Automatic Detection of Nutritional Deficiencies In Coffee Tree Leaves Through Shape And Texture Descriptors

Marcelo Vassallo-Barco, Luis Vives-Garnique, Victor Tuesta-Monteza, Heber I. Mejía-Cabrera
Señor de Sipán University
Peru

Raciel Yera Toledo
University of Ciego de Ávila
Cuba
yeratoledo@gmail.com

Journal of Digital Information Management

ABSTRACT: *Nutritional deficiencies in coffee plants affect production and therefore it is important its early identification. The current research is focused on the automatic identification of nutritional deficiencies of Boron (B), Calcium (Ca), Iron (Fe) and Potassium (K), by using shape and texture descriptors in images of coffee tree leaves. After the acquisition of images containing coffee tree leaves, they are subjected to a segmentation process using Otsu's method. Afterwards, for the resulting images they are applied the descriptors Blurred Shape Model (BSM) and Gray-Level Co-occurrence Matrix (GLCM) for extracting characteristics of shape and texture. Finally, the obtained image representation is used for training KNN, Naïve Bayes and Neural Network classifiers by using the extracted features, in order to infer the type of deficiency presented in each analyzed image. The experimental results show that the developed procedure has a high accuracy, being the better results associated to the identification of Boron (B) and Iron (Fe) deficiencies.*

Subject categories and descriptors
[H.2.4 Systems]: Textual databases; **[H.5 Information Interfaces And Presentation]: [I.2.7 Natural Language Processing]:** Text analysis

General Terms
Textutal Data, Data Processing

Keywords: Coffee tree leaves, Nutritional deficiencies, Image processing, Shape and textual description, Supervised classifier

Received: 19 September 2016, Revised 21 October 2016, Accepted 30 October 2016

1. Introduction

Agriculture has always been an important component of the economy of many countries across the world. Therefore, plants disease detection usually takes the attention of several researchers, in order to prevent and mitigate the negative effect of diseases in crops [1].

With this aim in mind, several efforts have been focused on exploiting digital image processing techniques and supervised classification approaches for detecting plants' diseases through the analysis of several parts such as roots, fruits, stems, and leaves. The main purpose of such efforts is the reduction of the subjectiveness arising from human experts in the manual detection of plant diseases [2].

Specifically, in the last few years there have been developed several research works focused on processing digital images of plants' leaves for detecting specific diseases. In this way, some key samples are the use of neural

networks for processing features of rice leaves [3], the use of feature-based rules for processing images with citrus's leaves [4], or the use of neural networks also for processing maize disease images [5]. However, it has been also showed by recent surveys such as Barbedo [1] and Majumdar et al. [2] that while most of the research is focused on popular crops such as maize, rice, or vegetables, there is a lack of works focused on a worldwide demanded crop like the coffee tree.

On the other hand, an important feature that characterizes plants, are the chemical components they are constituted with. Such chemical components are necessary for its metabolism, and can be divided into macronutrients and micronutrients.

Macronutrients: They are chemical elements found in large quantities in the plants, representing approximately the 96% of the composition of the plant. They are the responsible of the processes related to the acquisition of water and oxygen. Some macronutrients are Nitrogen (N), Phosphorus (P), Potassium (K), Calcium (Ca), Carbon (C), Hydrogen (H) , Oxygen (O), Magnesium (Mg) and Sulfur (S) [6].

Micronutrients: Represent nutrients that are also present in plants, but in lower quantities (4%). However, its presence is not less relevant than macronutrients. In this case, these chemical elements are sparse in the soil, and plants absorb them through the roots. Therefore, its presence in the plants could be insufficient to reach their nutritional requirements. These elements are Boron (B), Iron (Fe), Chlorine (Cl), Copper (Cu), Manganese (Mn), Zinc (Zn) and Molybdenum (Mo) [7].

Specifically, it has been considered that the most relevant nutritional deficiencies that coffee plants could have, are the lack of:

• **Potassium:** One of the visible symptoms is the presence of an upward-oriented curl at the leaves' tips [8].

• **Boron:** This deficiency produces leaves with an atypical shape and a leathery texture [9].

• **Calcium:** This deficiency results in the presence of wavy edges [9].

• **Iron:** Young leaves are larger than normal and channel-shaped [9].

These deficiencies affect the health of plants and fruits, causing crop losses or poor quality, and therefore negatively impacting the revenue resulting from these product sales and exportation.

Therefore, the current contribution aims at filling the gap related to the lack of works on the use of digital image analysis for detecting diseases in coffee trees, by verifying whether the use of traditional supervised classifiers such as KNN, Naïve Bayes and Neural Networks-based [10], could accurately identify such deficiencies.

Specifically, the research is novel in the sense that, according to the reviewed works, is one of the first attempts focused on nutritional deficiencies identification in coffee tree leaves using digital image processing techniques and computational intelligence tools. In this way, it will allow the characterization of specific nutritional deficiencies in coffee leaves, in terms of the potentialities of computational tools for detecting each particular deficiency.

In this direction, it is worthy to note that coffee is the main exportation product in our country, Perú. Hence, this fact raises the impact of our research for and beyond our country.

This research will be structured as follows. Section II presents a brief survey on the use of image processing techniques for analysis possible diseases in coffee plants (II.A), and on the supervised classifiers used as part of the proposal (II.B). Section III is focused on the proposed methodology, making references to the gathered image database (III.A), image preprocessing (III.B), feature extraction including the use of shape and texture descriptors (III.C), and classification (III.D). Section IV presents the experimental results regarding typical evaluation metrics, and Section V discusses the most interesting findings associated to such results. At last, Section VI concludes the contribution and points out future research directions.

2. Related Works

The current section presents a brief background on the related work associated to this contribution. Specifically, it is focused on two main research areas: 1) the use of digital image processing for detecting plant diseases, and 2) the supervised classification.

2.1 Digital Image processing for detecting plant diseases

The analysis of the literature related to the use of digital image processing techniques for detecting plant diseases shows an important amount of research contributions in the last few years [1, 11, 12]. With this aim in mind, several authors have proposed methods supported by digital image processing for pathologies detection in almost all the parts of plants, such as roots, fruits, stems, and leaves [1]. Considering that the current paper is focused on coffee tree leaves, this section will present a brief survey on the previous development focused on analyzing plant leaves for the disease identification.

With this purpose, in order to obtain a synthetic and also diverse screenshot that summarizes the most important previous works, it was taken as reference at first two of the most important crops across the world: maize and rice. At second stage, two emerging families of crops, such as citrus and vegetables, were considered. Finally, at last, they were considered the previous works focused on coffee trees. For each case, it was consulted Scholar

Google (through keywords such as plant disease image processing leaves, together with recent published survey on this area [1, 11]), to obtain the research works to be analyzed.

Table 1 shows the refined results of such search strategy, after discarding some retrieved papers not actually related with image processing. These results are grouped by culture (at columns), and by the main computational intelligence tool used at the proposal (at rows).

At first, the table shows that several very popular computational intelligence approaches such as neural networks, support vector machines (SVMs), and clustering, have been used to support the resolution of the current problem [13]. In this way, most of the presented works characterize images in terms of their texture, color and/or shape, and use such information for training the

	Maize	**Rice**	**Citrus**	**Vegetables (Cucumber, Lettuce, etc)**	**Coffee**
Neural Networks (NN)	Kai et al. [5]	Sanyal and Patel [3] Liu and Zhu [20]	Pydipati etal. [14]	Hetzroni et al. [21]	
SVM		Yao et al. [22]		Jian and Wei [23] Yao et al. [22] Youwen et al. [24]	
Feature-based rules	Martin and Rybicki [25] Sena Jr et al. [15] Romual-do et al. [26]	Kurniawati et al. [27] Phadikar, Sil, & Das, [16]. Anthonys and Wickramarachchi [28]	Zhang and Meng [4]		Mansingh et al. [18]
Self - organization maps		Phadikar and Sil [29]			
Clustering		Pugoy and Mariano [17] Zhou et al. [30]		Sekulska-Nalewajko and Goclawski [31]	
Regression analysis				Story et al. [32]	
Discriminant analysis			Pydipati et al. [33]		
Comparison of several approaches					Mengistu et al. [19]

Table 1. Related works on plants disease detection based on digital image analysis of their leaves

mentioned supervised/unsupervised approaches such as the referred neural network, SVMs, or clustering.

Specifically, the two more popular approaches are the neural networks (used for supporting maize, rice, citrus, and vegetables), and the feature-based rules (used for supporting maize, rice, and citrus). In the case of neural networks, some works such as Kai et al. [5] and Sanyal and Patel [3] use texture features as input for a multilayer perceptron architecture for diseases identification in maize and rice, respectively. Similarly, Pydipati et al. [14] identifies diseased and normal citrus leaves based on a Mahalanobis minimum distance classifier, using the nearest neighbor principle, as well as a neural network classifier based on the backpropagation algorithm and radial basis functions. On the other hand, the group identified as feature-based rules is composed by a diversity of proposals which oscillate from a direct association regarding some features of the processed images [15], to more complex models that consider rough set theory and production rules for knowledge representation [16].

Beyond these two group of works, Table 1 refers the development of some works supported by other computational approaches such as regression, discriminant analysis, self-organization maps, or SVM, also for plant disease detection. Similarly to other data analysis scenarios, there were also detected some works

that use traditional data clustering approaches such as the k-means or the fuzzy c-means algorithms for grouping interested regions into clusters [17], for facilitating a later disease detection.

Finally, an important finding suggested by Table 1 is the lack of works focused on processing coffee tree leaves, in contrast to the other analyzed crops. Specifically, according to our survey, the table presents the two research works which better fit with the focused research prototype. At first, Mansingh et al. [18] present CPEST, an expert system for managing pest and diseases of coffee in a developing country. Such system manages climate, topography, soil type of the farm, agronomic practices, crop phenology, biology and potential damage. However, it does not incorporate digital image processing techniques as a central component of the framework. In contrast, recently Mengistu et al. [19] employ image processing techniques for extracting information that is used for training several classifiers focused on detecting three kinds of diseases in coffee trees. However, only one of them is associated to coffee leaves, which is the interested region for our current contribution.

Therefore, this scenario evidences the presence of a research gap related to the disease identification of coffee leaves through image analysis, in contrast to similar works centered on other crops. Hence, the current research paper presents a novel contribution focused at this aim, which specific objective is the detection of nutritional deficiencies in coffee leaves.

2.2 On supervised classifiers

This section presents a brief reference to three supervised classifiers that are used as a component of the framework that will be proposed in the next section for detecting nutritional deficiencies in coffee tree leaves. Such classifiers are the k-nearest neighbors [34], the naïve bayes [35], and a neural network-based classifier [36].

The k-nearest neighbors classifier is a typical example of instance-based learning [34, 37]. In this approach, each new instance is compared with the existing ones using a distance metric, and the nearest instance is used to assign the class to the new one. Sometimes, more than one nearest neighbor is used, and the majority class of the closest k neighbors (or the distance-weighted average, if the class is numeric) is then assigned to the new instance.

In other direction, the naïve bayes approach is also a popular classification method that belongs to the statistical modeling category [35, 37]. It assumes that all the attributes of the instance to classify are equally important and independent of one another, given the class. Specifically, it is supported by the Bayes's rule of conditional probability. Even when such independence assumption is simplistic in real life, naïve bayes works very well when tested on actual datasets.

Finally, the classifiers based on neural networks have been very popular since several years ago [36-38]. Artificial neural networks can be viewed as weighted directed graphs in which artificial neurons are nodes and the directed edges are links between neuron outputs and inputs. There are two main categories where artificial neural networks can be grouped, which are feed-forward networks and feedback networks. Specifically, a very popular feed-forward network is the multilayer perceptron (MLP), where neurons are organized through layers that have unidirectional connections between them. Such network is trained through the presentation of training patterns, by updating its architecture with the use of errorcorrection approaches such as the back-propagation learning algorithm.

3. Methodology

Regarding the necessity of identifying nutritional deficiencies in images of coffee leaves using a computational approach, here it is proposed the development of a framework that is based on the usual architecture employed in approaches focused on images recognition through supervised classification (Figure 1). At first, it receives a set of original images obtained from the environment. These images are processed with the descriptors presented below, in order to extract the necessary features on their shape and texture. Finally, these data are used for training supervised classifiers in order to recognize nutritional deficiencies in new images. Therefore, this framework would allow an easy classification of new images.

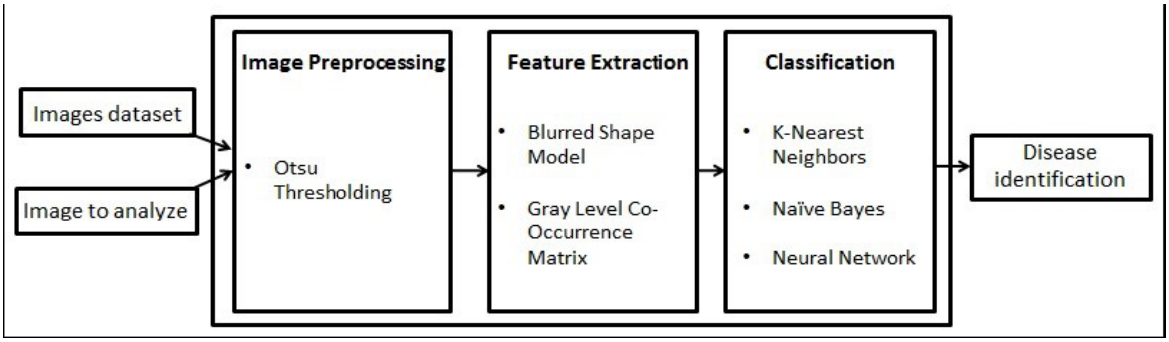


Figure 1. Framework for automatic detection of nutritional deficiencies in coffee tree leaves

The next subsections present the development of these stages.

3.1 Image databases

In the current paper it will be considered the classification of nutritional deficiencies associated to the lack of Boron (B), Iron (Fe), Calcium (Ca) and Potassium (K). These deficiencies are taken into account regarding they are the most significant ones in the coffee plants where the samples were obtained. It is worthy to note that although the deficiencies associated to the remaining nutrients are also important, that are not considered because they do not show relevant symptoms regarding leaves' texture and color; therefore their identification through computational techniques related to image processing is a very hard task.

Globally, it will be considered 269 images, including leaves with nutritional deficiencies of Boron (B), Iron (Fe), Calcium (Ca) and Potassium (K). Table 2 presents such distribution, which result in a balanced distribution.

Boron (B)	69 images
Iron (Fe)	70 images
Potassium (K)	56 images
Calcium (Ca)	74 images
Total	269 images

Table 2. Number of Leaves Images Used

The coffee tree leaves used in this research were recollected in coffee plantations located at San Miguel de las Naranjas and La Palma Central, Jaén province, Cajamarca, Perú. Specifically, it was recollected leaves from the CATIMOR, CATURRA and BORBON coffee varieties, possibly containing nutritional deficiencies. Such leaves were photographed in a controlled environment. Afterwards, the nutritional deficiencies were identified by agricultural engineers from Señor de Sipán University and CENTROCAFE, Perú (http://cenfrocafe.com.pe/).

3.2 Image preprocessing

The goal of the preprocessing step is the correction of defects that can occur during the capture and digitalization of the leaves images. Although it was taken care for obtaining a sample as clean as possible, due to the curved and irregular shape of the leaves, they could still have some noise (i.e. the projection of an unwanted shadow). In such cases, these shadows should be removed because they can negatively affect the performance of the classification procedure, and therefore induce errors in the results.

In order to remove such kinds of shadows, it is proposed the use of the Otsu's thresholding method [39] because it is a very efficient algorithm when there is a marked difference between the objects to extract, and the

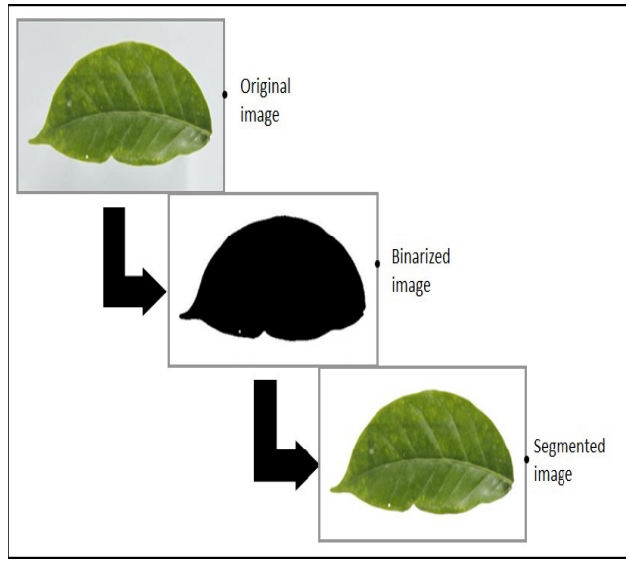


Figure 2. Digital image segmentation through Otsu's method

background of the used image. In this case, it is desired to separate the bottom sheet of uniform color, eliminating shadows. As a result of the application of the algorithm on the leaves, we obtain a binarized image where the proper management of the corresponding threshold guarantees the obtaining of the desired segmentation. At this stage, the leaf is shown completely black, while the rest of the image acquires a white background. As it is necessary to keep the leaf's true colors, it is taken as reference the black pixels in the binarized image, for obtaining the pixels values to retain in the original image. Figure 2 shows the scheme of this thresholding method.

3.3 Feature extraction

Once the image preprocessing is completed, it is necessary to obtain the most significant characteristics of the leaves for differentiating them regarding each deficiency. Specifically, here the purpose of feature extraction is the generation of a precise and compact numerical representation of the corresponding images. This way, an ideal feature vector should show small variations between objects of the same class, and large variations between objects those objects belonging to different classes. For feature extraction, in this research it will be used two popular descriptors, which are the *blurred shape model*, and the *gray level co-occurrence matrix.*

The next subsections explain the use of such descriptors in the current context.

3.3.1 Blurred shape model

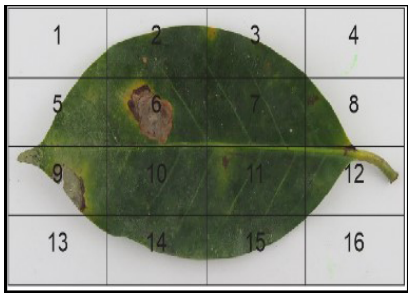
The blurred shape model descriptor is tolerant to the irregular deformations or the spatial distortions. Specifically, it is focused on the division of the image by using a grid, in order to perform the feature extraction [40].

The first step of this descriptor is based on the detection

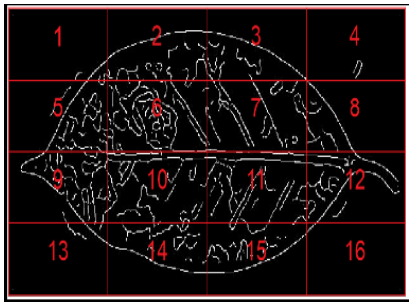
Figure 3. Image binarization through Canny's border detection algorithm

of edges in the image. With such aim, it uses the Canny's algorithm [41], regarding its proved effectiveness. As output, it is generated a binarized image. Figure 3 shows the results of the application of the Canny's algorithm.

Afterwards, the binarized image is divided into multiple regions by a grid of variable size (Fig. 4).



(a)



(b)

Figure 4. Image divided though a 4x4 grid (a). The divided image after
the application of the Canny's algorithm (b)

Then, it is stored the data related to the neighbor regions, associated to each region. In addition, the method takes the region itself as one of these neighbors. Therefore, each region is processed independently by analyzing each image's pixel. If the corresponding pixel has value 1 (belongs to a border), the following steps are performed [42]:

• The distances between the pixel and the centroids of the neighbor regions are calculated, including the centroid of the current region (Fig. 5).

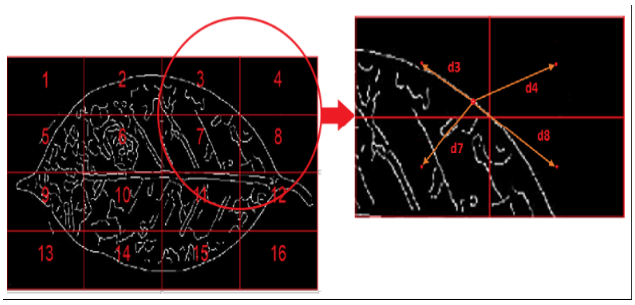


Figure 5. Finding the distances between an edge point and the centroids of
the neighbor regions. The vector associated to the represented pixel is
Vn = (0,0,d3,d4,0,0,d7,d8,0,0,0,0,0,0,0,0)

• It is generated a vector Vn composed by the calculated distances. Each vector represents the distance between the pixel and the corresponding regions. If some region is not a neighbor of the region associated to the current pixel, in such cases it is then assigned the value 0.

• It is normalized the obtained vector by dividing each distance by the total distance.

• It is calculated the inverse of each obtained distance, generating a new vector Vi.

• It is normalized the vector Vi in a similar way.

• It is calculated the output vector Vs as the sum of both vector Vn and Vi, Vs=Vn+Vi.

• The output vector is also normalized.

The output of the descriptor represents a probability distribution of the object's shape considering spatial distortions, where the distortion level is determined by the size of the grid [42].

3.3.2 Gray level co-occurrence matrix

For characterizing the texture in an image, the cooccurrence matrices, raised by Haralick et al. [43], can be used as texture descriptor. This approach defines the shape of distribution of different tones intensities in the image, which are calculated by obtaining the cooccurrence matrices of the image.

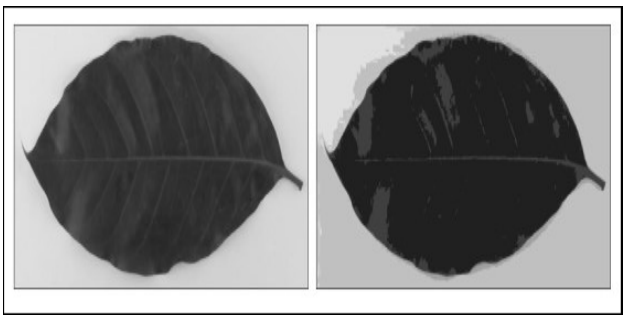


Figure 6. Image quantization before the co-occurrence matrix extraction

A co-occurrence matrix describes the frequency at which a particular gray level is displayed in a specific spatial relationship, in relation to another gray level in an image. Therefore, the co-occurrence matrix is a summary on how the pixels values are presented next to another value in a small window.

Regarding the high computational cost of generating co-occurrence matrices, at previous step usually it is reduced the number of colors in the image (Fig. 6). The use of 16 colors tends to be recommended [44].

Subsequently, the quantized image is divided into 64 segments. Therefore, the current descriptor will be applied to each segment, and the characteristics of each segment will composed the image features (Fig. 7).

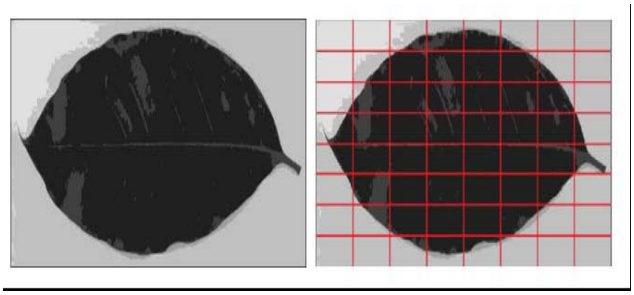


Figure 7. Division of the gray scale image in 64 segments

Afterwards, it will be generated the co-occurrence matrices for each segment, which contain the count of combinations of gray levels between two pixels at different distances (distance 1 and 2), and four directions (at 0 °, 45 °, 90 ° and 135 °) (Fig. 8).

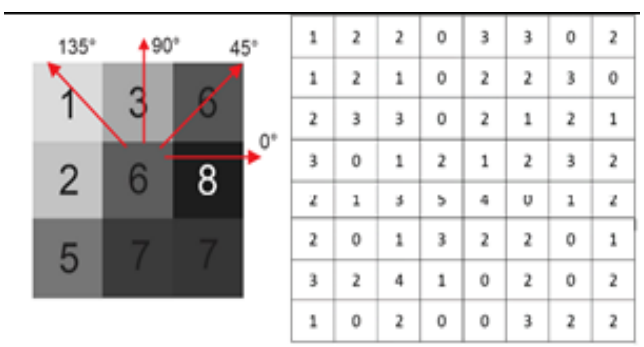


Figure 8. For generating the co-occurrence matrix, the gray tonalities of
each pixel and its neighborhoods (distance 1 and 2) are taken in the
directions 0°, 45°, 90° y 135°, regarding the current pixel

Once the co-occurrence matrix is built, it could be used for the derivation of some descriptor measures. Specifically, for the current research it will be used the measures entropy, contrast, and correlation. These measures are applied and the results are used to compose a vector that characterizes the image [43].

3.3.3 Classification methods

In order to classify the obtained samples based on the features extracted by the descriptors, three classifiers have been chosen: K nearest neighbors, a bayesian, and a neural network-based classifier [10].

To implement these classifiers, it was used the set of libraries provided by Java-ML [45]. This set of libraries developed in Java contains own classes as the K-NN classifier and also provides the possibility of using classifiers contained in other frameworks such as WEKA [46], widely used in studies on Machine Learning. Therefore, there were used the bayesian classifier and neural network-based classifier, implemented in this library.

For experimentation, they have taken into account the following specifications:

• K-NN: It was taken into consideration the use of K = 1 nearest neighbors.

• Bayesian classifier: It was used the Naïve Bayes, which is a simple but powerful classifier.

• Neural Network: The used neural network was a 3-layer perceptron trained using the back propagation algorithm. Four different classes was considered, which match with the four nutritional deficiencies (Boron, Iron, Potassium and Calcium), focused by the current contribution.

4. Experiments And Results

This section will present the results associated to the obtained descriptors, according to their accuracy for detecting the nutritional deficiencies. Specifically, it will be presented information related to the amount of correctly

$$precision = \frac{\# tp}{\# tp + \# fp} \quad recall = \frac{\# tp}{\# tp + \# fn}$$

$$F1 = \frac{2 * precision * recall}{precision + recall}$$

Figure 9. Definition for precision, recall and F1

		Prediction	
		Positive	Negative
Actual	Positive	TP	FN
	Negative	FP	TN

Figure 10. Confusion matrix

classified and incorrectly classified images, and the global accuracy. In addition, it will be use the evaluation metrics precision, recall and F1 [47] obtained for each class, in this case, for each kind of nutritional deficiency. In all case it was used a 10-fold cross validation approach.

Figure 9 presents the definition for precision, recall and F1 in terms of true-positive, false-positive, false-negative, and true-negative results. The exact meaning of such results is visualized in the confusion matrix (Figure 10), that shows how they are used for contrasting the predicted and the actual nutritional deficiency.

4.1 Blurred Shape Model

In the case of the Blurred Shape Model (BSM) descriptor, the evaluation was performed through a 24x24-sized grid. Specifically, it was obtained an overall accuracy of 46.09% (124 samples correctly classified) with the 1-NN classifier. In the case of the naïve bayes classifier, it was obtained a global accuracy of 65.05% (175 samples correctly classified). Finally, in the neural network classifier it was achieved a 59.11% overall accuracy (classifying correctly 159 samples).

Classified as→	***Boron***	***Iron***	***Potassium***	***Calcium***
Boron (B)	26	22	9	12
Inron (Fe)	0	62	5	3
Potassium (K)	1	40	12	3
Calcium (Ca)	13	22	15	24

Table 3. Confusion matrix using the BSM descriptor and the 1 - NN clasifier

	Presion	***Recall***	***F1***
Boron (B)	0650	0377	0477
Iron (Fe)	0425	0886	0574
Potassium (K)	0239	0214	0247
Calcium (Ca)	0571	0324	0414
Average	0485	0450	0428

Table 4. Precision, Recall And F1 Values For BSM And 1 - NN

Tables 3 and 4 show the evaluation results using the 1-NN classifier. Best results were obtained by classifying samples of Iron (Fe), achieving a F1 value of 0,574 and 62 of 70 samples correctly classified, obtaining a high recall value of 0,886. Additionally, Boron and Calcium averagely performed well by obtaining F1 values of 0,477 and 0,414, although there are not obtained relevant values for precision and recall independently. Finally, the Potassium classification performed worst in this experimental scenario. Overall, the global behavior obtained by the model is characterized by a F1 value of 0,428.

Classified as→	***Boron***	***Iron***	***Potassium***	***Calcium***
Boron (B)	48	5	3	13
Inron (Fe)	5	49	16	0
Potassium (K)	4	6	36	10
Calcium (Ca)	14	12	6	42

Table 5. Confusing matrix using the BSM descriptor and the Naive Bayes classifier

	Presion	***Recall***	***F1***
Boron (B)	0676	0696	0686
Iron (Fe)	0681	07	069
Potassium (K)	059	0643	0615
Calcium (Ca)	0646	0568	0604
Average	0648	0652	0649

Table 6. Precision, recall and F1 values for BSM and Naive - Bayes

Tables 5 and 6 show the results using the naïve bayes classifier. In contrast to the k-nearest neighbor classifier, in this case similar F1 values were obtained for the four kinds of nutritional deficiencies. Here, the best results were obtained at classifying Iron (Fe) and Boron (B) samples; achieving a F1 value of 0,69 and 0,686 and 49 and 48 of 69 correctly classified samples, respectively. Additionally, the results with the samples of Potassium (K) and Calcium (Ca) also reached high performance values, respectively F1 values of 0,615 and 0,609. Globally, the F1 value obtained for the model was 0,649.

Classified as→	***Boron***	***Iron***	***Potassium***	***Calcium***
Boron (B)	45	8	7	9
Inron (Fe)	4	58	5	3
Potassium (K)	6	24	19	7
Calcium (Ca)	14	12	11	37

Table 7. Confusion matrix using the BSM descriptor and the neural network classifier

Tables 7 and 8 show the test results using the neural network-based classifier. Here, the best results were obtained at classifying Iron (Fe) samples, achieving a F1 value of 0,674. The results associated to the accuracy of the Boron (B), Potassium (K) and Calcium (Ca) samples, reached F1 values of 0,652, 0,388, and 0,57, respectively. This results are highly correlated with the associated with the 1-NN classifier, where Iron and Potassium were the nutrients that respectively work best and worst. Globally,

the averaged F1 value obtained for the model was 0.571.

	Presion	Recall	F1
Boron (B)	0652	0652	0652
Iron (Fe)	0569	0829	0674
Potassium (K)	0452	034	0388
Calcium (Ca)	0661	05	057
Average	0583	058	0571

Table 8. Precision, recall and F1 Values for BSM and the neural network classifier

4.2 Gray-Level Cooccurrence Matrix

In the case of the evaluation of the Gray-Level Cooccurrence Matrix (GLCM) descriptor, it was used a similar experimental scenario, in relation with the BSM descriptor. Specifically, in this case it was used a 16x16-sized grid. Here, the 1-NN classifier obtained an overall accuracy of 46.84% (126 samples correctly classified). Similarly, the overall accuracy of the naïve bayes classifier was 46.09% (124 samples correctly classified). However, the highest accuracy was achieved by the neural network-based classifier, obtaining a 49.81% overall accuracy (correctly classifying 134 samples).

Classified as→	Boron	Iron	Potassium	Calcium
Boron (B)	34	5	4	26
Inron (Fe)	5	46	8	11
Potassium (K)	7	13	19	17
Calcium (Ca)	17	12	18	27

Table 9. Confusion matrix using the GLCM descriptor and the 1 - NN Classifier

	Presion	Recall	F1
Boron (B)	0540	0493	0515
Iron (Fe)	0605	0657	0630
Potassium (K)	0388	0339	0362
Calcium (Ca)	0333	0365	0348
Average	0467	0464	0464

Table 10. Precision, recall and F1 values for GLCM and 1-NN

Tables 9 and 10 show the detailed results using the 1- NN classifier. Here, the best results were obtained for classifying Iron (Fe) samples, achieving a F1 value of 0.630. On the other hand, the results associated to the samples of Boron (B), Potassium (K) and Calcium (Ca), were respectively of 0,515, 0,362, and 0,348. In this scenario, in a similar way to the results of the 1-NN classifier with the BSM descriptor, the best result was obtained for the detection of the Iron (Fe) deficiencies. However, in this case the F1 associated to the detection of the Potassium (K) deficiencies was improved in relation to Calcium (Ca), which was the nutrient with the worst performance here. Globally, the performance of the model was 0,464.

Classified as→	Boron	Iron	Potassium	Calcium
Boron (B)	33	7	13	16
Inron (Fe)	3	52	10	5
Potassium (K)	4	20	20	12
Calcium (Ca)	18	12	25	19

Table 11. Confusion matrix using the GLCM descriptor and the Naive Bayes classifier

	Presion	Recall	F1
Boron (B)	0569	0478	0520
Iron (Fe)	0571	0743	0646
Potassium (K)	0294	0357	0323
Calcium (Ca)	0365	0257	0302
Average	045	0459	0447

Table 12. Precision, recall and F1 values for GLCM and Naive Bayes

Tables 11 and 12 show the results of the evaluation using the naïve bayes classifier. These results are highly correlated with the previous results presented in Tables 9 and 10, using the 1-NN classification. The best results were obtained again at classifying Iron (Fe) samples, achieving a F1 of 0,646. Additionally, the results of the remaining samples were, in descendent order, of 0,520 (Boron), 0,323 (Potassium), and 0,302 (Calcium). Globally, the obtained F1 for the model was 0,447, which is an overall accuracy slightly lower than the obtained by the 1-NN classifier.

Classified as→	Boron	Iron	Potassium	Calcium
Boron (B)	29	4	5	31
Inron (Fe)	3	50	11	6
Potassium (K)	3	15	17	21
Calcium (Ca)	18	7	11	38

Table 13. Confusion matrix using the GLCM descriptor and the neural network- based classifier

At last, Tables 13 and 14 show the results of the evaluation using the neural network-based classifier. Here, the best results were obtained again at classifying Iron (Fe)

	Presion	*Recall*	*F1*
Boron (B)	0547	0420	0475
Iron (Fe)	0658	0714	0685
Potassium (K)	0386	0304	0340
Calcium (Ca)	0396	0514	0447
Average	0497	0488	0487

Table 14. Precision, recall and F1 values for GLCM and the neural network-based classifier

samples, achieving a F1 value of 0.685. In contrast, the results with samples of Boron (B), Potassium (K) and Calcium (Ca) achieved lower F1 values, reaching 0,475, 0,34 and 0,447 respectively. Such results are not correlated with the 1-NN and the Naïve Bayes classifier, because in this case the worst performance was associated to the detection of the Potassium deficiencies, and not to the Calcium deficiencies like in the previous two cases. Overall, the global performance obtained by the model was 0,487, being the best global F1 value for the current descriptor.

5. Discussion

This section presents a brief discussion on the accuracy in the detection of the mentioned nutritional deficiencies, as well as the performance of the used image descriptors and the supervised classifiers.

Summarizing, the referred experiments obtained the better results at the identification of Iron (Fe) and Boron (B) nutritional deficiencies. These results could be related to the fact that the symptoms associated to the Boron and Iron deficiencies are more remarkable than those associated to the other nutrients; therefore they could be identified in an easier way. Specifically, the best results associated to the GLCM descriptor were notably obtained in the identification of Iron deficiencies, with a large difference in relation to other nutritional deficiencies. However, in the case of the BSM descriptor, although the best results were also obtained for Iron deficiencies, the accuracy associated to the detection of Boron deficiencies was also high, in some case very close to the associated to Iron deficiencies.

In the cases of Potassium and Calcium, in several scenarios they were obtained F1 values that could be comparable to those associated to Boron and Iron. However, in some case they obtained values lied around 0.3, which could be considered low performance values.

Regarding a direct comparison between the performances related to the BSM and the GLCM descriptors, there is not a clear superiority of one descriptor over the other one. In the case of the naïve bayes classifier, the BSM descriptor leads to the best results in the detection of the four nutritional deficiencies. In the case of the 1-NN classifier, the best accuracy values were obtained by the GLCM descriptor for the Boron, Iron, and Potassium deficiencies, while for the Calcium deficiencies the best accuracy was associated to the BSM descriptor. Finally, in the neural network-based classifier the BSM descriptor leads to the best results in the case of the Boron, Potassium, and Calcium deficiencies, while the Iron deficiencies were characterized better by the GLCM descriptor.

Finally, a direct comparison between the three supervised classification approaches concludes that using the information associated to the BSM descriptor, for all the deficiencies the classifier with best accuracy results was the naïve bayes. However, for the GLCM descriptor the results do not evidence the superiority of some classifier over the remaining two. In contrast, the best results associated to each nutritional deficiencies, were shared across the three classifiers. In the case of Boron, the best result was obtained by the naïve bayes classifier; in the case of Potassium the best result was obtained by the 1-NN classifier; and finally, the neural network-based classifier obtains the best results for the detection of Iron and Calcium deficiencies.

6. Conclusions and Future Research

The identification of nutritional deficiencies by using image processing techniques in coffee tree leaves is a complicated task regarding the high amount and diversity of visible symptoms that they could contain. For these reasons, it is necessary to perform research and develop computational solutions that could help experts to accomplish such task. At this moment this task tends to be performed by the farmers themselves in coffee farms, therefore they are prone to introduce mistakes regarding the shortcomings of the human eye.

The presented contribution exposed the results associated to a field research focused at the combination of image processing techniques together with supervised classification algorithms, in order to identify nutritional deficiencies in coffee tree leaves. It showed how the use of appropriate images descriptors (such as the blurred shape model and the gray level co-occurrence matrix), and some popular supervised classifiers (such as KNN, Naïve Bayes or neural networks), could lead to a suitable identification of some deficiencies such as the lack of Iron or Boron. In contrast, for other nutrients such as Potassium and Calcium, there were obtained more modest results.

At future works, it will be considered the use of more sophisticated classifiers such as random forests [48], support vector machines [49] or deep learning-based approaches [50], to perform the classification task. In addition, it will be considered the application of further data preprocessing approaches [51-53], regarding that they have been successfully used in other practical scenarios for improving the performance of typical data mining tasks.

Acknowledgment

The authors would like to thank the editors and the anonymous referees for their constructive comments that have led to this improved version of the paper. This work is supported by the Research Project "Development of technological tools for preventive identification of nutritional deficiencies in coffee trees through digital image processing", funded by National Council of Science and Technology of Perú, and Señor de Sipán University.

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