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INTELLIGENT MODEL FOR THE DETECTION OF THE PHYTOPHTHORA IN THE COCOA CROPPING, "BLACK COB”

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ABSTRACT

In this work, an intelligent computer system capable of self-learning from RGB images to detect the disease of phytophthora in the cropping of cocoa is developed. The data used to learn the model are the set of images with the four stages of the phytophthora. The disease is caused by conditions of insufficient sunlight, rain, humidity, and temperature below 21 degrees Celsius. Brown spots appear on the cob, which in 11 days is mostly necrotic, easily spread causing large losses to farmers. The model construction was carried out with the acquisition of images, pre-processing, segmentation, training and classification. For system learning, a dataset of 1200 images of select cocoa crops in the study area was used. As a result, 80% of success with the developed model is achieved. This model is an import contribution because an intelligent model to detect the disease according to the literature had not been developed.

Keywords: self learning, phytophthora, cocoa crops.

1. INTRODUCTION

An intelligent model is a computer program to perform tasks of Human Intelligence, especially self-learning [1]. It is used in mechanical engineering, medicine, health care [2], and in crops [3] to classify fruits [4], custard apples [5], Tommy mango [6], in the recognition of ripe oranges in the tree [7], in the lemon selection [8], and the mature state of hilacha mango [8]. In the detection of the black cocoa cob has not been found until now.

The disease of the phytophthora or Black Cob present in the fruit of cocoa [9], affects worldwide because it attacks various cocoa areas [10]. The fungus that produces it is proliferated in conditions of rain, humidity, insufficient sunlight and temperature below 21 degrees Celsius [10]. The phytophthora has to be treated, as an imperative matter, it has an 11-day propagation cycle and easy contamination [10]. Brown spots that appear on the cob can be captured by using images. The implementation of an intelligent model helps in the early detection of the disease by reducing treatment costs and improving crop yield.

The images are used to build the dataset for the Smart model to learn. A two-dimensional image is represented as $\mathbf{F} \in \mathbb{R}^{\mathrm{M}\times\mathrm{N}}$ where M and N are the dimensions of the rows and columns. A pixel is defined with $\mathbf{F}(x, y)$ as a coordinate in space. The image taken from a camera in the colors red, green and blue (RGB) are given by R=$\mathbf{r}(x, y)$, G=$\mathbf{r}(x, y)$ and B= $\mathbf{r}(x, y)$and the vector $(\mathbf{r}(x, y), \mathbf{g}(x, y), \mathbf{b}(x, y))$shows the intensity and color of the pixel in the coordinate (x, y)[9].

The intelligent model performs the analysis, and extraction of information from one or multiple images, through different stages: image acquisition, preprocessing, segmentation, training, and classification. The quality is better, the noise is corrected (lighting, foreign objects to the studio). Adaptation to the information extraction phase to minimize computing requirements. Also, the clarity in the distinction of borders to identify, delimit, and recognize the character of the object [9], obtaining success of 80%.

2. MATERIALS AND METHODS

2.1 Obtaining Images

To obtain the images of the phytophthora it is necessary to know that the disease is caused by a microorganism known as phytophthora. It attacks several parts of the plant but, the important damages occur in the fruit, regularly those near maturity. A brown spot is created, which begins to grow rapidly, reaching 11 days to cover all the fruit [9]. The "black cob" has four stages. The zero, with a tiny brown spot is shown in Figure-1. The One increases the size and number of spots as shown in Figure-2. The two, the spots continue to invade the cob and start to form the creamy mycelium as detailed in Figure-3. Finally, in Figure-4 the entire black cob is shown.

Figure-1. Zero stage of the phytophthora, at the first 2 days of being infected, the fruit begins to appear small necrotic points.

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Figure-2. Stage one of the phytophthora, after 3 days of the appearance of these points, brown spots are formed.

Figure-3. Stage two of the phytophthora, after 2 days of the appearance of the spot, creamy mycelium begins to form in the fruit.

Figure-4. Stage three of the phytophthora, from day 11 when the fruit is completely affected, they begin to transport and spread the disease.

The images were captured in an uncontrolled light environment with RGB color space, at a focal length of 15 centimeters with the camera of a Samsung Galaxy S7 Edge mobile device, which has a Samsung SM-G935F camera, opening of F: 1.7, focal length 4.2 mm, exposure between 1/500 to 1/600 seconds, ISO 50, resolution of 3024x4032.

2.2 Re-Size

The resize is used to reduce the size of the initial images, with a resolution of 3024x4032 to 450x450 to decrease the computational cost [11].

2.3 Segmentation

Segmentation [12] is used to divide the image into two regions, cob affected and not affected by phytophthora as shown in Figure-5. The segmentation technique used is based on Canny's edge detection algorithm, which first performs a noise reduction to the image by applying a Gaussian filter. The Gaussian filter of size (2k + 1) x (2k + 1) is given by equation (1).

$$\mathbf{F}_{i,j} = \frac{1}{2\pi\sigma^2}\exp\left(-\frac{\left(i-(k+1)\right)^2+\left(j-(k+1)\right)^2}{2\sigma^2}\right) \quad (1)$$

$1 \leq i; j \leq (2k+1)$

Where i refers to the position of the pixel in the rows of the image matrix and j in the columns. k is the size of the filter, 3x3.

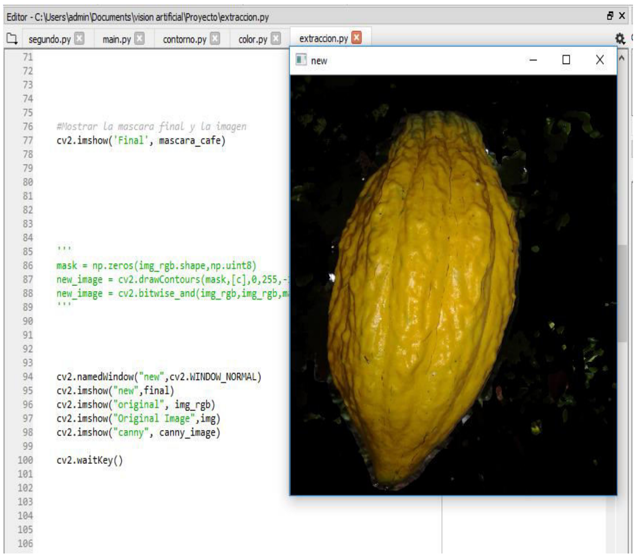

Figure-5. Segmented image.

2.4 Model Training

The ResNet50 convolutional neural network architecture is implemented in the classification of the images. The parameters used are shown in Table-1.

Table-1. Training parameters.

Parameters	Description / Values
$F_{1..n}$	Training images
$B_{1..n}$	Validation Images
Image size	450 x 450
batch_size	64
Learning_rate	0.001
epochs	100
Class_mode	“categorical”

The training algorithm uses the following: $model.fit\_generator(\mathbf{F}_{1..n}, 64, 'categorical', 100, \mathbf{B}_{1..n})$ function to allow layers to be added sequentially.

The model was trained with five sets, 80% of each for training and 20% for validation.From the first to the fourth, are is made up of the different stages of the black cob. The last one, the cob without the disease as seen in Table-2.

Table-2. Dataset used for training and model validation

Categories	**Training**	**Validation**
Black cob stage 0	192	48
Black cob stage 1	192	48
Black cob stage 2	192	48
Black cob stage 3	192	48
Cob without disease	192	48

3. RESULTS AND DISCUSSIONS

The first result was the construction of the dataset with images of the cocoa cob in different stages of maturation with and without phytophthora. The total images were 1200 each standardized to a size of 450x450 pixels, distributed as shown in Table-2, covering all the stages of the phytophthora. Figure-6 shows the cobs with two disease stages and Figure-7 the cobs without the disease. The images were taken from different varieties of cocoa crops in Colombia in the municipalities of Rivera and Campoalegre.

Figure-6. Cocoa cobs with phytophthora in different degrees of maturity.

Figure-7. Cocoa cobs without phytophthora in different degrees of maturity.

A second result, the system was made in the Python language with the built dataset. The images were applied with a softening filter with the function (cv2.bilateralfilter) [8] after, are passed to grayscale to applying the Gaussian filter. Then, extraction of the edges of the image was made with the Canny method, to dilate the edges. Then the edges were determined with the function (findcontours), resulting in the image with a brown mask. With the operator (bitwise) the pixel reading was obtained to make the union with the original image and obtain the regions of interest as shown in Figure-5.

Two simulations of the model were executed as shown in Table-3. The first, includes images with the different stages of the phytophthora, resulting in overtraining. The second, cob images were added without phytophthora reaching a success rate of 80%. High value

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because, according to the state of the art there are no known studies, in addition, the size of the data set can be increased with images of crops from other municipalities of Huila to improve its scope and result.

Table-3. Simulation results.

Simulations	Categories	Cantidad	Results
1	Black cob stage 0	240	overtraining
	Black cob stage 1	240	
	Black cob stage 2	240	
	Black cob stage 3	240	
2	Black cob stage 0	240	80%
	Black cob stage 1	240	
	Black cob stage 2	240	
	Black cob stage 3	240	
	Cob without disease	240	

4. CONCLUSIONS

The data set must be constructed in a balanced way including all categories of cocoa cob, with phytophthora at different stages, from 0 to 3 and without phytophthora so that the model has a success rate otherwise there may be overtraining.

The result obtained in the model is 80%, high value because until the present in the state of the art there was no information related to the phytophthora, a percentage that can be improved by increasing the size of the data set with images of crops from other municipalities.

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