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Automated Plant Disease Analysis

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ABSTRACT

We propose and experimentally evaluate a software solution for automatic detection and classification of plant leaf diseases. The proposed solution is an improvement to the solution proposed in [1] as it provides faster and more accurate solution. The developed processing scheme consists of four main phases as in [1]. The following two steps are added successively after the segmentation phase. In the first step we identify the mostly green coloured pixels. Next, these pixels are masked based on specific threshold values that are computed using Otsu's method, then those mostly green pixels are masked. The other additional step is that the pixels with zeros red, green and blue values and the pixels on the boundaries of the infected cluster (object) were completely removed. The experimental results demonstrate that the proposed technique is a robust technique for the detection of plant leaves diseases. The developed algorithms efficiency can successfully detect and classify the examined diseases with a precision between 83% and 94%, and can achieve 20% speedup over the approach proposed in [1]. General Terms Artificial Intelligence, Image Processing.

Keywords: Image processing; Plant disease detection; Classification

I. INTRODUCTION

Agriculture has become much more than simply a means to feed ever growing populations. Plants have become an important source of energy, and are a fundamental piece in the puzzle to solve the problem of global warming. There are several diseases that affect plants with the potential to cause devastating economic, social and ecological losses. In this context, diagnosing diseases in an accurate and timely way is of the utmost importance.

There are several ways to detect plant pathologies. Some diseases do not have any visible symptoms associated, or those appear only when it is too late to act. In those cases, normally some kind of sophisticated analysis, usually by means of powerful microscopes, is necessary. In other cases, the signs can only be detected in parts of the electromagnetic spectrum that are not visible to humans. A common approach in this case is the use of remote sensing techniques that explore multi and hyperspectral image captures. The methods that adopt this approach often employ digital image processing tools to achieve their goals. However, due to their many peculiarities and to the extent of the literature on the subject, they will not be treated in this paper. A large amount of information on the subject can be found in the papers by Bock et al. (2010), Mahlein et al. (2012) and Sankaran et al. (2010).

Most diseases, however, generate some kind of manifestation in the visible spectrum. In the vast majority of the cases, the diagnosis, or at least a first guess about the disease, is performed visually by humans. Trained raters may be efficient in recognizing and quantifying diseases, however they have associated some disadvantages that may harm the efforts in many cases. Bock et al. (2010) list some of those disadvantages:

- Raters may tire and lose concentration, thus decreasing their accuracy.
- There can be substantial inter- and intra-rater variability (subjectivity).
- There is a need to develop standard area diagrams to aide assessment.

- Training may need to be repeated to maintain quality. Raters are expensive.
- Visual rating can be destructive if samples are collected in the field for assessment later in the laboratory.
- Raters are prone to various illusions (for example, lesion number/size and area infected).

Besides those disadvantages, it is important to consider that some crops may extend for extremely large areas, making monitoring a challenging task.

Depending on the application, many of those problems may be solved, or at least reduced, by the use of digital images combined with some kind of image processing and, in some cases, pattern recognition and automatic classification tools. Many systems have been proposed in the last three decades, and this paper tries to organize and present those in a meaningful and useful way, as will be seen in the next section. Some critical remarks about the directions taken by the researches on this subject are presented in the concluding section.

Vegetable pathologies may manifest in different parts of the plant. There are methods exploring visual cues present in almost all of those parts, like roots (Smith and Dickson 1991), kernels (Ahmad et al. 1999), fruits (Aleixos et al. 2002; Corkidi et al. 2005; López-García et al. 2010), stems and leaves. As commented before, this work concentrates in the latter two, particularly leaves.

This section is divided into three subsections according to the main purpose of the proposed methods. The subsections, in turn, are divided according to the main technical solution employed in the algorithm. A summarizing table containing information about the cultures considered and technical solutions adopted by each work is presented in the concluding section.

Some characteristics are shared by most methods presented in this section: the images are captured using consumer-level cameras in a controlled laboratory environment, and the format used for the images is RGB quantized with 8 bits. Therefore, unless stated otherwise, those are the conditions under which the described methods operate. Also, virtually all methods cited in this paper apply some kind of preprocessing to clean up the images, thus this information will be omitted from now on, unless some peculiarity warrants more detailing.

II. METHODS AND MATERIAL

The overall concept that is the framework for any vision related algorithm of image classification is almost the same. First, the digital images are acquired from the environment using a digital camera. Then image-processing techniques are applied to the acquired images to extract useful features that are necessary for further analysis. After that, several analytical discriminating techniques are used to classify the images according to the specific problem at hand. Figure 1 depicts the basic procedure of the proposed vision-based detection algorithm in this research.

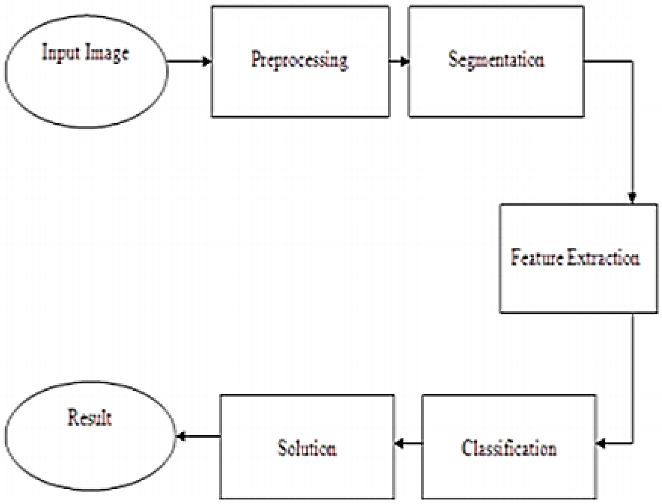


Figure 1. System Design

Image Pre-processing

We convert the input RGB image into HSV(Hue Saturation Value) format using rgb2hsv command. After this transformation we consider only Hue component. We will not consider saturation and intensity component. Because it does not provide any useful information.

$$\text{Hue (H)} = \begin{cases} \emptyset & \text{if } B \le G \\ 360 - \emptyset & \text{if } B > G \end{cases}$$

$$\emptyset = \cos^{-1}\left\{\frac{1/2[(R-G)+(R-B)]}{[(R-G)^2+(R-G)(G-B)]^2}\right\}$$

Hue saturation Value:

HSV color space is preferred manipulation of Hue and saturation(to shift color or adjust amount of color). To convert RGB colormap to HSV colormap.

Cmap=rgb2hsv(M)

Hsv image=rgb2hsv(rgb_image)

convert an RGB colormap M to an HSV colormap Cmap. Both colormaps are m –by-3 matrix. The element of both colormap are in range 0 to 1. The columns of input matrix M represent intensities of red,green,blue respectively. The columns of output matrix Cmap represent Hue,saturation & Value respectively. Hsv image=rgb2hsv(rgb_image) converts the RGB image to the equivalent HSV image. RGB is an m-by-n-by-3 image array whose three planes contain the red,green,blue components for the image. HSV is returned as an m-by-n-by- 3 image array whose three planes contain the Hue, saturation, value components for the image.

K-means Clustering Technique

There are two preprocessing steps that are needed in order to implement the K-means clustering algorithm: The phase starts first by creating device-independent color space transformation structure. In a device independent color space, the coordinates used to specify the color will produce the same color regardless of the device used to draw it. Thus, we created the color transformation structure that defines the color space conversion. Then, we applied the device-independent color space transformation, which converts the color values in the image to the color space specified in the color transformation structure. The color transformation structure specifies various parameters of the transformation. A *device dependent color space* is the one where the resultant color depends on the equipment used to produce it. For example the color produced using pixel with a given RGB values will be altered as the brightness and contrast on the display device used. Thus the RGB system is a color space that is dependent.

Features Extraction

In the proposed approach, the method adopted for extracting

Features Identification

The following features set were computed for the components H and S:

The angular moment (E) is used to measure the homogeneity of the image, and is defined as shown in Equation 8.

$$E = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}[p(i,j)]^2$$

The produc moment (cov) is analogous to the covariance of the intensity co-occurance matrix and is defined as shown in Equation 9.

$$cov = \sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}(i - I_2)(j - I_2)P(i,j)$$

The sum and difference entropies (se and de) which are computed using Equations 10 and 11 respectively.

$$se = \sum_{k=0}^{2(N_g-1)} P_{x+y}(k)\ lnP_{x+y}(k)$$

$$de = \sum_{k=0}^{N_g-1} P_{x-y}(k)\ lnP_{x-y}(k)$$

The entropy feature (e) is a measure of the amount of order in an image, and is computed as as defined in Equation 12.

$$\sum_{i=0}^{N_g-1}\sum_{j=0}^{N_g-1}$$

III. RESULTS AND DISCUSSION

In this section, the result of the stages involved in detection of the Leaf blast disease was shown:

Normal and Infected Image

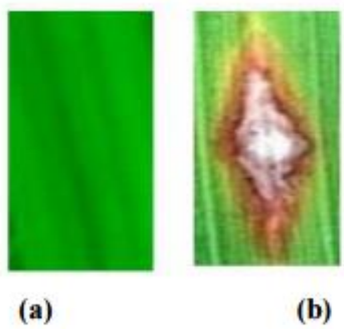
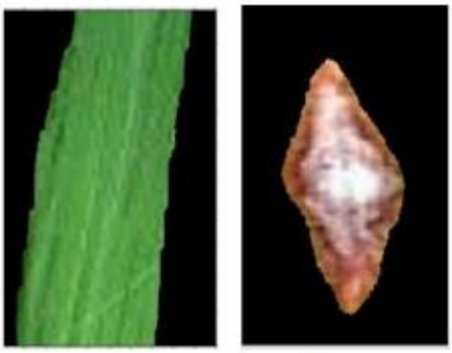


Figure 2. Input Image (a) Normal leaf (b) Infected leaf

Image Preprocessing

Figure 3. Contrast Enchancement

Segmentation Output



(a) (b)

Figure 4. Segmented Image (a) Normal image (b) Infected image

Classification Output

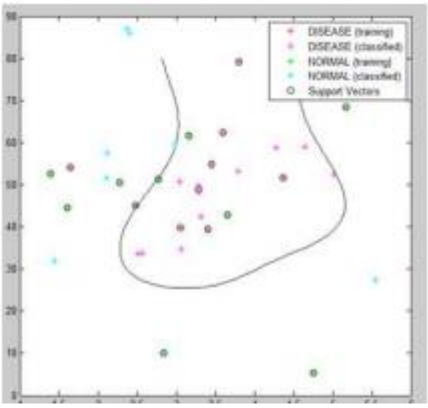


Figure 5. SVM Output

IV. CONCLUSION

In this paper, respectively, the applications of K-means clustering and Support Vector Machine (SVMs) have been formulated for clustering and classification of diseases that affect on plant leaves. Recognizing the disease is mainly the purpose of the proposed approach. Thus, the proposed Algorithm was tested on four diseases which influence on the plants; they are: Early scorch, Cottony mold, ashen mold, late scorch, tiny whiteness. The experimental results indicate that the proposed approach is a valuable approach, which can significantly support an accurate detection of leaf diseases in a little computational effort.

V. REFERENCES

[1]. T., Al-Bashish, D., M. Braik and S. Bani-Ahmad, 2011. Detection and classification of leaf diseases using Kmeans-based segmentation and neural-networks-based classification. Inform. Technol. J., 10: 267-275. DOI: 10.3923/itj.2011.267.275

[2]. Aldrich, B.; Desai, M. (1994) "Application of spatial grey level dependence methods to digitized mammograms," Image Analysis and Interpretation, 1994., Proceedings of the IEEE Southwest Symposium on, vol., no., pp.100-105, 21-24 Apr 1994. DOI: 10.1109/IAI.1994.336675

[3]. Ali, S. A., Sulaiman, N., Mustapha, A. and Mustapha, N., (2009). K-means clustering to improve the accuracy of decision tree response classification. Inform. Technol. J., 8: 1256-1262. DOI: 10.3923/itj.2009.1256.1262

[4]. Bauer, S. D.; Korc, F., Förstner, W. (2009): Investigation into the classification of diseases of sugar beet leaves using multispectral images. In: E.J. van Henten, D. Goense and C. Lokhorst: Precision agriculture ‟09. Wageningen Academic Publishers, p. 229-238. URL: http://www. precision-crop-protection.unibonn.de/gk_research/ project.php?project=3_09

[5]. Camargo, A. and Smith, J. S., (2009). An imageprocessing based algorithm to automatically identify plant disease visual symptoms, Biosystems Engineering, Volume 102, Issue 1, January 2009, Pages 9-21, ISSN 1537-5110, DOI: 10.1016/j.biosystemseng.2008.09.030.

[6]. Ford, A. and Roberts, A., (2010) Colour Space Conversions, August 11, 1998. http:// www.poynton.com/PDFs/coloureq.pdf, viewed on May 2010.

[7]. Hartigan, J. A.; Wong, M. A. (1979). "Algorithm AS 136: A K-Means Clustering Algorithm". Journal of the Royal Statistical Society, Series C (Applied Statistics) 28 (1): 100–108.

[8]. Hillnhuetter, C. and A.-K. Mahlein, Early detection and localisation of sugar beet diseases:

new approaches, Gesunde Pfianzen 60 (4) (2008), pp. 143–149.

[9]. Jun, W. and S. Wang, (2008). Image thresholding using weighted parzen-window estimation. J. Applied Sci., 8: 772-779. DOI: 10.3923/jas.2008.772.779. URL: http://scialert.net /abstract/?doi=jas.2008.772.779

[10]. MacQueen, J.. (1967). Some methods for classification and analysis of multivariate observations. In L. M. LeCam and J. Neyman, editors, Proceedings of the Fifth Berkeley Symposium on Mathematical Statistics and Probability, volume 1, pages 281--297, Berkeley, CA, 1967. University of California Press. URL: http://projecteuclid.org/DPubS?service=UI&version=1.0 &verb=Display&handle=euclid.bsmsp/1200512992.

[11]. Martinez, A., (2007). 2007 Georgia Plant Disease Loss Estimates. http://www.caes.uga.edu /Publications/ displayHTML.cfm?pk_id=7762. Viewed on Saturday, 15, January, 2011.

[12]. Otsu, N. (1979). "A threshold selection method from gray-level histograms". IEEE Trans. Sys., Man., Cyber. 9: 62–66. DOI:10.1109/TSMC.1979.4310076.