A low-cost 3-D printed smartphone add-on spectrometer for diagnosis of crop diseases in field

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ABSTRACT

We present our initial proof of concept study towards the development of a low-cost 3-D printed smartphone add-on spectrometer. The study aimed at developing a cheap technology (less than 5 USD) to be used for detection of crop diseases in the field using spectrometry. Previously, we experimented with the problem of disease diagnosis using an off-the-shelf and expensive spectrometer (approximately 1000 USD). However, in real world practice, this off-the-shelf device can not be used by typical users (smallholder farmers). Therefore, the study presents a tool that is cheap and user friendly. We present preliminary results and identify requirements for a future version aiming at an accurate diagnostic technology to be used in the field before disease symptoms are visibly seen by the naked eye. Evaluation shows performance of the tool is better than random however below performance of an industry grade spectrometer.

CCS CONCEPTS

• **Applied computing → Computer-aided design**; • **Computing methodologies → Machine learning algorithms**.

KEYWORDS

Low-cost, Spectrometery, Crop disease, Diagnosis, 3-D printed, Smartphone

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1 INTRODUCTION

The ability to detect crop disease in-field at a very early stage, especially amongst smallholder farmers, is still a big challenge. Usually disease identification happens at a stage when it is too late and little can be done to save the situation. This research is an extension of our previous work [8–10] where diseases in Cassava crop have been identified at an early stage using spectral data acquired by a commercially available spectrometer.

Initially, we analysed spectral data from visibly diseased parts of a leaf as well as parts that appear visibly healthy [8]. Findings of the study indicated that spectral data collected from asymptomatic parts of the leaf has implications for detecting disease in the plants before symptoms are visible. In [9], we investigate spectral data in terms of matrix relevance learning. The ultimate aim was to identify a specific feature representation contain most information for classification and will facilitate technical solutions using simple sensors. In [11], we carried out the experiments in a screen house, to rule out the influence of other diseases, pests or severe weather conditions. The results of the study indicate that the presence of the disease can be detected from leaf spectra six weeks earlier before the appearance of visual symptoms.

Although, good results have been attained with this approach, the ability to construct cheap and usable tools to diagnose crop diseases at an early stage is still vital. To tackle this problem, we propose the development of a 3-D printed smartphone add-on spectrometer that can determine the status of a crop from the leaves in field.

There have been some initiatives to build a small relatively cheap spectrometer to do these types of analyses e.g. [16], [4]. However, most of the studies on the application of this novel technology are carried out in isolation with no comprehensive information on the most suitable approach.

The key contributions of this research can be seen in two areas. (i) To provide evidence of building a really low-cost technology that can be easily scaled even without a large production line. (ii). To develop an artifact that will actually be able to identify disease early such that smallholder farmers can cause an intervention to their garden. We expect that success in this endeavor will result in a large trial to validate its applicability for use in early diagnosis of disease in the field before it is visibly symptomatic on the plant.

2 MATERIALS AND METHODS

We begin this section by describing the working of a commercial spectrometer that we used in our previous experiments. The

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sections that follow, we describe a setup for the customised spectrometer we constructed in this study.

2.1 Commercial spectrometer

Previously, we experimented with a CI-710 spectrometer manufactured by [2]. The device consists of two modules, a leaf probe and a CCD-based spectrometer, and is powered by a personal computer (PC) through a USB cable. The leaf probe is equipped with a tungsten-LED dual light source that provides a broad range of wavelengths of light, suitable for visible and near infrared spectroscopy. The light then passes through a bifurcated fiber optic cable and connects to one of the two sampling light ports on the side of the leaf probe for absorption spectrum or tramission spectrum, as well as reflectivity measurements for reflectivity spectrum.

2.2 Customised spectrometer design

2.2.1 Light source & Diffraction grating. The customised setup in this experiment used a watch battery of capacity 1.5 V and white light diode as a source of light as a low cost alternative to optical fibre and more powerful light sources. We used a peeled digital versatile disc (DVD) piece as the diffraction grating medium [18], [13].

2.2.2 The digital display. We use a smartphone camera as a receiver. The light split by the DVD falling on the camera is captured as spectrum image. The study also acquired spectral data using the AspectraMini Application [6] defined above. Our hypothesis in this study is that different diseases affect the metabolism of plants differently thus changes in light absorption properties.

2.2.3 Hardware design. We built a 3-D printed smartphone casing to integrate different components and our design aimed at the following: (i). To prevent much light scattering and splitting in order to retain enough information. (ii). To keep external light out of the experiment as to avoid information distortion. We also made the case adjustable to any phone controlling for where the camera is and the size of the phone. Figure 1 shows a full setup.

Figure 1: First prototype

2.3 Methods

We acquired data of two types: (i). Color histograms as a transformation from color RGB spectra. (ii). Spectral data using the already existing software (Aspectra mini Android application) [6]. The experiments in this study were performed in parallel with the previous work [11] under the same setup. Plants were grown in a screen house and at week four (4) of growth, they were split into two (2) separate groups. The first one (10 plants) was reserved as a healthy control class (HC) and no disease inoculation was applied to the group. The second group of plants (17 plants) was infected with the cassava brown streak disease (CBSD) virus using grafting inoculation technique [14, 17].

For spectral data we follow the same pre-processing methodology in [11]. We applied computer vision techniques to transform the image spectrum from RGB to HSV color space and attained histograms as image representation. Data from this experiment and the adapter design for the 3D-printed smartphone case and are available at https://github.com/godliver/3-D-Printouts.git.

3 RESULTS

We follow the same training and validation strategy (Leave-One-Out cross-validation) as the previous study [11]. We used standard algorithms: K-Nearest Neighbour (KNN) [3], Extremely Randomized Trees [5] and Linear SVM [7] defined under Scikit-learn [12]. We also used GMLVQ algorithm [15] via the open source GMLVQ toolbox [1]. Result Table 1 shows results for this pilot study. As indicated, we did not attain favourable results but this work serves as a baseline future work.

Table 1: Overall accuracy score in original feature space vs. dimensional reduction

Classifier	Aspectra Mini	Color Histograms
KNN	0.627	0.521
Extra Trees	0.671	0.556
LinearSVM	0.612	0.503
GMLVQ	0.570	0.522

4 DISCUSSION

We have presented an initial step towards the construction of an innovative low-cost spectrometer that can be used to diagnose disease in plants and infield. Our novel contribution in this area can be seen in the design of the prototype. Previous work [8, 9, 11] showed that spectrometry can gain the smallholder farmer an extra 8 weeks to apply an intervention before disease symptoms become visible. Our experiments in this study aimed at replacing the expensive spectrometer ($10K) with a cheap version to cost $5 – $8. While performance is clearly inferior to the one of the commercial spectrometer, we observe performance above mere guessing. This forms the basis for further improvements. One element to include in a future version is a powerful diffraction grating medium e.g. a prism. We will also experiment with different diodes. The explicit transformation of light emissions to actual spectrograms should facilitate further improvements. Literature [13] also shows efficacy for this type of handcrafted cheap DIY tools. We intend to leverage on that success to provide a diagnostic tool to be used by smallholder farmers in developing countries.

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