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IDENTIFICATION OF DEFICIENCIES OF IRON AND MANGANESE IN LEAVES OF BEAN USING A CLASSIFIER

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INTRODUCTION

- Common bean is an important protein source in the dietary intake of Mexico
- Some deficiencies may occur and must be identified before the symptoms appear; deficiencies of iron (Fe) and manganese (Mn), may be confused in the initial phenological growth stages
- A method of identification of those deficiencies with similar precision than a laboratory analysis should be developed
- The aim of this work was to evaluate combinations of color and textural features to identify different levels of Fe or Mn deficiencies in situ in bean leaves, using a probabilistic neural networks (PNN) classifier. According to Ushada *et al.* (2007), the PNN could provide a more accurate estimation in comparison with traditional statistical models

MATERIALS AND METHODS

- Fourteen treatments (also called outputs or classes) were set up, varying the concentration of Fe or Mn (0, 20, 40, 60, 80, 150, and 200%) to induce deficiencies or excess. Two additional treatments were included: one without Fe and Mn, and another with the full requirement of these elements in the nutrimental solution (control).
- Leaf samples were collected during vegetative growing stage (72 days after transplant); then, sub-samples were taken out from scanned digital images of these leaves to proceed with the image analysis.
- After image analysis, eight color and four textural features were obtained and used as inputs for the PNN classifier; the textural features were calculated from relative frequencies of a co-ocurrence matrix of paired pixels with variations in their distance of 1, 5, and 10 pixels.
- Different combinations of inputs (from 1 to 12) and outputs (8, 10 or16 classes) for the PNN were tested.

RESULTS AND DISCUSSION

- There were variations in distance when textural features were calculated; as distance increased, more space of variation between paired pixels was analyzed. The best global classification percentage was obtained by using eight treatments and textural features calculated from paired pixels with a variation in their distance of 10 pixels.
- There are more probabilities of assigning a correct class to the information provided by eight inputs than ten or more. The leaf symptoms caused by a difference in concentration between 40 and 60% of Fe or Mn in the nutrient solution should be barely perceptible for a PNN classifier since the variation in color or texture might be very slightly (Figure 1).

Table 1. Global correct classification percentages using 16, 10 and 8 classes, when textural features were calculated from a relative frequencies co-ocurrence matrix of paired pixels with variations of distance of 1, 5 and 10 pixels and then combined with color features.

Outputs	Distance 10	Distance 5	Distance 1
16¤	40.2	33.9	34.8
10§	51.7	46.2	48.3
8*	62.3	58.1	59.9

¤ Using all the concentrations or Fe or/and Mn as described in materials and methods.
§ Fe (0, 40, 80, 200%) or Mn (0, 40, 80, 200%); Fe and Mn (0%) and the control treatment.
* Fe (0, 60, 200%) or Mn (0, 60, 200%); Fe and Mn (0%) and the control treatment.

Table 2. Scenarios of inputs, and the global correct classification percentages using eight classes as outputs. Textural features were obtained from paired pixels with a variation in their distance of 10 pixels.

Inputs	ONN	TCCP (%)	VCCP (%)
R, G, B, ASM, EN, IN, LH	84	67.2	64.4
R, G, B, L, a, b, C, H, ASM, EN, IN, LH	96	70.5	64.4
L, a, b, C, H	100	64.2	63.1
R, G, B, C, H	100	64.5	61.8
R, G, B, L, a, b, C, H	99	68.4	57.8
			62.3

ONN: optimal neuron number; TCCP: Training correct classification percentage; VCCP: Validation correct classification percentage. R: red channel (RGB); B: blue channel (RGB); G: green channel (RGB); L: Luminosity (CIELab); a: red/green variation (CIELab); b: blue/yellow variation (CIELab); C: Chroma; H: Hue; EN: Entropy; IN: Inertia; HoL: Local Homogeneity

- Regarding Table 2, the best classifier was the combination of inputs that involved color and textural features. The use of only textural features showed low global correct classification percentages; these combinations of inputs were not presented. The scenarios that only included color features as inputs for the PNN classifier had as good global correct classification percentage as the best classifier obtained; some disadvantages should be considered, such as crop variety.

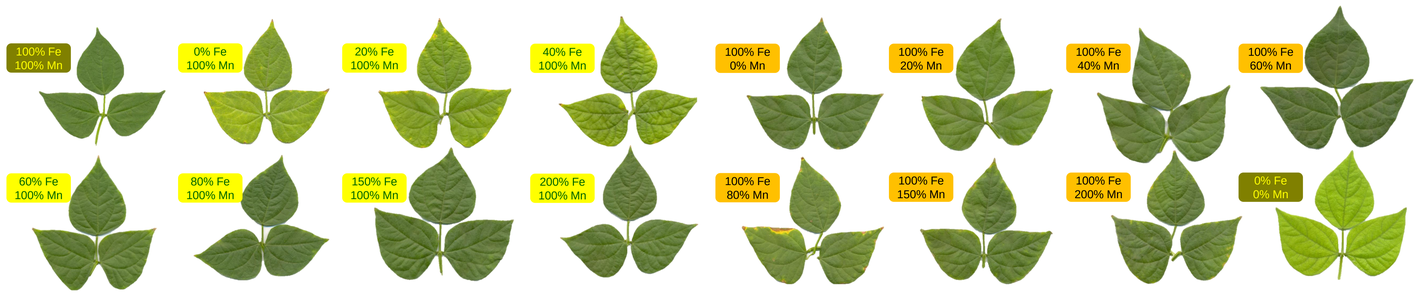


Figure 1. Graphic description of the 16 treatments and the variation in the concentration of iron and manganese based on the Steiner solution (Steiner, 1961).

CONCLUSIONS

- Color and textural features could be useful to identify Fe and Mn deficiencies in bean crop
- Other textural features as inputs for a classifier need to be investigated in order to improve the correct identification of Fe and Mn deficiencies

REFERENCES

- Ushada *et al.* 2007. Non-destructive sensing and its inverse model for canopy parameters using texture analysis and artificial neural network. Comput. Electron Agric. 57:149–165.
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