A Neural Network Classifier for Estimation of the Degree of Infestation by Late Blight on Tomato Leaves

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***Abstract*—**Foliage diseases in plants can cause a reduction in both quality and quantity of agricultural production. Intelligent detection of plant diseases is an essential research topic as it may help monitoring large fields of crops by automatically detecting the symptoms of foliage diseases. This work investigates ways to recognize the late blight disease from the analysis of tomato digital images, collected directly from the field. A pair of multilayer perceptron neural network analyzes the digital images, using data from both RGB and HSL color models, and classifies each image pixel. One neural network is responsible for the identification of healthy regions of the tomato leaf, while the other identifies the injured regions. The outputs of both networks are combined to generate the final classification of each pixel from the image and the pixel classes are used to repaint the original tomato images by using a color representation that highlights the injuries on the plant. The new images will have only green, red or black pixels, if they came from healthy or injured portions of the leaf, or from the background of the image, respectively. The system presented an accuracy of 97% in detection and estimation of the level of damage on the tomato leaves caused by late blight.

***Keywords*—**Artificial neural networks, digital image processing, pattern recognition.

I. Introduction

OVER the centuries, the science and technology in agronomy have been searched for ways to improve the productivity, in order to feed constantly growing populations, at the same time we face important climatic changes. An important field of research in this area is plant pathology, since many diseases can affect plants causing economic, social and ecological losses. In this context, it is very important to have means for rapid and accurate diagnosis of diseases for which a plant is susceptible.

In Brazil, where an important part of the economy depends on agriculture, it is essential that farmers maintain a strict control over the quality of their crops. In 2015, the agribusiness corresponded to 21.46% of the Brazilian GDP, or more than US$400.00 million [1], [2]. Particularly, the tomato (*Solanum lycopersicon*) crop occupies the 7th position in the rank of food plant tons produced per year [1]. However, that plant is vulnerable to many diseases and requires extreme care in terms of fertilization and phytosanitary treatment. Therefore, it ranks the 2nd position in pesticide consumption per planted area in Brazil [3]. In the same country, tomatoes are typically produced in small farms and require continuous monitoring from experts, which might be prohibitively expensive and time-consuming. Thus, the search for fast, less expensive and accurate methods to detect the foliage diseases is of great significance.

Many studies show the impact of plant diseases over the quality of agricultural products [4]-[7]. Plant diseases can modify or interrupt its vital functions such as photosynthesis, pollination, transpiration, fertilization and germination. They could be caused by different pathogens (fungi, bacteria, or viruses) and due to adverse environmental conditions.

The most common disease that affects tomato crops worldwide is the late blight, a very damaging disease also widespread in Brazil. Thus, its early detection may have positive impacts on economy and environment. The tomato late blight is caused by *Phytophthora infestans*, a fungus that inhabits the soil and disseminates through spores, and the disease occurs especially in cold and humid months. The dispersion of late blight spores is facilitated by wind and high humidity that help spores to reach the leaves, fruits, and branches, where they germinate, producing a new infection focus. The disease can spread quickly, and especially under favorable climatic conditions of the region, consisting of a combination of a relative humidity under 90% and a temperature around 20 °C (68 °F). As a result, we have an epidemic that can lead to considerable losses in production [8]-[10]. On the other hand, the indiscriminate use of pesticides in tomato fields brings serious problems not only to human health but also to the environment. Moreover, pathogens have started developing resistance to the conventionally used fungicides and a second generation of more expensive fungicides began to be used. Therefore, it is critical to use fungicides in proper doses and intervals [11], [12].

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The goal of this paper is to present a novel computer-based solution that may help farmers to make better decisions in their attempt to combat late blight on tomato crops, expanding previous works [13]-[15]. This research aims at helping the detection of late blight in tomato crops, and the measuring of the damage level at each plant, by using a pattern recognition system based on multilayer perceptron neural networks (MLP).

II. Information Technology in Agriculture

Agriculture production systems have frequently benefited from the incorporation of technological advances [16], [17]. According to [10], [18], [19], with the aid of information technology for early detection of crop diseases, it was possible to delay the beginning of pesticides spraying in comparison with the fixed schedule spraying method. We can find examples in the literature where results obtained by monitoring the spores of tomato late blight in the air allowed producers to obtain an average reduction of 50% in total sprays, reaching rates of 80% reduction in some cases [20]

A.Pattern Recognition in Diagnosis of Tomato Diseases

Farmers and workers visually recognize the disease by the appearance of dark brown lesions on tomato leaves that vary from brown or gray to pale green, often situated at the edges of the leaves. The disease may infect either young (upper) or old (lower) leaves and it first appears as water-soaked areas that enlarge rapidly, developing into large brown necrotic areas, causing loss of leaves and, in severe cases, the plant death. Although typically observed in leaves, symptoms may also appear on stems, fruits, and sprouts [9], [21]-[23].

In Brazil, the most common approach used in the fight of the disease involves naked eye observations and manual classification of the degree of infestation at each plant. This classification is based on a visual comparison between the infested leaf and some schematic images of tomato leaves that quantify the degree of infestation in a logarithmic scale [21]. After analysing some samples of plants from the farm, the mean of infestation degree at each sample is used to define a schedule of pesticide spraying.

B.Digital Approaches for Analysis of Plant Leaves

Image processing is a useful tool for analysis in various agricultural applications [18], [24]-[29]. In pre-processing tasks, it is usual to perform noise suppression, image rotation, and scale normalization, whereas shape extraction, which implies finding the shape position, orientation, and size are commonly used in the extraction of features [30]-[33]. Several studies have also investigated the use of broadband color, or chromaticity values, for plant species recognition [26]-[28]. One of the key advantages of these techniques is that pixel-based color classifiers tend to be less computationally intensive than shape-based methods [30]. In this paper, we used the color tones from individual pixels of the leaves to classify them in one of the seven possible degrees of the scale from [21].

While the red, green and blue (RGB) model is suitable for rendering colored images, the description capacity of this model is certainly limited since the color composition is defined by the overlay of the three color channels (red, green and blue) [32]. Natural factors as shadows and sunlight tend to generate a significant amount of interference in the RGB values. On the other hand, in the hue, saturation, and luminosity (HSL) color model the luminosity component is independent from the main color information. Therefore, a natural event like shadows should influence the luminosity component whereas the hue values do not vary. As a result, we can conclude that the HSL color model is extremely useful for image processing algorithms based on the color analysis. Due to this, we added the HSL values of each pixel to our previous model that used only the RGB values [13]-[15] to perform the pattern recognition tasks, as we will describe later.

Digital image filtering is used for the improvement of image quality, contrast increase, noise removal, focus improvement and attenuation of some characteristics [33]. In this work, we have used images captured directly from the field, and so it is expected that they contain a significant amount of noise from the background and shadows. Most of the energy contained in an image is concentrated in the low-frequency elements, whereas the high-frequency elements represent details as borders, sides and abrupt transitions between gray levels. The effect of a low-pass filter is the blurring of an image, that loses some of its high-frequency elements [25]. In this work, we have used a mean filter to reduce the details of abrupt color changes, which have improved the performance of our pattern classifier.

III. Material and Methods

A.Processing of Digital Images of Leaves

At the beginning of this research, we have decided to provide our target users the free use of our classification system, as soon as it would be in production. In addition, as they are small farmers, they may not afford expensive equipment or might be unable to operate it properly. Thus, we have not used any sophisticated machinery or proprietary software packages in order to lower the cost of the final system. Based on that premise, we have worked upon digital images obtained by low-resolution built-in cell phone cameras. The pictures have been taken in an open environment under natural sunlight conditions. The tomato plants have been cultivated in the experimental fields of the Horticulture Department of our institution in a cropping area historically linked with the natural occurrence of late blight. Besides, to simulate a real situation, the images may have some noise like soil, fruits, parts of the sky and the earth.

In [13], [14] each pixel of tomato images has been converted into a plain color by using a pre-fixed classification scheme built empirically, resulting in a new image that only contains green, red, or black pixels. After that, an artificial neural network (ANN) have classified each converted image as being healthy or not, providing no information about the degree of late blight infestation on the leaves.

In this approach, we have updated that methodology, by using a combination of two ANN's to perform, for each pixel, its classification into one of three possible categories: healthy, injured or background. After classifying all the pixels of one single image, we have used the class information of all these pixels to compute the final classification of the whole leaf, assigning it a degree of contamination, as defined in [21]. The main difference between those two works resides on how the ANN paradigm was used. In the first, the decision about how to classify each pixel is empirical. After the classification of all pixels, one ANN had to decide how to classify the whole leaf, based on the quantities of pixels in each color category. The combination of the results of two ANN's would provide the final classification of each pixel, and the computation of the infestation degree of a whole leaf is algebraic, as shown further.

In the sequence of processes performed over the digital images, the first step was to reduce the definition, achieving 70% of the original size, in order to speed up the performance of further procedures. After that, for each image, we generated a text file that contained, for each pixel, the X-Y coordinates of the pixel and its RGB and HSL values. Next, all variables were linearly normalized, generating a new data table containing RGB and HSL values, varying from 0 to 1, which suits better to the training process of an ANN. We have chosen that normalization technique because the variable scales are similar (R, G, and B varies from 0 to 255; H vary from 0 to 359; S and L varies from 0 to 100) and because, as the domain is limited, there is no possibility of occurring outliers.

B.Pattern Recognition System

Our first attempt to classify the pixels was to use a single ANN to classify pixels into one of the three possible classes: healthy, injured or background. Depending on the classification assigned, the color of each pixel was converted into green, red or black, respectively, and the new color values were used to rebuild the image of the whole leaf, as we will explain in details in the further sections. Unfortunately, the results of that experiment were not satisfactory (it scored less than 80% in pixel classification and visible mismatching in the rebuilt images) and so we changed our approach and conducted a new experiment using two different ANNs. The first ANN was trained to recognize green tones of the leaf or, in other words, healthy pixels. If a pixel was recognized as healthy, the ANN answer would be 1 (class 1), but if it was considered as belonging to the non-healthy class, the ANN answer should be 0 (class 0). The training of the latter ANN was similar, but it was conducted to recognize brown tones of the leaf, or injured pixels. For the ANN's training, we have first chosen some pixels from specific areas of our available pre-processed images. As each image can give us around 1500 pixels, we have used no more than four images to construct the training subset for the ANNs, where each record contained the color information plus the class label. The classification of each pixel takes into account the values of their R, G and B components from the RGB color system plus H, S, and L components from the HSL color system. We selected over 6.000 different labeled pixels, where around 2.000 came from each class. The classes could be *green* (corresponding to the different green tones a healthy leaf could have), *red* (the different brown tones a leaf, affect by late blight, could have), or *background* (which includes earth, sky, sticks and other noise colors). Examples of healthy pixels, injured pixels and backgrounds are shown in Fig. 1.

(a) (b) (c)

Fig. 1 Each image shows one subset of pixels used to train the pair of ANNs. Each subset corresponds to one different class and was built by pixels extracted from digital images of tomato leaves (a) Green: pixels from healthy areas of the leaves, (b) Red: pixels from injured areas and (c) background pixels.

After labeling each pixel, according to their classes, the three datasets were joined, shuffled, and linearly normalized. We divided the resulting dataset in a 5:2 proportion, and then circa 5000 records were used for the pair of ANN's training and around 2000 for testing them.

We have evaluated many ANN configurations, varying the learning rate from 0.4 up to 0.8 (with steps of 0.2), the momentum from 0.5 up to 0.9 (with steps of 0.2), and the number of hidden neurons from 4 up to 20, for one or two hidden layers of neurons. We have also tested different activation functions (such as hyperbolic tangent, sigmoid and purelin) in different combinations through the neuron layers.

Each different configuration was trained and tested 20 times, to find the best one in average, in a total of 1728 different ANN models. For each training, we randomly choose 1200 records from our labeled training dataset. Similarly, for each test, we randomly selected 500 labeled records from the testing dataset. The parameters of the architectures that presented the highest classification performance during the training phase are identified in Table I.

Finally, we choose the configuration with the best performance for each ANN. For the *green*-ANN, the best configuration was the 16-8-1 network, with training rate equal to 0.8, *momentum* equal to 0.9, and sigmoid activation function at all levels and a value of 0.5 for the threshold between the outputs. After analyzing each network from the total amount of 20 networks trained and tested with this configuration, we chose to use the one that achieved the best accuracy rate, which was a rate of about 97.99% in correct pixel classification. For the *red*-ANN, the best configuration was the 16-16-1 network, with training rate equal to 0.6, *momentum* equal to 0.7, and sigmoid activation function at all levels and the same value of 0.5 for the threshold. For that configuration, we chose the one with a rate of about 97.92% in correct pixel classification.

The presented approach used an Intel(R) Core(TM) i7-3517U CPU, 1.90 GHz, and 6 GB RAM, with an onboard Intel(R) HD Graphics Family card for developing and running the system, and only free license software: Eclipse IDE for Java and free packages such as Neuroph [34], AWT Image, Java Advanced Imaging (JAI), plus the MySQL as the relational database system. The images were taken at an experimental field using a built-in cell phone camera; the resolution of the images was reduced to only 0.3 megapixels, and each image files were less than 100 KB.

TABLE I
PERFORMANCE RESULTS OF THE ANNS.

		***Green*-Class**				***Red*-Class**			
H1	***H2***	***FUNC***	***LR***	***M***	***PERF***	***FUNC***	***LR***	***M***	***PERF***
4	0	logsig	0.80	0.90	97.78	logsig	0.60	0.50	96.39
4	2	logsig	0.60	0.90	97.85	logsig	0.40	0.50	96.53
4	4	logsig	0.80	0.50	97.78	purelin	0.60	0.90	96.60
8	2	purelin	0.40	0.70	97.92	logsig	0.40	0.90	96.74
8	4	purelin	0.60	0.50	97.92	purelin	0.60	0.90	97.22
8	8	purelin	0.40	0.90	97.85	purelin	0.40	0.70	96.88
16	4	purelin	0.60	0.70	97.71	logsig	0.80	0.50	96.81
16	8	purelin	0.80	0.70	97.99	logsig	0.40	0.90	97.08
16	16	logsig	0.40	0.90	97.85	logsig	0.60	0.70	97.92
20	8	purelin	0.80	0.50	97.78	logsig	0.60	0.70	96.74
20	16	logsig	0.60	0.50	97.71	logsig	0.80	0.90	97.08
20	20	purelin	0.40	0.50	97.36	purelin	0.80	0.70	96.81

Best recognition performances among all different neural networks configurations tested. H1 and H2 are the numbers of neurons in the first and second hidden layer, respectively. All hidden layers used sigmoid activation function while the activation function of the exit layer is shown in column FUNC. LR is the learning rate; M is the momentum and PERF is the average performance calculated over 20 trainings.

IV. RESULTS AND DISCUSSION

After the training phase, we tested the ANN system with 60 new different leaf images. First, each image was pre-processed, having its definition reduced and being mean-filtered. Second, for each image, we extracted the x and y coordinates and the RGB and HSL values of each pixel, and those information were stored in a different file for each image. Last, each record of a file was presented to the pair of ANN's and classified by it. This final step generates a new file, containing, for each pixel of the original image, its x and y coordinates plus its final classification.

The final classification of each pixel from one single image was used to reconstruct the leaf image, and converted into a three-colored codification, where the new image contains only green, red or black pixels. During the conversion processes, we also calculated the ratio of red pixels over green pixels for each image. That ratio was then used to define the degree of late blight infestation of each leaf.

The step-to-step, from the original digital image until the definition of infestation degree of a single leaf, is conducted as follows:

1. A JPEG image of a leaf, took in the open field, has its definition reduced, is mean-filtered and processed into a text file that contains, for each pixel, its x and y coordinates, RGB values, and HSL values.
2. Each line of the text file generated in step 1 was converted into a register in a CSV spreadsheet. Each column, or variable, from the spreadsheet is linearly normalized.
3. Each record from the CSV file is presented to both ANN's, already trained, and a new text file is built. That last file contains, for each pixel, only its x and y coonrdinates, and its final class, assigned from the combination of answers of the two ANN's , as follows:

3.1. The responses of each ANN are rounded to fit to zero or one.

3.2. If the *green*-ANN response is greater than the *red*-ANN response, which corresponds to an answer equal to 1 for the *green*-ANN and 0 for the *red*-ANN, the pixel will be classified as *healthy*, and will be converted into just green, or RGB=(0,255,0).

3.3. If the *red*-ANN response is greater than the *green*-ANN response, which corresponds to an answer equal to 1 for the *red*-ANN and 0 for the *green*-ANN, the pixel will be classified as *injured*, and will be converted ito just red, or RGB=(255,0,0).

3.4. If the *red*-ANN and *green*-ANN answers are equal, which corresponds to both answers being equal to 1, or equal to 0, the pixel will be classified as *background* and will be turned to black, or RGB=(0,0,0). .

4. The text file constructed, for each image, in step 3 was used to reconstruct the JPEG image, and to generate the classification, based on [21], of the whole image (Table I), as shown in (1):

$$injured\ level = \frac{number\ of\ injured\ pixels}{total\ number\ of\ leaf\ pixels} \times 100 \quad (1)$$

In (1), the *total number of leaf pixels* accounts only for pixels belonging to the leaf itself (healthy plus injured), despising all background pixels, whereas the *injured level* indicates the percentage of injured areas over one leaf. We did not count black pixels, as they were not relevant to the final goal, which is to discover the damage extension over the leaf. Fig. 2 shows some examples of original images and their respective codified images.

TABLE II
CLASSIFICATION KEY FOR EACH RANGE OF INFESTATION [21].

Class	0	1	2	3	4	5	6
% of infestation	≈ 0	≈ 3	≈ 12	≈ 22	≈ 40	≈ 60	≈ 77

The system as a whole has been tested using images taken in the experimental field. The results were very satisfactory, but we faced some problems when processing the images. The first problem was with the areas with high luminosity, where all pixels tended to be classified as red, no matter the original color. To solve this, we decided to remove the L (luminosity) component from the ANN's inputs, and this minimized the problem. After that, we conducted a relevant analysis of all five remaining parameters, which resulted in the elimination of the G (green) and the B (blue) components from the input records of the red-ANN. That analysis, based on Bayes' Theorem, used the same approach presented in [13], [14], and [35] and will not be explained here due to scope limitations. After that adjustment, the final performance improved in more than 30%.

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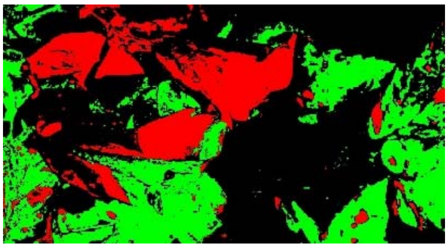
(a)

(b)

(c)



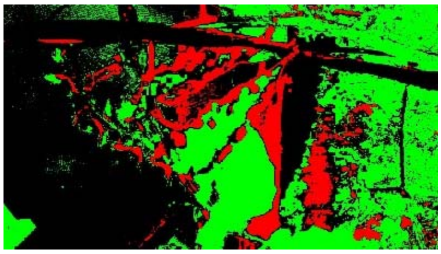
(d)

Fig. 2 Examples of injured leaves from tomatoes, taken in our experimental field, infected by *P. infestans*. The images illustrate the images before and after the classification process. (a) was accounted as having a 15% of damage, whereas (d) was accounted for 32%. It is important to notice that the account was made considering the whole group of leave captured by the camera, that was considered to belong to the same plant

(a)

(b)

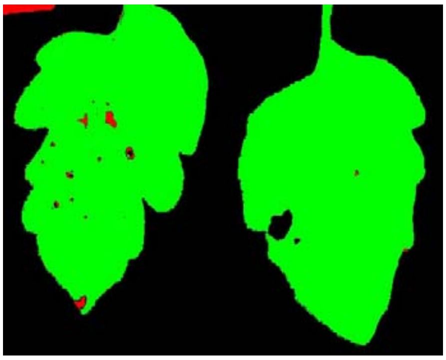
(c)



(d)

Fig. 3 Examples of misclassified pixels, due to the high level of noise of the image. (a) was accounted as having a 5% of damage, whereas (d) was accounted for 26%.

(a)



(b)

Fig. 4 Examples of noise elimination by adding a white background

Another problem we faced was the noise level of images, as the occurrence of tomatoes fruits in the picture, which were always classified as red. With the occurrence of that kind of noise, the estimative of the infestation level of the plant was always overestimated. Some examples of those problems are shown in Fig. 3. However, most of the pictures processed by the system have a considerable number of background elements that cause interference on the classification process. Even after we have reduced the noise by the mean-filtering process, these background elements remained, sometimes with the same color tonalities of the healthy areas, and sometimes with the same color tonalities of the sick areas of the plants. We have also tested what happens when we take the photos using a white background (for instance, using a sheet of paper to isolate the leaf). When doing that, we easily eliminate both problems, bringing the results to an optimal level, as shown in Fig. 4. Despite that, our goal is to use a drone to take the photos in the future so, in our next studies, we will try to deal automatically with those problems.

V. Conclusions

This paper presented and evaluated a computational approach for detecting the most common tomato disease all over the world, where the experiments conducted were based on images taken at an open environment of tomato farms. The pattern recognition of late blight using the neural networks paradigm presented an effective performance, with results in classification that were similar to the results given by human experts [21].

Our approach was to convert the original JPEG images into codified red/green images, what proved to be effective in highlighting the injuries of the leaves [29]. On the other hand, the codification process was able to overcome problems such as low resolution, focus, and image blur of the digital images, with no need to use more sophisticated digital image algorithms (e.g. contour detection).

Once we have worked with images captured in the field, in natural sunlight and taken by cell phones cameras, it was expected that they contain a large amount of noise. As future work, we will include more image filtering processes, aiming at noise removal or attenuation. We are currently working in a module that uses the low-pass Median Filtering, and some Background Subtraction techniques to improve the data quality, and the results will be present soon.

We estimate that this research is a suitable contribution to help small farmers in the early detection of late blight. Currently, the only effective way to combat late blight is by using pesticides, but we are facing the emergence of resistant fungus variants, making the control of this disease increasingly difficult [36], [37]. The alternative we presented can accelerate the identification of the disease and help measuring the extension of the infestation. This can help small farmers to plan better for when to begin the spraying of fungicides, protecting the environment while reducing the plantation costs.

References

[1] IBGE (Instituto Brasileiro de Geografia e Estatística). *Sistema IBGE de Recuperação Automática - SIDRA*, Retrieved from http://www.sidra.ibge.gov.br/bda/agric/default.asp?z=t&o=11&i=P, in October 18, 2016.

[2] MAPA (Ministério da Agricultura Pecuária e Abastecimento), *Estatísticas e Dados Básicos de Economia Agrícola*, Retrieved from http://www.agricultura.gov.br/arq_editor/Pasta%20de%20Setembro%20-%202016.pdf, in October 10, 2016.

[3] E. M. Neves, L. Rodrigues, M. Dayoub, and D. S. Dragone, "Bataticultura: dispêndios com defensivos agrícolas no quinquênio 1997-2001," *Batata Show*, vol. 6, pp. 22-23, 2003.

[4] F. Zamberlan, et al., "Produção e manejo agrícola: impactos e desafios para sustentabilidade ambiental," *Engenharia Sanitária Ambiental*, Edição Especial, pp. 95-100, 2014.

[5] F. C. Bauer and F. M. Vargas Jr., "Fitossanidade e produção agrícola," *Produção e Gestão Agroindustrial*. Campo Grande: UNIDERP: ch. 44, 2005.

[6] D. Tilman, et al., "Agricultural sustainability and intensive production practices," *Nature*, Aug 8, 418(6898), pp.: 671-677, 2002.

[7] E. Rembialkowska, "Quality of plant products from organic agriculture," *J. Sci. Food Agric*., vol. 87, pp.:2757–2762, 2007.

[8] E.S.G. Mizubuti, J.M.N. Maziero, L.A. Maffía, F. Haddad, and M.A Lima, "CGTE Program: Simulation, Epidemiology and Management of Late Blight," in *Global Initiative on Late Blight Conference*, Hamburg, Germany, 2002.

[9] USDA (United States Department of Agriculture), *USABlight Project*, Retrieved from https://usablight.org/node/29, in October 4, 2016.

[10] W.F. Becker, "Validação de dois sistemas de previsão para o controle da requeima do tomateiro na região de Caçador, SC," *Agropecuária Catarinense*, vol.18, pp. 63-68, 2005.

[11] A. Saxena, B.K. Sarma, and H.B. Singh, "Effect of Azoxystrobin Based Fungicides in Management of Chilli and Tomato Diseases," *Proced. National Academy of Sciences*, India: Springer, 2014.

[12] O. Goufo, T. Mofor, and D. Ngnokam, "High Efficacy of Extracts of Cameroon Plants Against Tomato Late Blight Disease," *Agronomy for Sustainable Development*, vol. 8, INRA, EDP Sciences, pp.567-573, 2008.

[13] G.K. Vianna and S.M.S. Cruz, "Análise inteligente de imagens digitais no monitoramento da requeima em tomateiros," *Anais do IX Congresso Brasileiro de Agroinformática*. Cuiabá, Brazil, 2013.

[14] G.K. Vianna and S.M.S. Cruz, "Redes neurais artificiais aplicadas ao monitoramento da requeima em tomateiros," *Anais do X Encontro Nacional de Inteligência Artificial e Computacional (ENIAC)*, Fortaleza, Brazil, 2013.

[15] D. Nunes, C. Werly, G.K. Vianna, and S.M.S. Cruz. "Early Discovery of Tomato Foliage Diseases Based on Data Provenance and Pattern Recognition," *5th International Provenance and Annotation Workshop (IPAW)*. Cologne, Germany, 2014.

[16] N. Zhanga, M. Wangb, and N. Wanga, "Precision agriculture-a worldwide overview," *Computers and Electronics in Agriculture*. vol. 36, issues 2-3, pp.:113-132, 2002.

[17] B.M. Whelan, A.B. McBratney, and B.C. Boydell, "The Impact of Precision Agriculture". *Proceedings of the ABARE Outlook Conference*: *'The Future of Cropping in NW NSW'*, p. 5, Moree, UK, 1997.

[18] S. Sankaran, A. Mishraa, R. Ehsani, and C. Davis, "A review of advanced techniques for detecting plant diseases," *Computers and Electronics in Agriculture*, vol. 72, n.1, pp.:1-13, 2010.
[19] A.K. Mahlein, E.-C. Oerke, U. Steiner, and H.-W. Dehne, "Recent advances in sensing plant diseases for precision crop protection," *European Journal of Plant Pathology*, vol. 133, n.1, pp.:197-209, 2012.
[20] R. Bugiani, et al., "Monitoring airborne concentrations of sporangia of Phytophthora infestans in relation to tomato late blight in Emilia Romagna, Italy," *International Journal of Aerobiology*, vol. 11, pp.:41-46, Elsevier Science, 1995.
[21] F.M. Correa, J.S.S. Bueno Filho, and M.G.F. Carmo, "Comparison of three diagrammatic keys for the quantification of late blight in tomato leaves," *Plant Pathology*, vol. 58, pp.:1128-1133,2009.
[22] J.R. Macedo, C.L. Capeche, A. Melo da S., and S.B. Bhering, "Recomendações Técnicas para a Produção do Tomate Ecologicamente Cultivado," *Manejo do Solo - Circular Técnica*, vol. 33. Rio de Janeiro: Embrapa Solos, 2005.
[23] F.A.R. Filgueira, *O novo manual de olericultura*, 3rd ed., Viçosa: Editora da UFV, 2008.
[24] J.C.A. Barbedo, "Digital image processing techniques for detecting, quantifying and classifying plant diseases," *SpringerPlus*, 2:660, 2013.
[25] A. Vibhute and S.K. Bodhe, "Applications of image processing in agriculture: a survey," *International Journal of Computer Applications*, vol. 52, n.2, pp.:34-40, 2012.
[26] R. Zwiggelaar, "A review of spectral properties of plants and their potential use for crop/weed discrimination in row-crops," *Crop Protect*, vol. 17 (3), pp.:189–206, 1998.
[27] R.B. Brown and S.D. Noble, "Site-specific weed management: sensing requirements—what do we need to see?," *Weed Sci*., vol. 53, pp.:252–258, 2005.
[28] I.M. Scotford and P.C.H. Miller, "Applications of spectral reflectance techniques in Northern European cereal production: a review," *Biosyst. Eng*., vol. 90, n.3, pp.:235–250, 2005.
[29] C.H. Bock, G.H. Poole, P.E. Parker, and T.R. Gottwald, "Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging," *Critical Reviews in Plant Sciences*, vol. 29, n. 1-3, pp.:59–107, 2010.
[30] M.S. Nixon and A.S Aguado, *Feature Extraction and Image Processing*, 2nd Ed, Elsevier Ltd, 2008.
[31] H. Freeman, "Boundary encoding and processing," *Picture Processing and Psychopictorics*, B.S. Lipkin and A. Rosenfeld, Editors, Academic Press: New York, pp. 241-266, 1970.
[32] R.C. Gonzalez and R.E. Woods, *Digital Image Processing*, 3rd Ed, Prentice-Hall, 2008.
[33] A. Conci, E. Azevedo and F.R. Leta, *Computação Gráfica*. Teoria e Prática. Rio de Janeiro: Ed. Campus, vol 2, 2007.
[34] Sevarac, Z. "*Neuroph - Java neural network framework*". Retrieved from http://neuroph.sourceforge.net/, in January, 2012.
[35] G.K. Vianna and A.C. Thomé, "Neuro-fuzzy system for diagnosis of engines, based on oil aamples analysis," *Annals of 4th World Multiconference on Systemics, Cybernetics and Informatics*, Florida, USA, pp.290-295, 2000.
[36] C. Zhang, et al. "Fine mapping of the Ph-3 gene conferring resistance to late blight (Phytophthora infestans) in tomato," *Theor. Appl. Genet.*, vol. 126, Springer-Verlag, pp.:2643-2653, 2013.
[37] D.H. Park, Y. Zhang, and B.S. Kim, "Improvement of resistance to late blight in hybrid tomato," *Hort. Environm. Biotechnol*, vol. 55(2), Springer, pp.:120-124, 2014.