

Computer vision and artificial intelligence for assessing plant diseases in data-driven agriculture: a case study of downy mildew in grapevine

Javier Tardaguila¹✉, Ines Hernandez¹, Salvador Gutierrez², Ignacio Barrio¹, Ruben Iñiguez¹,
Fernando Palacios¹, María P. Diago¹

¹Televis Research Group, University of La Rioja, Logroño, Spain

²Dep. of Computer Science, University of Cádiz, Puerto Real, Cádiz, Spain

javier.tardaguila@unirioja.es; ines.hernandez@unirioja.es; salvador.gutierrez@uca.es; ignacio.barrio@unirioja.es;
ruben.iniguez@unirioja.es; fernando.palacios@unirioja.es; maria-paz.diago@unirioja.es

Corresponding Author: javier.tardaguila@unirioja.es

Abstract

Downy mildew is an important disease in grapevine, which causes large losses of grape commercial production. The aim of this work was to investigate non-invasive sensing technologies and artificial intelligence applications for assessing downy mildew in grapevine under laboratory and field conditions. Machine vision was applied to assess visual symptoms while hyperspectral imaging was used to explore its potential capability towards an early detection of this disease. Image analysis applied to RGB leaf disk images taken under laboratory conditions was used to estimate downy mildew severity in grapevine (*Vitis vinifera* L.). Under laboratory conditions, a determination coefficient (R^2) of 0.76 and a root mean square error (RMSE) of 20.53% were observed in the correlation between downy mildew severity by computer vision and expert's visual assessment. Furthermore, an accuracy of 81% was achieved for an early detection of downy mildew using hyperspectral images. The classification of images of healthy and infected leaves, assessed on RGB images taken under field conditions yielded an accuracy of 89% using machine learning and deep learning techniques. These results indicated that non-invasive sensing technologies and computer vision can be applied for assessing and quantify visual symptoms of downy mildew in grapevine leaves. Severity of this key grapevine disease can be evaluated under laboratory conditions, but also under field conditions in commercial vineyards. In conclusion, computer vision, machine learning, and deep learning could be applied for key disease detection in grapevine in data-driven viticulture.

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1 Introduction

Plant diseases, pests and weeds cause large losses of food production in agriculture. Traditionally, plant diseases are identified by visual observations by the growers in the field or biological techniques in the laboratory [1]. Nevertheless, these techniques are time-consuming, susceptible to human error and/or require qualified personnel [1, 2]. Non-invasive sensing technologies as RGB (Red, Green and

Blue) images, thermography, multispectral and hyperspectral imaging have been postulated as potential non-invasive technologies for detecting plant diseases in agriculture with several advantages versus conventional methods [1, 2, 3], even detecting diseases when the symptoms are not visible [4]. Computer vision, machine learning, deep learning and artificial intelligence technologies can be applied to identify, classify and quantify crop diseases in data-driven agriculture [5, 6, 7, 8].

In the European project NoPest (Novel Pesticides for a Sustainable Agriculture), non-destructive proximal sensing technologies and artificial intelligence are being developed for assessing fungal diseases in key crops as grapevine and potato. Downy mildew is a key grapevine disease in world viticulture (Figure 1). Nowadays, the evaluation of this disease has been based mostly on visual assessment of leaves in the vineyards or histological analyses at the laboratory [9]. Computer vision and artificial intelligence could be very useful to recognize and quantify some diseases in grapevine [10, 11, 12].



Figure 1: Downy mildew infection in grapevine reflecting the symptoms in leaves (left) and bunch (right).

The aim of this work was to examine non-invasive imaging technologies and artificial intelligence applications for assessing downy mildew in grapevine under laboratory and field conditions in the context of the NoPest project. Computer vision was applied to evaluate visual symptoms while hyperspectral imaging was used for the early detection of downy mildew.

2 Material and Methods

This approach could be separated in three main sections (Figure 2): i) image acquisition under laboratory and field conditions, ii) image processing using computer vision techniques and hyperspectral pre-processing to improve image features and highlight downy mildew symptoms and iii) machine learning modeling, used for the classification of RGB images of healthy and diseased leaves taken under field conditions and for the location of leaf spectra and early detection of disease using hyperspectral imaging.

2.1 Image acquisition under laboratory and field conditions

In laboratory conditions, leaf disks from grapevine (*Vitis vinifera* L., cv. Tempranillo) plants were placed in Petri dishes with the abaxial side up.

Two groups of study were defined: one group was infected with the downy mildew agent (*Plasmopara viticola*) and the other group was used as control. Images were taken in the laboratory every day until nine days after inoculation using a digital RGB camera (Canon EOS 5D, Japan). Additionally, a push broom hyperspectral visible (VIS) camera (spectral range from 400 to 1000 nm) and the hyperspectral near infrared-short wave near infrared (NIR-SWIR) camera (spectral range from 1000 to 1700 nm) were used for early detection of downy mildew under lab conditions (Figure 3). For validation, the percentage of leaf area showing downy mildew sporulation in the leaf disks was visually evaluated by a panel of eight experts.

Under field conditions, images were acquired in a commercial vineyard (*Vitis vinifera* L.) located in the northern Spain. Downy mildew symptoms (Figure 1) were observed in leaves in several grapevine

plants. RGB images of the vineyard canopy were taken manually in the field using a digital camera (Canon EOS 5D, Japan). Furthermore, a push broom hyperspectral visible camera (Resonon, USA) was used for imaging grapevine leaf disks taken under field conditions in the vineyard.

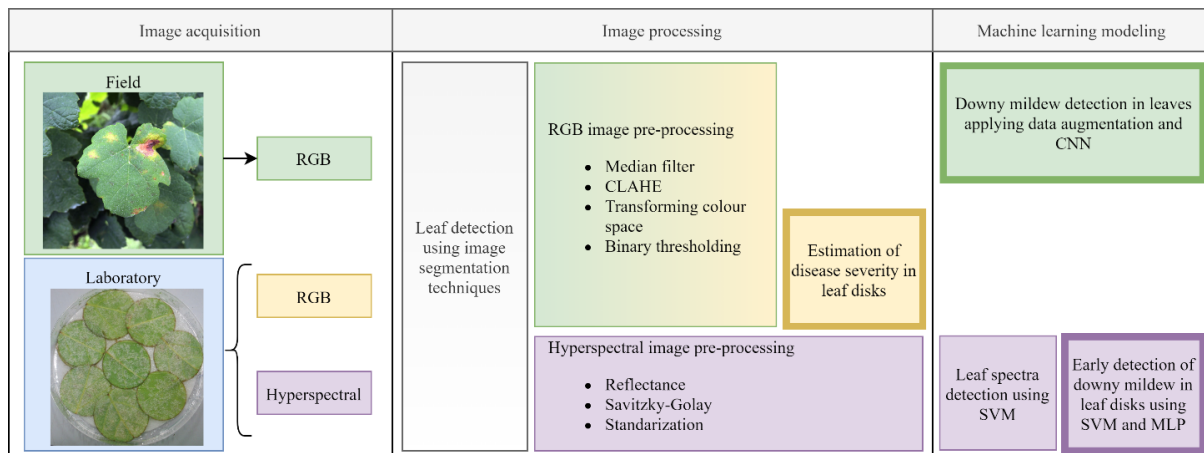


Figure 2: Flowchart of the use of non-invasive sensing technologies for assessing downy mildew in grapevine: RGB images taken under field conditions (green boxes) were used for disease detection, RGB images taken under laboratory conditions (orange boxes) were used for disease severity estimation and hyperspectral images (purple boxes) were applied towards the early detection of the disease.

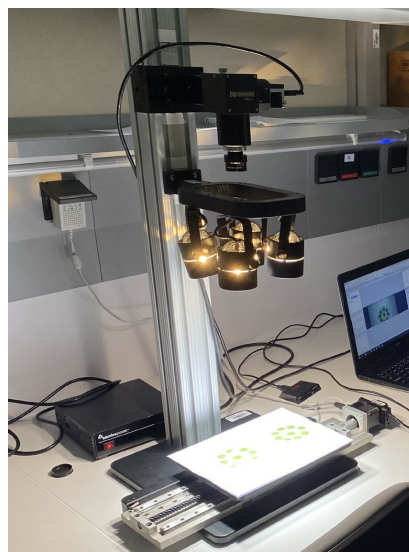


Figure 3: A push broom hyperspectral visible camera (400–1000 nm) used for early detection of downy mildew in grapevine under lab conditions.

2.2 Processing of RGB and hyperspectral images

The RGB images were processed to detect and quantify downy mildew symptoms in grapevine leaves. Different segmentation algorithms were applied to highlight relevant regions of the images.

Watershed [13] was used to separate the leaf disks in the images taken in the laboratory. GrabCut [14] was used to discard the pixels not belonging to the focused leaf in the images taken under field conditions. Classical pre-processing techniques were applied, such as median filter, used to smooth the image, and Contrast Limited Adaptive Histogram Equalization (CLAHE) [15], used to improve contrast. The colour space was transformed to HSV (Hue, Saturation, Value) or HLS (Hue, Lightness, Saturation) to bring the perception of the colour reflected in the digital image closer to the human eye by obtaining separated colour, saturation and brightness values from the red, green and blue values of the images. Depending

on the type of symptoms in the leaves captured in the images, different values of the colour space were considered, with yellowish and reddish colours standing out for symptoms in the adaxial side of the leaf and lower saturation values for symptoms in the abaxial side of the leaf. These symptoms were highlighted using a binary threshold with a specific value and using the Otsu method [16], respectively, thus dividing the pixels representing disease symptoms in the leaves from those of the rest of the leaf (Figure 4). The segmentation of leaf disk images was used to estimate downy mildew severity as the percentage of downy mildew symptoms that appear in the grapevine leaves.

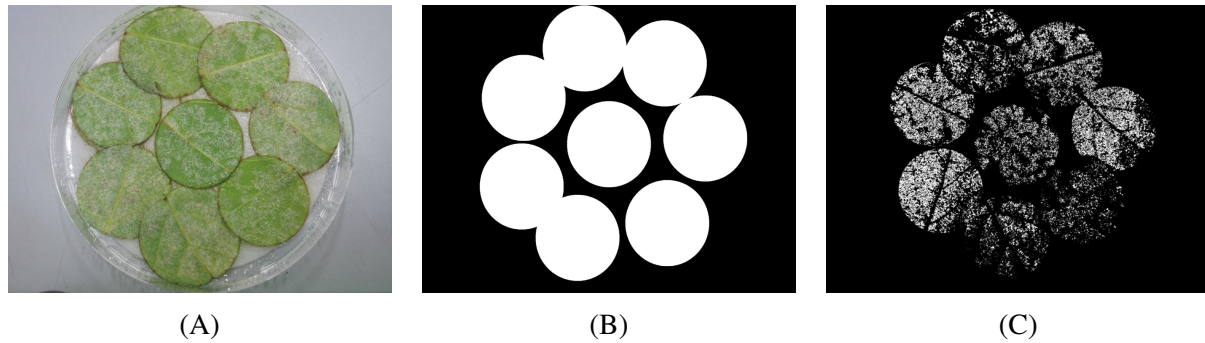


Figure 4: Computer vision was used for assessing downy mildew severity in grapevine leaves. A) Original RGB image B) Background removal and C) Processed image with downy mildew symptoms (in grey) in leaf disks.

On the other hand, hyperspectral images were processed (Figure 5). The values (I) were transformed to reflectance (R) with a dark current (DC) and white reference (WR) values using the following equation:

$$R = \frac{I - DC}{WR - DC} \quad (1)$$

Savitzky-Golay filter [17] was also applied to smooth the spectra of each image, with a grade 2 polynomial and a size 15 window. Finally, a standardization was applied.

2.3 Machine and deep learning modelling

For hyperspectral images, a two-stage machine learning analysis was designed for (i) the detection of spectra belonging to leaves (segmentation) and (ii) modelling and prediction using the leaf spectra as input. The segmentation of the leaves was carried out by manually selecting spectra belonging to the positive class (leaf spectra) and negative class (spectra from the background elements). From these data, a binary classifier was trained using Support Vector Machines (SVMs) and applied for the automated segmentation of all the images.

The modelling for the pathogen detection was done after leaf spectra extraction in the previous step (thus generating the samples) and the training of the machine learning models using SVMs and Multi-layer Perceptrons (MLPs). Both algorithms were validated using a 5-fold cross validation.

For RGB images taken under field conditions, modelling was performed using deep learning techniques. Data augmentation was applied to improve the dataset, adding new artificial images from original ones. Convolutional Neural Networks (CNNs) were used to binary classify leaves with downy mildew symptoms and healthy leaves. The CNN architecture consisted of a block with convolutional, batch normalization and max pooling layers that automatically extract features of images and a block with fully connected, batch normalization and dropout layers that uses these features for image classification. The model was validated with a hold-out approach.

2.4 Implementation

All the experiments were developed with the Python 3.7.4 programming language. The RGB and hyperspectral images acquired under laboratory conditions were processed using the OpenCV 4.2.0.32 and scikit-learn 0.22.2 libraries on an Intel Core i7 4770 CPU (16 GB RAM). On the other hand, RGB images taken under field conditions were processed with a NVIDIA GeForce RTX 2080 Ti GPU (11 GB memory), optimizing the execution of the CNN developed with the Keras 2.3.1 framework and the Tensorflow 2.1.0 backend.

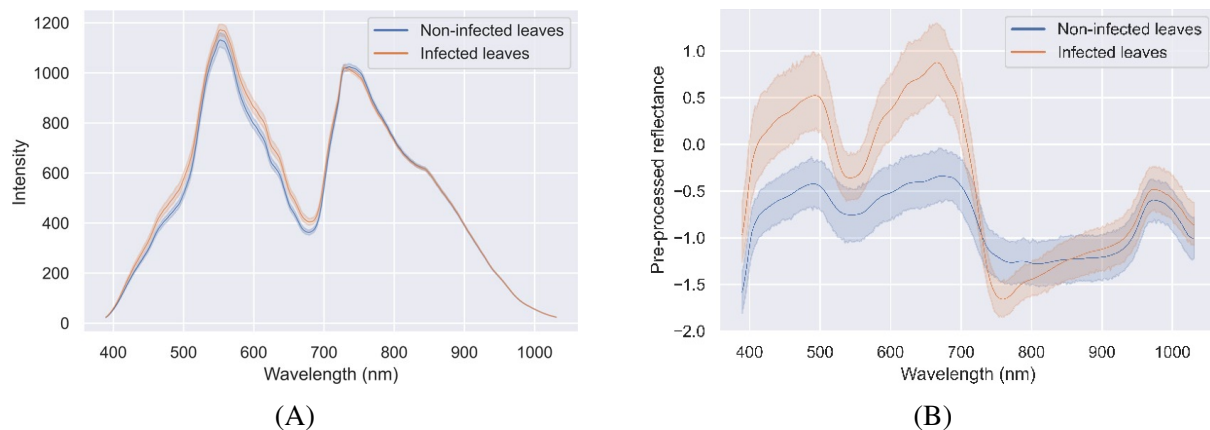


Figure 5: Spectra of non-infected and infected grapevine leaves with downy mildew: A) Original spectra B) Pre-processing spectra by transforming their values to reflectance, applying a Savitzky-Golay filtering and standardization.

3 Results and Discussion

The method employed using computer vision techniques required no training, so its computational cost was low. As well as this method, the one used to classify the hyperspectral images, despite requiring training of the machine learning models, could be executed with a CPU, in less than one hour. On the other hand, for the classification of RGB images taken in the field, a GPU was used to train the CNN, which took several days. This type of neural network has a high computational cost in its training, but its prediction is fast, classifying more than 100 images in less than a minute.

Under laboratory conditions, a strong and significant relationship (determination coefficient of 0.76** and a root mean square error of 20.53%) was observed between downy mildew severity measured using computer vision and visual assessment by the experts in grapevine leaf disks. Additionally, an accuracy of 81% was achieved in the classification of hyperspectral images of grapevine leaves with and without downy mildew symptoms after a few days of the inoculation. Disease severity estimation of downy mildew using simple computer vision techniques obtained similar results to expert evaluation. This severity estimation could consider the expert subjectivity, achieving a greater relationship between automatic and manual assessment, using fuzzy logic [11].

In RGB images taken under field conditions, an accuracy of 89% was obtained in the classification of healthy and infected grapevine plants.

Downy mildew detection using machine learning techniques achieved high accuracies in RGB images and hyperspectral images. These methods could be combined with that used to estimate the severity of the disease to obtain a localisation and quantification of the symptoms or by applying deep learning techniques for image segmentation [7, 18].

These results indicate that computer vision can be applied for assessing and quantify visual symptoms of downy mildew in grapevine leaves. Moreover, hyperspectral imaging could be applied for early detection of this disease in grapevine. Machine learning algorithms can be very useful for downy mildew detection in grapevine, while deep learning techniques can be applied for modelling crop disease incidence. CNNs

were applied to classify healthy and downy mildew leaves with high accuracy in grapevine.

Our results indicate that downy mildew can be evaluated under laboratory conditions but also under field conditions using new sensing technologies and artificial intelligence techniques in data-driven agriculture.

4 Conclusions

New sensing technologies and data analysis have shown promising results for assessing downy mildew disease in grapevine. Computer vision, hyperspectral imaging and artificial intelligence can be applied for monitoring downy mildew in grapevine.

This key disease can be evaluated under laboratory and field conditions in commercial vineyards. These technologies could be also applied in grapevine and in other key commercial crops in data-driven agriculture for reducing yield losses and environmental impact of pesticides.

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