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A CASE-STUDY VISION

Mobile application for the detection of black Sigatoka

Aplicativo móvil para la detección de Sigatoka negra

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ABSTRACT

Black Sigatoka is key disease affecting the quality and production of the Colombian banana crop. Thus, systems that can be used to detect diseases are critical to farmers. We propose a system that leverages mobile smartphone technologies to implement computer vision techniques to determine the percentage of affected area of the plant. Smartphones cameras are used to acquire data via image capture, and the detection of diseased pixels is performed using a segmentation algorithm with histogram analysis of the image library. A model for the calculation of the affected area is then computed. Finally, the information is presented through a user interface. To validate the proposed method, a database is created with the composed image dataset to compare its efficiency by measuring the root mean-square error between manual segmentation and the result of the algorithm. Finally, usability and response-time tests are performed.

RESUMEN

La Sigatoka Negra es uno de los principales problemas que afectan la producción del cultivo de plátano, es por esto, que el desarrollo de sistemas que permitan la detección de enfermedades, generan una herramienta importante para el monitoreo y control realizado por el agricultor. El sistema propuesto, aprovecha el hardware en dispositivos móviles para implementar técnicas de visión por computador que permitan determinar el porcentaje de área afectada de la planta. El Smartphone es utilizado para adquirir datos y capturar la enfermedad a través de imágenes. Después se realiza la detección de los píxeles enfermos a través de un algoritmo de segmentación con análisis por histograma. Posteriormente se computa un modelo para el cálculo del área afectada. Por último, se presenta la información a través de la interfaz de usuario. Para validar el método propuesto, se crea una base de datos con imágenes tomadas por medio del aplicativo para comparar su eficiencia a través del error RMS entre la segmentación manual y el resultado del algoritmo. Finalmente se realizan pruebas de usabilidad y tiempo de respuesta.

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1. Introduction

The tropical climate and fertility of the Colombian soil provide the necessary conditions for successful banana crops in the various regions. In 2018, banana production reached 4,316,726 tonnes, generating more than 1,500,000 jobs, making it one of the most representative crops in the country [1]. In spite of this, Colombia wielded the second-highest importation of bananas in Latin America, presenting a worrying situation, considering that there is enough quantity with the soil quality needed to meet national demand. Another worrying fact is that only 26 % of the national production was generated by small farmers, because the banana sector is dominated by multinational corporations [1].

Small farms generally lack technical processes and specialized equipment for competitive crop management. Furthermore, the industry lacks sufficient and cheap technology for disease detection and prevention. Therefore, small farms lack efficient control over variables directly affecting their crops, increasing the likelihood of their crops suffering from harmful fungi. Black Sigatoka is a representative fungal disease that generates dark spots on banana leaves, altering their photosynthetic capability sometimes causing total losses if proper controls are lacking [2]. On the other hand, computer vision and digital-image processes provide capabilities of detecting diseases based on defined visual characteristics. Such technologies are relatively inexpensive and have the potential to reduce the quality gap between small farms and multinationals [3, 4].

We found extant methods that detect different diseases that produce visual changes in the leaves or fruit of plants. Disease segmentation methodologies are commonplace. One of the most common metrics used for this process is the hue–satu–ration–value (HSV) colour space [5], with which, operations are performed using Gaussian or morphological filters. Then, images are binarised using known thresholds [6]. Unfortunately, these developments are limited to the use of synthetic databases having a reduced number of samples. Other approaches have used supervised learning methods that extract descriptors, such as the wavelet, histogram and scale- invariant feature transforms (SIFT) [7], for use in representation colour-space systems (e.g. HSV) [8]. These techniques allow us to extract distinctive information of a disease under study. Healthy and diseased images are classified using support vector machines, neural networks and decision trees [9, 10].

Most of the proposed developments have contemplated theoretical solutions, and they lacked the specific cultural and economic limitations of small farmers who need systems the most. Current studies reveal that 9 out of 10 Colombians connect to the internet at least once per week using smartphones [11]. The Colombian government has further established policies seeking the proliferation of new technologies. Therefore, it is easy to find farm families that have at least one smartphone at home. This allows them to use social networks, email and other similar tools for information exchange. This now-commonplace technology provides readily available and useful features for the inexpensive information capture and analysis we are looking for. Most smartphones come equipped with data-capture tools that instantaneously analyze physical variables using transducers, accelerometers, gyroscopes and digital cameras. The proliferation of these tools provides a clear opportunity to support agricultural processes, especially disease detection and analysis.

Solutions to similar problems have already been provided by smartphone technologies, including applications (app) for classifying sign language, identifying diseases in the tongue and ear and monitoring reference patterns in augmented reality apps [12–14]. Still, few apps currently serve as tools for improving agricultural processes. In [15], a mobile app was developed to classify 20 types of plants from images of leaves using SIFT and bag-of-words features. However, the system was limited to determining the type of plant and could not detect diseases in the sampled leaves. In other mobile apps, image distortion was eliminated using a threshold that segmented healthy and diseased pixels for later cluster composition that generated distinctive information [16]. In [17], a mobile app was developed that allowed filtering, feature extraction and classification operations using a Bayesian model to detect borer beetles in coffee crops from a digital image.

Because black Sigatoka can be determined via visual inspection, systems have been developed whose purpose it is to detect the disease from digital images. In [8], a smoothing and segmentation filter was applied using a threshold to detect the disease. In [18], a pre- trained convolutional neural network (i.e. MobileNetV1) was used to classify banana leaves to determine whether they were healthy or sick. However, the proposed apps were limited to discriminating healthy and diseased labels, ignoring the fact that the disease has different levels of severity and that, for each example, it was necessary to apply a different corrective action. However, in [19], red–green–blue (RGB) analysis was performed using histograms in the RGB colour spaces, wherein segmentation of the diseased pixels was identified, further calculating the percentage of area affected. However, the proposed database did not have an adequate capture protocol, and a theoretical solution was generated, ignoring the possibility of field implementation. Consequently, there remains a clear need to create a mobile app for the detection of black Sigatoka, which will allow a farmer to comprehend the percentage of affected area of each leaf, providing adequate information for the control of the disease. A system with these characteristics would provide a technological tool that could increase the efficiency and quality of agricultural processes for small farms.

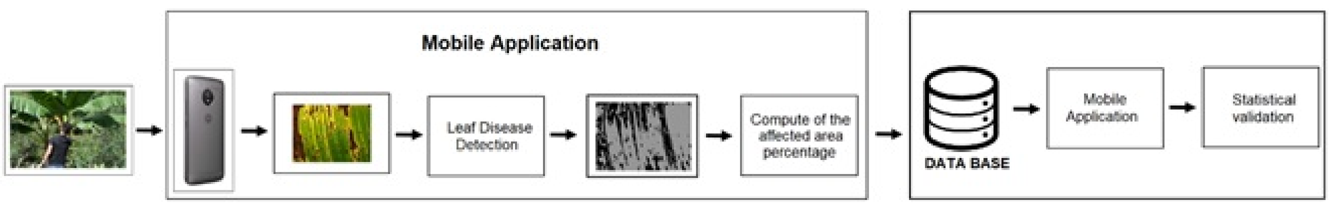
This document presents the design and implementation of a mobile app that uses digital images to compute the percentage of an affected area of a banana leaf infected with black Sigatoka disease. The main contribution of this article is a method for black Sigatoka detection that can be implemented as a smartphone app, from which the percentage of affected leaf area can be quickly determined. This capability has not been presented by other works.

We apply a two-phase process. During the first phase, we design a detection algorithm with a database of black Sigatoka-stricken banana-leaf images and an image processing algorithm that segments diseased pixels to later compute the affected area percentage. During the second phase, the smartphone app is implemented using the given algorithm. The app uses the smartphone's camera and image gallery. Finally, we validate both the operation of the app and the detection algorithm against a manual method of calculating the area of the diseased leaf.

2. Materials and Methods

This section presents the proposed work structure shown in Figure 1. A mobile app that detects the black Sigatoka disease in banana crops was developed with a visualization component that allows a farmer to comprehend the percentage of affected leaf area. This was achieved by leveraging a digital-image processing algorithm that segments the image. Then, the percentage of the affected diseased area was calculated and presented in the user interface (UI).

Figure 1: Block diagram of the proposed methodology.



Source: own

2.1. *Mobile application*

The mobile app was implemented using Android Studio, which allowed the integration of the Kotlin language using methods of image processing from the OpenCV library. The app is compatible with all devices that use the Android operating system. It comprises two sub-stages: the UI and the algorithm.

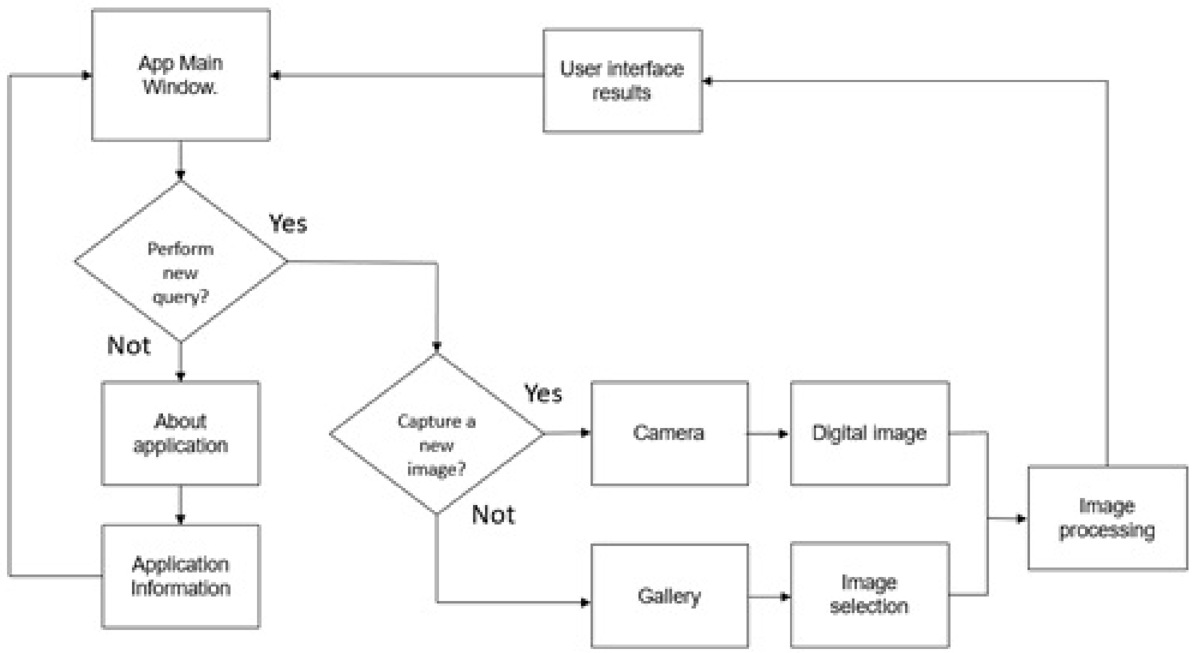
2.1.1. *The UI*

The UI of the mobile app was designed to allow easy and intuitive use by farmers, as shown in Figures 2 and 3. The main app window has three buttons: 'About', which displays information about the app with instructions; 'Camera', which allows new sample images to be captured; and 'Gallery', through which an image library can be viewed. After selecting an image, pixel disease detection is performed, as presented in Figures 2 and 3.

2.2. *Automatic disease detection*

Because current mobile devices retain limitations of data processing capacity, we, at this stage, sought to develop a methodology having a low computational cost to allow the detection of black Sigatoka disease from an image captured on a smartphone.

Figure 2: Block diagram of the mobile-app functionality.



Source: own

Figure 3: Main window of the mobile application.

Source: own

The implemented algorithm resized the image 1000 × 1000 pixels. The size was heuristically selected so that disease detection would not be affected and that the smartphone could respond appropriately during processing. Then, a Gaussian filter that smooths the noise generated when the image is scanned was applied, transforming the RGB colour space to HSV. The V channel was selected to allow a greater separability of disease detection [8, 20]. Then, the mean and standard deviation for the selected channel were calculated. Subsequently, a threshold of $\mu \pm 3\sigma$ was established. Any pixel outside of that range would be considered sick, and its value would become zero. Figure 4 shows the implemented pseudocode.

2.2.1. *Percentage of affected area computation*

After the segmented image was obtained, the percentage of affected area was calculated. For this, the ratio of the number of pixels having the disease and the total number in the image was calculated, as shown in Eq. (1).

$$\text{Percentage of affected area}(\%) = \frac{\text{Number of sick pixels}}{\text{Total number of pixels}} * 100 \tag{1}$$

2.2.2. *Statistical validation*

To validate the proposed methodology, a database was created, and the algorithm was executed, whose results were then analyzed using a manual segmentation method, as presented next.

Figure 4: Algorithm for automatic disease detection.

// Image Disease Detection

Input: Image (I)
Output: Segmented image (Irgb)

Start

Resize image to size 1000x1000
Apply Gaussian space filter to Iv (x, y), σ=5
$Ihsv \leftarrow rgb2hsv(I)$
$Iv \leftarrow Ihsv(:,:,3)$
Compute the statistical Moments to Iv
$M \leftarrow Mean\ (Iv)$
$D \leftarrow Std(Iv)$

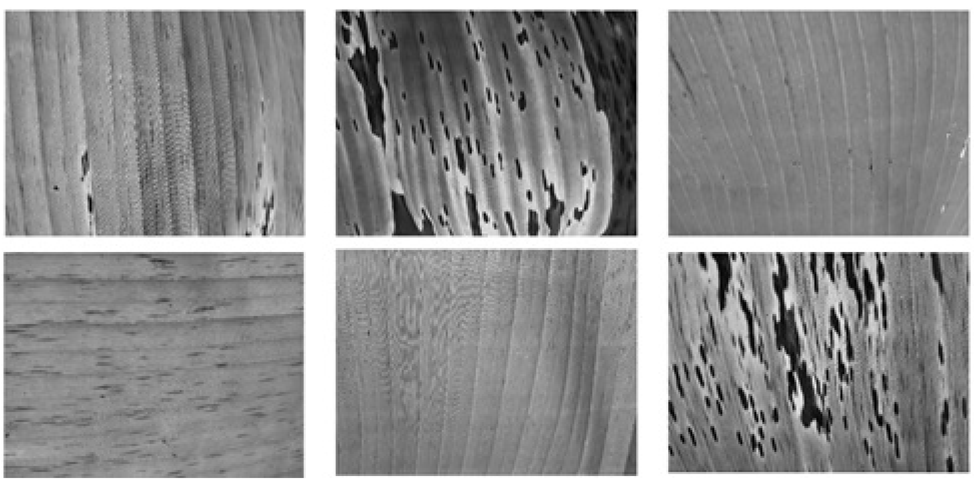
$$A(i,j) = \begin{cases} 1, & if\ Iv(i,j) \leq \left(\mu - (\sigma * 4)\right)\ ||\ if\ Is(x,y) \geq (M + (D * 4)) \\ 0, & Other\ Case \end{cases}$$

$$I_{RGB}(x,y) = \begin{cases} R = I(x,y)(:,:,0), G = R = I(x,y)(:,:,1), B = R = I(x,y)(:,:,2), & If\ A(x,y) = 1 \\ pixel = pixels + 1 & If\ A(x,y) = 1 \\ R = 0, G = 0, B = 0, & If\ A(x,y) = 0 \\ pixels2 = pixels2 + 1 & If\ A(x,y) = 0 \end{cases}$$

End

Source: own

Figure 5: Samples of the database.



Source: own

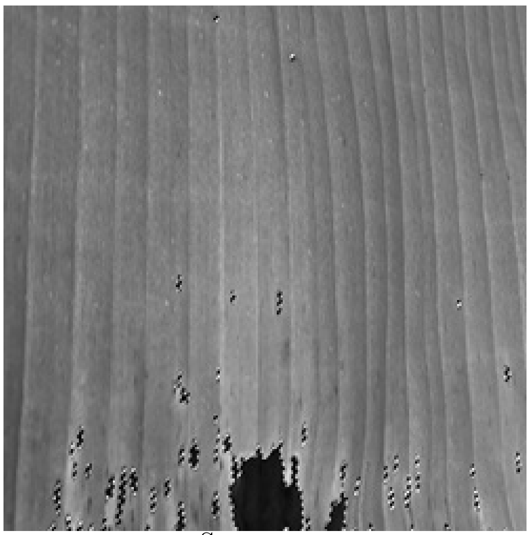
2.3. Database

There exist state-of-the-art databases of leaves affected by black Sigatoka. However, the samples were not obtained using appropriate capture protocols [16], or they were of closed access [21], rendering it impossible to replicate and compare similar proposals. Owing to this, a new database was constructed with the characteristics required for this work. 100 samples were captured on banana farms at the Department of Risaralda using two smartphones with digital cameras in automatic mode. Camera resolution was 9.6 Mp (4128 × 2322) and 13 Mp (3120 × 4160) in JPG format. Samples were captured at a distance of 30 cm in sunny conditions with backlighting, sampling only the banana leaf and avoiding the background, central rib or any aspect other than the leaf. See Figure 5.

2.4. *Segmentation of the region of interest*

To validate the proposed methodology, a manual segmentation process of the disease pattern was carried out based on expert visual inspection using the Stover procedure. For this, GIMP software, a free and open-source raster graphics editor, was used to obtain the number of pixels selected as sick. From this value, the RMS error was calculated using the proposed automatic detection algorithm. The result of manual segmentation is presented in Figure 6.

Figure 6: Manual segmentation of the disease.



Source: own

In this section, we show the results of the experiment by applying the proposal methodology.

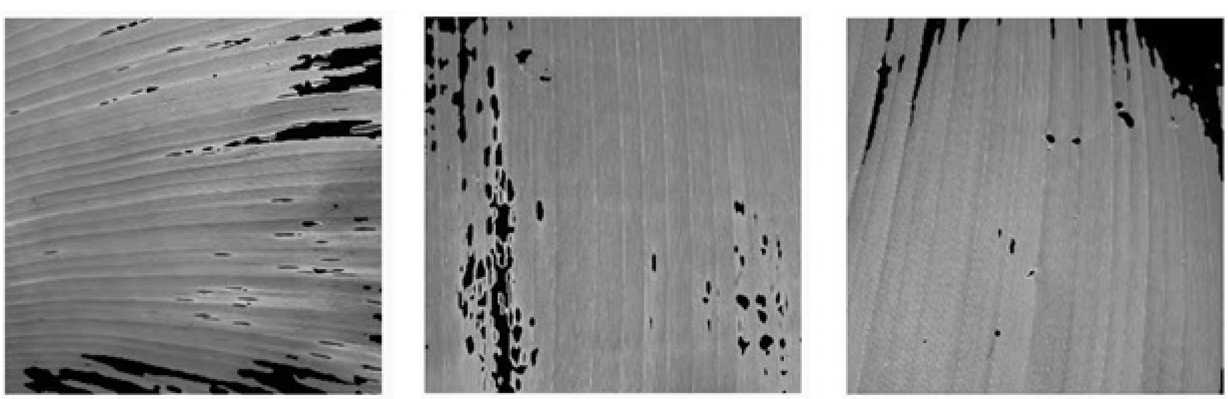
Figure 7 shows the segmented pixels found via the automatic detection algorithm. (a), (b) and (c) correspond to a leaf having high, middle and low states of the disease, respectively. The segmentation of the first cases as good. However, in (c), the algorithm detected pixels that were not sick. Nevertheless, the results were suitable for a famer's regular control regime. We computed the entire set of images and obtained the total database error: 2.97 % ± 3.04 %. The value of the standard deviation was influenced by an error increase during the early steps, as shown showed in Figure 7(c). However, the algorithm detected most pixels correctly.

We captured the app's computational cost by analyzing new samples with two mobile devices, as shown in Table 1. Moreover, we present the features of each device. The times are suitable, because they allow implementation using low-cost devices.

3. Conclusions

We designed a mobile app that executed an algorithm for black Sigatoka automatic detection and successfully calculated the affected area percentage of the disease in banana leaves. The system represents a valuable tool for disease detection, allowing small farms to improve their disease detection and remediation processes inexpensively. The detection algorithm was efficient when the disease characteristic pattern clearly appeared in an image. However, in samples wherein small traces were shown (State 1 according from the Fouré Scale), the error's value was 9.21 ± 1.4 %. Therefore, an increased computational capacity is expected to allow greater success in future devices. However, today, there remain limitations that restrict the accuracy. Nevertheless, we have clearly demonstrated a viable and valuable new technology that any farmer in Colombia could immediately use to quickly assess disease conditions and apply countermeasures.

Figure 7: Automatic detection algorithm's results of disease detection.



Source: own

Table 1: Algorithm computational costs.

Mobile Devices	Tech Features	Time (s)
Samsung J7 prime 2016	RAM 2GB at 1.6Ghz, Processor Cortex-A53	22.78 ± 0.25
Huawei Mate 20 Lite	RAM 4GB a 2.2Ghz, Processor Kirin 710	3.37 ± 0.21

Source: own

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