INFERRING CROP PESTS AND DISEASES FROM IMAGERY SOIL DATA AND SOIL PROPERTIES

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ABSTRACT

80Uganda are known to be agricultural products mainly coffee, tea, cotton, among others , this being dominated by coffee whose percentage is 22 on the total exports. However, a decrease was registered in the last financial year that depicted a drop by 5% as a result of the different challenges that the farmers are encountering which were reported to be mainly pests and diseases. The production of coffee is more likely to drop according to some farmers. Numerous approaches have been provided in line with other crops such as cassava, bananas, tomatoes and can be extended to other cops however, these are registered under active procedures when the crops are already affected.

1 INTRODUCTION

Proponents of organic farming have long promoted the view that the likelihood of pest outbreaks is reduced with organic farming practices, including establishment and maintenance of ”healthy” soil [1][2][3]. Recent studies have shown that plant resistance to pests and diseases is linked to optimal physical, chemical, and—perhaps most importantly— biological properties of soil [4][5]. In major agricultural crops , pests, diseases and weeds cause considerable yield losses [6]. Climate in terms of temperature, CO2 and rainfall and prevailing weather conditions at a time has direct and indirect effects on the crop pests and diseases.

Coffee is produced in many countries and there are pests and diseases in every area[7]. But the specific pests and diseases vary dependent on soil and environmental conditions[7]. Agriculture being the major sector contributing to Uganda’s economy takes up 80% of the total exports. Among all the exports, coffee has the largest portion of up to 22%. Small holder farmers whose average farm sizes range from 0.5 to 2.5 ha produce 90% of Uganda’s coffee.

However, in the last financial year a deduction of 5% on coffee production was observed due to various challenges, majorly related to pests and diseases. This makes the livelihood of smallholder coffee farmers very vulnerable as they highly depend on the yield from their farms. Predictive information about pest and disease is extremely important to optimize pest and disease management practices, so as to maintain and increase the productivity of crops, such as coffee, in Uganda..

1.1 JUSTIFICATION

Numerous approaches to crop pest and disease monitoring, such as automated monitoring of viral cassava disease by collecting and analyzing leaves of cassava plants; have been provided in line with other crops such as cassava [8], bananas, tomatoes [9] and can be extended to other cops [10] [11] however, these are registered under active procedures when the crops are already affected. Preventing agricultural diseases before plantation remains a challenging and fundamental problem.

Our research attempts to revolutionize the pest and disease monitoring procedure through use of Artificial Intelligence on data collected on soil images and soil properties to mediate soil-pest/disease relationships by building a proactive surveillance model that monitors coffee pest and disease conditions. Hence, aiding coffee farmers determine the optimal pest and disease management practices which will lead to increased yields of coffee production.

1.2 DATA

The dataset used in this research is comprised of Training Set and the Test Set, the Training Set is comprised of 4,893 images, of these 961 belong to the Healthy Class; 2,230 belong to the American Leaf Spot (ALS) Class and 1,702 belong to the Cercospora Leaf Spot (CS) Class while the Test dataset comprised of 1,209 unlabeled images. Samples of images are depicted in Figure 1. The images are resized for scale augmentation and annotated using labeling.

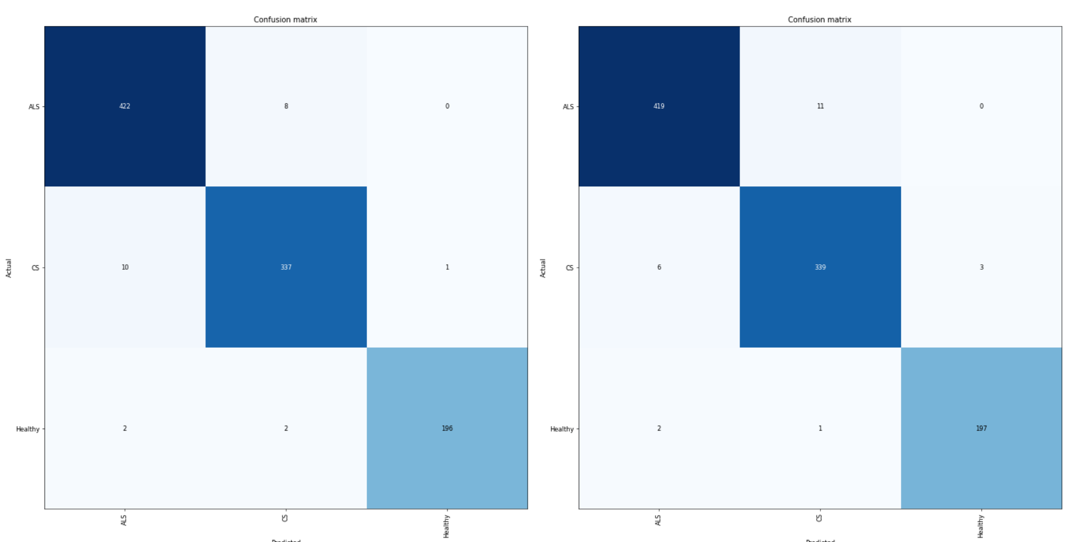
(a) American Leaf Spot (ALS) (b) Cercospora Leaf Spot (CS) (c) Healthy

Figure 1: Soil Images Samples.

2 MODELS, METHODS, RESULTS AND DISCUSSIONS

2.1 TRAINING PHASE

Using FASTAI, through transfer learning we performed two pre-trained models RESNET50 and VGG16BN on the training dataset. During training the training data was sliced into X and Y at a ratio of 20% (X - validation set) and 80% (Y- training set), this was done for 15 epochs.



(a) ResNet50 Confusion Matrix (b) VGG16BN Confusion Matrix

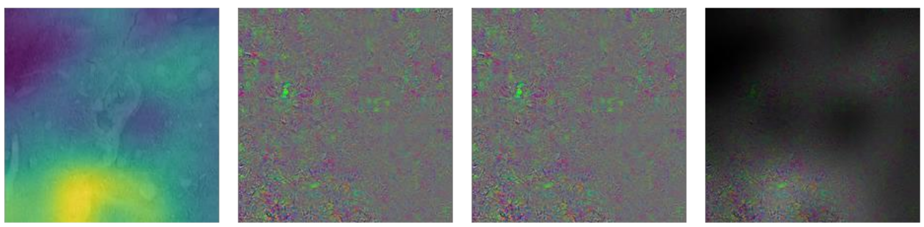
Figure 2: Confusion Matrices

Table 1: Training Accuracy of Classification Models

MODEL	**ACCURACY**	**ROC**
VGG16	0.97546	0.99763
ResNet50	0.97648	0.99791

2.2 Heat Maps

To be able to obtain insights and validation that our model works well, We employed a combination of both Guided Back-propagation and GradCAM. We analyzed saliency maps to find out what exactly the networks were relying on to make their predictions.



(a) (b) (c) (d)

Figure 3: Heat Map

2.3 Testing Phase: Predictions on the Test Dataset

The Test Dataset comprised of 1,209 images, of these 244 belonged to the Healthy Class; 425 belonged to the American Leaf Spot (ALS) Class and 540 belonged to the Cercospora Leaf Spot (CS) Class.

Table 2: Number of Class Predictions by Classification Model

		Vgg16	**Resnet50**	**Vgg16**	**Resnet50**	**Vgg16**	**Resnet50**
ACTUAL	***ALS***	305	310	51	45	69	70
	CS	54	52	439	442	47	46
	Healthy	60	65	16	6	168	173
		ALS		***CS***		***Healthy***	
		PREDICTED					

Table 2 shows the number of correctly and incorrectly classified images per class by classification model. Table 3 shows the percentages of correctly and incorrectly classified images per class by classification model.

We performed two models (VGG16 and ResNet50) on the test dataset, 71.8% of the ALS samples were correctly classified as ALS by VGG16 while 72.9% of ALS were correctly classified as ALS by ResNet50, 81.3% of the CS samples were correctly classified as CS by VGG16 while 81.9% of CS were correctly classified as CS by ResNet50 and 68.9% of the Healthy samples were correctly classified as Healthy by VGG16 while 70.9% of Healthy samples were correctly classified as Healthy by ResNet50

Table 3: Percentage Class Predictions by Classification Model

		Vgg16	**Resnet50**	**Vgg16**	**Resnet50**	**Vgg16**	**Resnet50**
ACTUAL	***ALS***	71.8%	72.9%	12.0%	12.5%	16.2%	16.5%
	CS	10.0%	9.6%	81.3%	81.9%	8.7%	8.1%
	Healthy	24.5%	26.6%	6.6%	2.5%	68.9%	70.9%
		ALS		***CS***		***Healthy***	
		PREDICTED					

3 CONCLUSIONS

Soil Testing is significant to ascertain the presence of pathogens in the soil that favor the existence of various pests and diseases which results in low and poor yields in crops. We harness the potential of Artificial Intelligence Deep Neural Networks to determine the existence of microorganisms in the soil before plantation using soil imagery data.

Our work is still in its initial stages, at this stage we are testing our initial model on our initial dataset of soil images to be able to ascertain how the model(s) performs.

4 FUTURE WORK

Our baseline model focuses on soil images of two (2) disease types in coffee and in future we hope to extend the model to more coffee disease and pest types and also apply different deep neural networks such as DenseNet [13] on a dataset of both soil images and soil properties such as temperature, PH etc..

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