Vision-Based Analysis on Leaves of Tomato Crops for Classifying Nutrient Deficiency using Convolutional Neural Networks

Claudio Cevallos, Hiram Ponce, Ernesto Moya-Albor, Jorge Brieva
Universidad Panamericana. Facultad de Ingeniería.
Augusto Rodin 498, Ciudad de México, 03920, México
0161568@up.edu.mx, hponce@up.edu.mx, emoya@up.edu.mx, jbrieva@up.edu.mx

***Abstract*—Tomato crops are one of the most important agricultural products at economic level in the world. However, the quality of the tomato fruits is highly dependent to the growing conditions such as the nutrients. One of consequences of the latter during tomato harvesting is nutrient deficiency. Manually, it is possible to anticipate the lack of primary nutrients (i.e. nitrogen, phosphorus and potassium) by looking the appearance of the leaves in tomato plants. Thus, this paper presents a supervised vision-based monitoring system for detecting nutrients deficiencies in tomato crops by taking images from the leaves of the plants. It uses a Convolutional Neural Network (CNN) to recognize and classify the type of nutrient that is deficient in the plants. First, we created a data set of images of leaves of tomato plants showing different symptoms due to the nutrient deficiency. Then, we trained a suitable CNN-model with our images and other augmented data. Experimental results showed that our CNN-model can achieve 86.57% of accuracy. We anticipate the implementation of our proposal for future precision agriculture applications such as automated nutrient level monitoring and control in tomato crops.**

***Index Terms*—Agriculture, image processing, deep learning, computer vision, color analysis**

I. INTRODUCTION

Currently, approximately one third of food for human consumption is wasted in the various stages of the supply chain. It is estimated that 40% of agricultural production is directly affected by poor plant care, being reactive to pests and diseases that the plants present [1]. Based on data from the Food and Agriculture Organization (FAO), an estimated 1.3 billion tons of food is wasted every year in the world, which it is equivalent to one third of the food designated for human consumption [2]. Moreover, the waste existing during the production phase reaches 28% of the total evaluated [2]. On the other hand, food waste in Latin America is considered to be 127 million tons per year which means 9.8% of world waste [2]. Thus, having efficient agricultural practices allows obtaining an optimum use of the crop, a reduction of environmental pollution, and reduction of waste [3]. At present, these practices allow the farmer to supply the necessary amount of nutrients to the plants, at the time they need them.

One of the most important agricultural products at an economic level in the world is the tomato [4]. Thanks to the production standards that this fruit has achieved over the years, it has allowed the demand to have increased considerably nationally and internationally for its quality, performance, and profitability. For example, in Mexico, tomato crops have increased by 50% over the years. Thus, in 2010, more than 54 thousand hectares for its cultivation were destined. In 2014, based on data obtained by the Mexican Agrifood and Fisheries Information Service (SAGARPA, from Spanish), tomato crops took second place while chili cultivation continued taking first place in crops in Mexico. [4]. Moreover, Mexico is considered the main tomato supplier worldwide with a market share of 25.11% of all world exports [5].

Tomato is a perennial plant that grows as an annual crop belonging to the *Solanaceae* family which includes different crops such as chili peppers, potatoes and eggplant, among others [6]–[9]. Tomato harvesting can be carried out throughout the year. However, it is important to take into account frost and extreme heat, as they can damage the plant [10].

One of the problems in tomato crops is nutrient deficiency because it impacts on the quality of the plant and the fruits. Nitrogen, phosphorus and potassium are known as primary nutrients vital for many plants including tomatoes. Literature [11], [12] has reported symptoms in the leaves of tomato crops where those nutrients are deficient, as shown in Figure 1. For example, large leaves of the plant change from green to yellow and the small ones turn pale when there is lack of nitrogen. Leaf veins of the plant turn purple color in absence of phosphorus, and lacking of potassium turns the edges of leaves yellow [11], [12].

Tomato has become, over the decades, one of the star crops as commercial and homegrown crops. This product is used in a large number and variety of dishes and can be consumed in different presentations, which allows its great acceptance by consumers and one of the sources of vitamins and minerals present in their diet [13]. As consequence, searching for technological solutions to improve the best practices in these types of crops has increased, due to the importance present in the different aspects mentioned above. For example, precision agriculture and robotics have been implemented [14], as well as sensor-based and vision-based monitoring [15]–[19].

In this work, we propose a supervised vision-based monitoring system of the leaves of tomato for predicting nutrients deficiencies in the crops. It uses a Convolutional Neural Network (CNN) to recognize and to classify the type of

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Fig. 1. Thumbnails of examples in the dataset created for this work. First row are leaves with nitrogen deficiency (yellow leaves); second row are leaves with phosphorus deficiency (purple veins of leaves); third row are leaves with potassium deficiency (yellow in edges of leaves), and fourth row are leaves with in normal levels of nutrients.

nutrient deficiency in tomato plants. First, we create a data set of images of leaves of tomato, where the images show different symptoms that the tomato plant present when one of its main nutrients –nitrogen, potassium and phosphorus– is missing. The data set was validated by chemical measurements made on the soil without nutrients and with the presence of them. Secondly, we performed four experiments to compare the accuracy of the classification of the CNN: (i) using the images of the data set, (ii) using the images with contrast enhancement, (iii) augmenting the data set with images obtained from the Internet with a protocol-basis, and finally, (iv) using the augmented data set with contrast enhancement of the images.

The contribution of this work consists of developing a computer system for monitoring nutrients deficiencies in tomato crops through the visual analysis of their leaves. To the best of our knowledge, this is the first time that a vision-based analysis is done over tomato leaves for monitoring nutrient deficiency. Moreover, this work is an on-going research for enhancing tomato crops by modifying nutrients, in an informed way, even before fruits have been grown in the plant.

The remainder of the paper is organized as follows. Section II presents the related work of relevant technologies use in agriculture, giving some examples. Section III presents an overview of our proposal and the methodology followed. In Section IV, we show the experimental protocol carried out to generate the data set. Section V presents the results of the prediction of the CNN, whereas Section VI offers the conclusions of this work.

II. Related Work

Over the years, advances in technology using robotics in agriculture has become more popular. Based on the needs of each country or region, projects and research have been carried out to meet them. In Japan, for example, Noguchi and Barawid [20] investigated the usage of mobile robots in the form of tractors to perform the necessary tasks within a rice, soybean and wheat crop. These tasks begin with the sowing of seeds and continue with the cultivation of plants, fertilization and monitoring of the crops and harvest of final product. The project was designed to cover large farmland, focusing on user safety with the use of multiple inexpensive sensors and having a system for locating and searching for better trajectories.

Pollution and variety of climates have been issues of concern in agriculture activities, so different investigations have been carried out to protect crops from these factors. In [15], Hemming et al. presented a room equipped with different robots, sensors and specialized areas in each type of cultivated plant. This room can control temperature, humidity and pressure, allowing it to adapt to any type of plant. However, this has not been fully automated, requiring human intervention to perform certain tasks such as supervision of the tasks performed by the robots or detection of color of the fruits to be harvested.

On the other hand, precision agriculture has get involved in combination of robotics and agriculture. To achieve high quality in the cultivated food and crop safety for the user and the final product, projects based on GAP (Good Agricultural Practices) have been carried out with the help of measurement tools, performance sensors and analysis software seeking to implement a controlled harvest [14].

Due to the increase in environmental awareness in recent years, it is perceptible and necessary to use new technologies to obtain better crops and provide greater security for the user. And because these technological advances have their advantages and limitations, it is important working with them to obtain greater benefits. For example, to calculate the necessary amount of treatment to achieve specific exterior maturation of freshly harvested oranges for final consumption, a project based on image processing was carried out to detect their coloration [21]. To carry out the evaluation it was necessary to have an Android device and the use of its camera. The calculation obtained from the detected image shows the amount of treatment necessary based on the established color indices. Furthermore, vision-based systems have been used for color detection and analysis of the tomato during its growth [16]–[19], and thus finding the ideal date to harvest and sell the product. Also, this type of technology has been used during the

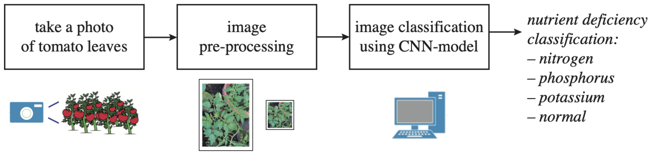

Fig. 2. Proposed vision-based monitoring system for detecting nutrients deficiencies in tomato plants.

phase of accommodation and distribution of the product, where the tomato can be classified as defective or non-defective, and mature or immature for its separation.

Thus, based on the detection of the color of fruits, it is possible to determine the ripeness of the fruit at different stages of the supply chain, being the main ones during the growth and the harvest of the plant. There are different works based on the color of the fruit peel to be evaluated. For example, in [22] the authors analyzed the coloring of papaya for its final harvest. With this, it is sought to obtain better products for sale and final consumption without having to use physical and chemical processes to obtain the required maturation.

As described above, the previous projects have the advantage of using accessible technologies for a better quality of the final product, however, it only focuses on the analysis of a single fruit (e.g., tomato or papaya) and its harvest time, not on the rest of the plant and its complete life cycle.

Recently, deep learning methods have been used to analyze the characteristics of the leaves of different plants and thus to detect diseases or pests. In [23], it is presented a system capable of detecting the lack or excess of nutrients in plants. It is important to work with plant pests and diseases to save on resources such as pesticides, however, it is equally important to focus on plant nutrients and deficiency thereof to obtain healthy plants and quality products. In this work, we take advantage of deep learning to analyze the leaves of the tomato crops for detecting nutrients deficiency.

III. Description of the Proposal

This section describes the proposed vision-based system for monitoring nutrients deficiencies in the leaves of tomato crops.

The proposal consists of using a single RGB-camera that takes photographs of tomato plants. Contrast enhancement and resizing are applied to the images for further analysis. Then, each image is input into a pre-trained CNN-model that is able to classify three possible nutrient deficiencies (i.e. lack of nitrogen, lack of phosphorus and lack of potassium) or normal level of nutrients in the plant. Figure 2 shows the proposed system. Furthermore, the methodology for developing our monitoring system comprises the following steps: (i) data acquisition, (ii) data pre-processing, (iii) CNN-model construction, and (iv) CNN-model evaluation. Figure 3 summarizes the workflow of the monitoring system implementation. The details of the steps are described following.

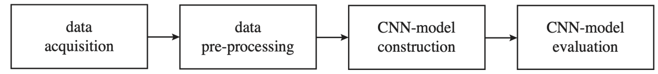

Fig. 3. Workflow of the vision-based monitoring system implementation.

(a) (b) (c)

Fig. 4. Examples of the chemical testers used in the dataset protocol: (a) sample test of nitrogen deficiency, (b) sample test of phosphorus deficiency and (c) sample test of potassium deficiency. In each pair of images, the tester is shown to the left and the corresponding state of the plant is shown to the right. Five levels of nutrients can be measured with the tester: depleted, deficient, sufficient, adequate and surplus.

A. Data Acquisition

This step consists of creating a dataset of multiple images of leaves of tomato plants and the associated level of nutrients. In that sense, we collected data, during 10 weeks, from tomato plants harvested in separate pots located at the backyard of a house in Mexico City, Mexico. At the beginning, the soil was washed with water several times to eliminate any nutrient. Then, three plants were grown in the pots with that neutral soil. We added the primary nutrients once per week to those plants. At the end of the period, all the plants had sufficient nutrients to be considered with normal levels. We measure the level of nutrients manually, using chemical nutrient testers as depicted in Figure 4. One time per week, we tested the nutrients in the three plants following the next steps:

1) Take a sample of soil 5 cm deep from the surface of the pot and place it in an isolated container.
2) Add water to the container (5 times the amount of the soil sample).
3) Stir the water with the soil and let stand until the soil settles at the bottom of the container.
4) With a dropper, take the water from the surface of the container to fill the samples of each element (nitrogen, phosphorus and potassium).
5) Add the associated chemical reagent to each sample and stir until combined with water.
6) Wait for the reaction to occur and evaluate the amount of nutrient in the pot (see Figure 4).

After the ten weeks, the reported levels of nutrients for each of the three plants were summarized as shown in Table I. This table summarizes the pH values measured in the soil (not used in this work), the level of nitrogen, the level of phosphorus and the level of potassium, where each column corresponds to one plant. Five different levels of nutrients can be reported (as specified in the testers): depleted, deficient, adequate, sufficient and surplus.

During the ten weeks, 596 images of 3024×4032 pixels size were obtained at different hours of the day and shooting in different angles to maximize the diversity of images. From this

TABLE I
LEVEL OF NUTRIENTS IN THE SOIL. MEASURES DONE ONCE PER WEEK.

Week	pH	Phosphorus	Potassium	Nitrogen
1	6.5	adequate	depleted	depleted
2	6.5	adequate	depleted	deficient
3	6.5	adequate	depleted	deficient
4	6.5	adequate	deficient	adequate
5	6.5	adequate	deficient	surplus
6	6.5	sufficient	deficient	surplus
7	6.5	sufficient	deficient	surplus
8	7	adequate	deficient	surplus
9	7	adequate	adequate	surplus
10	6.5	adequate	adequate	depleted

set of images, 213 were tagged as lack of nitrogen (*nitrogen*), 168 as lack of potassium (*potassium*), 94 as lack of phosphorus (*phosphorus*), and 121 as normal level (*normal*). Figure 1 shows some examples of the created dataset. We considered lack of nutrient if the chemical tests were found depleted or deficient; otherwise, the level of nutrient was tagged as *normal*.

B. Pre-processing

This step comprises two main data pre-processing: contrast enhancement and image resize. In the first case, we applied contrast enhancement to original images to emphasize the color in the leaves. For that pre-processing, we computed a gamma transformation on the RGB channels of the images [24], as it is shown in Eq. (1):

$$s(r) = \begin{cases} 0 & ; r < a \\ (L-1)\left[\frac{r-a}{b-a}\right]^{\gamma} & ; a \leq r \leq b \\ (L-1) & ; r > b \end{cases} \tag{1}$$

where the images have, for each RGB channel, gray levels in the range $[0, L-1]$; r is the input gray level to the gamma transformation, s is the resulting output gray level, and $[a, b]$ It is the input range of gray levels of interest (i.e., to be enhanced). For all images in the experimentation, the γ value was set to 1 and we used the following input range of gray levels to contrast enhancement: $[0.2*(L-1), 0.6*(L-1)]$ for the red channel, $[0.3*(L-1), 0.7*(L-1)]$ for the green channel, and$[0, (L-1)]$ for the blue channel.

In the second step of data pre-processing, we reduce the original images (3024×4032 pixels) to 28×28 pixels size to reduce the computing task in the CNN-model for further analysis, as described below.

C. CNN-model Construction

After pre-processing the images, we trained a CNN classifier model to detect four different classes related to the nutrients deficiencies in the tomato plant. Those classes are: *nitrogen*, *phosphorus*, *potassium* and *normal*. We selected CNN as classifier based on its ability to handle images and to automatically extract features from them. In a nutshell, CNN is a type of machine learning that learns to perform a regression or classification task from images, multimedia or texts [25].

In this work, we designed a CNN that receives as input a 28×28 pixel size of an RGB color image. The image

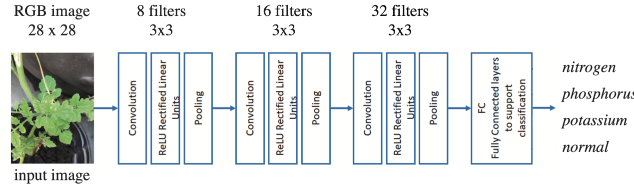

Fig. 5. Architecture of the CNN-model implemented in this work.

inputs into a network of three convolutional layers with 8, 16 and 32 filters of 3×3 size. Each of these layers continues with a rectification layer that activates a nonlinear function (rectified linear unit, ReLU) and reduces the spatial size of the maps in order to avoid redundant information. At the end, there is a fully connected layer in which all neurons are connected with the units of the previous layer. The last of these layers is the one that contains the characteristics to classify the images. A softmax layer normalizes the output of the last fully connected layer. Finally, it computes the classification for detecting nutrient deficiency in the input image. Figure 5 shows the architecture of the CNN-model used in this work.

To get a suitable trained CNN-model, we used the stochastic gradient descent with momentum (SDGM) algorithm for training, and we varied two hyper-parameters: the initial learning rate (ranging from 1×10^{-6} to 1×10^{-2}) and the maximum number of epochs (from 200 to 500). We fixed the momentum value to 0.9 and the regularization term to 1×10^{-4}.

D. CNN-model Evaluation

The last step of the methodology is to test the performance of the trained CNN-model classifier. We calculated the accuracy metric of the output response of the CNN-model as expressed in Eq. 2), where TP, TN, FP and FN represent the true positive, true negative, false positive and false negative values, respectively.

$$accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

IV. EXPERIMENTATION

From the above methodology, one critical part is to train and test the CNN-model performance. However, CNN-models depend on a diverse of settings such as the choice of the hyper-parameters to find a suitable architecture, or the preparation of input data [26]. In that sense, we carried out four experiments related to the preparation of input data as follows:

- *Experiment 1:* use the original images as input data.
- *Experiment 2:* use the contrasted images as input data.
- *Experiment 3:* use the original images augmented with a subset of images from Internet (see below) as input data.
- *Experiment 4:* use the contrasted images augmented with a subset of contrasted images from Internet (see below) as input data.

In all the cases, the input data was partitioned into 70% for training (418 images) and 30% for testing (178 images). For the augmentation procedure, we extended the training set

TABLE II
RESULTS OF PERFORMANCE OF THE CNN-MODEL IN *Experiment 1*.

Test	Learning rate	Epochs	Test acc. (%)	Training acc. (%)
1	0.000001	350	41.90	43.88
2	0.000001	500	34.64	43.88
3	0.00001	350	43.58	82.01
4	0.00001	400	46.37	88.49
5	0.00001	500	45.81	89.93
6	0.00005	200	45.81	99.04
7	0.00005	300	50.84	99.52
8	0.0001	200	51.96	99.76
9	0.0001	250	54.75	99.04
10	0.0001	300	49.72	99.76
11	0.0001	350	**56.42**	99.28
12	0.0001	400	50.84	99.04
13	0.0001	500	50.84	99.28
14	0.0005	200	43.02	99.04
15	0.001	300	55.31	99.52
16	0.001	350	49.72	99.04

TABLE III
RESULTS OF PERFORMANCE OF THE CNN-MODEL IN *Experiment 2*.

Test	Learning rate	Epochs	Test acc. (%)	Training acc. (%)
1	0.00001	250	44.69	76.74
2	0.00001	300	39.11	84.65
3	0.00001	350	43.58	85.61
4	0.00001	400	48.60	89.21
5	0.00001	500	46.37	92.09
6	0.00005	350	49.72	99.52
7	0.0001	250	**54.75**	99.52
8	0.0001	300	43.02	99.28
9	0.0001	350	49.16	99.52
10	0.0001	400	46.37	99.76
11	0.0005	350	52.51	99.76
12	0.0005	450	45.81	99.76
13	0.001	300	45.25	99.28
14	0.001	350	50.84	99.28
15	0.001	400	47.49	99.04
16	0.001	800	43.58	99.28

with 58 images retrieved from the Internet. The latter were collected manually by inspection and the level of nutrients were tagged using the information in the description of the web sources. In *Experiment 4*, those images from Internet were also contrasted using the same pre-processing method as the ones in the dataset.

We varied only two hyper-parameters of the CNN during each experiment. Those are the initial learning rate and the maximum number of epochs (see Section III-C). We conducted 16 combinations of these hyper-parameters to evaluate the performance of the CNN-model. The accuracy metric was chosen for the evaluation.

All the experiments were implemented in Matlab using the Deep Learning Toolbox. A personal computer with the following characteristics was used for experimentation: MacBook Pro (13 inch, Late 2011), processor Intel Core i7 at 2.8 GHz, two CPU cores, and RAM of 4GB 1333 MHz DDR3.

The dataset used in this work, as well as the codes for experimentation, can be found in the GitHub repository (https://github.com/ccevallo/Monitoreo_Jitomate).

V. RESULTS AND DISCUSSION

As explained earlier, four experiments were carried out. The details of each one are presented as follows.

A. Experiment 1 – Original images

We tested the performance of the CNN-model trained with the original images in our dataset. Table II summarizes the results of this experiment. As shown, the obtained CNN-model was over-fitted because in the training phase, it performed $\sim 99\%$ of accuracy while in the testing phase, 50% of the results range between 45% and 52% of accuracy; and the best performance of the CNN-model was 56.42% of accuracy. For the best CNN-mode, the initial learning rate was set to 0.0001 and the maximum number of epochs was 350.

B. Experiment 2 – Contrasted images

This experiments considers the contrasted images of our dataset. Table III summarizes the results of performance of the CNN-model. It can be observed that 50% of the test results are between 44% and 49% of accuracy. This experiment stills reported over-fitting as shown in the table. Furthermore, the best CNN-model performed 54.75% of accuracy using an initial learning rate of 0.0001 and the maximum number of epochs of 250. It can be said that, compared to *Experiment 1*, this experiment was not better since the test accuracy tends to be less than 50%.

TABLE IV
RESULTS OF PERFORMANCE OF THE CNN-MODEL IN *Experiment 3*.

Test	Learning rate	Epochs	Test acc. (%)	Training acc. (%)
1	0.00001	300	67.60	79.83
2	0.00005	350	83.24	99.16
3	0.0001	300	84.36	99.79
4	0.0001	350	85.47	98.95
5	0.0001	400	77.65	98.95
6	0.0005	300	82.68	98.95
7	0.0005	350	84.36	99.16
8	0.0005	400	79.33	99.37
9	0.001	250	84.36	99.16
10	0.001	300	**86.59**	99.58
11	0.001	350	84.36	99.37
12	0.001	400	83.24	99.37
13	0.001	550	82.12	99.16
14	0.01	250	79.33	99.95
15	0.01	300	82.12	99.74
16	0.01	350	82.12	99.16

C. Experiment 3 – Original and augmented images

This experiment consisted of augmented our dataset with images found on the Internet. The results of the experiment are reported in Table IV. It shows an increasing of the test accuracy, reporting the 50% of the results to be between 82% and 84%. The best test result was 86.59%, while 67.60% was the lowest of the results. The hyper-parameters configuration that allowed the best CNN-model was 0.001 of initial learning rate and 300 epochs. Thus, data augmentation improves the performance of the CNN-model.

D. Experiment 4 – Contrasted and augmented images

The last experiment was conducted using the contrasted images of our dataset and contrasted images augmented from

TABLE V
RESULTS OF PERFORMANCE OF THE CNN-MODEL IN *Experiment 4*.

Test	Learning rate	Epochs	Test acc. (%)	Training acc. (%)
1	0.00005	350	80.45	98.74
2	0.0001	200	82.68	99.37
3	0.0001	250	85.47	99.16
4	0.0001	300	83.24	98.53
5	0.0001	350	82.12	98.95
6	0.0005	300	80.45	99.79
7	0.0005	350	**86.59**	99.37
8	0.001	250	86.03	99.37
9	0.001	300	**86.59**	99.37
10	0.001	350	85.47	99.58
11	0.001	400	83.80	99.37
12	0.001	450	84.92	99.37
13	0.01	250	83.80	99.16
14	0.01	300	85.47	99.37
15	0.01	350	84.36	99.74
16	0.01	400	84.36	99.37

TABLE VI
SUMMARY OF RESULTS PERFORMED BY THE CNN-MODEL.

Experiment	Learning rate	Epochs	Test acc. (%)	Training acc. (%)
1	0.0001	350	56.42	99.28
2	0.0001	250	54.75	99.52
3	0.001	300	86.59	99.58
4	0.0005/ 0.001	350 / 300	86.59	99.37

the Internet. Table V summarizes the results of this experiment. It can be seen that 50% of the results are between 83% and 85% of test accuracy. As in *Experiment 3*, the best result was 86.59% but the lowest result was 80.45% of accuracy. For the best CNN-models, the initial learning rate was set to 0.0005 and 0.001 while the number of epochs was set to 350 and 300, respectively (tests number 7 and 9).

E. Discussion

Based on the results obtained in the experiments, it can be seen that *Experiment 4* reports the best test accuracy. In addition, over the tests, the CNN-model performed consistently, obtaining 84.11 ± 1.93 of accuracy. In addition, Table VI summarizes the performance of the CNN-model in the different experiments carried out. It reports the initial learning rate, the maximum number of epochs, the test accuracy and the training accuracy of the best models in each of the experiments. Also, Figure 6 shows the accuracy of each experiment. It can be observed that the augmentation of the images highly increases the performance of the CNN-model going up to the mean test accuracy (71.09%) of the best models in the experiments.

Some advantages of this vision-based monitoring system can be summarized as follows. It is possible to anticipate the insufficiency of primary nutrients in the tomato crops using this monitoring system over the leaves of the plants. Since the dataset was created using different distances and angles for shooting the camera, then the detection of the nutrients does not require specifications in the method of gathering the images. In addition, the adoption of this system would lead on saving resources of nutrients, and increasing the quantity and quality of the plants.

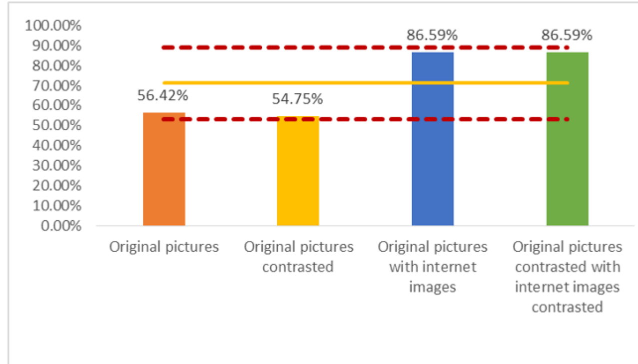

Fig. 6. Summary of the test accuracy performed by the best CNN-models at each experiment. The dashed lines represent the minimum (54.75%) and maximum (86.59%) values, and the straight line represents the mean accuracy (71.09%).

However, there are still some limitations that should be solved before its implementability. For example, the architecture of the CNN-model proposed here has three degrees of depth, but more accurate solutions might require a more complex architecture. Also, the augmentation procedure is limited to a manual research on Internet; thus, it requires more images to achieve better training of the CNN-model. Furthermore, this work does not consider a rigorous study on the light conditions and the effect of the contrast enhancement. Thus, a study on the robustness of this and other environmental conditions should be done. In addition, this CNN-model is focused on the classification of deficiency or normal levels of the three primary nutrients; but the prediction of the nutrient level is still challenging and not provided by our proposal. In terms of the training process, this approach looks to be overfitted as shown in training versus testing accuracy values (see Table VI). In this regard, a more in-depth exploration of the CNN architecture is required. Also, it is important to consider the resizing of the images from 3024×4032 to 28×28 pixels in which it is possible that important information has lost. Lastly, this monitoring system works for tomato crops, but other plants are not considered so far.

To this end, and to the best of our knowledge, this is the first time a vision-based monitoring system for detecting the nutrient deficiency in plants, over the leaves and before the fruits, is proposed. Thus, we consider our ongoing research very promising for future precision agriculture applications.

VI. CONCLUSIONS

Throughout this paper, we presented a vision-based monitoring system for detecting nutrients deficiencies in tomato crops by taking images from the leaves of the plants.

In this work, we created a dataset with images of tomato leaves with different symptoms suffered by the lack of primary nutrients (i.e. nitrogen, phosphorus and potassium) in the soil. This dataset was used for trained a CNN-model for classifying four levels of nutrient absence in the plant: lack of nitrogen, lack of phosphorus, lack of potassium, or normal presence.

We carried out four experiments to determine two hyper-parameters in the CNN-model and the input data that best influences in the performance of the classification model. After the experiments, we trained a CNN-model that performed 86.57% of accuracy, using contrasted and augmented images from our dataset and from the Internet.

As future work, we are considering to increase the number of images in the training set to study the robustness of the CNN-model due to light conditions and the effect of the contrast enhancement, as well as, to optimize the architecture of the model. Also, it is important to determine the impact of image reduction in the predictability of the CNN. Lastly, we are interested on implementing this approach in a precision agriculture application.

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