Thesis Proposal

Tardif Malo | IMS, France; PFR, New Zeeland | March 2021

Table of contents

Abstract

Insects, fungi and viruses are disease vectors for grapevines. Some of these diseases can cause multiple drops in yield and mortality of the vine stocks. These diseases are called vine dieback diseases and should be diagnosed and treated as a priority before they spread. There are certainly ecological practices to reduce the risk that the vine is affected by these diseases but the only really effective measure to date remains the use of phytosanitary products. Moreover, the transition towards the use of less pesticides is very complicated to implement for a farmer because he exposes himself to a loss in quantity and quality of grapes. Carrying out treatments adapted to the real phytosanitary situation of the plot would help to reduce this consumption. The only method to do so is the prospecting of each plot by experts in vine diseases and this several times a year. But this practice is far too time consuming and impossible to implement at the present time. It is then necessary to facilitate the survey of vineyards so that it can be carried out more often, which would allow an earlier detection of diseases and adapted treatments.

Recent advances in new technologies, particularly in the fields of image acquisition (improved sensors and on-board acquisition systems, better resolutions, lower costs) and image processing methods (more powerful computers, artificial intelligence and powerful computer vision algorithms) have already allowed real progress in many areas.

These advances are extremely promising and seem to be transposable to our subject of study. This is why in this project, we wish to facilitate prospecting through its automation, by equipping agricultural machines with an acquisition device in order to take advantage of their passage through the rows of vines. The acquired images would be processed automatically and the farmer or the prospectors would be given a map of the areas of high risk of disease, in order to guide them in their prospecting or to help them in their diagnosis. This project will focus on the detection of vine dieback diseases that need to be detected and treated as a priority before their damage becomes extensive and irreversible. Several elements complicate the detection of diseases on images, such as the variation of symptoms of a disease from one variety to another, the different phenological stages of the vine, the sometimes very similar symptoms between different diseases and the foliage that can cover the visible symptoms.

The collaboration of laboratories in France and New Zealand has enabled this project to see the light of day and research will be targeted on the most present and devastating diseases in these territories, namely *flavescence dorée* in France and *Eutypa dieback* in New Zealand.

Introduction

Viticulture faces several problems and is subject to numerous criticisms, particularly with regard to its impact on the environment. The introduction new pesticides in the 1970s–1980s contributed greatly to pest control and agricultural output: they allow a better productivity, offer a better protection of crop losses and yield reduction, increase the quality of the food and control the vector of disease. But there is now overwhelming evidence that their debits have resulted in serious health implications to man and his environment. So, if we need to think about tomorrow's agriculture, pesticide reduction must be a priority working area. Especially, viticulture needs plenty of pesticides, mainly because of fungicides. Although viticulture represents 3% of France's agricultural land, the sector spreads 20% of the country's fungicides (Robert 2019).

The amount of pesticides used can be explained by the importance of the international wine market. Based on information collected on 30 countries, which represent 84% of the world production in 2019, 2020 world wine production (excluding juices and musts) is estimated between 253.9 and 262.2 mhl, with a mid range estimate at 258 mhl (International Organisation of Vine and Wine 2020). In 2018 the world wine market, considered here as the sum of the exports of all countries, reach 31.3bn EUR (International Organisation of Vine and Wine 2019). Wine tourism has also strongly developed in recent years: there were 7.5 million in 2009, but it is now estimated that 10 million came in 2016 to discover French wines and vineyards. This represents a growth of more than 30% and a total spend of 5.2 billion euros. So to continue to have the same yields each year, it is very complicated at the moment for the wine growers to do without pesticides.

Unfortunately, a large part of the traditional vineyards (such as the Mediterranean vineyards) could disappear: "if the current trend continues we may see temperature increases 3-5 degrees Celsius by the end of the century" Secretary-General Petteri Taalas said in the WMO's annual statement on the state of the climate (Taalas 2018). Such a climate scenario would lead to a 1000 km northward shift of vines in the northern hemisphere. This climatic disruption could also increase the resistance of vine diseases and pests to the cold of winter. Hypothetical new disease vectors could emerge. Faced with this vision of the future of viticulture and the obligation to reduce the use of pesticides harmful to the environment and our health, there is a real need to adapt the current protection measures of the vine. Certain governments, such as the French government, are taking steps in this direction. An ordinance resulting from the law "Egalim" separates the advice and the sale of phytopharmaceutical products, the advice activity having for objective the more reasoned use of these products. For human health, the system of protection of local residents, in force since January 1, 2020, requires wine growers to respect safety distances between areas of phytosanitary treatments and homes or any water point. The French government is also banning certain plant protection products deemed too harmful to the environment or human health. The French wine industry has committed itself to reducing the use of phytosanitary products by 50% by 2025, thanks in particular to the use of alternative products and the replacement of two thirds of the sprayers by confined sprayers (with recovery panels) within five years. The fight against certain diseases is also highly regulated, with the obligation for winegrowers to ensure a general surveillance of the vines, to immediately declare the presence of flavescence dorée and to uproot as soon as possible the vine identified as contaminated. If more than 20% of the vineyard is contaminated by flavescence dorée, the whole plot must be uprooted.

There are currently phytosanitary strategies in line with sustainable viticulture. This can be defined as a viticulture that "must ensure the sustainability of the vineyard and an income for the farmer through a regular and quality production, while preserving the environment and man "(Ministère de l'Agriculture, de la Pêche et de la Ruralité 2005). More concretely, integrated viticulture consists of a set of cultural practices, such as limiting the use of phytosanitary treatment products, fighting against soil erosion and limiting soil and water pollution (Boulanger-Fassier 2007). Examples include effective drainage of the soil, selection of resistant plants and varieties, removal of dead plants, and treatment with lime and copper sulfate to control fungal diseases. But the best strategy is to detect phytosanitary problems as early as possible in order to carry out a targeted and adapted treatment before the disease spreads. Plot inspections are therefore the key element for a more sustainable viticulture, in order to limit systematic preventive spraying in favor of a precise intervention. Unfortunately, the inspection of each vineyard plot is a very constraining work impossible to set up several times a year at the present time. It seems important to provide assistance to the prospection so that this practice can be carried out as often as possible.

In this way, vine decline diseases could be detected early. These diseases cause a decrease in quality and yield, and eventually lead to the death of the vine. All wood diseases (esca, eutypa dieback, botrispaeria), virus diseases (leafroll) and phytoplasma diseases (flavescence dorée) are included in this term. Grapevine trunk diseases are considered the most destructive diseases of grapevine for the past three decades and are of rapidly growing concern in all wine producing countries. The worldwide economic cost for the replacement of dead grapevines is roughly estimated to be in excess of 1.5 billion dollars per year (Hofstetter et al. 2012). Esca, Eutypa and Botryosphaeria dieback are the leading players of these decay diseases. These three diseases lowered potential wine production by 13% in France in 2014, according to the agriculture ministry and French Wine Institute (IFV). The diseases are costing France the equivalent of 1bn euros ($1.14bn) annually in lost wine production, IFV said and means more than 100,000 hectares of vineyard was lost in 2014 and between 10 to 15% of potential production was lost last year. In addition to these wood diseases, flavescence dorée has become a real scourge in France. Flavescence dorée was classified as a quarantine disease at the European level in 1993 (European Directive 2000/29/EC) and is subject to mandatory reporting. This means that when an outbreak of this disease is detected, the farmer must inform the competent associations. A compulsory control perimeter can then be defined, with a compulsory insecticide control. In 2018 in France, 75% of the vineyard is within the compulsory control perimeters (PLO) defined in the prefectural decrees, i.e. 568,507 ha (Barthellet, Goglia, et Groman 2018). A plant affected by flavescence dorée is impossible to save due to the inability to directly attack the phytoplasma. This plant must then be uprooted as soon as possible to avoid the spread of this disease. Here again, prospecting appears to be the best way to fight against this disease.

The bibliographical study on the aid to the prospection or detection of vine diseases led to the identification of several gaps in the literature. Firstly, there are few studies carried out in the field, i.e. developed from data acquired in the plot and tested in real time in the field. And when the study is done in the field, only one organ of the vine (the leaves) is studied to detect and diagnose a phytosanitary problem. However, we know that grapevine disease experts associate the symptoms present on the different organs (leaves, bunches and shoots) to distinguish between diseases and make the most reliable diagnosis possible. A real gap is present in the literature on this subject. This study will fill this gap since we wish to detect and associate the symptoms present on the different organs of the vine in order to establish its phytosanitary state. The study will focus on the detection of vine decline diseases, diseases to be diagnosed in priority before their propagation because of the damage they cause. The expression of these diseases varies from one grape variety to another, the study will not be able to cover all the grape varieties. A choice of grape varieties will then be made according to the availability of our data acquisition.

Issue

Prospecting is the most effective way to date to control grapevine decline diseases. Its application on a larger scale i.e. more often, on more plots is necessary to limit inputs and reduce the spread of diseases and their impact of diseases on yield. At present, it is impossible to survey all the vineyards once a year: the practice as it is carried out requires too much time (surveying each vineyard row of each plot) and too many people. Prospecting also has a high economic cost since it is necessary to pay the prospectors during their prospecting but also to train them to recognize vine diseases. Indeed, correctly diagnosing a disease can be complex for several reasons. Firstly, the expression of symptoms varies from one grape variety to another. Secondly, many diseases present similar symptoms, especially symptoms expressed on leaves. Finally, symptoms evolve over time and take on different appearances depending on the intensity of the disease. A good knowledge of the plot, of its sensitivities and of the history of contamination can then help during the diagnosis. To correctly identify the phytosanitary problem during the survey, the expert proceeds in several steps: the symptoms expressed on the leaves are first analyzed because they attract the eye during the surveyar's walk. Once these symptoms have been studied, a doubt often persists because of the similarity of the leaf symptoms of different diseases. The expert then studies in a second time the symptoms present (or not) on the bunches and branches to make the distinction between these diseases and correctly diagnose the phytosanitary problem from which the vine suffers. There are also some cases where only a sample analyzed in a laboratory allows to distinguish diseases between them. This method is applied for example to differentiate between flavescence dorée and bois noir disease.

One solution to make the practice of prospecting more adopted and systematic is its automation. By developing a robust system with the support of experts in the field, it also seems possible to make prospecting more comprehensive and reliable. This solution seems more and more feasible in view of current advances in data acquisition devices and computer vision algorithms. Technology has been evolving rapidly in the field of image acquisition for several years, whether in the industrial and scientific fields or in the general public. We can note as notable improvement the higher resolution of acquisition, the better focus, the reduction of noise of the processing chain or the greater storage capacity of devices to keep in memory thousands of images. Improvements in image acquisition are accompanied by great progress in the field of algorithmic image processing, in particular through the advent of artificial intelligence. Artificial intelligence has existed since the 1950s but its use has exploded in recent years due to advances in computing capacity and the development of deep learning.

Deep learning corresponds to a set of machine learning methods that aim to model data representations of high level of abstraction. An artificial neural network (collection of software "neurons" connected together, allowing them to send messages to each other) is trained with what is called a training set containing starting and ending data. The network is asked to learn how to pass from the starting data to the ending data, which it attempts to do over and over, each time strengthening the connections that lead to success and diminishing those that lead to failure. Once the network is able to correctly switch from departure to arrival data, it can then be applied to new data to obtain reliable predictions. In the field of image processing, one type of neural network is currently very efficient. These are convolutional neural networks (CNNs), which are inspired by the organization of animal visual cortex and designed to automatically and adaptively learn spatial hierarchies of features, from low- to high-level patterns. These methods obtain very interesting results in many fields. For example, the study of images by artificial intelligence is widely used in the field of medicine with a problem similar to ours: the detection and diagnosis of disease. Examples include the classification of X-ray images of healthy and sick patients (Yadav et Jadhav 2019), the automatic segmentation of brain tumors (Wang et al. 2019)or the detection of hemorrhages in fundus images (Grinsven et al. 2016). CNNs obtain excellent results for each of these studies and make artificial intelligence tools very promising for our research problem.

Objectives

In this study, we will try to evaluate the performance of artificial intelligence and computer vision tools for the detection of areas at high risk of vine decline diseases. The algorithmic diagnosis of diseases will mimic that of experts in the field, with first the detection of symptoms on the various organs of the vine and then the association of these symptoms to determine the phytosanitary problem.

The general objective of this project is to develop an aid to vine disease prospecting by automating it, by equipping agricultural machines with an image acquisition and processing device and by taking advantage of their passage through the vineyard plots to detect areas of high risk of phytosanitary problems. The prospectors would thus be guided in their prospecting and could go directly to the diseased plants instead of prospecting the whole plot. This device could also help them in their diagnoses if any doubt exists. To achieve this result, several underlying objectives will have to be met:

1) To develop an algorithm for detecting isolated, unitary symptoms that is robust to their different expressions depending on the disease, its intensity and the grape variety studied.

2) To develop an algorithm associating the detected symptoms in order to diagnose the disease at the level of the vine and to deliver a map of the zones of high risks of phytosanitary problems.

An important criterion in the choice of these algorithms will be their calculation time. Indeed, even if it is not the priority, we wish to embed the algorithms on the acquisition device, because there are too many data to stock or upload them and then process the images at the office or on the cloud. The choice of the algorithm will not be based on the one with the best accuracy but rather on the ratio of accuracy to calculation time.

These objectives are in agreement with the projects and researches in image processing and viticulture of the IMS (Laboratoire of Material System Integration) in France and Plant and Food Research (PFR) in New-Zealand, the laboratories having financed this thesis project. The detection will focus on the diseases of vine decline since it will support this thesis will support existing projects in these laboratories, with the ProspectFD project (Davy 2020) in France, which aims to develop a decision support tool for the survey of flavescence dorée in vines. Flavescence dorée has the particularity of presenting its symptoms on three different organs: yellowing or reddening of the leaves depending on the grape variety, unlignification of the shoots and drying of the bunches (Jollard 2017). Moreover, this disease is very worrying in France: According to the Groupement de Défense contre les Organismes Nuisibles de la vigne (GDON) of Bordeaux, in 2017, 58% of the French vineyard is in a zone contaminated by flavescence dorée, i.e. approximately 439,500 hectares. A vine contracting this disease must be uprooted as soon as possible. This is why we have targeted this disease as a first case study.

This study will also be at the heart of the New Zealand Plant and Food Research project on the automatic detection of eutypa dieback. Eutypa dieback delays shoot emergence in spring, and the shoots that eventually do grow have dwarfed, chlorotic leaves, sometimes with a cupped shape and/ or tattered margins.

Botryosphaeria disease will also be studied at the same time, these 2 grapevine trunk diseases have very similar symptoms and are present in New Zealand. An other trunk disease, esca, will also be studied since it is very present in France and New Zealand, it will be easy to obtain images of vines suffering from this disease. One of the characteristic symptoms of this disease is the 'stripped' appearance of the symptomatic leaves. Finally, the detection of symptomatic leaves of the leaf roll disease also present in New Zealand will be tested. These leaves show a symptomatic downward curling as well as a diffuse yellowing or reddening depending on the grape variety.

These are the targeted diseases for the moment but everything can evolve according to the acquisition carried out in the future: It is possible that we miss acquisition presenting the symptoms of the diseases quoted above and that another disease is finally more represented in our images.

Literature Review

In the last few years, research in the field of automatic detection of crop diseases has multiplied. Indeed, the new technological tools (better acquisition devices, more powerful computer, artificial intelligence, drone) as well as the requirements for farmers of yield coupled with a more sustainable practice make it a subject of study very requested and whose results are very promising.

Firstly, the democratization of the use of UAVs has offered an extremely practical means of acquiring images of plots of land due to its speed of execution. The use of UAVs to acquire images in research was not long in coming and many studies are available on the processing of images from this acquisition vector. Successfully, some studies have shown that drone acquisitions allowed to correctly estimate biomass, canopy temperatures, size and nitrogen consumption of crops (Holman et al. 2016; Madec et al. 2017; Ludovisi et al. 2017). Based on these successes, it has also been tried to diagnose crop diseases by this means of acquisition, in particular to detect diseases of the vine. For example, we can cite studies (Kerkech, Hafiane, et Canals 2020b) and (Kerkech, Hafiane, et Canals 2020a) that, with a segmentation approach, assign a class to each pixel among 4 classes: either the pixel studied is a soil pixel, a shadow pixel, a healthy vine or a sick vine. The results of these studies are quite good, with the first study having an accuracy rate of 92% for the diseased vine class. It is also possible to calculate vegetation indices from UAV images such as Excess Green (ExG), Green-Red Vegetation Index (GRVI) to detect diseased vineyard areas (Kerkech, Hafiane, et Canals 2018). The patch classification (group of pixels 16x16, 32x32 or 64x64 pixels) even reaches 95% in conclusion of this study. The results of these 3 researches are extremely high and this is explained by the fact that only the distinction between healthy and diseased vines is made and not the distinction between diseases. According to the bibliographic research, there is no study allowing the diagnosis of vine diseases. This can be explained by the fact that during the acquisition of images by drone, the bunches and shoots can not be seen. It remains only the leaves to make the distinction between diseases. Moreover, the resolution of drone images (1 pixel equivalent to several centimeters) does not allow the detection of certain symptoms such as small spots allowing the diagnosis of the disease. This vector seems to offer real advantages during data acquisition, but these data seem very limited for a task such as distinguishing between diseases, which requires as much detail as possible. To obtain these details, an acquisition vector present in the literature is the camera in order to photograph the leaves in close-up, either in the field with the foliage in the background, or in the laboratory with the leaf placed on a plain background. In this way the symptoms on the leaves can be detected much more precisely. Many studies use this type of image to detect certain diseases but also to differentiate between them. A spectral and textural analysis allows to differentiate with more than 85% accuracy a healthy leaf from a diseased leaf, with more than 74% the degree of infection and distinguish with more than 75% the diseases of flavescence dorée, bois noir and esca (Al Saddik 2019). A classifier can also be used as in (Pantazi et al. 2016), with upstream color space changes, texture operator application and parameter extraction. This method achieves over 93% accuracy in classifying leaves with symptoms of 3 diseases: powdery mildew, downy mildew and black rot. But the most used algorithmic approach to process this type of image is the use of deep learning and more particularly CNNs (Convolutional Neural Network) which obtain excellent results: More than 99% accuracy in leaf classification in 4 classes: healthy leaves, black rot, esca and isariopsis leaf spot (Ji, Zhang, et Wu 2020). The use of CNNs also allows them to obtain 97% accuracy in classifying vine leaves into 6 classes: leaves showing symptoms of Anthracnose, brown spot, moths, black rot, downy mildew and leaf blight (Liu et al. 2020) . These methods are also applied to other types of crops with the same high level of precision: In the study (Ferentinos 2018), 99.53% accuracy was obtained in the identification of the couple (plant, disease) among 12 possible couples, from a dataset containing 25 different plants and 58 couples: only the couples presenting images in the field and in the laboratory were studied. It is also shown in this study that images acquired in the field are more complicated to diagnose than those from the laboratory and that images acquired in laboratory conditions cannot be used to develop a recognition tool in the field. The application of CNNs for the classification of symptoms of isolated leaves or close-up images obtained very good results for tomato leaves (Ashqar et Abu-Naser 2018), of wheat (Lu et al. 2017) or manioc (Ramcharan et al. 2017). Unfortunately, this method does not seem to be suitable for automated detection in the field of grapevine diseases: it seems impossible to cut a leaf to place it on a plain background or to directly photograph symptomatic leaves in close-up. This brings us to studies using data acquired in the vine rows. There are few studies using images of vine photographed from 50 centimeters to few meters distance to diagnose grapevine diseases. One study evaluates the effectiveness of a vehicle-mounted device to characterize vine foliage but only vegetation indices are calculated (Bourgeon 2015). A computer vision approach using color analysis and structure tensor has been tried to differentiate vine organs on images acquired in the field, then in a second step, to evaluate the potential of high-resolution embedded imagery for epidemiological monitoring with as a case study the mildew (Abdelghafour 2019). The results obtained for this second step are promising and show that it is initially possible to estimate the sanitary state at the plot level scale without having a high precision for each vine. Finally, a recent study (Boulent 2020) obtains a true positive rate of 98.48% when classifying images of grapevines affected by florescence dorée using deep learning methods such as CNNs and FCNs (Fully Convolutional Network). Images of healthy and diseased grapevines were acquired by a camera at a distance of about 1 meter. This result demonstrates the ability of neural networks to detect grapevine diseases other than on close-up leaves, but it must be qualified. Indeed, the 98.48% rate is only true for images of Chardonnay grape variety, it goes down to 8.3% for a Ugni-blanc grape variety. This paper proves that the strong difference in the expression of symptoms of the same disease between 2 grape varieties is a point not to be neglected. Moreover, only symptoms on leaves were used in this study, but we know that experts take into account the symptoms expressed on all organs to deliver their diagnosis. Finally, the presence of confounding diseases of flavescence dorée in the data set obtaining 98.48% is not clearly explained.

There are also different types of data acquisition, each one having its specificities and delivering different information. It is therefore important to use the type of sensor that offers the most useful information for research, knowing that it is often not possible to embark all the desired sensors. Either because of the cost of these sensors, or because of the lack of space on the embedded system or because of the weight for the drones for example. For our field of study, two types of sensors are widely used: RGB and multispectral cameras. The first one delivers 3 bands and tries to recreate exactly what our eyes see. The second one allows to obtain as many bands as wavelength chosen for the same scene. The studies using the drone as an acquisition vector have used both types of sensors for their acquisitions (Kerkech, Hafiane, et Canals 2020b; 2020a; 2018). While multispectral information can be used to calculate useful vegetation indices for characterizing foliage, it does not appear to provide additional information to RGB information for disease detection and diagnosis. Among the papers studied attempting to diagnose grapevine diseases by studying symptomatic leaves in close-up, only one uses multispectral information (Al Saddik 2019) to extract texture descriptors, resulting in 85% accuracy in distinguishing between symptomatic and healthy leaves. All other researches studying this type of data by CNNs on RGB images obtain a better accuracy in disease diagnosis from symptomatic leaves. (Ferentinos 2018; Boulent 2020; Ji, Zhang, et Wu 2020; Liu et al. 2020; Xie et al. 2020; Lu et al. 2017). Finally, studies acquiring images containing all the organs of the vine to diagnose diseases do so only with RGB sensors (Boulent 2020; Abdelghafour 2019), only one study (Bourgeon 2015) uses a multispectral sensor but to characterize the foliage in the plot. The use of a thermal camera has also been studied and improves the results for early stage detection compared to a color/texture analysis approach for various crop varieties (Han et Cointault 2013). Finally, luminance processing has been tried but does not seem to bring additional information to the RGB or multispectral information for our problem (Al Saddik 2019). It appears that the information from RGB sensors is sufficient for our study, the best results being obtained via data acquired by this type of device. The multispectral information is interesting but does not bring any real value.

According to this bibliographic study, the type of algorithms obtaining the best precision in the detection and diagnosis of grapevine disease are the deep learning algorithms, obtaining more than 99% precision in the classification into 4 classes of symptomatic grapevine leaves (Ji, Zhang, et Wu 2020) and over 97% for 6 classes (Liu et al. 2020). These two researches use the same type of deep learning algorithm to achieve this result: CNNs. CNNs are the preferred networks for analyzing images in 2 or 3 dimensions, the input image undergoing convolutions and changes of dimensions to arrive at the desired result. At each of these steps, the network learns parameters and adjusts them to get closer to the desired result at each iteration. These results can be of a different nature depending on the task we wish to achieve and we distinguish three main categories of networks: classification, segmentation and detection networks. Image classification networks are the simplest of the three since they consist in assigning a class to a given image. The studies of classification of symptomatic leaves cited above (Ji, Zhang, et Wu 2020; Kerkech, Hafiane, et Canals 2020b; Liu et al. 2020) use this type of network. The advantage of these networks is the low cost in terms of image annotation and computation time, the disadvantage is that they do not offer more information than a name on an image, so we can not locate the information or have several classes present on the same image. In our case, that is to say the diagnosis of disease using symptoms present on several organs, symptoms often similar to each other, we need to understand how each information has been processed by the algorithm. Classification algorithms do not seem appropriate, unless one image is split into many smaller image patches on which we expect to find only one class at a time. Segmentation algorithms offer more information: instead of assigning a class to the whole image, they assign a class to each pixel of the image, for a very detailed information this time. We can then know in our case if the studied pixel is part of a set of pixels representing a symptom x, while another one represents a symptom y. This type of network has been tested to segment flavescence dorée areas (Boulent 2020) and offers rather promising results. Unfortunately, preparing learning data for segmentation network is very time consuming for experts with the difficulty of finding the limits between "diseased" and "healthy" pixels. Moreover, these networks are more expensive in terms of computation time than the 2 others and would not be suitable for the objective of real-time detection of the disease. There remain the detection networks which combine the localization of objects of interest by enclosing them in a rectangle and the attribution of a class to each localized object. The task then seems more complicated than for the two other types of networks but would be perfectly suited to our objective of detecting symptoms. Moreover, these networks have the advantage of a fast annotation via dedicated software and a computation time in adequacy with the real-time image processing. Algorithms such as YoloV4 (Bochkovskiy, Wang, et Liao 2020) and Faster-RCNN (Girshick 2015) seems interesting to test for our case study, as no research in crop disease detection has yet used this type of network.

Once the symptoms have been detected, a diagnosis must be assigned. A more reliable detection of diseases requires to relate spatially distributed symptoms: identical or different symptoms, spatially distributed at the scale of a plant or a group of plants, possibly "drowned" in the middle of other symptoms or confounding factors. To diagnose a disease from different criteria, one possible approach would be to use more classical machine learning approaches We can then think of classical statistical methods of decision making such as SVM (Evgeniou et Pontil 2001), multi-label decision trees or Random Forest algorithms. An innovative and interesting method in the literature that has been developing in recent years is that of neural network graphs. (GNNs) (Zhou et al. 2019). These deep learning algorithms allow to represent the information in the form of a non-oriented graph (in our case the vertices would be for example the detected symptoms) and allows to perform graph classification (does this graph represent a diseased or a healthy vineyard?) or graph detection (to detect the high risk areas of diseases at the plot level) The interest of this type of method is to be able to visualize the symptoms detected at the scale of several rows of vines. The association of symptoms to diagnose the disease and to deliver a map of the plot indicating the high risk areas of diseases will be a real challenge as there is no written material on the subject.

Methodology

There are many diseases and deficiencies that the vine can suffer from. These pathologies result in symptoms that are sometimes visually similar to each other. In order to differentiate between these diseases, when inspecting the vines, the association of the symptoms present on different organs allows for a better diagnosis. This is why in this study we think about a two-step approach: A first algorithm will be responsible for predicting the symptoms potentially present on a given image, while a second one will have the role of associating these detected symptoms in order to deliver a diagnosis, either at the vine plant level or at the plot level by indicating the areas of high risk of disease.

For the first studied disease, flavescence dorée, several acquisition campaigns have already taken place and we have a first set of several thousand images coming from the acquisition device fixed either on a wheelbarrow or on a harvesting machine. The vines photographed from the wheelbarrow have been the subject of the expertise of a prospector, so we know precisely the disease(s) the photographed vine is affected by. We also call upon experts in vine diseases (people form BNIC: Bureau National Interprofessionnel du Cognac, GDON of Bordeaux: Groupement de Défense contre les Organismes Nuisibles de la vigne and FREDON of acquitaine: Fédérations Régionales de Défense contre les Organismes Nuisibles) to annotate our images: using a dedicated software, each symptom on leaves and grapes will be enclosed in a rectangle and each rectangle will be assigned a class according to the symptom it contains. The case of unlignified shoots is more complex for two reasons. Firstly, their shape is not suitable for annotation via a rectangle (the rectangle contains more harmful information than the undignified shoot in question). Second, the shape and color of the thin unlignified shoots coincides with those of the petioles, which makes them very difficult to discriminate. Experts will therefore annotate these unlignified shoots with broken lines and attempts will be made to differentiate them from the petioles by morphological or statistical studies.

Thanks to these annotated images, several deep learning algorithms can be trained to automatically detect disease symptoms. These algorithms will be classified according to their performance in terms of precision and computation time in order to determine the optimal algorithm in relation to our constraints. Indeed, the chosen algorithm will have to ensure the processing of live images when it will be embedded in the acquisition device fixed on an agricultural machine, the computation time of the algorithm will therefore be a very important criterion when choosing the algorithm for symptom detection.

The difference in the expression of symptoms of the same disease according to the grape variety will also be an important point to study. Let's study our example, flavescence dorée: the presence of the disease in a vine of a white grape variety causes a yellowing of the leaves, whereas it causes a reddening on a vine of a red grape variety. Moreover, the different varieties of a white or red grape variety do not show the same leaf symptoms. In the case of white grape varieties, the leaves may undergo partial yellowing and be difficult to detect even for experts in vine disease or a deep and clearly visible yellowing. The intensity of leaf curling can also vary from no curling at all to a very pronounced curling of the leaf tips downwards. A recent study (Boulent 2020) shows that an algorithm can obtain very good results in the diagnosis of flavescence dorée on one white grape variety and very poor results on another white grape variety. A study will therefore be carried out to compare the performance of a single algorithm detecting flavescence dorée symptoms for all grape varieties, an algorithm specialized in white grape varieties and one in red grape varieties and finally an algorithm by grape variety. The advantage of the first option is that each class will contain a large number of images, which is decisive in the accuracy of the predictions. But the large intra-class variance may affect the quality of the predictions. The last option would minimize this intra-class variance but each class would contain a lower number of training images. It seems necessary to test these different options.

It is planned to have identified and developed a reliable and time-sensitive flavescence dorée symptom detection algorithm by the end of summer 2021. This would allow it to be integrated into the on-board system and tested under real conditions during the flavescence dorée acquisition campaign scheduled for September 2021.

First developments and tests of algorithms for the detection of areas with high levels of disease risk are also planned before this date. This would aim to realize the necessary needs in terms of image, annotation and expertise for this type of method. For this diagnosis of the disease according to the previously detected symptoms, two approaches will be confronted. An approach known as "image-scale" for which each image is analysed separately from the others. Several types of algorithms will be tested (SVM, Random Forest, decision tree) in order to diagnose the state of the photographed vine according to the symptoms detected. The second approach envisaged is called "plot scale". The symptoms detected on all the images of the plot will be displayed, linked and spatially recalibrated thanks to the geolocalization device integrated to the embedded system to form a non-oriented graph. By using deep graph learning algorithms (GNN, graph neural network), it seems possible to detect areas of high disease risk.

The acquisition of some images of Eutypa dieback is planned in July 2021 in France. The acquisition will not be large scale but will be aimed at familiarizing with this disease. Indeed, this disease is very present in New Zealand, country in which I will have the chance to work during two stays of about 6 months. The first stay will take place from October 2021 to March 2022. Symptom detection will be at the heart of this period, with at least two new diseases to be integrated into the algorithms: Leaf roll and Eutypa dieback. Upon my return to France, the first months will be devoted to writing a first paper on the detection of symptoms of grapevine diseases.

The number of papers is obviously not fixed and depends on the progress of the thesis but two papers will be written at least, the one just mentioned and one on the detection of areas of high risk of vine disease.

Once the first paper has been finalized, the work will essentially focus on the development of algorithms for the diagnosis of grapevine diseases. For each new acquisition campaign and set of expert images, the symptom detection algorithm will be re-trained and tested. At this stage, at least five diseases should be detected and diagnosed: Flavescence dorée and esca, which are very present in France, leaf roll, eutypiosis and botryosphaeria, which are developing strongly in New Zealand.

This will be followed by the writing of the second paper dealing with the detection of areas at high risk of disease, then the last months will be devoted to the writing of the thesis.

References

Abdelghafour, Florent. 2019. « Potentialités de l'imagerie couleur embarquée pour la détection et la cartographie des maladies fongiques de la vigne ». Theses, Université de Bordeaux. https://tel.archives-ouvertes.fr/tel-02499420.

Al Saddik, Hania. 2019. « Spectral and textural analysis of high resolution data for the automatic detection of grape vine diseases ». Theses, Université Bourgogne Franche-Comté. https://tel.archives-ouvertes.fr/tel-02408995.

Ashqar, Belal A M, et Samy S Abu-Naser. 2018. « Image-Based Tomato Leaves Diseases Detection Using Deep Learning » 2 (12): 7.

Barthellet, Brigitte, Raphaella Goglia, et Jacques Groman. 2018. « Flavescence dorée, bilan de la surveillance en 2018. » Ministère de l'agriculture et de l'alimentation. http://draaf.auvergne-rhone-alpes.agriculture.gouv.fr/IMG/pdf/1-Bilan_2018_Flavescence_doree-V-def-pub_2_cle0f2948.pdf.

Bochkovskiy, Alexey, Chien-Yao Wang, et Hong-Yuan Mark Liao. 2020. « YOLOv4: Optimal Speed and Accuracy of Object Detection ». *arXiv:2004.10934 [cs, eess]*, avril. http://arxiv.org/abs/2004.10934.

Boulanger-Fassier. 2007. « Viticulture durable et valorisation de l'espace en Alsace et dans le Jura ». In , 81,82. Aix-en-Provence.

Boulent, Justine. 2020. « Identification des problèmes phytosanitaires de la vigne au sein de la parcelle : association de l'imagerie à ultra-haute résolution spatiale et de l'apprentissage profond ». http://hdl.handle.net/11143/17855.

Bourgeon, Marie-Aure. 2015. « Conception et évaluation d'un dispositif d'imagerie multispectrale de proxidétection embarqué pour caractériser le feuillage de la vigne ». Theses, Université de Bourgogne. https://tel.archives-ouvertes.fr/tel-01291695.

Davy, Alexandre. 2020. « Présentation du projet Prospect-FD ».

Evgeniou, Theodoros, et Massimiliano Pontil. 2001. « Support Vector Machines: Theory and Applications ». In , 2049:249-57. https://doi.org/10.1007/3-540-44673-7_12.

Ferentinos, Konstantinos. 2018. « Deep learning models for plant disease detection and diagnosis ». *Computers and Electronics in Agriculture* 145: 311-18. https://doi.org/10.1016/j.compag.2018.01.009.

Girshick, Ross. 2015. « Fast R-CNN ». *arXiv:1504.08083 [cs]*, septembre. http://arxiv.org/abs/1504.08083.

Grinsven, M. J. J. P. van, B. van Ginneken, C. B. Hoyng, T. Theelen, et C. I. Sánchez. 2016. « Fast Convolutional Neural Network Training Using Selective Data Sampling: Application to Hemorrhage Detection in Color Fundus Images ». *IEEE Transactions on Medical Imaging* 35 (5): 1273-84. https://doi.org/10.1109/TMI.2016.2526689.

Han, Simeng, et Frédéric Cointault. 2013. « Détection précoce de maladies sur feuilles par traitement d'images ». In *Orasis, Congrès des jeunes chercheurs en vision par ordinateur*. Cluny, France. https://hal.archives-ouvertes.fr/hal-00829402.

Hofstetter, Valérie, Bart Buyck, Daniel Croll, Olivier Viret, Arnaud Couloux, et Katia Gindro. 2012. « What if esca disease of grapevine were not a fungal disease? » *Fungal Diversity* 54 (1): 51-67. https://doi.org/10.1007/s13225-012-0171-z.

Holman, Fenner H., Andrew B. Riche, Adam Michalski, March Castle, Martin J. Wooster, et Malcolm J. Hawkesford. 2016. « High Throughput Field Phenotyping of Wheat Plant Height and Growth Rate in Field Plot Trials Using UAV Based Remote Sensing ». *Remote Sensing* 8 (12). https://doi.org/10.3390/rs8121031.

International Organisation of Vine and Wine. 2019. « State of the vitiviniculture world market, state of the sector in 2018 ».

———. 2020. « 2020 wine production, OIV first estimates ».

Ji, Miaomiao, Lei Zhang, et Qiufeng Wu. 2020. « Automatic grape leaf diseases identification via UnitedModel based on multiple convolutional neural networks ». *Information Processing in Agriculture* 7 (3): 418-26. https://doi.org/10.1016/j.inpa.2019.10.003.

Jollard, Camille. 2017. « La Flavescence Dorée de la vigne : Identification et caractérisation des protéases de surface FtsH du phytoplasme de la FD et Caractérisation de la sensibilité variétale par comparaison de cépages très sensibles et peu sensibles. » Phdthesis, Université de Bordeaux. https://tel.archives-ouvertes.fr/tel-01718515.

Kerkech, Mohamed, Adel Hafiane, et R. Canals. 2018. « Deep learning approach with colorimetric spaces and vegetation indices for vine diseases detection in UAV images ». *Computers and Electronics in Agriculture* 155: 237-43. https://doi.org/10.1016/j.compag.2018.10.006.

Kerkech, Mohamed, Adel Hafiane, et Raphael Canals. 2020a. « Vine disease detection in UAV multispectral images with deep learning segmentation approach ». *Computers and Electronics in Agriculture* 174 (juillet): 105446. https://doi.org/10.1016/j.compag.2020.105446.

———. 2020b. « VddNet: Vine Disease Detection Network Based on Multispectral Images and Depth Map ». *Remote Sensing* 12 (20): 3305. https://doi.org/10.3390/rs12203305.

Liu, Bin, Zefeng Ding, Liangliang Tian, Dongjian He, Shuqin Li, et Hongyan Wang. 2020. « Grape Leaf Disease Identification Using Improved Deep Convolutional Neural Networks ». *Frontiers in Plant Science* 11: 1082. https://doi.org/10.3389/fpls.2020.01082.

Lu, Jiang, Jie Hu, Guannan Zhao, Fenghua Mei, et Changshui Zhang. 2017. « An In-field Automatic Wheat Disease Diagnosis System ». *Computers and Electronics in Agriculture* 142 (novembre): 369-79. https://doi.org/10.1016/j.compag.2017.09.012.

Ludovisi, Riccardo, Flavia Tauro, Riccardo Salvati, Sacha Khoury, Giuseppe Mugnozza Scarascia, et Antoine Harfouche. 2017. « UAV-Based Thermal Imaging for High-Throughput Field Phenotyping of Black Poplar Response to Drought ». *Frontiers in Plant Science* 8: 1681. https://doi.org/10.3389/fpls.2017.01681.

Madec, Simon, Fred Baret, Benoît de Solan, Samuel Thomas, Dan Dutartre, Stéphane Jezequel, Matthieu Hemmerlé, Gallian Colombeau, et Alexis Comar. 2017. « High-Throughput Phenotyping of Plant Height: Comparing Unmanned Aerial Vehicles and Ground LiDAR Estimates ». *Frontiers in Plant Science* 8: 2002. https://doi.org/10.3389/fpls.2017.02002.

Ministère de l'Agriculture, de la Pêche et de la Ruralité. 2005. « Guide pour une protection durable de la vigne : stratégie de protection pour une utilisation raisonnée et durable des intrants phytosanitaires en viticulture ».

Pantazi, Xanthoula Eirini, Dimitrios Moshou, Alexandra A. Tamouridou, et Stathis Kasderidis. 2016. « Leaf Disease Recognition in Vine Plants Based on Local Binary Patterns and One Class Support Vector Machines ». In *12th IFIP International*

Conference on Artificial Intelligence Applications and Innovations (AIAI), édité par Lazaros Iliadis et Ilias Maglogiannis, AICT-475:319-27. Artificial Intelligence Applications and Innovations. Thessaloniki, Greece. https://doi.org/10.1007/978-3-319-44944-9_27.

Ramcharan, Amanda, Kelsee Baranowski, Peter McCloskey, Babuali Ahmed, James Legg, et David P. Hughes. 2017. « Deep Learning for Image-Based Cassava Disease Detection ». *Frontiers in Plant Science* 8: 1852. https://doi.org/10.3389/fpls.2017.01852.

Taalas, Petteri. 2018. « World Meteorological Organisation ». Présenté à United Nations, Geneva, novembre 29.

Wang, Guotai, Wenqi Li, Sébastien Ourselin, et Tom Vercauteren. 2019. « Automatic Brain Tumor Segmentation Based on Cascaded Convolutional Neural Networks With Uncertainty Estimation ». *Frontiers in Computational Neuroscience* 13: 56. https://doi.org/10.3389/fncom.2019.00056.

Xie, Xiaoyue, Yuan Ma, Bin Liu, Jinrong He, Shuqin Li, et Hongyan Wang. 2020. « A Deep-Learning-Based Real-Time Detector for Grape Leaf Diseases Using Improved Convolutional Neural Networks ». *Frontiers in Plant Science* 11: 751. https://doi.org/10.3389/fpls.2020.00751.

Yadav, Samir S., et Shivajirao M. Jadhav. 2019. « Deep convolutional neural network based medical image classification for disease diagnosis ». *Journal of Big Data* 6 (1): 113. https://doi.org/10.1186/s40537-019-0276-2.

Zhou, Jie, Ganqu Cui, Zhengyan Zhang, Cheng Yang, Zhiyuan Liu, Lifeng Wang, Changcheng Li, et Maosong Sun. 2019. « Graph Neural Networks: A Review of Methods and Applications ». *arXiv:1812.08434 [cs, stat]*, juillet. http://arxiv.org/abs/1812.08434.