

Development of a computational tool to identify nutritional deficiencies in plants (*Passiflora tripartita* var. *mollissima*)

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Abstract: Nowadays, the determination of nutritional deficiencies in plants has become one of the most important analyses of crop growth. This analysis is always performed manually by specialized personnel for a long period of time, leading to an error in the procedure. The purpose of this research is to develop a computational tool for the identification of nutritional deficiencies such as nitrogen, potassium and phosphorus in Curuba plants. The methodology includes 3D designs, tool construction and the detection of nutritional deficiencies by image processing techniques in MatLab. Finally, the results obtained by the developed computational tool with respect to the data provided in a traditional way by the technical experts presented an accuracy of 100%, 80%, 91% and 94% for the identification of nutritional deficiencies of nitrogen, potassium, other type of deficiency and phosphorus respectively. On the other hand, it provides a technological support for growers during the life cycle of the plant, determining quickly and accurately the characteristic patterns that allow differentiating a plant with nutritional deficiencies, allowing specialists to reduce time periods and perform a more objective and reliable analysis for the identification of nutritional deficiencies.

Keywords: nutritional deficiencies, growth indices, computational tool

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1 Introduction

The nutritional deficiencies that affect the crops are generally produced by the lack of minerals in the soil in the medium of propagation, which prevent the normal growth and development of the plants, thus triggering anomalies in the internal structure that negatively affect area, leaf quality, fruit quality and leaf shade changes, among others (Martínez et al., 2009). When the visual inspection is carried out on the crops, it can be made subjective errors by the expert at the time of making a diagnosis of the conditions in which the leaves are found (Vargas et al., 2009). This is due to several reasons such as: ocular tiredness that occurs by performing the analysis repetitively or by adverse conditions in the environment

where it is being performed.

Agriculture has different purposes in society such as providing the food required by the population and providing resources to growers (Pérez, 2014). According to the National Agricultural Survey, by 2015 in Colombia were seeded 19,171 hectares of the cultivation of curuba and presented a yield of 8.9 tons of fruit per hectare, mainly exported to countries such as Germany and the Netherlands (DANE, 2017). Therefore, inadequate or erroneous detection of nutritional deficiencies leads to large losses in crop production due to reduce yields and the useful cycle of plants.

The objective of the research was to develop a computational tool to identify the main nutritional deficiencies (nitrogen, phosphorus and potassium) in plants of Curuba, which would allow to accelerate the identification process and at the same time reduce the errors that occur daily through the visual inspection, implementing artificial vision techniques and digital image processing.

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The implemented methodology in the development of the computational tool is based on a modular system integrated with an easy-to-drive graphical interface for user. Initially it was conditioned a structure to carry out the image capture, then using the MatLab software it was performed the pre-processing stage, obtaining only the area of interest, later each of the deficiencies were identified through a characterization by color. Finally, the classification was performed and the results validated with respect to the analyzes performed by an expert in the traditional way.

In the present research the results of the validation of a computational tool for the determination of nutritional deficiencies in Curuba plants are shown, starting from a set of 253 leaves with deficiencies and without deficiencies.

2 Materials and methods

The proposed methodology for the identification of nutritional deficiencies in Curuba plants consists of 8 phases, as evidenced in Figure 1. In the first phase, the analysis of requirements and restrictions of user was performed, in the second phase the design was realized in the software Sketchup pro 2016, later the assembly of each of the modules was performed. In the four phase the images were acquired, then in the fifth phase the pre-processing stage was applied, then in six phase extraction of the area belonging to the leaf was released. Subsequently, in the seventh phase, a classification of nutritional deficiencies was performed and finally the results were validated with respect to the manual analysis developed by an expert technician.

In the first instance, the missing nutrient technique was used with the presented methodology (Barrera et al., 2011) in order to obtain the deficiencies in the plants. The technique of the missing nutrient consists in controlling the effect of the nutrients in the plant, therefore, to ensure that its development is adequate. It is necessary to have its basic nutrients and in the adequate quantities, besides being available the necessary time, both in macro nutrients (N, P and K) and micro nutrients (Ca, Mg, S). The implementation of this technique was carried out in the department of Cundinamarca at 1728 msnm (Meters above sea level), one of the departments with the largest presence of curuba crops in the country, the first step was

to eliminate the substrate in which the plants were sowed, in order to transplant them to a mixture of husk and white sand which lack of nutrients. Four groups were arranged in which 10 plants were conditioned for each treatment (nutrient missing N, P, K and complete solution).

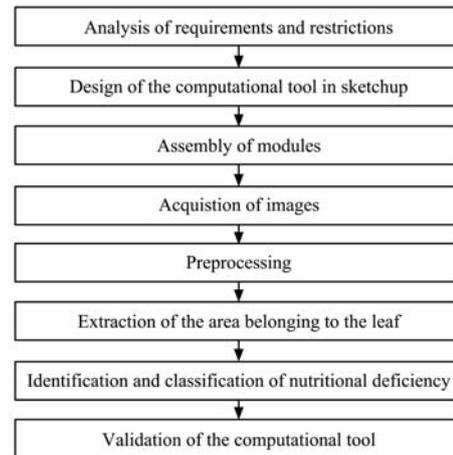


Figure 1 Proposed methodology

2.1 Computational tool design in SketchUp pro 2016

For the computational tool design, the SketchUp Pro 2016 software was used, which allows design and modeling in 2 or 3 dimensions in a flexible and intuitive way. The design was done at scale as shown in Figure 2, taking into account the measurements of the Curuba leaves which have a range from 7 to 10 cm long, 6 to 12 cm wide as described in (Bernal and Diaz, 2005) and the required height by the camera to focus the entire area of the leaf was 16 cm. Subsequently, the construction of the physical structure was carried out with the following measures: 34 cm wide, 33 cm deep and 28 cm high, following user requirements.

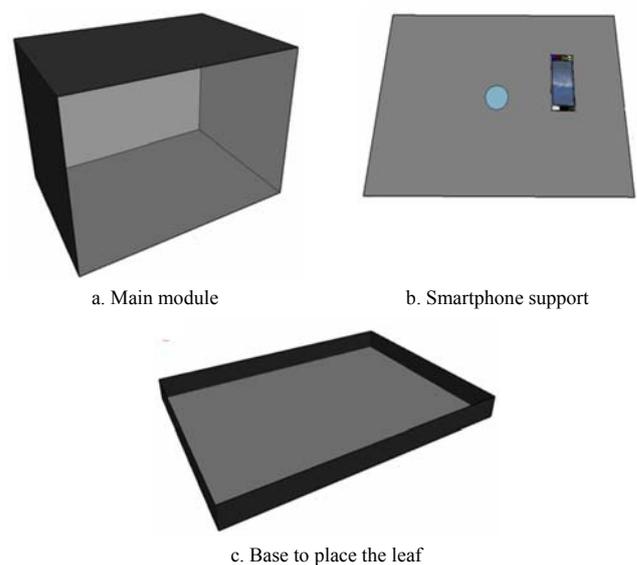


Figure 2 Tool Design

2.2 Implementation of the computational tool

The materials used for the elaboration of the physical structure that compose the computational tool were black acrylic of 3 mm, foam paper, 2 fluorescent lights of 8 W and 3 mm crude glass. The tool was constructed taking in mind the dimensions of the design. It was decided to use a lightweight and resistant material that completely obstruct the exchange of light from the exterior to the interior, as shown in Figure 3. The interior was equipped with a coating of foam of gray color, in order to greatly reduce the reflection of light on the glass. Finally, not to alter the colors of the leaves, the levels of light oscillate in a range of 6.000 K to 6.400 K (Kelvin).



Figure 3 Design of the computational tool in SketchUp

2.3 Acquisition and pre-processing of images

Once the leaf is found prepared on the basis of the tool, it is focused by the ZTE Blade G Lux mobile device, then through the DroidCam application the images were acquired with a resolution of 640×480 pixels from MatLab, allowing to improve parameters such as capture speed, image resolution and the manufacture of a lightweight and portable device. After obtaining the image in RGB format with a resolution of 640×480 pixels, to extract the area of interest it was necessary to decompose the image, because they do not present blue coloration, which allows to define the edges of the leaf, as it can be observed in Figure 4c. Subsequently, the filtering step was applied through MatLab's *medfilt2* function, in order to reduce abrupt variations in the intensity of the color presented in the image.

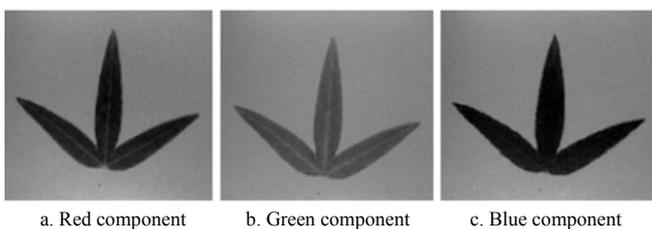


Figure 4 RGB color components

2.4 Assignment of the segmentation method

For the extraction of the leaf area, the edge detection technique combined with morphological operations is used. Initially, edge detection was applied using the Roberts operator in MatLab as shown in Equation (1), which analyzes the image and identifies the significant changes of intensity and assigns white color to these pixels, in order to obtain the edges of objects within an image.

$$Bw = \text{edge}(ima', \text{roberts}') \quad (1)$$

where, Bw is the variable that stored the image with the edges and ima is the grayscale original image corresponding to the blue component and Roberts is el operator of function.

Following this, the result image Bw is expanded by morphological operations as shown in Equation (2), in order to obtain a continuous edge and in this way the object is extracted in its entirety.

$$ImB = \text{imdilate}(Bw, SE) \quad (2)$$

where, ImB is the variable where the image is stored with the continuous edges, and SE is the structuring element that allows the pixels to expand.

Subsequently, the inside of the leaf was converted into white and the exterior in black. In order to not affect the area of the leaf, the pixels are compressed in the same proportion as the expansion, to remove pixels that do not belong to the object as shown in Equation (3).

$$Bin = \text{erode}(ima, SE) \quad (3)$$

where, Bin is the variable where the image is stored with the continuous edges, and SE is the structuring element that allows the pixels to erode.

Finally, areas lower than a threshold of 100 pixels that do not correspond to the object are eliminated, because a Curuba leaf has a normally higher area.

2.5 Identification and classification of deficiencies

To classify the nutritional deficiencies, the clustering method was used. With this technique it is possible to group objects with similar color characteristics. In the case of two classes the color mean is identified for each class, then the classification was made by comparing the distance in the color space of each image pixel with respect to the average of each class, using the Equation (4).

$$d_E(P, Q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \dots + (p_n - q_n)^2} \quad (4)$$

where, p_1 , p_2 and p_n represent the components of each pixel of the input image, while q_1 , q_2 and q_n represent the color components of the average threshold that was determined to be extracted from the image. Finally, the pixel is assigned to the class whose distance was minimal, it is shown the grouping of the pixels of an image into two classes by its color in Figure 5.

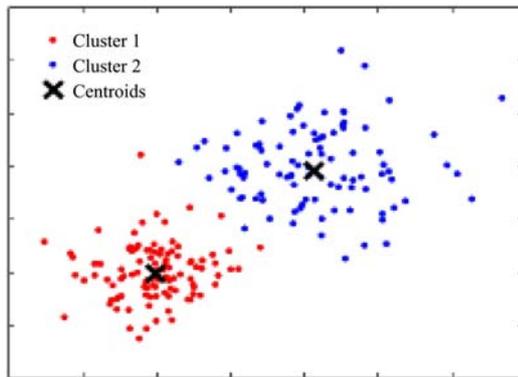


Figure 5 Grouping by Cluster (MathWorks, 2016)

With the number of pixels of each color the classification is started as follows: the leaves with a percentage of color yellow major to 75% belong to the nitrogen deficiency, between 30% and 75% present a different deficiency from (N, P, K), from 1% to 30% corresponds to the potassium deficiency and finally the leaves that do not present deficiencies are found with less than 1%. While that for the phosphorus the blue component was used to identify the deficiency, for this the percentage of red color in the whole leaf was evaluated, which should be mayor than 1.4%. Following this, the amount of red pixels at the apexes of the leaf is evaluated to ensure that it is a phosphorus deficiency and the percentage in each of the apexes should be less than 25% of the red color throughout the leaf.

3 Analysis of results

Taking into account the measurements and materials, we proceeded to perform the assembly of the system for capturing the images as shown in Figure 6.



Figure 6 Real model of the computational tool

3.1 Acquisition and pre-processing of images

The first phase tested was the acquisition and pre-processing of the images. In this phase, it was necessary to use the application DroidCam for Android in order to enable the Smartphone as Webcam, allowing the tool to obtain versatility and portability in the identification of nutritional deficiencies. Afterwards, the communication between the Smartphone and the computer was made through a Wifi network, the application in Android generates an IP address which must be entered into the computer, finally MatLab recognizes this device as another webcam and the images are acquired with a resolution of 640×480 pixels, Figure 7 shows the results of the acquisition of the images.

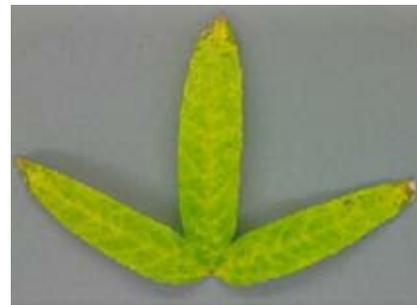


Figure 7 Image obtained with ZTE Blade G Lux

On the other hand, shadows were generated around the leaf due to the curvature of the same affecting the image processing, as evidenced in Figure 7. For correcting this problem, a transparent glass was used in order to eliminate the defects caused by the pronounced curvature of the leaves. Then in Figure 8, it is shown the results of an image obtained with the Smartphone ZTE Blade G Lux and the transparent glass, evidencing the removal of the shadows, this in turn allows better results in the process of leaf segmentation.

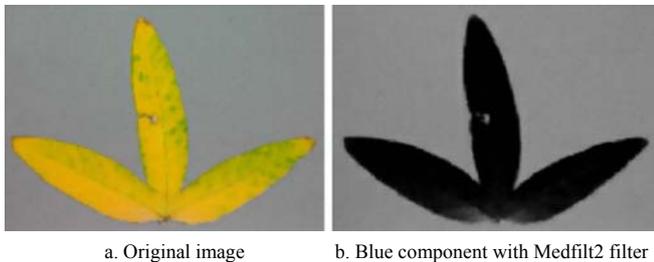


Figure 8 Final image obtained with the tool

After the acquisition of the images, the pre-processing was performed by the decomposition of the RGB image using Equation (5).

$$Ima = [ima(:, :, 1), ima(:, :, 2), ima(:, :, 3)] \quad (5)$$

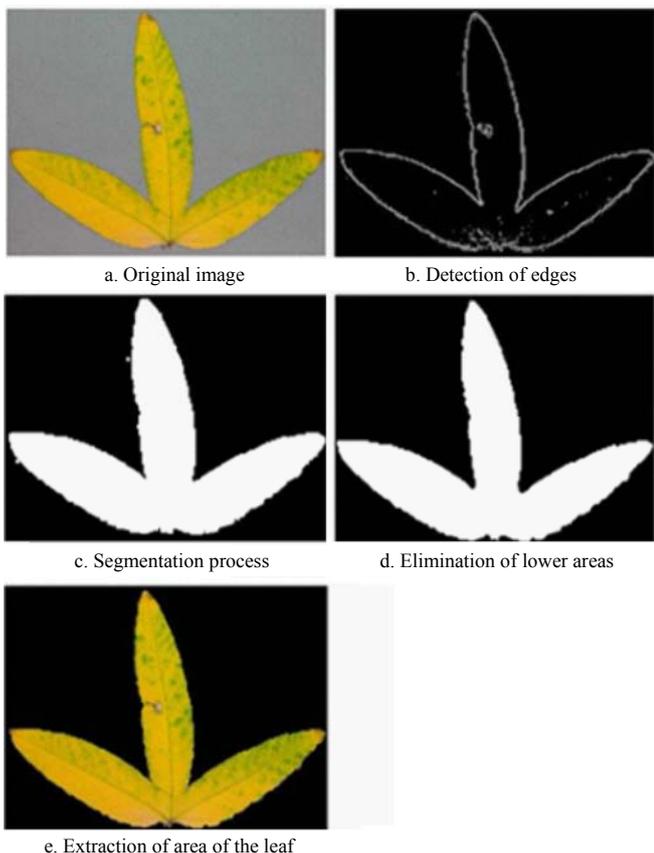
It was determined that the blue component of image better defines the edges of the leaf. Later the filtering stage was applied through a medium filter in MatLab, obtaining a compact image with less intensity variation in the pixels as is shown in Figure 9.



a. Original image b. Blue component with Medfilt2 filter
Figure 9 Pre-processed images

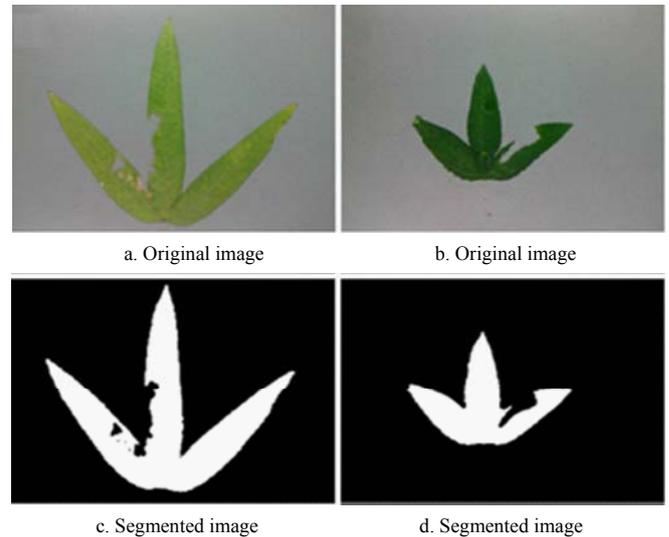
3.2 Extraction process of leaves

In the process of leaf segmentation, it was used the edge detection to obtain the contours corresponding to the object as shown in Figure 10b, followed by the morphological operations of dilation, erosion, and filling holes to improve the contour of the leaf, as shown in Figure 10c. Finally, lower areas that do not belong to the object were removed, in order to extract only the contour of the leaf as evidenced in Figure 10d and 10e respectively.



a. Original image b. Detection of edges
c. Segmentation process d. Elimination of lower areas
e. Extraction of area of the leaf
Figure 10 Segmentation process

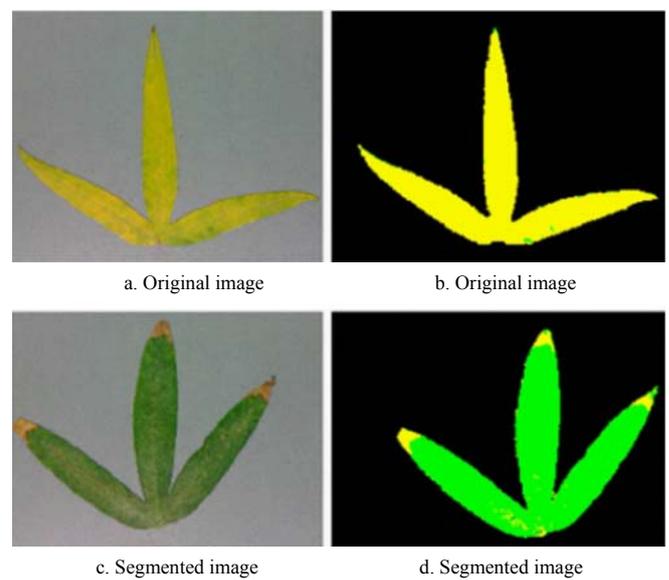
In order to corroborate the correct operation in the segmentation process, tests were performed on leaves that presented damages or anomalies in their shape as shown in Figure 11a and 11b, resulting in an excellent performance regarding to the correct detection of deformed edges and other defects as holes within the leaf as shown in Figure 11c and 11d.



a. Original image b. Original image
c. Segmented image d. Segmented image
Figure 11 Result segmentation

3.3 Application of the classification method

For the classification of the leaves with deficiencies of nitrogen and potassium, the Clustering algorithm was implemented. It is necessary that the points around the leaf in different leaves should be extracted, in order to obtain a mean for each color (green and yellow). In this way two groups are obtained to perform the classification and the result of the classification of N and K is shown in Figure 12.



a. Original image b. Original image
c. Segmented image d. Segmented image
Figure 12 Classification of nitrogen and potassium

Figure 12a presents the nitrogen deficiency which is evidenced with a uniform yellow color throughout the area of the leaf and Figure 12c corresponds to the potassium deficiency, which presents yellow color at the apex of the leaf. The result of the process carried out by means of the Clustering technique is shown in Figures 12b and 12d, where it is evident the segmentation accuracy of each of the tonalities in both the leaf with nitrogen deficiency and the leaf with potassium deficiency. While for the phosphorus deficiency the method of Clustering did not present good results, because the shades of red color on the back of the leaf presented coloration like the coloration of other deficiencies produced errors in the outcomes. For this reason, the RGB image was decomposed into the shades (red, green and blue) and the following condition was determined to effectively extract phosphorus deficiency: phosphorus deficiency was assigned by color red to those

pixels that had a tonality less than 92 in a range of (0 to 255) in the green component and a tonality less than 68 in a range of (0 to 255) in the blue component and the others pixels were assigned color green and yellow respectively, as shown in Figure 13b, showing good results as evidenced by comparison with the original image.

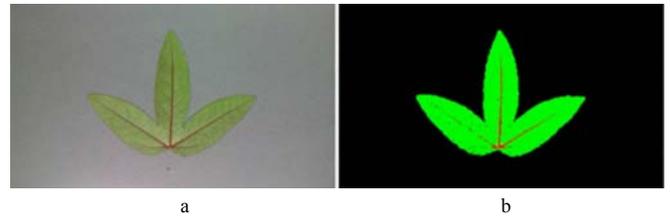


Figure 13 Phosphorus classification

3.4 Graphic interface design

For the interaction of the user with the software, a graphical interface was designed and implemented through MatLab's GUIDE programming environment, as shown in the Figures 14 and 15 with phosphorus deficiency and nitrogen deficiency respectively.

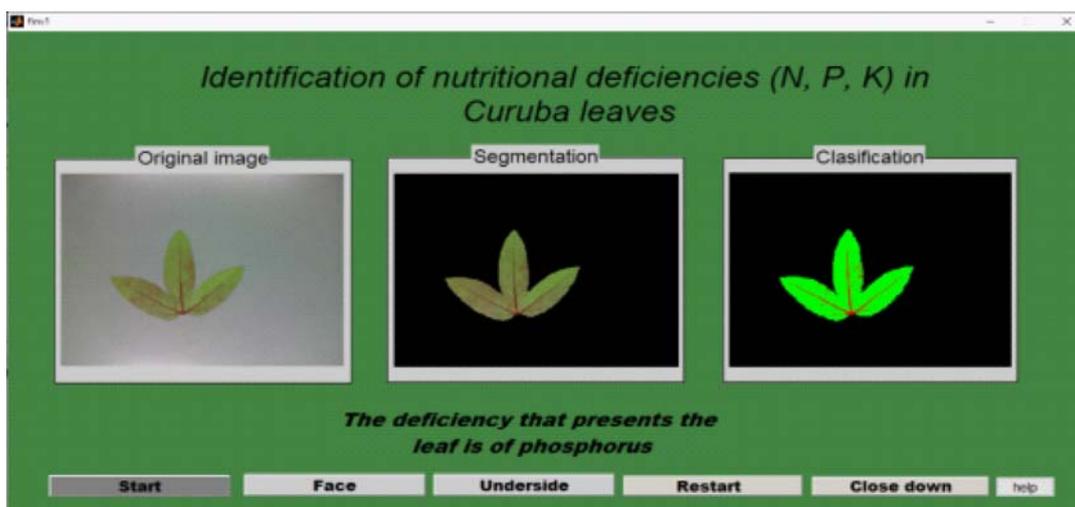


Figure 14 Graphical interface in guide with nitrogen deficiency

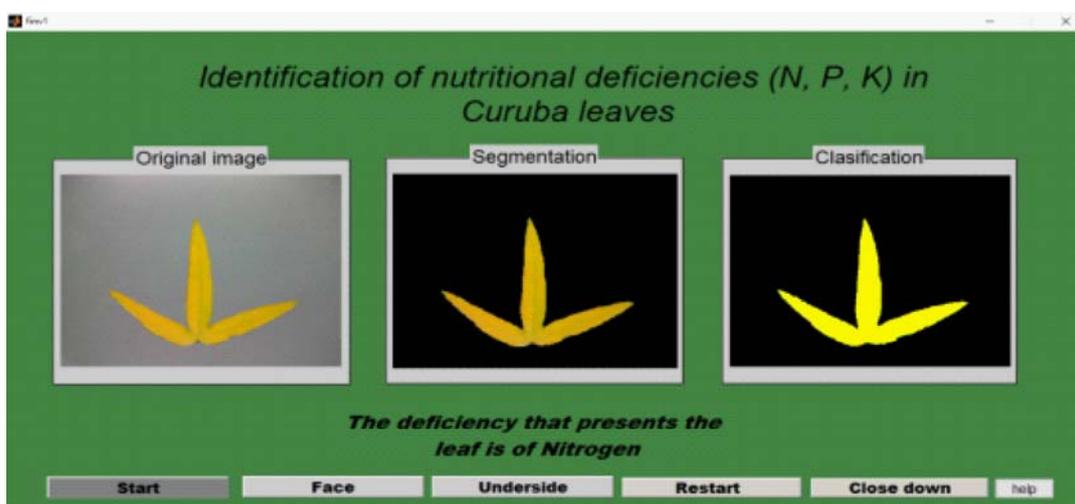


Figure 15 Graphical interface in guide with other type of deficiency

The design took into account the social sector for which it is directed, being a friendly graphical interface, easy to use and demand a basic knowledge in Android.

4 Validation of results

For the validation of the computational tool, two methodologies were used by comparing the deficiencies obtained by the system in comparison to the measurements obtained by the expert technician. Initially, a statistical correlation was performed between the two measures mentioned above as shown in Table 1. In the validation, 253 leaves were used, among which 34 presented nitrogen deficient, 30 presented potassium deficiency, 19 presented phosphorus deficiency, 125 did not present deficiencies and 45 with another type of deficiency. Also, the Figure 16 shows that for each deficiency, there was high correlation with respect to manual analysis.

Table 1 Correlation results

Expert technical correlation and computational tool		
Deficiencies	Expert Technician	Computational tool
Nitrogen	34	34
Potassium	30	24
Phosphorus	19	18
Without deficiency	125	125
Another type	45	41

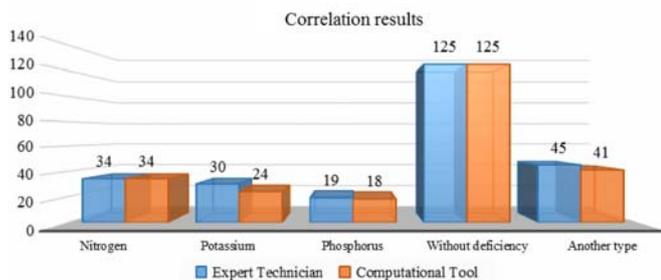


Figure 16 Graph correlation between expert technician and computational tool

Moreover, the determination coefficient was calculated in order to predict future results in the analysis of the nutritional deficiencies. The statistical validation allowed to show for 253 leaves with deficiencies and without deficiencies, that the computational tool determines 96.68% of the cases in which was tested with regard to expert technician, with a bias of 3.4369 representing a very low interval between the two methodologies, as shown in Figure 17.

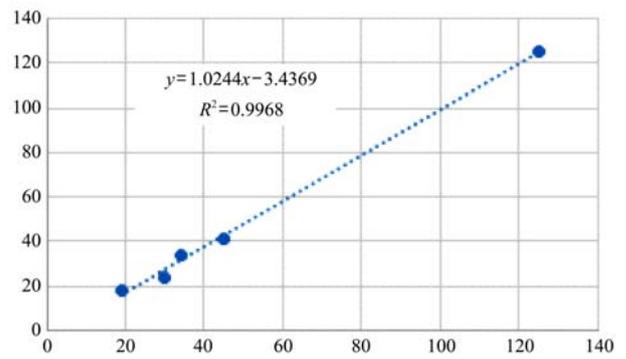


Figure 17 Coefficient of determination between the computational tool and the expert technician

Subsequently, the performance of the classifier algorithm was validated through a confusion matrix, allowing to identify quantitatively the success or mistakes in the classification process. For the validation, a table was made with *n* classes as shown in Table 2, where the columns of the table represent the results obtained with the algorithm and the rows represent the real values analyzed by the expert by the method of missing nutrient. By means of a confusion matrix we can calculate the precision index for each class, this index ranges from 0 to 1 where 1 represents 100% accuracy. Initially, the overall accuracy of the computational tool was determined in comparison to the traditional missing nutrient method elaborated by specialists in plant physiology using Equation (6).

$$\text{accuracy} = \frac{\text{Total correct detections}}{\text{Total detections}} \times 100 \quad (6)$$

Then, to calculate the precision of each class the confusion matrix is used as show in Table 2, the precision for each class is obtained by Equation (7) through true positives and false positives.

$$\text{Precision} = \frac{tp}{tp + fp} \quad (3)$$

Table 2 Confusion matrix

True	Prediction	
	Positive condition	Negative condition
Positive condition	True positives (tp)	False negatives (fn)
Negative condition	False positives (fp)	True negatives (tn)

For this investigation, 5 different cases were determined in which are the corresponding deficiencies of nitrogen, phosphorus, potassium, leaves without deficiency and leaves with another type of deficiency, from a set of 253 leaves of Curuba. Table 3 shows the

results obtained from the detection of nutritional deficiencies estimated by the computational tool in

comparison to the analysis performed by the expert technician.

Table 3 Matrix of general confusion

Confusion matrix		Results from the computational tool				
		Nitrogen	Potassium	Phosphorus	No deficiency	Other type
Results from the expert using the missing nutrient method	Nitrogen	34	0	0	0	0
	Potassium	0	24	0	2	4
	Phosphorus	0	0	18	1	0
	No deficiency	0	0	0	125	0
	Other type	1	2	0	1	41

The overall accuracy of the tool presented a 95.6% success rate, indicating that the tool identified nutritional deficiencies in a manner similar to that performed by skilled specialists in plant physiology, as shown below.

$$\text{Accu} = \frac{\text{Total of correct detections}}{\text{Total of detections}} \times 100 \quad (8)$$

$$\text{Accu} = \left(\frac{34 + 24 + 18 + 125 + 41}{253} \right) \times 100 = 95.6\% \quad (9)$$

On the other hand, the accuracy of the tool for each case was determined by Equation (8). The accuracy of the tool for each nutritional deficiency is shown below. Subsequently, the confusion matrix was generated for each of the classes of deficiencies as shown in Tables 4-8 and their accuracy was determined by Equation (9) for all classes.

Accuracy for phosphorus deficiency.

Table 4 Confusion matrix for phosphorus deficiency

Expert	Tool	
	Phosphorus	Other classes
Phosphorus	18	1
Other classes	0	234

Note: Precision P = $\left(\frac{18}{18+1} \right) \times 100 = 94.7\%$.

Table 5 Confusion matrix for potassium deficiency

Expert	Tool	
	Phosphorus	Other classes
Potassium	24	6
Other classes	2	221

Note: Precision K = $\left(\frac{24}{24+6} \right) \times 100 = 80\%$.

Table 6 Confusion matrix for nitrogen deficiency

Expert	Tool	
	Phosphorus	Other classes
Nitrogen	34	0
Other classes	1	218

Note: Precision N = $\left(\frac{34}{34} \right) \times 100 = 100\%$.

Table 7 Confusion matrix for leaves without deficiency

Expert	Tool	
	Phosphorus	Other classes
Without deficiency	125	0
Other classes	0	221

Note: Precision NDef = $\left(\frac{125}{125} \right) \times 100 = 100\%$.

Table 8 Confusion matrix for leaves with another type of deficiency

Expert	Tool	
	Phosphorus	Other classes
Another type	41	4
Other classes	4	204

Note: Precision Otipo = $\left(\frac{41}{41+4} \right) \times 100 = 91.1\%$.

The precision results of the tool in the determination of nutritional deficiencies in Curuba plants presented high correlation indices compared to the expert technician using the missing nutrient method, showing percentages higher than 80% meaning a technological support in the area of plant physiology for a more accurate detection of nutritional deficiencies. A comparison between the proposed system and similar techniques for identification of nutritional deficiencies is automatically shown in Table 9.

5 Conclusions and discussion

At the present time, in the national agriculture, different technological tools have been incorporated that allowed to improve the growth of the crops, generate a production with greater benefits for both the producers and the consumers. Also, these systems seek the optimization of natural resources and land use, one of the commonly used technologies in different sectors of agriculture is the artificial vision due to its advantages to identify patterns from images that are not easily noticeable by human eyes.

Table 9 Comparison between systems for the identification of nutritional deficiencies vs developed algorithm

Techniques	Characteristics	Results
Proposed system	Classification of nutritional deficiencies (N, P and K) in Curuba leaves	In the classification was obtained a precision of 100% for nitrogen, in phosphorus 94.7% and finally in potassium 80%.
(Monsalve et al., 2015)	Automatic detection of nutritional deficiencies in coffee plants using the SIFT descriptor.	Classification of nitrogen, phosphorus, potassium, calcium, magnesium, manganese, boro and iron with a precision of 67.5%.
(Nachtigall et al., 2016)	Detection and classification of nutritional deficiencies in apple trees.	A precision of 97.3%
(Dhawale et al., 2016)	Analysis of leaves in citrus fruits to identify nutritional deficiencies using the Clustering technique and the Kirsch operator.	96.54% precision for identification of nitrogen, phosphorus, potassium, magnesium, manganese, boron, zinc, chloride and sodium.
(Hairuddin et al., 2011)	Identification of nutritional deficiencies in African palm by means of conversion to YCbCr color space.	Identification of nitrogen, potassium and pagnesium with a precision of 100%, 90% and 100%
(Chen et al., 2014)	Identification of nutritional deficiencies nitrogen, phosphorus and potassium in rice by means of static scanning.	Identification of N, P and K with a precision of 90.7%
(Butler et al., 2017)	Identification of calcium deficiency before and after the onset of symptoms in the plant using infrared micro-spectroscopy.	The authors were able to identify the deficence Ca and Ca deficient treatments at above 90% classification accuracy

The preparation and sowing of curuba seedlings was carried out using the missing nutrient technique according to the protocols established in the plant physiology experiments, proposed by the physiology and biochemistry laboratory of the National University of Colombia (Melgarejo, 2010), to obtain the different nutritional deficiencies in the leaves of safe way.

The lighting system is a determining factor because it can significantly affect the color characteristics within an image, since the generated brightness is interpreted by the software as a white hue, causing errors in the detection of the deficiencies (Bishop, 2006).

The Droidcam application made it possible to improve the image acquisition process because it is done by means of a wireless network, without relying on wired equipment, it also allows communication over long distances and substantially improves the quality and resolution of the images compared to traditional webcams described in (Sabrol and Kumar, 2015).

The classification of the leaves with nitrogen and potassium deficiencies was made by Clustering technique, obtaining excellent results thanks to the fact that the leaves by the beam have distant ranges in each of the shades. It was not possible to implement this technique for the classification that was performed on the underside of the leaf due to the similarity of the RGB components of the image. For this reason, a comparison was made with the three components, obtaining better results than those found with the Cluster technique in (Opstad et al., 2015).

The precision in the nutritional deficiencies classification in Curuba leaves presented high correlation

for each, an accuracy of 100% was obtained for nitrogen, 94.7% for phosphorus and finally in 80% for potassium, besides these three deficiencies were identified without non-deficiency leaves yielding a percentage of 100% and 91% for leaves with another type of deficiency, compared to other techniques such as micro-spectroscopy used in (Butler et al., 2017) or the SIFT descriptor used in (Monsalve et al., 2015).

In future works, it is proposed to adapt the computational tool for mobile devices, allowing the identification of the deficiencies directly in the plants without being destroyed, at the same time expanding the range including new varieties of plants.

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