantly reduced over the last few years and its decline has been attributed to various factors however the attack by pest and diseases has been severe (Edema,Adipala and Florini, 1997). Disease symptoms in cowpea are so confusing that farmers cannot easily tell if the crop is sick or not. And as such, they end up waiting until in the latest stages when little can be done to save the situation. The current disease control methods in use have not been successful and hence the need for exploring possible alternatives. Accurate diagnosis is the key to mitigating all associated consequences with the transmission of cowpea viruses and bacteria. The most common method of diagnosis adopted by cowpea seed banks is monitoring of viral-like symptoms on plants grown to propagate seed stocks. Other methods that have been used include determining the biological and serological properties of the viruses.

At times these methods are used in parallel for greater effectiveness, this intensifies existing efforts and resources devoted to diagnosing disease in cowpea. A study in molecular biology has led to progress of Reverse Transcription Polymerase Chain Reaction (RT-PCR) based methods that facilitate the accurate, rapid and less labor-intensive detection of some of the cowpea infecting viruses (Akinjogunla,Taiwo and Kareem, 2008).

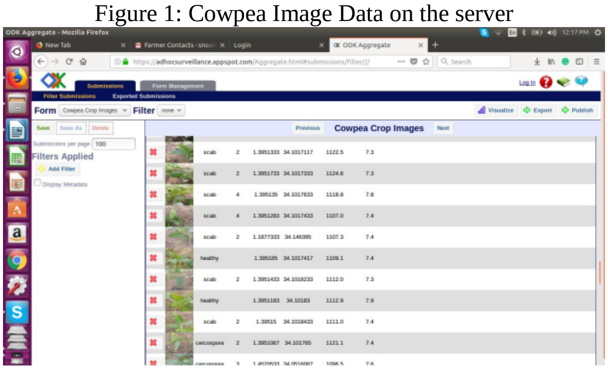
All the methods mentioned here require having experts to perform the necessary tasks in diagnosing cowpea diseases. The equipment and chemicals used in the experiments carried out are also very expensive that a smallholder farmer is not able to afford. These methods also take time to deliver results thus the need for a real-time disease diagnosis mechanism that is cheap for the smallholder farmers. New machine learning methods offer an avenue for image recognition and classification models to be easily deployed on mobile devices. Using datasets of plant disease images taken in fields deep convolutional neural network models have been trained to identify plant diseases (Karpathy et al., 2014). In this paper, we discuss automated disease detection model for cowpea based on deep neural network computational techniques that can be used by non-experts and smallholder farmers to do the field-based diagnosis of cowpea diseases.

2 The Cowpea Image Dataset

The cowpea leaf images were taken using a form in open data collection toolkit (ODK), the form allowed us to capture the image of the diseased cowpea leaves, assign the disease label based on the symptoms that the leaf showed and it also enabled us to capture the location of the plant from which these leaves were being captured. Data was captured from a total of six districts, four districts from Eastern Uganda and these are Bukedea, Kumi, Ngora, and Serere. More data was collected from Arua district in Northern Uganda and lastly, we collected data from Wakiso district which is in Central Uganda from experimental fields belonging to Kabanyolo Agricultural Research Center under Makerere University in Uganda.

A total of 2500 images were collected. The disease classes for which data was collected were Cercospora, powdery mildew, mosaic virus, bacterial blight, scab and healthy. This exercise was done for a period of one-two weeks. All the collected data was uploaded to the server on GoogleApp Engine.

Figure 1: Cowpea Image Data on the server



The number of collected was sufficient to form the required number of images needed to train the convolutional neural network model, we downloaded the data from the server into the different disease classes and some preprocessing was done to get a clean data set for model training. We ended up with 400 leaf images under each of the disease classes and health class.

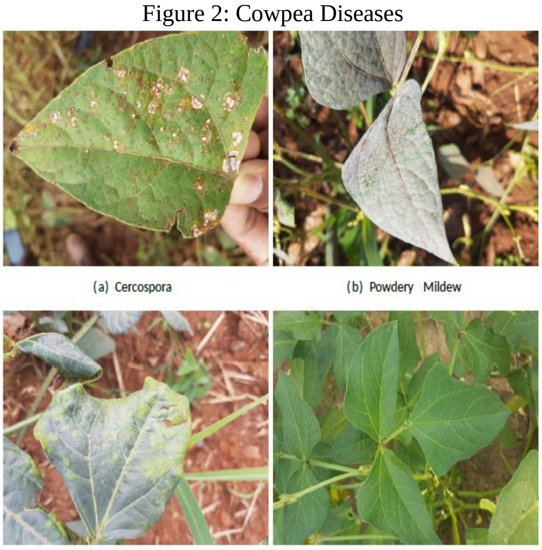
Viral diseases are more severe in low plant populations. During the wetter season, there is always a higher incidence and severity of viral diseases, anthracnose, and scab. Other diseases observed in the other season include rust, powdery mildew, and aphid born mosaic virus. A description of several cowpea diseases follows.

Cercospora: Chlorotic spots on upper surfaces of leaves; necrotic spots on leaves; masses of spores on lesions which resemble black mats on lower leaf surface; defoliation of plants; yellowing of leaves; circular, red lesions on leaves and it is a fungal disease.

Powdery mildew: White powdery fungal growth on upper surfaces of leaves; chlorotic or brown patches on leaves; leaves dropping from the plant and is also a fungal disease.

Aphid-borne mosaic virus: Various mosaics and mottling. Some strains of this disease produce characteristic green-vein banding but this is not accurate for diagnosis.

Figure 2: Cowpea Diseases



(a) Cercospora (b) Powdery Mildew

(c) Aphid borne mosaic virus (d) Healthy

2.1 Approach

Deep learning models have been implemented by major tech companies to help in solving real word problems, Google, in particular, has had a lot of work done with image classification models (Szegedy et al., 2016). In this work, we opted to use one of the models that Google has and that is the inception model which was trained on a very large image dataset. We mainly retrained the top layer of the model to identify our classes of cowpea diseases, right operations were added to the graph along with the required variables to hold the weights. During training, images were run through some simple distortions like crops, scales, and flips to help improve the results. This was done to reflect the kind of variations that one would expect in the real world, and so can help train the model to cope with natural data more (Szegedy et al., 2016). The model parameters implemented in this study included the number of training steps (500), the learning rate (0.035), train batch size (100), test batch size (-1; the entire test set), and the validation batch size (100). Transfer learning retrains the final layer of the MobileNet model to classify a new dataset by exploiting a large amount of visual knowledge already learned from the Imagenet database. Previous research has shown that transfer learning is effective for many applications and has much lower computational requirements than learning from scratch (Yosinski et al., 2014). We analyzed the performance of training the final layer of MobileNet with the original inception softmax layer.

2.2 Performance

In order to perform a very good validation and test for any inherent bias in our datasets, experiments were run for a range of training-testing data splits.

During model the training, 20% of the dataset was used to validate training steps, thus 80% of the dataset was split into different training and testing dataset configurations. The training-test splits were as follows: 80-10 (80% of dataset for training, 10% for testing respectively),60-30 (60% of dataset for training, 30% for testing respectively), 50-40, (50% of dataset for training, 40% for testing respectively), 40-50 (40% of dataset for training, 50% for testing respectively), and 20-70 (20% of dataset for training, 70% for testing respectively). For each individual experiment, the overall accuracy is reported as the number of samples in all classes were similar.

2.3 Results

The MobileNet V1 Softmax layer model performed well with accuracies ranging between 73%-98% for the different disease classes. We got a batch of input bottleneck values that were calculated fresh every time with distortions applied and from the cache stored on disk. The bottlenecks and ground truth we then fed into the graph, and the training was started. Every so often, a printout was made to show how well the graph was training. The figures below show the print out of these accuracies and the confusion matrix for the healthy leaves and the diseased leaves.

Figure 3: Training accuracy curve

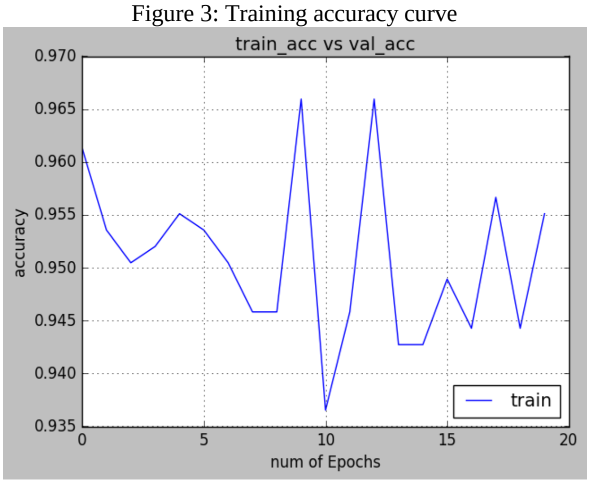


Figure 4: Training loss curve

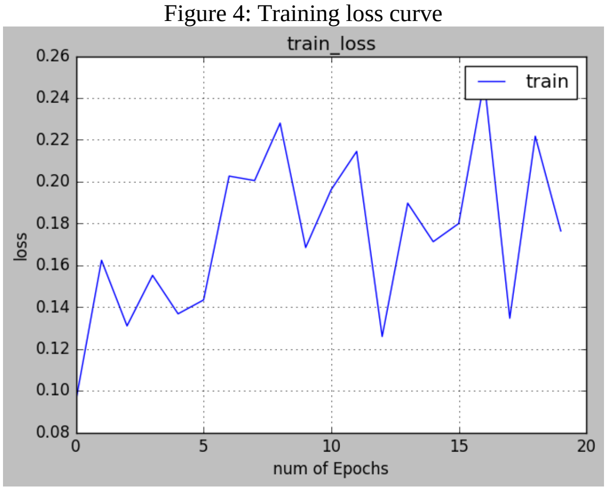
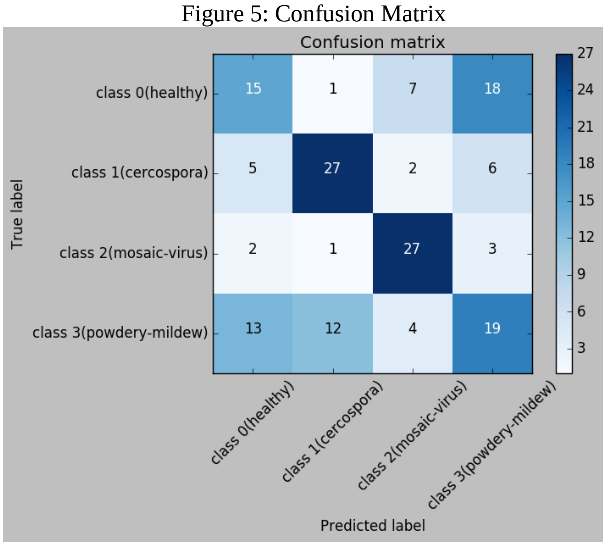


Figure 5: Confusion Matrix



2.4 Deployment of model into a mobile Application

A mobile app makes sense when there is a poor or missing network connection, or where sending continuous data to a server would be too expensive. We made a lean mobile app using the trained disease classify model, the mobile model supported quantization and lower precision arithmetic that reduced model size making it deployable onto a mobile device A device running Android 5.0 (API 21) or higher was required to run the prototype of our disease diagnosis app due to the use of the camera2 API, although the native libraries themselves were able to run on API level 14 and above devices. The app used our disease classification trained model to classify frames of diseased or healthy cowpea leaves in real-time, displaying the top results in an overlay on the camera image.

Optimizing the model for mobile

Mobile devices have significant limitations. So, any pre-processing that can be done to reduce an app's footprint is worth considering. We had to optimize the model for inference in order to remove all nodes that were not needed for a given set of input and outputs.

The figure below shows the screenshots taken from the app that will allow for infield cowpea disease detection.

Figure 6: Cercospora Detection using phone

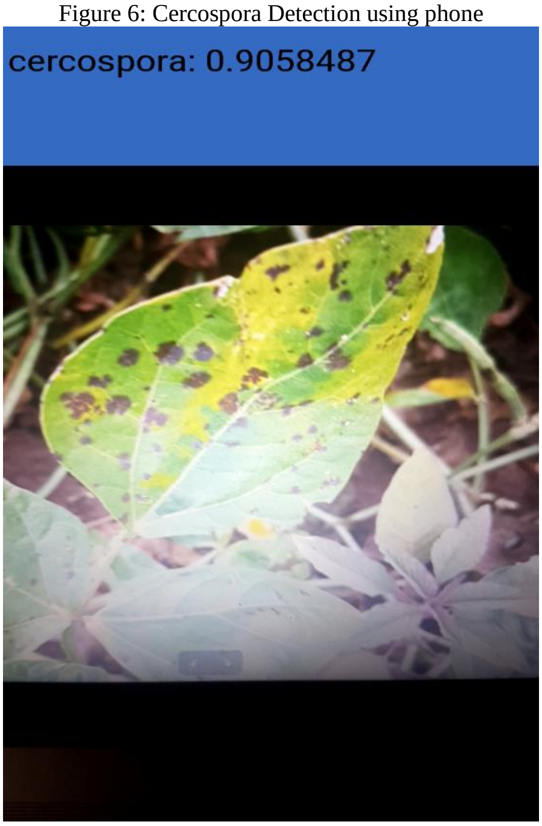


Figure 7: Powderly Mildew detection on phone

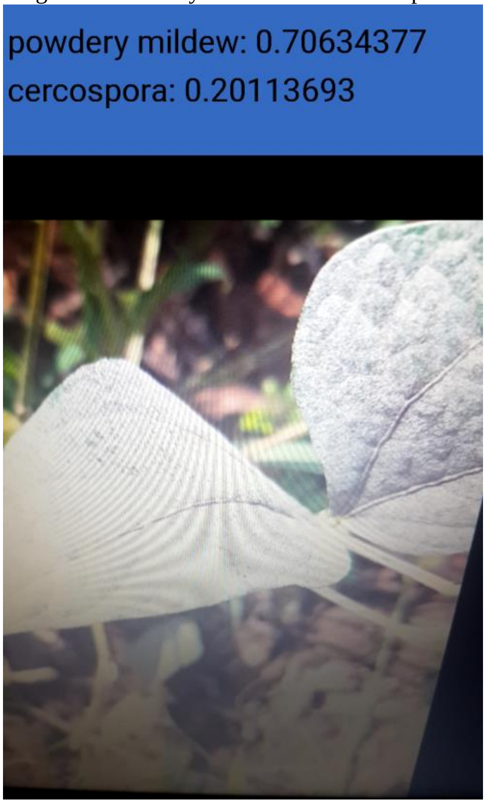


Figure 8: Mosaic-virus detection on phone

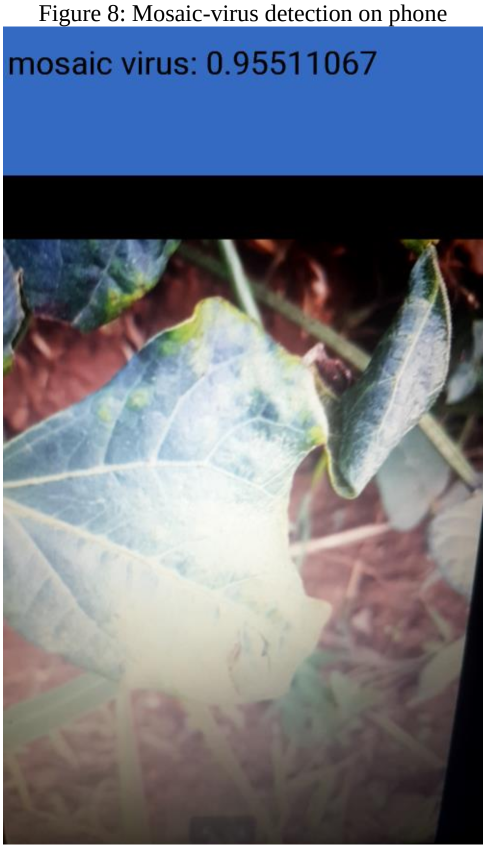
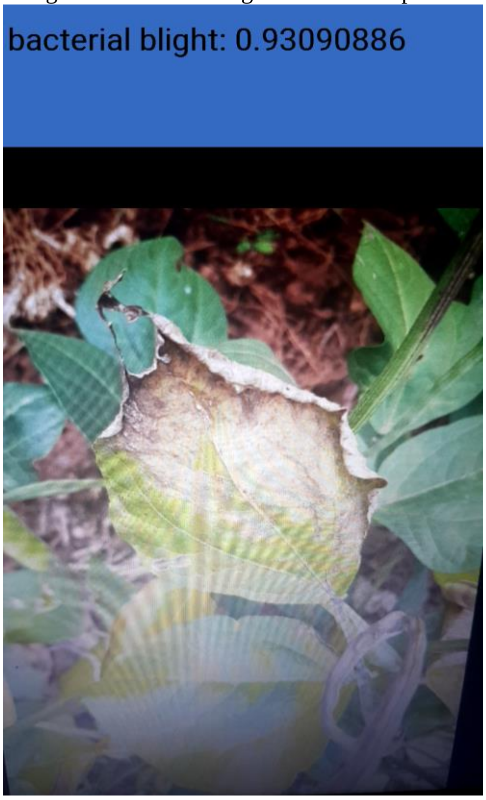


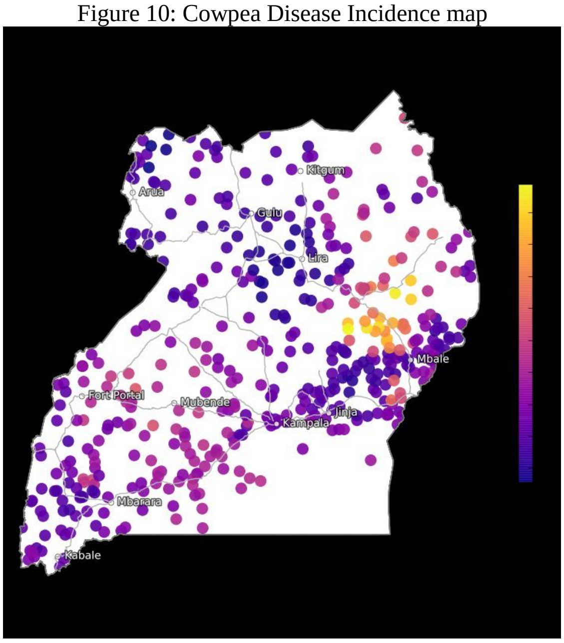
Figure 9: Bacterial Blight detection on phone



2.5 Spatial Distribution of Cowpea Diseases

Below is the map of how cowpea diseases are spread across the country and in our work, we intend to build more informative disease density maps that will guide experts to areas that are more inflicted with certain cowpea diseases.

Figure 10: Cowpea Disease Incidence map



The map shows the mean values for cowpea disease distribution in Uganda
For our disease prediction modelling we shall look at many options including
_ Neighbourhood and distance-based predictions
_ Gaussian processes
_ sklearn.linearmodel.LinearRegression
_ sklearn.tree.DecisionTreeRegressor
_ sklearn.ensemble.RandomForestRegressor

3 Discussion and Conclusion

The results of this study show that image recognition with transfer learning from the convolutional neural network mobileNet v1 is a powerful method for automated cowpea disease detection. This method avoids the complex and labor-intensive step of feature extraction from images in order to train models.

Transfer learning is also capable of applying common machine learning methods by retraining the vectors produced (Ramcharan et al., 2017, Mohanty,Hughes and Salathé, 2016). In this study, one machine learning method was used, and results showed the model had prediction accuracies for the four classes. With respect to specific cowpea diseases, model accuracies were 98% for Healthy, 95% for Powdery Mildew, 98% for Cercospora, and 96% for the mosaic virus. The best model achieved an overall accuracy of 93%.

This study, therefore, shows that transfer learning offers a promising avenue for in-field disease detection using convolutional neural networks with relatively small image datasets. Work has been done in getting the developed model working on the phone after optimizing the trained model to meet the restrictions that are presented by mobile applications. Future work will aim at implementing spatial models to show the cowpea disease densities in Uganda.

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