Scientific Papers. Series B, Horticulture. Vol. LXIII, No. 1, 2019
Print ISSN 2285-5653, CD-ROM ISSN 2285-5661, Online ISSN 2286-1580, ISSN-L 2285-5653

GRAPES' LEAVES DISEASE DETECTION THROUGH IMAGE PROCESSING

Rodica SOBOLU[1], Mirela CORDEA[1], Ioana POP[1], Daniela POPESCU[2], Dana PUSTA[1]

[1]University of Agricultural Sciences and Veterinary Medicine of Cluj-Napoca, 3-5 Calea Manastur St., Cluj-Napoca, Cluj, Romania
[2]SC Jidvei SRL, Research Department, 45 Garii St., Jidvei, Alba, Romania

Corresponding author email: mcordea@usamvcluj.ro

Abstract

Automatic detection of vineyards' Downey Mildew based on image processing techniques provides better results compare to visual observation performed by farmers. This technique can detect leaf attack even in the onset phase and it can prevent the spread of infection throughout the vineyard. In addition, this technique can be implemented into relative giant fields, requires a reduced amount of time, lower costs and identifies the disease fast and accurate. In this work, we monitored the degree of attack of two cultivars of vines, Sauvignon Blanc and Fetească Regală, from the vineyard of UASMV Cluj-Napoca. The images taken from the vineyard were loaded into the Matlab application. In the first stage, leaves were preprocessed with a median filter. In the next step, in order to detect the typical spots, we transformed the images into color spaces: RGB, YcbCr, HSV and CieLab. In these color spaces we applied the image segmentation techniques based on threshold methods. The experimental results obtained show that in HSV model space the disease was quite correctly recognized and Sauvignon Blanc variety was most severely affected.

Key words: *Downy Mildew, image processing, intelligent viticulture, segmentation.*

INTRODUCTION

Downy mildew is a very destructive fungal disease of grapes caused by the *Plasmopara viticola* pathogen. It has the capability to develop and spread very quickly and according to the weather conditions can causes crop losses. Is important that farmers to be able to correctly identify early infections of the disease so that the appropriate remedial treatments can be applied. Farmers must also decide how often to apply pesticides and what types of substances to use. They also need to reduce the number of splashes in order to reduce costs and environmental pollution, but in the meantime to minimize the risk of downy mildew infection.

Excessive application of synthetic chemicals implies additional costs for vine growers, pollutes the environment and causes a lot of negative consequences which finally may affect the human health.

Grapevines are one of the most widely grown fruit crops in the world with significant surfaces in Romania, about 180 ha. Romania ranks 5th in the EU on the cultivated surfaces with vines (www.zf.ro). Grapes are used in the production of wine, brandy, or non-fermented drinks and are eaten fresh or dried as raisins. Intelligent viticulture is a solution for a healthy and friendly environment that optimizes the quality and quantity of production by minimizing costs, human intervention and variation caused by the unpredictable nature. In the context of the implementation of Directive 128/2009/EC regulating integrated pesticide management in order to reduce their negative impact on human health and the environment, several European countries have already adopted support systems for the detection of diseases affecting different cultures, as well as for decision making in the application of pesticides/fungicides (Belkaroui et al., 2018; Perez-Exposito et al., 2018, Orlandini et al., 1993, Prevostini at al., 2015).

The potential offered by image processing plays an essential role in the automation of viticulture management: the preparation of the phytosanitary treatment plan, the identification of the onset of the phenological phases, the determination of the time needed for the application of the irrigation, the assessment of new cultivars and the efficiency of the grapevine management practices.

The information extracted from image processing has the potential to train viticulture management, so that in the future it becomes as close as possible to reality.

A lot of current studies have embraced the advanced technology of digital image processing in order to obtain quick and accurate decisions about the degree of damage attack on some crops, such as: grapevine (Sushil, 2016; Saradhambal, 2018; Tuba et al., 2017), cucumbers (Wei et al., 2018), roses (Tuba et al., 2017), apple, grapes and mango fruits disease detection (Sandesh et al., 2017), sugarcane (Prajakta et. al, 2016), cotton (Naik et al., 2015).

Downy Mildew is a highly destructive disease of grapevines in all grape-growing areas of the world where, in spring and summer, it rains at temperatures between 11ºC - 24 ºC.

Early in the spring season, the vine leaves infected with *Downy Mildew* shows lesions on their upper surface. As these lesions progress, the affected areas become brown, necrotic or mottled. The most attacked leaves may curl and fall from the grapevine. The disease expands on older leaves in late summer and autumn, producing a mosaic of small, angular, yellow to red-brown spots on the upper leaf surface (Sushil, 2016). As the harmful effects of *Downy Mildew* propagate in the production of the next season, prompt intervention is required with appropriate treatment at the right moment to prevent and reduce these damages, in terms of quality, quantity and finance. Diagnosis of *Downy Mildew* based on image processing and leaves pattern recognition can be implemented into relative giant fields, requires a reduced amount of time, lower costs and identifies the disease fast and accurate compare to visual observation performed by farmers.

In this context, the goal of this work is to identify and classify the degree of attack with *Downy Mildew* disease of two cultivars of vines, *Sauvignon Blanc* and *Fetească Regală*, from UASVM Cluj-Napoca vineyard.

MATERIALS AND METHODS

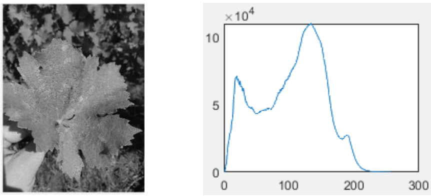
The main purpose of this work is to identify the leaf disease severity on grapevine infected by *Downy Mildew*. Disease intensity is a generic term used for quantifying the amount of disease per sampling units. The percentage of disease severity is defined as the diseased leaf area, l^2 divided by the total leaf area L^2, all multiplied by 100, $[(l^2/L^2) \times 100]$.

The experiments were carried out at the vineyard of UASVM Cluj-Napoca. Ten grapevine leaves of the *Sauvignon Blanc* variety respectively ten grapevine leaves of *Fetească Regală* variety were randomly chosen. Selections samples of infected leaves were considered at the beginning of the first stage of ripening. The colour images of vine leaves are captured using a mobile phones camera. Images are stored in jpg format and were processed with *Matlab2018b* application. *Matlab* is highly-performant software for technical computing that integrates computation, visualization and programming in an easy-to-use environment. *Matlab* stores images as matrices and each element of the matrix represents a pixel of the image. Colour features are very important for plant disease detection.

Image Processing and Computer Vision tool implemented in *Matlab* handles colour images indexed as *RGB* (red, green, blue) images. An *RGB* colour image is an $m \times n \times 3$ array of colours pixels, where each colour pixel is a triplet corresponding to the red, green and blue components of an *RGB* image at a specific spatial location. The data class of the component images determines the data range of values. The range of values of an *RGB* double class image is [0,1] respectively [0,255] for an class uint8 *RGB* image. The number of bits used to represent the pixel values of the component images determines the bit depth of an *RGB* image. The number of possible colours in an *RGB* image is$(2^b)^3$, where b is the number of bits in each component image. A colour model is an abstract mathematical model by which colours are specified, created and visualised. *RGB* colour model refers to the biological processing of colours in the human visual system. They are also others colour models more meaningful for different application categories: *YCbCr*, *HSV*, La*b*, *CMY*. In *YCbCr* colour space, the component *Y* comprises the luminance information, and colour information is stored as two colour difference components, *Cb* and *Cr*. *Cb* represents the difference between the blue

component and a reference value and *Cr* is the difference between the red component and a reference value. *HSV* colour space is a cone – shaped model useful for shading colours. *HSV* (Hue, Saturation, Value) colour model corresponds to the human perception of colour similarity. It is closer than *RGB* model to the way in which human experience describes and perceives colour sensations. Hue describes the dominant colour of the object based on *RGB* colour space, saturation is the degree to which Hue differs from neutral gray (100% is fully saturated and 0% is shade of gray) and value is the height along the central vertical axis.
HSI, a variant of *HSV* colour space takes the intensity component I (brightness of each Hue) from Hue and Saturation information in a colour image. *HSI* model space is an ideal tool for developing image processing algorithms based on colour descriptions that are natural and intuitive to humans. Image processing applications like histogram operations, intensity transformations and convolutions operate are performed much easier on an image in the *HSI* colour space.
Hue and Saturation components taken together are called chromaticity. Chromaticity and brightness are features that help to differentiate one colour from others. The amounts of red, green, and blue included to any particular colour, denoted by X, Y respectively Z represent the tristimulus values. Any colour can be expressed by its trichromatic coefficients, defined as: $x = \frac{X}{X+Y+Z}$, $y = \frac{Y}{X+Y+Z}$, $z = \frac{Z}{X+Y+Z}$, where $x + y + z = 1$.
CIE XYZ colour space is defined by tristimulus values. *Y* component is a measure of brightness and *X* respectively *Z* values can be computed from the *x, y* and *Y* values. *CIE L*a*b** colour space presents two key advantages over *CIE XYZ* space: more clearly separates gray scale information contained in L^* values from colour information (expressed by a^* and b^* values). This space was created so the Euclidian distance corresponds well enough with perceiving differences between colours.
CMY is a main colour model used in the printed industry that uses a uniform mix of cyan, magenta and yellow. The cyan pigment subtracts red light from the light reflected by a surface.

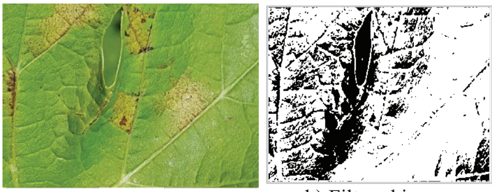
Segmentation is the technique of identifying objects within an image. In this study, we used the image processing tool to achieve segmentation. The following steps were followed to determine the severity of the disease: image pre-processing, image thresholding segmentation. Then, according to the surface of infected area we classified the stage of the disease.
The main objective of image pre-processing is to reduce the influence made by the background, to eliminate the unneeded spots generated by the presence of vein within the plant leaf and to enhance the quality of the image. A 5x5 median filter was used to remove noise spots. Median filter is a nonlinear filter that replaces the value of the central pixel by the median of the grey values of neighbouring pixels. The pattern of neighbours is called the "window", which slides, pixel by pixel over the entire image. This type of filtering involves arranging pixels values in ascending order, then calculating the median value and finally assigning the median value to the window central pixel (Figure 2.b).
The colours features of the sample images are analysed to separate diseased leaf area (spotted area) from the healthy ones. The computer vision technology can identify a wide range of colour spectrum compared to human vision. So, in order to detect the disease spots, applying image processing technique, each sample leaf image have been converted into different colour spaces such as: *RGB , YCbCr, HSV* and *La*b**, using *Image Processing and Computer Vision* application implemented in *Matlab2018b*.
We have done *Downy Mildew* spot detection calculating a threshold value to highlight pixels belonging to the diseased regions. Histograms are a useful tool for grayscale image analysis. It graphically displays the number of pixels at each different intensity value found in that image.
We have analysed the histogram of the intensity grey levels (Figure 2.b). We have got the threshold value as the local minimum point of pixels intensity.



a) Grayscale Image b) Image Histogram

Figure 1.Grayscale image (a) and image histogram (b)

We have performed thresholding image segmentation in the *RGB*, *YCbCr*, *HSV* and La*b* colour spaces. The results are shown in the Figure 3.a), Figure 3.b), Figure 3.c) respectively in the Figure 3.d). We compared the obtained results and we proposed the appropriate space that identified the disease spots most accurately.



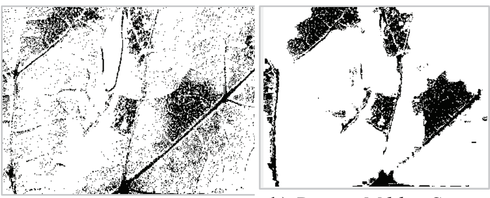
a) Leaf infected with *Downy Mildew* b) Filtered image

Figure 2. Original leaf infected image (a) and filtered image (b)

In order to separate and evaluate the leaf diseased area we applied image segmentation by using *Colour Thresholding* tool implemented in *Matlab2018b Apps*. Figure 4 and Figure 5 show the segmentation results applied for the aim to isolate spot features and their' area.

RESULTS AND DISCUSSIONS

The experimental results of the thresholding image technique applied in the *RGB*, *YCbCr*, *HSV* and *La*b** colour spaces, are shown in Figure 3.



a) *Downy Mildew* Spots detection in *RGB* colour space b) *Downy Mildew* Spots detection in *YCbCr* colour space

c) *Downy Mildew* Detection in *HSV* colour space d) *Downy Mildew* Detection in *La*b** colour space

Figure 3. *Downy Mildew* detection in different colour spaces

Figure 3.a) have demonstrated that the *RGB* colour space is not a suitable model for successful spots detection because of the leaf veins.

In the case of *YCbCr* colour space we have applied threshold segmentation on *Cr* component on filtered *YCbCr* colour image. The results outlined in Figure 3.b) have revealed good spots detection compare to *RGB* colour space. In *YCbCr* colour space, more downy mildew spots were detected that there were in reality.

Threshold segmentation on *H* component considered into *HSV* colour space has proved that the diseases spots were mostly correctly marked compared to the previous spaces. The results are displayed in Figure 3. c).

Also, we have applied threshold segmentation on a* element of *La*b** colour space. In this space the *Downy Mildew* spots have not been fully identified, as shown in Figure 3. d).

In the *HSV* colour space we have perceive better visual recognition of disease spots compared to the other tested spaces because we minimised the noise of samples pictures turning them out of the *RGB* space into the *HSV* colour space. Then, we considered this colour space to identify the degree of disease attack on leaves.

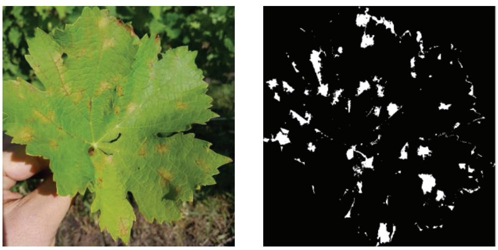


Figure 4. Original image of *Downy Mildew* infected leaf compare to segmentation of spots at *Sauvignon Blanc* variety

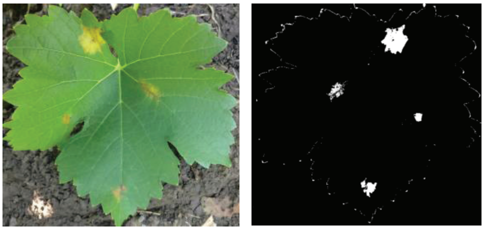


Figure 5. Original image of *Downy Mildew* infected leaf compare to segmentation of spots at *Fetească Regală* variety

The grapevine disease degree of attack is expressed as the percentage of disease spots area to total leaf area. Using *regionprops* function implemented in *Matlab2018b*, we calculated the number of pixels of the infected spots and the number of pixels of the entire leaf. In this way, we identified the level of leaf infection and we expressed it as a percentage. The obtained results relative to the analysed vine varieties are shown in Table1 and respectively in Table2.

Table 1. The percentage of spotted area at *Sauvignon Blanc* Variety

Sauvignon Blanc Variety	Number of pixels in the spotted area	The percentage of spotted area
Sample1	4127429	15.63
Sample2	3851420	15.26
Sample3	4562650	16.44
Sample4	3978367	15.76
Sample5	4689754	16.10
Sample6	4001342	14.50
Sample7	3567980	14.34
Sample8	3456325	14.25
Sample9	4327895	15.95
Sample10	4556705	16.50

Table 2. The percentage of spotted area at *Fetească Regală* Variety

Fetească Regală Variety	Number of pixels in the spotted area	The percentage of spotted area
Sample1	2517685	11.42
Sample2	2978367	12.13
Sample3	2112376	10.84
Sample4	3323504	13.54
Sample5	2055304	10.20
Sample5	1876506	9.20
Sample6	1678000	8.24
Sample7	2023412	9.50
Sample8	1554670	8.70
Sample9	1240005	7.50
Sample10	987453	5.50

The experimental results shown that the *Sauvignon Blanc* variety was most severely affected by *Downy Mildew*.

The leaf surface damaged by *Downy Mildew* expressed as percentage, identified the level of leaf infection. According to the key established by Orlandini et al., 1993, for determination of the *Downy Mildew* intensity on grapevine leaves, ours study detected the stage described as a few oilspots only. The values presented by Orlandini et al., 1993, range between 1-25% for few oil spots only and we obtained values ranging between 5-17%.

CONCLUSIONS

In this paper, we have implemented thresholding image processing algorithms for segmentation of spotted region of *Downy Mildew* disease in grapevine leaves. We have applied the proposed method for the diagnosis of two varieties of vines and we deduced that disease severity level at *Sauvignon Blanc* variety was higher than for the *Fetească Regală*. Image processing based on thresholding technique, applied for extraction of leaf detail, represents an important stage of a complex process of automatic diagnosis and classification of the *Downy Mildew* disease carried out with computer vision technology. This approach can provide *Downy Mildew* forecast and control of disease stage, in real time and accurately. Once implemented this method can be an easy-to-use tool for the farmers and a very efficient one in real time.

Thus, the amount and the frequency of pesticides to be applied can be adjusted. A more effective use of chemicals can improve the environmental performance. The farmers can customize their activities and optimize their resources according to the state of their vineyards. A decision-making system implemented on high-tech platforms, based on technologies applied in every day practices, will help farmers to planning strategies and sharing useful information that can protect their crops and increase their production.

ACKNOWLEDGEMENTS

This research work is funded by the Ministry of Research and Innovation of Romania, Projects for Financing the Excellence in CDI, Contract no. 37PFE/06.11.2018.

REFERENCES

Belkaroui, R., Bertaux, A., Labbani, O., Hugol-Gential, C., Nicolle, C. (2018), Towards Events Ontology Based on Data Sensors Network for Viticulture Domain, *Proceedings of the 8th International Conference on the Internet of Things (iot'18)*, doi: 10.1145/3277593.3277619.

Gonzalez, R.C., Woods, R.E., Eddins, S.L., (2009), Digital Image Processing Using MATLAB, Gatesmark Publishing.

Kumar, A., Sharma, M., Meshram, M.R., (2016), Image processing Based Leaf Disease, Detection of Betel Vine, Procedia Computer Science, 85,784-754.

Naik, D.M., Vyavahare, A.J., (2015), Disease Detection of Cotton crop using Image Processing Technique: A Survey, IJRASET, 3(6), 204-210.

Orlandini, S., Gozzini, B., Rosa, M., Egger, E., Storchi, P., Maracchi, G., Miglietta, F., (1993), PLASMO: a simulation model for control of *Plasmopara viticola* on grapevine, *Bulletin OEPP/EPPO*, 23, 619-626.

Perez-Exposito, J.P., Fernandez-Carames, T.M., Fraga-Lamas, P., Castedo, L., (2018), VineSens: An Eco-Smart Decision-Support Viticulture System, *Sensors*, 17(3), doi:10.3390/s17030465.

Prajakta, M., Priyanka, P., Mira, N., Priyanka, B., Mira, P., Priti, N., (2016), Leaf Disease Detection and Prevention Using Image Processing in Matlab, IJRTER, 2(2), 26-30.

Prevostini, M., Taddeo, A.V.,Germini, Petit, A., M., (2015), Monitoring Scaphoideustitanus and related in-Field Activities: the experience in Switzerland and France using PreDiVine DSS, *Proceedings of IOBC-WPRS Conference of the Working Group on „Integrated Protection and Production in Viticulture",*20th-23rd October, 2015, Vienne, Austria.

Sandesh, R., Amit, F., (2017), Plant Disease Detection in Image Processing Using MATLAB, *IJIRSET*, 6(6), 10373-10381.

Saradhambal, G., (2018), Plant Disease Detection and Its Solution using Image Classification, International *Journal of Pure and Applied Mathematics*, 14(119), 879-883.

Seng, K.P., Ang, L.M., Schmidtke, LM.,Rogiers, S.Y, (2018), Computer Vision and Machine Learning for Viticulture Technology, *IEEE ACCESS*, 6, 67494-67510.

Shen, W., Wu, Y., Chen, Z., Wei, H., (2008), Grading Method of Leaf Spot Desease Based on Image Processing, *Proceedings of Computer Science and Software Engineering*, International Conference, 491-494.

Sushil, R.K., (2016), Detection of Plant Leaf Disease Using Image Processing Approach, *International Journal of Scientific and Research Publications*, 6(2), 73-76.

Tuba, E., Jovanovic, R., Tuba, M., (2017), Plant Diseases Detection Based On Color Features and Kapur's Method, *Wseas Transactions on Information Science and Applications,* 14, 31-39.

Zarco-Tejada, P., Hubbard N., Loudjani, P., (2014), Precision Agriculture: An Opportunity for EU Farmers – Potential Support with the CAP 2014-2020, Study, June, 2014.

Wei, Y., Chang, R., Wang, Y., Liu, H., Du, Y., (2012), A Study of Image Processing on Cucumber Disease, *Springer, IFIP Advances in Information and Communication Technology*, AICT-370, 201-209.

*** https://www.mathworks.com