
Inferring Crop Pests and Diseases from Imagery Soil Data and Soil Properties

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Abstract

1 80% of the total exports made in Uganda are known to be agricultural products
2 mainly coffee, tea, cotton, among others, this being dominated by coffee whose
3 percentage is 22 on the total exports. However, a decrease was registered in the
4 last financial year that depicted a drop by 5% as a result of the different challenges
5 that the farmers are encountering which were reported to be mainly pests and
6 diseases. The production of coffee is more likely to drop according to some
7 farmers. Numerous approaches to dealing with crop pests and diseases have been
8 provided in line with other crops such as cassava, bananas, tomatoes and can be
9 extended to other crops however, these are registered under active procedures when
10 the crops are already affected.

11 1 INTRODUCTION

12 Proponents of organic farming have long promoted the view that the likelihood of pest outbreaks is
13 reduced with organic farming practices, including establishment and maintenance of "healthy" soil
14 [1][2][3]. Recent studies have shown that plant resistance to pests and diseases is linked to optimal
15 physical, chemical, and—perhaps most importantly—biological properties of soil [4][5]. In major
16 agricultural crops, pests, diseases and weeds cause considerable yield losses [6]. Climate in terms
17 of temperature, CO₂ and rainfall and prevailing weather conditions at a time has direct and indirect
18 effects on the crop pests and diseases.

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

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

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

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

39 1.1 DATA

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

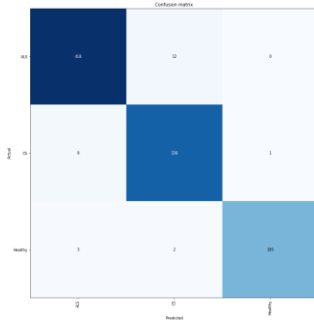


Figure 1: Soil Images Samples [ALS, CS, Healthy.]

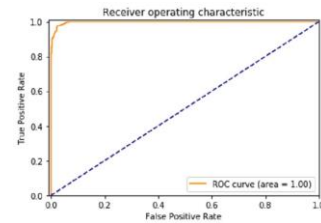
45 2 MODELS, METHODS, RESULTS AND DISCUSSION

46 2.1 Training Phase

47 Residual Networks [12] introduce residual learning by getting the difference between learned feature
48 and the input of that layer. Using FASTAI, through transfer learning we performed a pre trained
49 model RESNET 50 on the training dataset. During training the training data was sliced into X and
50 Y at a ratio of 20% (X - validation set) and 80% (Y- training set), this was done for 5 epochs. The
51 results are presented in a confusion matrix as shown in Figure 2 and a ROC Curve as shown in Figure
52 3. The results in the confusion matrix are used to measure the performance of the model on various
53 classification metrics. The model returns an accuracy of 97.3% and ROC area is 99.8%.



(a) Confusion Matrix.



(b) ROC Curve.

54 2.2 Testing Phase (Predictions on Test Dataset)

55 The Test Dataset comprised of 1,209 images, of these 244 belonged to the Healthy Class; 425 belong
56 to the American Leaf Spot (ALS) Class and 540 belong to the Cercospora Leaf Spot (CS) Class.
57 We performed the model on the test dataset 71% of the American Leaf Spot samples were correctly
58 classified as ALS, 73% of the Healthy samples were correctly classified as Healthy and 82% of
59 Cercospora Leaf Spot samples were correctly classified as CS.

60 12.5% of the American Leaf Spot (ALS) samples were incorrectly classified as CS, 16.5% of the
61 American Leaf Spot (ALS) samples were incorrectly classified as Healthy, 8.2% of Cercospora Leaf
62 Spot (CS) samples were incorrectly classified as Healthy, 27% of Healthy samples were incorrectly
63 classified as American Leaf Spot (ALS), 9.8% of Cercospora Leaf Spot (CS) samples were incorrectly
64 classified as ALS.

65 3 Conclusion

66 Soil Testing is significant to ascertain the presence of pathogens in the farm that bring about various
67 diseases which results in low and poor yields in crops. We harness the potential of Artificial
68 Intelligence Deep Neural Networks to determine the existence of microorganisms in the soil before
69 plantation using soil imagery data. The baseline model focuses on 2 disease types in coffee and in
70 future we hope to extend the model to more coffee disease types and also apply different deep neural
71 networks such as DenseNet [13].

72 References

- 73 [1] Howard, A. 1940. An agricultural testament. Oxford University Press, London.
- 74 [2] Oelhaf, R. C. 1978. Organic farming: Economic and ecological comparisons with conventional methods.
75 John Wiley, New York.
- 76 [3] Merrill, M. C. 1983. Bio-agriculture: A review of its history and philosophy. *Biological Agriculture and Hor-*
77 *ticulture* 1: 181–210.
- 78 [4] Altieri, M. A., & C. Nicholls. 2003. Soil fertility and insect pests: Harmonizing soil and plant health in
79 agroecosystems. *Soil Tillage Research* 72: 203–211. (Available online at: [http://dx.doi.org/10.1016/S0167-](http://dx.doi.org/10.1016/S0167-1987(03)00089-8)
80 [1987\(03\)00089-8](http://dx.doi.org/10.1016/S0167-1987(03)00089-8)) (verified 11 March 2010).
- 81 [5] Zehnder, G., G. M. Gurr, S. Kühne, M. R. Wade, S. D. Wratten, & E. Wyss. 2007. Arthropod management
82 in organic crops. *Annual Review of Entomology* 52: 57–80.
- 83 [6] Prakash, A., Rao, J., Mukherjee, A. K., Berliner, J., Pokhare, S. S., Adak, T., ... & Shashank, P. R. (2014).
84 Climate change: impact on crop pests. Applied Zoologists Research Association (AZRA), Central Rice Research
85 Institute.
- 86 [7] <https://www.perfectdailygrind.com/2019/01/a-guide-to-common-coffee-pests-diseases/>
- 87 [8] Llorca, C., Yares, M. E., & Maderazo, C. Image-Based Pest and Disease Recognition of Tomato Plants
88 Using a Convolutional Neural Network.
- 89 [9] Mohanty, S. P., Hughes, D. P., & Salath, M. (2016). Using deep learning for image- based plant disease
90 detection. *Frontiers in plant science*, 7, 1419.
- 91 [10] Mohanty, S. P., Hughes, D., & Salathe, M. (2016). Inference of plant diseases from leaf images through
92 deep learning. *Front. Plant Sci*, 7, 1419.
- 93 [11] Witten, I. H., Frank, E., Hall, M. A., & Pal, C. J. (2016). *Data Mining: Practical machine learning tools and*
94 *techniques*. Morgan Kaufmann.
- 95 [12] He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings*
96 *of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).
- 97 [13] Szegedy, C., Vanhoucke, V., Iosifidis, S., Shlens, J., & Wojna, Z. (2016). Rethinking the inception architecture
98 for computer vision. In *Proceedings of the IEEE conference on computer vision and pattern recognition*
99 (pp.2818-2826).