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Data Acquisition for Testing Potential Detection of Flavescence Dorée with a Designed, Affordable Multispectral Camera

Marko Barjaktarović, Massimo Santoni, Michele Faralli, Massimo Bertamini, and Lorenzo Bruzzone

***Abstract* — There is a constant push on agriculture to produce more food and other inputs for different industries. Precision agriculture is essential to meet these demands. The intake of this modern technology is rapidly increasing among large and medium-sized farms. However, small farms still struggle with their adaptation due to the expensive initial costs. A contribution in handling this challenge, this paper presents data gathering for testing an in-house made, cost-effective, multispectral camera to detect Flavescence dorée (FD). FD is a grapevine disease that, in the last few years, has become a major concern for grapevine producers across Europe. As a quarantine disease, mandatory control procedures, such as uprooting infected plants and removing all vineyard if the infection is higher than 20%, lead to an immense economic loss. Therefore, it is critical to detect each diseased plant promptly, thus reducing the expansion of Flavescence dorée. Data from two vineyards near Riva del Garda, Trentino, Italy, was acquired in 2022 using multispectral and hyperspectral cameras. The initial finding showed that there is a possibility to detect Flavescence dorée using Linear discriminant analysis (LDA) with hyperspectral data, obtaining an accuracy of 96.6 %. This result justifies future investigation on the use of multispectral images for Flavescence dorée detection.**

***Keywords* — Flavescence dorée detection, Multispectral and Hyperspectral imaging.**

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I. Introduction

AGRICULTURE is under high pressure to increase production [1] to meet the needs of a population that has more than tripled from 1950 to 2022. At the same time, the expansion of cultivated areas has only been 30% [2], which is why agricultural intensification is necessary to fulfill that growing demand. Intensification includes higher use of inputs such as fertilizers, pesticides, and water. However, it imposes negative environmental impacts, like contamination of drinking water and aquatic ecosystems [3] and reduces economic gain if used in a suboptimal way. Precision agriculture (PA) is an essential tool of sustainable agriculture in the 21st century [4] that seeks to address these issues. PA is a field-specific crop management that relies on measuring and responding to crop variability to maximize yields while reducing environmental impact.

Although there are many measurement devices for observing both proximal and remote crop conditions, the vast majority of data is obtained by multispectral (MS) imaging. The crop status is assessed through vegetation indices, and the Normalized Difference Vegetation Index (NDVI) is the most used indicator of plant health condition [3]. There are diffident ways to acquire MS images, from unmanned aerial vehicles (UAV), airplanes, or satellites, but only satellite images can be obtained free of charge, like from Sentinel 2 constellation. These satellite images have several constraints: although they are available with a frequency of a few days from the same spot on the Earth, typical clouded weather in Europe regions complicates their processing [5]. Next, the resolution (10 m per pixel) can be inefficient for detecting stressed or infected crops due to the fact that the pixel contains only measure of average reflectance in its corresponding area. In addition, open-source software solutions can be challenging for non-expert use, while usage of commercial software for satellite and for drone images (e.g., SkyWatch, Pix4D Additionally, etc.) can be relatively costly for small farm users.

With the widespread use of UAV and MS cameras, issues with resolution and cloud cover can be overcome. This flexible and effective solution became the classical tool for PA, enabling crop status and site-specific application with simple-to-use decision support system. This crop management principle is already widely adopted by large and medium-scale farms. Unfortunately, small farms are struggling with the implementation of PA, primarily due to high initial costs, especially for them in areas with highly fragmented cultivated land, like Greece and Italy [6]. However, small-scale farms count more than 2/3 of all farms in the EU [7], and for them, it is essential to apply PA promptly and to become sustainable, as their importance is not only economical, they contribute to social capital, local knowledge, and cultural heritage [7].

Yield estimation, water and fertilization management, disease monitoring and weed suppression are the most common example of PA usage [8]. Specific PA's application is region-dependent, where someone tries to address local issues. For example, in Trentino (Italy), the most dominant cultivated plants are apples and grapevines. In recent years, grapevine makers, particularly in Mediterranean countries, commonly face a severe epidemic, Flavescence dorée (FD). FD is an incurable, destructive phytoplasma–borne disease spread from one plant to another with grafting or by the leafhopper Scaphoideus titanus Ball. It is regarded as one of the most significant threats to the European wine-production areas and the European economy. In Europe is about 45 % of the world's total wine-growing areas, of which three-quarters belong to Spain, France, and Italy [9]. Uprooting has been causing a significant financial loss for a couple of years since time is needed for new plants to ensure a meaningful yield. Only in 2005, grapevine producers in Italy were compensated with 34 million euros [10].

Additionally, FD's transmission is on a constant increase. For example, from 2003 to 2018, FD advanced from a tiny zone in Piedmont to almost 1/4 of the whole grapevine surface [11]. In Trentino Alto-Adige, in just one year, from 2021 to 2022, the area under FDs is doubled [12]. Therefore, it is crucial to discover even a single infected trunk to prevent the transmission of FD not only inside an inspected vineyard but also to nearby ones [13]. Currently, the only accessible procedure is to observe vineyards for plants with the disease, looking for FD's dominant signs, which are visible in summer, as leaves rolling downwards and becoming reddish or yellowish in red and white cultivars, respectively (Fig. 1). On shoots, there is no lignification, and berries are wilting and drying out [10]. Furthermore, visible symptoms usually express at least one year after infection, with progress in manifestation as the vegetative season goes [5].

Fig. 1. Symptoms of FD in Cabernet Sauvignon (left) and Chardonnay (right).

For the vineyard, scouting is time-consuming and requires trained agronomists, which are missing, so observation is carried out once in one or two years, leaving too much room for FD to expand around [10],[14]. Hence, there is a significant number of requests for an automatic tool in FD discovery. Further, with automatic detection, measures can be applied only to contaminated zones, reducing soil and water pollution compared with the standard procedure that prescribes spraying treatments in the whole vineyard up to 10 times a year [15].

This paper addresses both stated issues, implementation of PA at small farms and possible automatic detection of the FD in the field. Here, preliminary work on designing an affordable multispectral camera, data acquisition in the field, and the first results, which show some potential for discovering FD using hyperspectral imaging, is presented.

As for commercially available MS cameras, a number of different spectral bands dictates prices. They can be found in a range of several hundred euros for RGB + NIR (near-infra red), like Mapir Survey3, up to almost twenty thousand euros for the Sentera 6X model with a thermal camera. The amount of narrow bands differs from 4 to 5 for some solutions in a price range of 4000 euros to less than 10 thousand, like Parrot Sequoia, Sentera Double 4K Sensor, or RedEdge-P. There are some models with 9 or 10 narrow bands in the visible and near-infrared range, like MAIA S9 (9 narrow bands), Agrowing Multispectral Quad Camera (10 narrow bands), and Silios Toucan (10 narrow bands), all in the price of 15000 euros or more, among which Toucan model uses only one lens which eliminates further image alignment. Additionally, some designs can be found in scientific literature, usually constructed with special sensors or optics. Ono [16] described an MS device consisting of an industrial camera with four directional polarization filters on each quad pixel and a special design lens incorporating nine bandpass filters. Lapray et al [17] presented a realization built on a standard CMOS (Complementary metal–oxide–semiconductor) camera with a specially designed nine bands multispectral filter array placed on the top of the sensor. Both solutions expressed good performance but used components that had to be custom-made, imposing high investment. A different and exciting idea was independently demonstrated in [18] and [19], where the authors suggested a design based on color cameras, triple/quadruple bandpass filters either with a beam splitter, or a rotating wheel, obtaining 8 or 18 spectral bands, respectively. The problem with these two designs is a bulky system (two cameras and beam splitter) or the possibility of imaging only slowly moving objects (one camera and rotating wheel), which is inappropriate for mounting on UAV.

To tackle the issue of Flavescence dorée detection, which has a high impact on Italy agriculture as Grapevine is one of the most cultivated plants, possibility of using hyperspectral imaging for this task was investigated in this paper. In literature, several findings demonstrate that FD influences photosynthetic performances and other morphological changes, like leaf curling. Hyperspectral images can reveal subtle spectral changes caused by plant stress progress [21]. This approach was addressed in a couple of scientific attempts to detect FD using hyperspectral or multispectral data.

Using a commercially available multispectral camera (5 narrow bands), in [13] the authors concluded that although FD detection is likely, the accuracy depends on the variety (red or white grapes) and on a particular vineyard. Bendel et al. [22] investigated the detection of the FD with a hyperspectral camera. They obtained a high accuracy rate but in a controlled laboratory environment, with constant illumination, where leaves were fixed on the surface. The authors also stated that additional research must be done to choose the most appropriate spectral bands for field testing. A group of authors [23] with the same approach for acquiring hyperspectral data and after applying deep learning for FD detection, came to a similar conclusion. AL-Saddik et al [24] conducted several studies with hyperspectral data collected in the vineyards by a portable point spectrometer, acquiring four samples per leaf. Their first conclusion was that there is no single, most adequate spectral index for detecting FD in various situations, like different soil varieties, vegetation, and weather conditions. However, FD detection is possible, and the approach should be adjusted to the specific circumstances. Then, AL-Saddik et al [25] continued work choosing eight optimal spectral bands in all available wavelength ranges, for 350 nm to 2500 nm. Their next idea was to take seven wavelengths up to 1000 nm [14], because Silicon, as a low-cost material, is sensitive below 1 μm. Their recent work suggested a protocol for designing a multispectral system that consists of 4 c-mount industrial cameras, each with a different narrow, single-band filter [15]. To fulfil the weight and space limit, the number of spectral bands was reduced from seven to four, as the final goal was a device appropriate for low-altitude UAV. In addition, the authors include four Haralick texture characteristics in the feature vector to improve classification accuracy, as spectral data contain only four reflectance values. Classification accuracy was between 80.7 % and 92.8 %, depending on the grapevine varieties. As a suggestion for future researchers, the authors proposed that the following should consider geometric and radiometric correction to compensate for the shadowing effect and reflectance from other surrounding sources, followed by adding other pattern recognition methods together with spatial variability of data from the same vineyard.

This research was initiated with a similar approach to the previously mentioned. However, in this approach, hyperspectral and multispectral images were collected from the same position in the field, as designed multispectral camera should be used as a final tool for scouting vineyards. This provides data to assess the possibility of FD detection from spectral data altered with leaf orientation, shadowing, and multi-scattering effect, similar to real scenarios. The results were promising, showing a classification accuracy of 96.6 %. This finding and acquired data are starting points for future research that should test FD detection using the proposed multispectral camera as a low-cost solution, which is also much easier to manipulate in the field. The next section presented a developed multispectral camera, followed by a description of hyperspectral and multispectral data acquisition. Section IV presents the initial findings, while section V contains the conclusion and a proposal for future research.

II. Designed Low-Cost Multispectral Camera

The multispectral camera was constructed with the idea of using multiband optical filters [18],[19]. It was decided that only commercially available components should be used, easily accessible, with open software support. The design includes Raspberry Pi 4, Arducam Quad-Camera Bundle Kit, and four single/dual/triple bandpass optical filters. Raspberry PI 4 is powerful enough to handle all components and has additional interfaces, providing that other sensors can be added, like a GPS receiver for georeferencing and a multispectral point sensor to monitor the spectrum of incident radiation. Arducam Quad-Camera Bundle Kit comprises four 1 MPx OmniVision OV9782 global shutter color sensors. All four cameras have a common trigger that secures synchronization for all four images. The lens's focal length is 6 mm. On each lens, a different optical filter is mounted, one single, one dual, and two triple band filters, resulting in nine different spectral bands with the following central wavelengths 432, 517, 550, 577, 615, 660, 690, 750, 850 nm. In addition, this design does not include moving mechanical parts or precisely aligned optical components. As some research showed a detectable difference in temperature between healthy and infected plants [20], a thermal camera was added, Fig. 2. It is Seek Mosaic Core, with a resolution of 320x240 pixels, can detect temperature differences less than 100 mK, and contains a lens with almost the same field of view as visible cameras. This thermal camera can be excluded from design easily as all parts of the enclosure were 3D printed, which will reduce the total price by some 30%, although the total price of all components (around two thousand euros) is still far below standard multispectral cameras with a similar number of bands and thermal imaginer, which drastically lowers initial spending for the PA implementation at small farm level.

Fig. 2. Proposed multispectral camera.

After assembling, calibration was performed in a similar way as it was suggested in [18],[19], where the reconstruction process for response at each band is based on linear regression. Target was X-Rite® ColorChecker Classic, A4 size, with 24 patches of different uniform colors and spectral reflectivity. Actual values of spectral radiances were measured with hyperspectral scanner HySpex Mjolnir V-1240 (200 channels from 400 nm to 1000 nm range) using QTH (Quartz Tungsten Halogen) as a broadband source of illumination. Results after reconstruction of spectral radiance for one uniform patch and one spectral band are shown in Fig 3, demonstrating good accuracy for predicting actual value, with R^2 higher than 0.95 for all bands.

The calibration of the thermal camera was performed by comparing the temperature of the plate heated from room temperature to 80 °C, with the temperature measured by a high-resolution thermal camera, FLIR Duo Pro R.

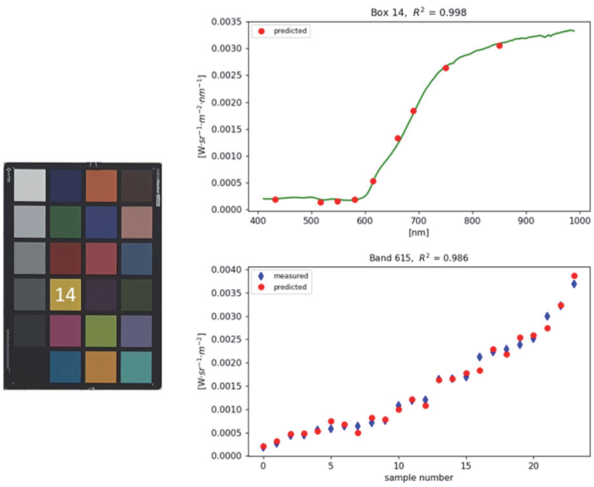

Fig. 3. Calibration target (left). Reconstructed radiance at the central wavelengths for patch 14 (top right). Reconstructed radiance at 577 nm for each patch sorted in ascending order of radiance (bottom right).

III. Data Acquisition

Two vineyards near Riva del Garda were selected for the location where the data would be acquired. At those two places, several plants with symptoms of FD were detected during 2021, so it was likely that new infections would be presented at the time of getting images. For obtaining both hyperspectral and multispectral images on the same date, two campaigns were done, the first one on 12th July, in the period of the season when symptoms are not highly expressed, and on the 22nd September 2022, when usually symptoms of FD are easier to spot. In addition, these two vineyards were selected as they contain two grapevine varieties, red Cabernet Sauvignon and white Chardonnay, which are among the most susceptible to FD [26].

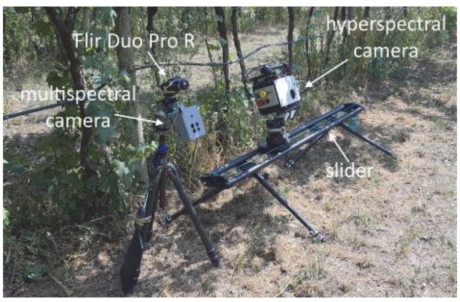

Fig. 4. Equipment used for acquisitions.

The setup for hyperspectral, multispectral, and thermal image acquisition is shown in Fig 4. The hyperspectral scanner can take only one line per frame, and to get an image of the full field of view, it was mounted on a slider. This configuration is not the most suitable for field conditions, but it was only feasible. Designed multispectral camera and FLIR Duo Pro R used as a thermal reference sensor were placed on a standard photographic tripod, which is a much more convenient way to go around the vineyard.

Local expert, who periodically searches in vineyard for new infestation of FD, conducted an field assessment of plant status (healthy or infected).

IV. Results

After data acquisition, it was started with dataset design. For each hyperspectral image, between 30 and 90 patches were selected. In total, 1067 were generated. These patches belong to the healthy (471) or infected (596) class depending on the previous assessment. For each patch, average spectral reflectance in a single channel is one value of the feature vector with 160 coordinates, as higher wavelengths were excluded due to a high noise level in that part of the spectra [21]. In Fig. 5, these patches for one hyperspectral image can be noticed.

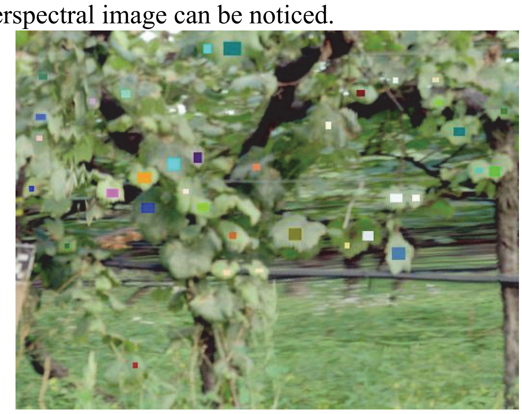

Fig. 5. Selected patches in one hyperspectral image of an infected plant.

For hyperspectral data, first, reflectance is calculated from radiance by dividing each spectral profile with the radiance profile of reference white target for which spectral reflectance is known. Next is preprocessing to remove multi-scattering effects, the influence of the leaf's inclination toward the camera, and the distance between leaves and the camera. There are several methods to reduce the scattering and to eliminate the outliers, but the most used one is Standard Normalize Variate (SNV) [21], as it does not require a reference spectrum, which is also applied here. With SNV, from each spectral profile its average value is subtracted, and the result is divided by the standard variance of the initial profile. In Fig. 6 the effect of SNV correction is presented.

As an algorithm for classification, linear discriminant analysis (LDA), was chosen, as it was suggested in a study that used hyperspectral imaging for the detection of another grapevine illness, Downy mildew, showing promising results [27]. The output of the LDA training is a weight vector. For the classification of new profiles as healthy or infected, the profile is multiplied with a weight vector, summed over all channels, and compared with a threshold. If the obtained value is above the threshold, that profile belongs to the infected class, as class one was chosen to represent the spectrum influenced by FD.

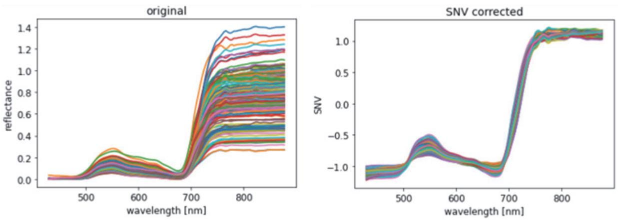

Fig. 6. Reflectance spectra before (left) and after applying SNV correction (right).

During the training, to prevent model overfitting on training data as this dataset can be considered as small size, and to classify with more accuracy unseen data, *k*-fold cross-validation was used [28], with *k* equal to ten and dataset-wise split. Mean model performances were the final measure, with $n = 5$ repeats. All code was written in Python, and the ENVI software packet was used to select patches in hyperspectral images.

As a result, a mean accuracy of 0.966 (0.017) was achieved with a mean precision of 0.969 (0.018) and mean recall of 0.971 (0.024), showing the good performance of the LDA as a model (values in brackets are a standard deviation).

V. Conclusion

This paper presents data acquisition for investigating the possibility of FD detection with an in-house designed multispectral camera and initial testing of FD prediction with hyperspectral data. First, in a nutshell, developed multispectral camera based on commercially available components was described. The proposed camera is characterized by the price being several times smaller than similar commercial solutions. This reduces initial investment for applying precision agriculture in small farms, which will improve their chances of becoming sustainable. In future work it will be compared the performance of designed low-cost multispectral camera with the commercially available ones that would be available at the time of testing.

Acquisition of both hyperspectral and multispectral images was conducted with equipment not very suitable for in-field use, but it generated data for assessment of possible usage of a designed camera for the important task of FD detection. Among the grapevine diseases, FD has become the dominant threat to many grapevine producers across Europe due to its devastating consequences. In the initial research, FD detection by hyperspectral data was tested, to check if detection by multispectral images is even feasible. Although some research had shown that FD detection is possible with hyperspectral data, unlike those researches, here, in this research, hyperspectral images were collected in the field, where there is influence from factors like nonuniform illumination, multi scattering, different leaves inclination, and distance to the camera. All these factors do not exist in laboratory conditions, and they influence detection performance. This research shows that with LDA, a simple and robust classifier, good performances can be achieved, obtaining mean precision of 96.6 %.

Furthermore, this finding shows that investing in further research and designing a protocol based on multispectral imaging is justified. Also, contrary to other attempts to detect FD, in this approach, data from both varieties were used together, as the goal is to provide a tool that does not require much adoption for different scenarios and grapevine varieties, and it can be used for fast FD scouting in the field. This idea was verified with an experiment.

Acquired data provide enough material for future research. The first idea is to test the possible detection of FD with the nine mentioned bands. Next is adding image features, like texture-based, to improve classification accuracy as a multispectral image contains significantly less information than a hyperspectral camera. Also, recent object detection algorithms may apply to FD detection. Still, instead of standard RGB images, the algorithm will be trained with multispectral images as input, testing if available thermal data further enhances classification accuracy. If the results are satisfying, the procedure to verify these approaches in the field will be designed for the following season. Furthermore, the acquired data contains only hyperspectral images of two grapevine varieties, and additional work is needed to inspect how this approach can be adapted to other grapevine varieties or to different locations. However, as the FD symptoms do not depend on the region and with grapevine variety, except for distinguishing between red and white, it is expected that this method would require only minor changes to apply in different circumstances, which will be tested in future research.

Finally, by employing low-altitude UAV, the time needed to collect data in the whole vineyard can be drastically reduced.

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