RoCoLe: A robusta coffee leaf images dataset for evaluation of machine learning based methods in plant diseases recognition

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ABSTRACT

In this article we introduce a robusta coffee leaf images dataset called RoCoLe. The dataset contains 1560 leaf images with visible red mites and spots (denoting coffee leaf rust presence) for infection cases and images without such structures for healthy cases. In addition, the data set includes annotations regarding objects (leaves), state (healthy and unhealthy) and the severity of disease (leaf area with spots). Images were all obtained in real-world conditions in the same coffee plants field using a smartphone camera. RoCoLe data set facilitates the evaluation of the performance of machine learning algorithms used in image segmentation and classification problems related to plant diseases recognition. The current dataset is freely and publicly available at https://doi.org/10.17632/c5yvn32dzg.2.

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The robusta coffee leaf images dataset (RoCoLe) provides images that can be used to train and validate the performance of machine learning algorithms used in binary and multiclass classification problems as well as in segmentation tasks specially related to plant diseases recognition. The RoCoLe dataset contains imagery of upper and back sides of coffee leaves collected from robusta coffee crops showing different states (healthy and unhealthy) as well as presence of disease (rust\(^1\) and red spider mite\(^2\) presence) and infection severity. A total of 4 images are included per each one of the 390 coffee plants available in the study area (Fig. 1). Thus, in total, 1560 images of robusta coffee leaves are included in the data set.

2. Experimental design, materials, and methods

The coffee plants images of healthy and unhealthy leaves were acquired using a 5-MP smartphone camera at a working distance of 200–300 mm without zoom. The images were taken daily under real conditions such as multiple lighting brightness (cloudy, sunny and windy days), backgrounds (other plants and weed) and temperature levels (high and low humidity levels) to have real and representative samples of coffee plants. In the study area, we considered a crop with 390 coffee plants. On each

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1 Rust is a disease caused by the hemileia vastatrix fungus.
2 The tetranychus urticae is a specie of plant-feeding mite. It is commonly known as red spider mite.
coffee plant in the crop, we taken images of upper and back sides of healthy and infected leaves which yielded the total of 1560 images.

To provide to RoCoLE the capacities to evaluate the performance of the mentioned and other machine learning methods, we carried out an annotation data process to obtain a fully-labeled of the 1560 coffee leaf images using a data labeling web-tool called ©Labelbox. Two types of annotations were made: (1) object segmentation and (2) classification.

In machine learning area, object segmentation aims separating parts of an image into pieces which are conceptually meaning. Methods as artificial neural networks, genetic algorithms and clustering have been used to perform segmentation tasks [2–4]. Meanwhile, classification aims finding a class to which an item belongs as from patterns in a labeled data set. Here, methods as artificial neural networks, SVM (Support Vector Machine) and decision trees have been used to perform classification tasks [5–7].

Our dataset includes annotations of object segmentation, where the labeler recognizes and segments each object (leaf). Each object was further annotated as healthy or unhealthy. For annotations of classification, the leaf was labeled as healthy, red mite presence, rust level 1, rust level 2, rust level 3 or rust level 4. To set the rust infection severity we consider the OIRSA method [1]. It is summarized in Table 1.

Table 1 shows the descriptions of the levels or severity grades of the rust. On annotations, each level is set according to the percent of affected leaf area. For instance, when the number of spots is more than half the leaf, the image is classified with the maximum level, i.e., rust level 4. Infection severity up to such level is considered, because we used the OIRSA method.

The fully-labeled image dataset can be used for reproducible research where machine learning methods are used to tackle segmentation and classification problems.

For segmentation problems, RoCoLe provides object annotations to segment the leaves (Fig. 2).

Fig. 2 shows an example of the visual appearance of annotated images for segmentation purpose. Here, an object is identified through a mask or an orange limited-area denoting the segment in the image where a leaf is located. Moreover, it also includes the type of object, i.e., unhealthy leaf.

| Level | Affected leaf area (spots) |
|-------|---------------------------|
| 1     | 1–5%                      |
| 2     | 6–20%                     |
| 3     | 21–50%                    |
| 4     | >50%                      |
For classification problems, RoCoLe provides labels of six classes: healthy, red spider mite presence, rust level 1, rust level 2, rust level 3 and rust level 4 (Fig. 3). For each one, there are 791, 167, 344, 166, 62 and 30 images, respectively.

![Figure 2](image1.png)  
**Fig. 2.** Annotation examples of a segmentation mask in RoCoLe dataset.

![Figure 3](image2.png)  
**Fig. 3.** Example of coffee leaf with different states (classes). A) healthy. B) Red Spider Mite. C) Rust level 1. D) Rust level 2. E) Rust level 3. F) Rust level 4.
Fig. 3 shows examples of the upper side of leaf images for each class. From this type of image, the labels are set by performing a visual inspection to establish the leaf state. All this labeled process is validated by an expert.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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