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

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1 Introduction

80% of the total exports made in Uganda are known to be agricultural products mainly coffee, tea, cotton, among others. Of these agricultural products that formulate Ugandas exports- Coffee is the major export with a percentage of 22 of the total exports. However, a decrease was registered in the last financial year that depicted a drop by 2% as a result of different challenges that the farmers are encountering which were reported to be mainly pests and diseases. Without a proactive measure for this challenge, the production of coffee is more likely to drop according to some farmers. Various approaches have been provided in line with other crops such as cassava[1], bananas, tomatoes [2] and can be extended to other crops [3][4] however, these are registered under active procedures- when the crops are already affected.

2 Our Idea

Our idea is to revolutionize the pest and disease monitoring procedure through use of Artificial Intelligence on data collected on soil properties to mediate soil-pest/disease relationships and create a proactive model for pests and disease surveillance which will help farmers determine the optimal pest and disease management practices.

3 Our Goal

Our goal is to develop the model using Deep Learning inception algorithms [5][6][7] to understand and learn of the soil representation, imagery patterns in relation to pests and diseases and be able to do predictive analysis on unprecedented datasets.

4 Essential Data to be Collected

Images of soil samples from over 100 farms in 25 different districts using cameras/phones; Additional data will be collected on soil properties using soil sensors to determine the texture, temperature, humidity, reaction, moisture, nutrients, organic matter of the soil, weather and climate Conditions among others;

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