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REVIEW

Close proximity aerial image for precision viticulture. A review

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Abstract
Accurately detecting and localizing vineyard disease detections are essential to reduce production losses. A great variety of scientific work focuses on remote sensing methods, while with current learning-based techniques, a continuous paradigm shift is happening in this domain. Based on a thorough literature review, the need for a remote assistance survey for the detection of vine disease was motivated by the adoption of recent machine learning algorithms. Thus, in this work, the research outputs from the past few years are summarized in the domain of grapevine disease detection. A remote sensing-based distance taxonomy was introduced for different categories of detection methods. This taxonomy is relevant for differentiating among the existing solutions in this domain, the resulting methods being grouped according to the proposed taxonomy. The articles and public datasets cited are collected on the website of this project (https://molnarszilard.github.io/VinEye/).

Keywords Vine disease detection · Review · UAV remote sensing · Artificial intelligence

Introduction

Agriculture also faces a paradigm shift in the era of big data and advanced artificial intelligence algorithms. The demand for doubling agricultural production by 2050 and the technical challenges associated with climate change require an interdisciplinary approach that benefits from domains such as cybernetics (Zhang 2024). The well-established theoretical foundation in the cybernetics domain could be imported into the agricultural one to increase autonomy and support the interpretation and understanding of the specific technological challenges in agriculture (Zhang and Huang 2022). A key element in automatization is *loop closure*, or in other words, the observation of the process, which in the cyber agricultural approach has as equivalent the remote sensing of crops (Huang et al. 2023) for disease detection (Zhang et al. 2019), plant phenotyping (Yang et al. 2017), or plant counting (Wang et al. 2021b) using advanced autonomous vehicles from the ground, Wu et al. (2024), or air (Shammi et al. 2024).

This trend is reflected in *precision viticulture (PV)*, which becomes evident by the growing number of articles published yearly since 2010 in this domain, with hundreds of articles related to *PV* published since 2019. To support the global overview of *PV* through visual inspection, we propose a survey that focuses on recent trends and techniques for *PV* in the state of the art.

We have found a few recent surveys (Bischoff et al. 2021; Ouhami et al. 2021). However, these sources are already a few years old. Furthermore, Bouguettaya et al. (2023) list methods that only use *unmanned aerial vehicle (UAV* s), which tend not to be used in proximal sensing applications. Other surveys (Abbas et al. 2023) feature vineyard-related applications but do not focus on them in detail. Section 2 presents more information on previous vineyard-related surveys.

Therefore, in this work, we organize our selected articles into a survey on computer vision applications in the field of *PV*, more precisely, the detection of vine disease, focusing on the studies published in the last four years (2019–2023). The primary purpose of this survey is to evaluate current research trends and to support other researchers in choosing the best-suited method for their work. Our goal is not to reexplain the contribution of the authors but to provide an overview and brief description of the topics covered and techniques in a synthetic manner. Section 1.1 deals with the basic concepts of viticulture, such as history, grape varieties,

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diseases, and remote sensing. In Sect. 3, we describe the search and filtering of applications and then group them according to a taxonomy based on the distance between the camera acquisition system and the plants. The last part of Sect. 3 lists the available datasets for *PV* in general, not limited to disease detection applications. The last section summarizes all the methods analyzed, offers a few observations, and presents generalizations of the articles, followed by the appropriate conclusions.

Importance of grapevines

Viticulture is the science of the cultivation and harvesting of grapevines (*Vitis vinifera*, Winkler (1965)). These are the fundamentals for winemaking, or *enology* (Robinson et al. 2017), which has had a deterministic role in culture, economics, politics, social and ideological contexts throughout the millennia. Like salt, wine was a currency in Roman times (Unwin 2005).

Even today, the economic impact of wine is vast. The average annual wine production in the last 60 years has been around 30 million tons. Italy alone produces more than 20 million hectoliters of wine per year. It is the largest grape producer in the world, contributing approximately 17% to worldwide wine production in 2014, closely followed by Spain, France, and the USA (Castriota 2020). We want to mention that winemaking accounts for about 80% of grape production, while the remaining is used for direct consumption, and these grape varieties are called table grapes. Among wine grapes, there is a wide variety including *Cabernet*, *Merlot*, *Tempranillo*, *Syrah*, *Garnacha Tinta*, *Airen*, *Chardonnay* just to mention the most popular varieties, which are commonly planted on all continents (Kerridge and Antcliff 1999).

In this section, we would like to present an overview of grapevine-related notions, offering the reader a comprehensive understanding of the different aspects of vine growth, and providing the fundamentals for the expressions used later in the survey. The main aspects include grape phenotyping, diseases, and remote sensing.

We present numerous disease detection methods focusing mainly on the most widespread diseases. These include diseases using agents such as pathogens (bacteria, viruses), fungi, and insects. In this review, the main factor is the *visibility* of the diseases, which appear mainly on the leaves, while in other cases, the trunks, fruits, or veins are also visible. However, in specific cases, the symptoms are not visible to the human eye but to a camera that senses a range of wavelengths from the range of light radiation (e.g., color, ultraviolet, infrared). From a technical point of view, once the symptoms are visible, the main focus is on the underlying detection method, while the type of disease can be the topic for a more specific use case. However, in this case, background knowledge about the similarities between different types of disease is mandatory.

The worldwide loss of crops due to diseases is estimated at around 20–40% (Wang et al. 2022). These data reflect the amount of money and time spent on disease prevention, detection, and treatment, depending on profit. The cost of these detection operations scales with the size of the vineyards. The fixed cost of parts distributed over small-scale owners can be higher than that of large-scale operators. Another difference between small and large operations is the scale, which requires different equipment and methods. As discussed in Bischoff et al. (2021), Kamilaris and Prenafeta-Boldú (2018), Liakos et al. (2018), different platforms result in different costs for the end user. Other reviews (Ammoniaci et al. 2021; Moysiadis et al. 2021; de Oliveira et al. 2021; Sassu et al. 2021) provide further information on existing solutions in the field. However, actual costs are not mentioned since products and their absolute costs fluctuate depending on the scale of deployment, availability, location, and technological advancements. In short, there exists a scaling limit for the minimal size of the vineyard for the initial investment, while increasing the scale, the automation scales well. The economic feasibility will always depend on multiple factors, such as profit, profit margin, and scarcity of the workforce, as suggested in Schieck et al. (2023), where they asses the impact of drones on viticulture was assessed compared to backpack and tractor-mounted sprayers. They conclude that backpack sprayers cost about 3 times more than a tractor-mounted sprayer. At the same time, the drone might be slightly more cost-effective than a tractor-mounted sprayer, but only if we consider at least 400 h of usage per year, while the overall time for spraying a hectare is also slightly less. On the other hand, Cavalaris et al. (2023) claims that the human workforce can be more cost-effective than tractor-mounted systems, while *UAV* s are the least cost-effective variants.

Fundamentally, image processing needs visual differences between healthy and diseased plants. As long as they are present, image processing should be able to work relatively similarly on various types of disease. One challenge arises when the attack vector changes due to climate change (Chedea et al. 2021). A vineyard that sets up a system to detect one disease might need to migrate over time to another disease detection method due to the disappearance and appearance of disease types. Although the speed of climate change is difficult to assess, the most challenging part is the uncertainty of weather conditions, which affects the various types of grapes and the vectors of disease differently. To this end, the solution could have multiple forms: domain adaptation (training the task in one dataset, then applying it to another dataset with minor adjustments) (Quénol et al. 2014; Wang et al. 2024), or creating a general disease detector. Although

there are methods that detect multiple diseases simultaneously, a generic detector cannot be found.

Over time, we can observe a gradual increase in detection accuracy, which is due to advances in the field, including more precise image sensors, higher computational power, and more efficient approaches (Rançon et al. 2023). However, in many cases, the improvements are only marginal due to the complex nature of this problem. Furthermore, only a few authors test their methods on the same dataset, making the question of improvement unanswerable. This is mainly due to the fact that most researchers test their approaches in their local vineyards; therefore, their training and testing datasets constantly change over time. Additionally, problem statements also tend to be more complex over time, and a task that started as disease classification using an image of a single leaf becomes a task that either detects the exact location of the diseased leaf in the vineyard or even detects the number of diseased plants in an entire vineyard using a satellite image. Vrochidou et al. (2021) presents the advancements on a massive scale from the 1700s when any type of vineyard-related experiment had to be conducted in a laboratory due to the apparatuses of the time to the current year when portable sensors and later machine vision made it possible to make in-field measurements. The initial sensors were *hydrometer* or *pH meter*. At the same time, technology advancements later provided new means of analysis, such as *near-infrared (NIR)* spectrometers, colour imaging, colour imaging, and hyperspectral imaging. The last one or two decades have brought about the advent of machine learning and other autonomous robots in the field. Ouhami et al. (2021) lists the topics covered between 2017 and 2020.

Managing vineyards: grape phenology

The research of tracking, recognizing, understanding, and describing the annual stages of growth and development of grapevines is called *grape phenology* (Giese et al. 2020). *Yield estimation* is one of the elements of *grape phenology*, which deals with approximating the volume and weight of the fruit and the percentage of foliage. All of these indicators provide information on the overall health of plants and the vineyard, including *water stress levels* (Williams and Ayars 2005), *nutrient excess* or *deficiency* (Wolf 2008), and *plant stress* (McCarthy et al. 2008). All of these may be potential risks to yield reduction, challenges facing vineyard owners, and for which a possible solution is the detection of foliage or *yield estimation*. Roby et al. (2008) conclude that measuring the size of the fruits allows estimating *water deficiency* and identifying *lack of homogeneous maturation*. The soil moisture level and seasonal changes in local weather represent critical factors that affect the quality of the grapes (Bramley 2003). Another aspect of vine growing is the appearance of various diseases.

Diseases and other harmful factors

In viticulture, the literature catalogs numerous diseases such as *esca* (Fig. 1a), *black rot* (Fig. 1b), *flavescence dorée* (Fig. 1d), *leaf blight* (Fig. 1c), *powdery mildew* (Fig. 1e), *downy mildew* (Fig. 1f), *leafroll* (Fig. 1g), or pests, such as *Stictocephala bisonia* (Fig. 1h), etc. (Wilcox et al. 2015). The different diseases affect vine growth in different ways, such as destroying plants or reducing fruit quality and quantity. Stummer et al. (2003) prove that including even 1−5% of *downy mildew*-affected grapes into the production can alter the taste of wine. In Australia, winegrowers are often penalized if the rate of botrytis affected plants exceeds 3 5% (Nair and Hill 1992), while, according to Taylor and Cook (2018), since 1998 the cumulative losses due to *downy mildew* reached AUD 140$ million.

These facts show the high priority of *disease detection*, and prevention is a notable approach. Fungicides that prevent diseases can cause environmental and health damage while reducing product quality. In severe cases, the only solution is to eliminate the contaminated plants from the vineyard. Another consideration is to use genetically more resistant grape varieties (Wiedeman-Merdinoglu et al. 2002), but this often requires an effective resistance assessment method, such as *bacterial cell counter*, which is an invasive method that destroys *sporangia*, making the disease monitoring of that plant impossible (Bellin et al. 2009). Bischoff et al. (2021) mention that the occurrence

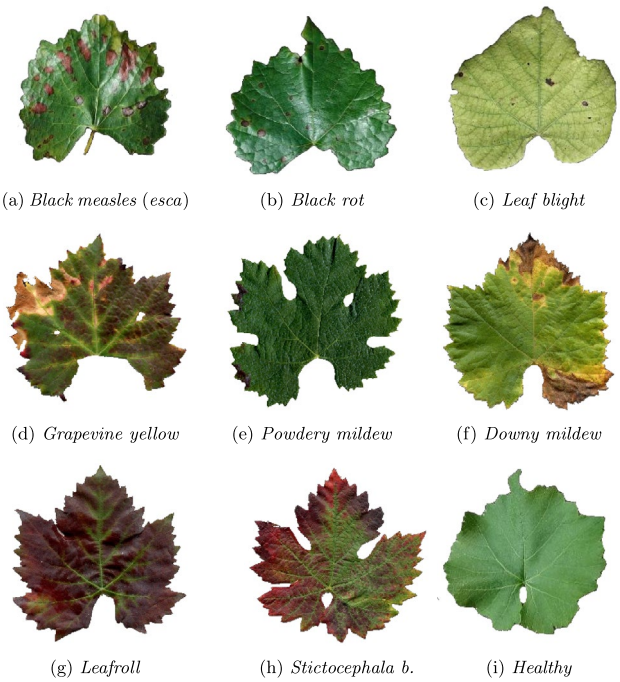


Fig. 1 Typical grapevine diseases (Cruz et al. 2019; Ampatzidis et al. 2018)

of a disease depends on the susceptibility of the host, the pathogen, and the environment. Alternatively, disease prevention and treatment are possible through efficient monitoring, which was previously based on humans. The current survey presents a growing trend for computer vision-based monitoring.

Overview of remotOverviewg in precision viticulture

Since vineyards occupy large areas, many researchers recommend the remote sensing approach versus close range analysis, although the latter approach ensures more precise measurements. *Remote sensing* refers to the acquisition of data from a distance by measuring the reflection or radiance of a given area, such as a mountain range or a vineyard field. At this point, the choice of the most appropriate vehicle comes into play. Satellite-based setup, while effective, often provides data periodically, not on demand (Matese and Di Gennaro 2015), except for the high rent costs. The second type of vehicle is an aircraft, which is more frequent than a satellite but requires a pilot; therefore, it entails a risk factor (Matese and Di Gennaro 2015). The third vehicle type, arguably the most popular method in recent times, is *UAV*. In the case of a vineyard, the most suitable *UAV* s are relatively small drones, usually with four to eight rotors, or occasionally a fixed-wing drone (Hafeez et al. 2023).

In most cases, remote sensing methods collect data through *RGB* or spectral imaging systems. Spectral sensors, such as *hyperspectral*, *multispectral*, and *infrared (IR)*, provide useful information about the different reflectance values of the vegetation surfaces (Matese and Di Gennaro 2015). The main difference between the sensors is the measured wavelength domain: *visible light*—400 to 700 nm, *NIR*—700 to 1300 nm, *thermal infrared (TIR)*—7500 to 15,000 nm. The *multispectral* domain includes the wavelengths from the *visible* spectrum to the *TIR*, while the *hyperspectral* domain is broader and less erratic.

Due to the high distance, the resolution of these images is not suitable for conventional image recognition systems and is slightly less used (Matese and Di Gennaro 2015). Therefore, various *vegetation indices* are calculated from these data (Bannari et al. 1995). These include, but are not limited to, *crop surface model*, *crop water stress index (CWSI)*, *digital elevation model*, *digital surface model (DSM)* or *digital terrain model (DTM)*, *enhanced vegetation index*, *excess green index*, *green-red vegetation index (GRVI)*, *leaf area index (LAI)* and *normalized difference vegetation index (NDVI)*. These indices can describe the status of the plants (Musci et al. 2020) and help estimate the structure of the plants and the vineyard in general through 3D reconstruction and creation of orthomozaics (Pádua et al. 2020).

Previous surveys

Vine growing is a popular topic with an expanding scientific community around *PV*. Surveys of this domain exist, which collect part of these works to provide an overview and guidance about a specific topic. In addition to categorizing recent articles, this survey aims to provide a summary of previously published surveys, focusing on *PV* using computer vision. This list includes papers from earlier than 2019 to provide a source and review of documents before 2019.

Whalley and Shanmuganathan (2013) examine multiple aspects of viticulture, including *yield estimation*, *quality evaluation*, *disease detection*, and *grape phenology*. The enumerated methods date back to the early 2000s up to 2013. Being a relatively early publication, Whalley and Shanmuganathan (2013) describes the first phase of *PV*. Some examples of notable methods for specific domains from this period are: Chamelat et al. (2006) and Reis et al. (2011) for grape detection, Rabatel and Guizard (2007) for berry size estimation and Meunkaewjinda et al. (2008) for disease detection.

Matese and Di Gennaro (2015) categorize applications for viticulture, such as *geolocation*, *remote sensing*, *soil monitoring*, *crop monitoring*, *yield*, and *quality monitoring*. Their collection of publications and projects in the field *PV* is up to 2015. They also claim that *farmbots*, or *agbots*, is the future of agriculture. Furthermore, wireless sensor applications are common to provide *site-specific micro-climate monitoring* (Matese et al. 2013).

Pereira et al. (2017) present papers from 2007 to 2017 on the use of image processing in *precision agriculture (PA)*. The listed works segment the plant's canopy, including the grapevine, detecting diseases on the leaves and analyzing fruits. This survey includes methods classified as *segmentation*, *image enhancement*, *detection*, and *classification*. Most of the methods are compared on the basis of their accuracy.

Seng et al. (2018) show that, although laboratory methods are considered straightforward to create, most of the image processing techniques of vineyards between 1997 and 2017 are field approaches. These approaches include *yield estimation*, *disease detection*, and *grain phenology*. The authors also propose a grape dataset, named *GrapeCS-ML*, more information is provided in Sect. 3.5, mainly for *grape bunch detection* using different colour space techniques, including chemical analysis of grapes, such as *sugar content* or *acid levels*.

Abbas et al. (2020) focus on intelligent spraying systems in agriculture, including some examples for vineyard applications. Despite their hazardousness, different chemicals, such as pesticides, are becoming increasingly used,

and hence, the importance of targeted spraying systems is increasing. The presented methods are categorized according to plant species, sensor types, and platforms.

Ammoniaci et al. (2021) briefly present the different aspects of *PA*, more specifically *PV*, starting from the first recorded application *PA* (Linsley et al. 1929). The authors also describe the available solutions on the market and the common monitoring platforms at the time of publishing.

Barriguinha et al. (2021) gather 82 peer-reviewed journals, conference articles, and book chapters published between 1987 and June 2021, according to the statement *Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA)* (Page et al. 2021). The presented papers are categorized into ten data-driven model categories: computer vision and image processing, vegetation indices, pollen, crop simulation models, trellis tension, laser data processing, radar data processing, radio frequency data processing, ultrasonic signal processing, and other factors. These articles focus on *yield estimation* in vineyards, while the authors emphasize that the applicability of the described methods in a commercial vineyard is limited.

Bischoff et al. (2021) review *PA* applications from the point of view of *disease detection*. They explain many aspects using possible sensing techniques in a vineyard, for which relevant examples are given. Possible gaps, trends and challenges are highlighted in *disease detection* in *PV*. The authors describe the main disease factors while providing a case study of *downy mildew*. The analyzed articles are from 2008 to 2018, while carefully specifying the filtering process, which led to 56 notable articles from the original 668.

Carvalho et al. (2021) approach the existing vineyard processing methods from a phenotyping point of view; in other words, they review papers with high impact in *yield estimation*, *vine genom approximation*, and *stress resistance*. They collect articles in different categories, depending on the acquisition devices, including *RGB*, *IR*, *light detection and ranging (LiDAR),* and *multispectral* ones.

Madroñal et al. (2021) show a wide range of methods using *UAV* s, not only in *PV* but also in the agricultural domain, while also focusing on future possibilities, such as Single European (2017). The authors mention three methods for vineyards by Primicerio et al. (2012), Santesteban et al. (2017), Vasudevan et al. (2016), but their functionalities are only briefly discussed, the main focus is on possible hardware requirements in the field of *PA*, therefore, the approach of Madroñal et al. (2021) is recommended for embedded computer-based processes, such as autonomous vehicle applications.

Moysiadis et al. (2021) presents several types of agricultural tasks, including grapevines, mainly from Europe. Although the main focus is not on *PV*, they offer numerous articles in this domain and mention two existing projects on the market. In addition to the target plant species, the general list of applications *PA* is analyzed based on the type of task and the country of origin.

The survey of de Oliveira et al. (2021) mainly analyses the currently available *PA* applications in general. At the same time, among the examples, they list some papers on vineyard management. This survey provides a basic definition of *PA* and highlights the challenges of this domain.

Ouhami et al. (2021) approach the review of *PA* applications that focus on combining computer vision and the internet of things for *disease detection*. They also list numerous methods designated for grapevines that use machine learning in different monitoring platforms and sensors in various environments.

Sassu et al. (2021) review the available *UAV*-based vineyard analyser solutions. The tasks include *row segmentation*, *crop feature detection*, *variability monitoring*, *row area* and *volume estimation*, *prescription maps* for spraying management and *disease detection*, which are based on indices-ground measurement relationships. Furthermore, the authors investigate the use of different types of *UAV* s and conclude that although fixed-wing drones can cover larger areas than multirotor ones, due to the ability of accurate data acquisition and navigability of proximal sensing, multi-rotor drones are preferred in the literature.

Tardaguila et al. (2021) gather papers between 2001 and 2021, briefly discussing the platforms on which they are based, the sensors used, and the tasks in focus. Platforms are mainly *UAV* s or *unmanned ground vehicles*, while sensors include *RGB*, *multispectral*, *hyperspectral*, *LiDAR*, *X-Ray*, *fluorescence*, and *thermography*. The main tasks are to analyze the: *soil properties*, *topography*, *vegetative growth*, *nutritional status*, *canopy architecture*, *diseases*, *water status*, and *yield*.

Vrochidou et al. (2021) analyze the potential, performance, and input data of the available methods in vineyards, including applications such as the use of *agrobots*, *grape ripeness classification*, and *vegetative indices*. Furthermore, this survey describes the specific characteristics of grapevines compared to other fruits, while *grape maturity indices* are also discussed separately.

Bouguettaya et al. (2023) concentrate on papers designated for *UAV*-based *disease detection* using deep learning techniques, mentioning 45 papers from a period of 17 years. These methods differ in the type of *UAV* (*rotary-wing*, *fixed-wing*, *hybrid*), the sensor used (*RGB*, *multispectral*, *hyperspectral*, *NIR*) and the adopted methods. This survey mainly contains vineyard-specific applications, such as *mildew disease* identification.

Wang et al. (2022) presents various plant viral disease detection algorithms, including vineyard applications. The authors review camera systems and spectral data analysis using the following criteria: impact, diagnostic methods, traditional detection methods, optical

sensing technologies, data processing, modeling, and cost comparison.

Hafeez et al. (2023) list applications in *PA* about drone monitoring systems for precise *pesticide spraying*. The authors mention papers about grapevine *remote sensing* using *UAV* s, computing *CWSI*, and *crop monitoring*. The evolution of *UAV* usage in *PV* is presented in a timeline from 2010 to 2020.

He et al. (2022) provides a general review of empty estimates for vineyard applications. The papers are organized according to platforms, tasks (detection or analysis), and methods. Although this survey contains relatively few articles related to the vineyard, many techniques for other types of fruit also apply to grapevines.

Mohimont et al. (2022) provides a detailed overview of computer vision and deep learning applications used in viticulture. This survey is a follow-up work to the overview of Seng et al. (2018), complete with more recent work. They list possible tasks, such as *flower counting* or *grape detection*, while considering the difficulties of the domain of *PV*. Classical methods, such as *keypoint detection* and *thresholding*, are briefly compared to deep learning-based methods; however, the authors agree on the consensus: deep learning applications outperform classical methods in a variety of cases as long as sufficient training data is provided and enough computing resources are available.

Abbas et al. (2023) focus on disease detection using *UAV* s for plants in general, but methods with vineyards are also mentioned. The structure of this survey is based on comparisons. Regarding the methods, old and new methods are presented, while the advantages and disadvantages of different sensor types (*RGB*, spectral), *UAV* types (fixed wing, rotary wing) are also reviewed. In this survey, a list of specific drones and sensors is also available.

Moreno and Andújar (2023) approach the overwhelming amount of articles in the domain by focusing on different 2D and 3D modeling techniques in vineyards. The methods are mainly based on proximal sensing but also mention the possibilities and differences toward remote sensing. This review proposes possible paths for future research while providing recommendations on the methods to be used in specific tasks, such as canopy characterization, yield estimation, segmentation, or modeling of the structure of the vineyard and plants.

The survey of Rançon et al. (2023) is unconventional in that it does not list articles from the general literature, but rather their experience in the domain of *PV*, which covers eight years. The tasks presented range from *yield estimation* (Keresztes et al. 2018) to *disease detection* (Abdelghafour et al. 2020; Rançon et al. 2019; Tardif et al. 2022), using various ground vehicles (guided and unguided) as a platform. The main thread between these works is pursuing a camera system that provides reliable, consistent data while being cheap, robust, and trim. The result of this research is a camera system that uses a 5-megapixel *RGB* camera, supplying images to a *Raspberry Pi* (occasionally *Jetson Xavier/Nano* board, if processing on site is necessary). The system also includes a *global navigation satellite system (GNSS)* system for global positioning and a distance sensor. The most important part of the system is a high-power xenon flash, which generates well-lit foliage with dark backgrounds, almost achieving an on the spot *canopy segmentation*. Although each vehicle type requires unique mounting mechanisms, this system suits most *PA* applications well.

Kunduracioglu and Pacal (2024) focus on the computational difficulties of processing grapevine leaves in a controlled environment, comparing existing models based on convolutional neural networks and vision transformers. The authors focus on two datasets: Hughes et al. (2015), Koklu et al. (2022), to classify diseases. Training is further improved by normalizing the data, improving the image, and pre-training on the *ImageNet* dataset (Deng et al. 2009). While the authors train the model parameters using the training split of the dataset, in the validation phase, they fine-tune the hyperparameters. In their experiments, the method of Liu et al. (2022c) has perfect accuracy.

Remote sensing-based disease detection

This section presents 44 papers, focusing on their underlying architecture. For a better overview, we decided to organize the methods into groups. After a tedious procedure to search, filter, and categorize the techniques described in Sect. 3.1, we chose three groups based on the distance between the acquisition system and the plant: extreme proximal, proximal, and remote sensing. After presenting the papers, we provide a table that lists the methods and relevant keywords in each section. Lastly, Table 5 lists the various available datasets that we accessed at the end of 2023.

Filtering and taxonomy

In this section, we describe the procedure for sorting methods and present the taxonomy of the organization of the techniques described. We use the statement *PRISMA* (Page et al. 2021) as a guide for the search and filtering of the articles.

As we mentioned in Sect. 1, our main objective for this survey is to investigate the currently available methods to detect vine diseases that are applicable in the field. Therefore, we explicitly focus on the detection of vine diseases instead of yield estimation, plant structure estimation, or navigation. In addition, disease detection methods that operate in a laboratory environment are excluded. However, a few exceptions are made if the presented method evaluates

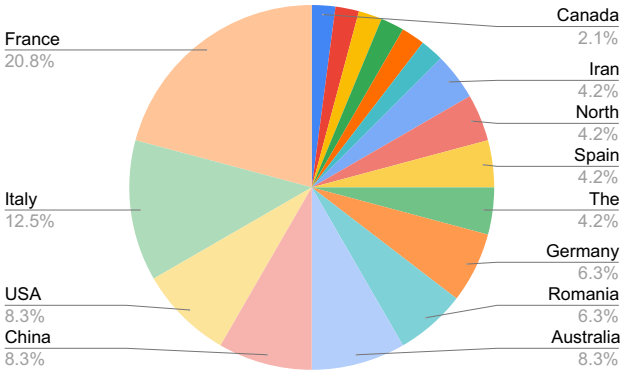


Fig. 2 The distribution of the articles presented in this survey by country. (Other countries, each with 2.1%, are Greece, Morocco, New Zealand, Portugal, and Russia)

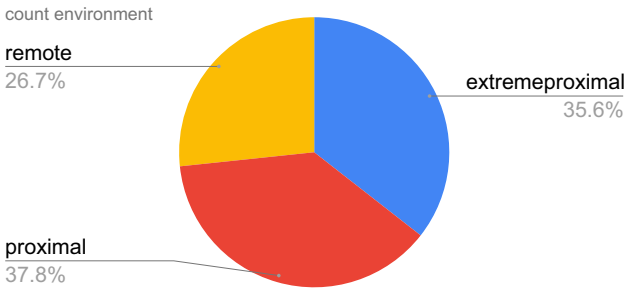


Fig. 3 The distribution of the articles by environmental perception type

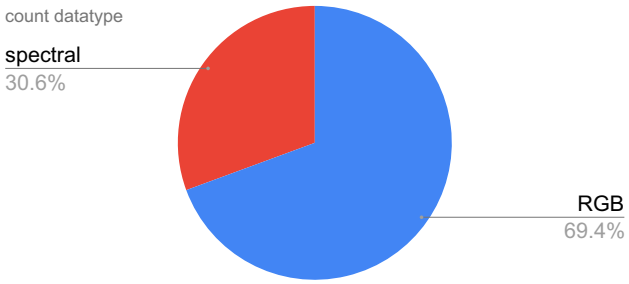


Fig. 4 The distribution of the articles by data type

the results on in-field images, even if the core of the used dataset contains harvested plants.

We searched for articles in the *Google Scholar* dataset[1] using the following terms: *computer*, *vision*, *grape*, *vine*, *disease*, *viticulture*. We want this survey to be as openly accessible as possible. Hence, we excluded paid papers and kept only the ones that we found for free (in a few cases, we contacted the authors for a copy). Then, we eliminated those that were not in our aim by interpreting the paper's title, abstract, or content. This resulted in 44 articles presented in detail in this survey.

We wanted to categorize the papers based on a taxonomy for a cleaner organization. We started by assigning a few keywords to each paper. For example, a possible organization could have included the country of origin. In this case, we listed the affiliation countries and got the distribution in Fig. 2. On the one hand, this chart is an interesting representation of countries that focus more on the detection of vineyard disease. The most significant information is that France and Italy produce the third of all articles in this domain, which is closely correlated with the findings in Sect. 1.1 (Castriota 2020). However, the country of origin does not have a qualitative value. Therefore, we think that another category is needed.

Therefore, we analyze the distance between the image acquisition system and the grapevines. We identified three categories: remote (more than 5 m), proximal (between 0.5 to 5 m), and extreme proximal (close-up, the processed image contains only a tiny part of a plant, usually only one leaf). We refer to these as environment types; their distribution can be seen in Fig. 3.

Although the environment-type categorization gives a relevant split, we also verified other possibilities. Different data types are used in the various articles: *RGB*, *HSV*, *L*a*b*, multispectral, hyperspectral, *TIR*, depth, and orthomozaic. However, most of the favored types are derivatives of another type, mainly *RGB* or spectral data. The distribution of these two data types can be seen in Fig. 4. *HSV* and *L*a*b* are usually converted from *RGB*, while spectral refers to multispectral, hyperspectral, or *TIR*. 3D shapes can be estimated from all of these data types. Papers using 3D sensors for initial data acquisition are rare and usually capture data in the main two categories. In some cases, both *RGB* and spectral data are captured. The distribution is in favor of the *RGB* images. Furthermore, the spectral data are scattered across the three previously established environment types. Therefore, we did not consider the data types used as relevant subsections, and in the end, we used only the environment-based taxonomy.

Therefore, the following three subsections correspond to the three types of environment: extreme proximal, proximal, and remote. The articles are organized alphabetically by the first author's name in each section. A tabular representation summarizes the articles at the end of each section, including essential references.

Concerning the cost of the presented approaches, various outlets discuss the advantages and disadvantages of vehicle base, as well as sensor types. Between these outlets, the focus shifts around as (Abbas et al. 2023; Hafeez et al. 2023; Bouguettaya et al. 2023) undertake the differences for various *UAV* s, such as satellites, fixed-winged or rotary

[1] https://scholar.google.ro/.

drones, but also the different image acquisition devices such as *RGB*, thermal infrared, or multipectral cameras. However, Abbas et al. (2020) only compares the diverse choices of sensors for ground use. Ammoniaci et al. (2021), Matese and Di Gennaro (2015), Madroñal et al. (2021), Bischoff et al. (2021) provide wider coverage, mentioning all 3 approaches to a certain extent. In Table 1, we summarize a few aspects of these surveys, starting with *setup cost*, which can be neglected if the user does not own the equipment but rents it. The *Care cost* can be viewed as rental cost, salaries, repair, or energy usage. Further advantages and disadvantages are also mentioned. In this table, we listed acquisition vehicles; however, most of them could be included in more than one category: Manual image acquisition can be proximal or extreme proximal, and a drone can be considered proximal or remote sensing. Additionally, each base can be equipped with specific sensors that reflect not only their types but also their qualities.

Extreme proximal sensing

This section presents methods that operate on data captured at a very close range. The camera often sees only one organ of the plant, such as a leaf or a bunch. Since our goal is to provide disease detection methods for vineyard applications, we tried to neglect methods that use laboratory environments for their tests. This usually means destroying organs or entire plants and analyzing them in a controlled environment. However, we included papers that evaluated their methods using in-field images, even if their primary dataset looks more synthetic.

Bendel et al. (2020a), continue their spectral-based disease detection (Bendel et al. 2020b), this time focused on *esca* disease, and instead of cutting off several branches for laboratory evaluation, a phenoliner tractor is used. They compare proximal detection (from a tractor) with remote sensing (using a *UAV*) for detection. In proximal sensing, the reflectance is calculated from the hyperspectral data. However, for remote sensing, in addition to the vegetation indices, the pipeline is more complex, containing the quantization algorithm *multi-layer perceptron (MLP)* (Cybenko 1989), *standard average variate normalization* (Asaari et al. 2018), *support vector machine (SVM)* (Hearst et al. 1998), *radial basis function (RBF)* (Backhaus et al. 2011), and *Neural gas* quantization algorithm (Martinetz et al. 1993).

Gutiérrez et al. (2021) propose a detector and differentiator of *downy mildew* and *spider mite* using *RGB* images, acquired by manual proximity imaging. The preprocessing phase starts with manual background cropping, leaving one leaf per image, and then segmenting the leaf using the *GrabCut* method from the *OpenCV* libraries. After this, the *RGB* colour space is converted to *HSV* (Smith 1978) for better robustness against changes in illumination (Hamuda et al. 2017), which is one of the main drawbacks of the *RGB* images in outdoor scenes(Siogkas and Dermatas 2006). The authors highlight that by using *hue thresholding* and only the *H* channel, they achieve a more accurate *CNN* (Kamilaris and Prenafeta-Boldú 2018).

Jovanovska et al. (2022) propose a *GIS* dashboard to overview an *internet of things (IoT)* application for the detection of vineyard disease. They use a static camera mounted on a pole with solar panels and an Internet connection to identify diseases with an algorithm based on *ResNet* (He et al. 2016; Broome et al. 1995). Although the author's focus is on *downy mildew* and *powdery mildew*, their algorithm is pre-trained on the *PlantVillage* (Hughes et al. 2015) dataset, which contains more diseases, however, in a laboratory environment.

Liu et al. (2020) detect vine diseases from *RGB* images of grape leaves. Their *DICNN* tackles the different leaf sizes that appear in the images by introducing the *dense inception* module of *GoogLeNet* (Szegedy et al. 2015). In addition to the main inspirations from *VGG* (Simonyan and Zisserman 2015), *ResNet* (He et al. 2016), and *DenseNet* (Huang et al. 2017), *asymmetric factorization approach* (Szegedy et al. 2016) is applied to reduce computational cost. The result of this network is a heatmap of possible disease patches on the close-up images of the leaves.

Math and Dharwadkar (2022) achieve an F1 score of 0.9934 on the *PlantVillage* dataset Hughes et al. (2015) using their CNN-based method. In their architecture, they modify the models from Bhatia et al. (2020) and Trivedi et al. (2020) by replacing the *flattening layer* with a *global average pooling* layer (Lin et al. 2014).

Miranda et al. (2022) approach the problem of grapevine berry disease detection using a *variational autoencoder*

Table 1 Comparing various platforms for visual monitoring for precision agriculture

Approach	Initial cost	Running cost	Advantages	Disadvantages
Satellite	Low	Very low	Very large area and autonomy	Very infrequent, very low details
Fixed winged aircrafts	Very high	High	Large area	Infrequent, low details, hours of autonomy
Rotary winged drones	Medium	Medium	Frequent, medium detail	Medium area, minutes of autonomy
Ground robots	Medium	Medium	Frequent, high details	Small area, varying autonomy
Manual	Low	Low	Very high detail	Very small area, infrequent

(VAE)-based anomaly detection algorithm. The first step is to extract the regions of interest, which are the berries, using the work of Zabawa et al. (2020), which is further based on the architectures *MobileNetV2* (Sandler et al. 2018) and *DeepLabV3+* (Chen et al. 2018) architectures. After berry detection, the architecture *VAE* (Kingma and Welling 2014) architecture learns to encode healthy berries into the latent space. This approach could be considered a follow-up work of Strothmann et al. (2019), where anomaly detection is based on the simpler *autoencoder* architecture (Vincent et al. 2010). Then, instead of the more conventional comparison of the input image with the reconstructed image, the authors apply an additional *VGGNet* (Simonyan and Zisserman 2015) before the comparison. This approach is called *feature perceptual loss*, and is claimed to measure the difference between the hidden layers. Part of the used dataset is publicly available; more information is given in Sect. 3.5.

Molnár et al. (2023) evaluate the performance of several architectures in detecting diseases in grapevine leaves. The architectures tested are the following: *feature pyramid network (FPN)* (Lin et al. 2017), *MobileNetV3* (Howard et al. 2019), *Mask-RCNN* (He et al. 2017), *SegNet* (Badrinarayanan et al. 2017), and *Otsu's thresholding* (Otsu 1979). Apart from the last, all of them are neural networks. This method is on the edge of being considered an outdoor method trained in both laboratory and field data. The main dataset is the *PlantVillage* (Hughes et al. 2015) dataset; however, the authors conduct an extensive evaluation of the capabilities of the models trained in laboratory images and predict cropped images from various other datasets. The main takeaway from this testing is that adding a few images from the target domain significantly improves the cross-domain predictions.

Morellos et al. (2022) experiment with vineyard disease detection (*esca*, *powdery mildew*) detection and classification using transfer learning. They analyse three architectures: *AlexNet* (Krizhevsky et al. 2012), *VGG* (Simonyan and Zisserman 2015), and *Inception v3* (Szegedy et al. 2016). During training, multiple scenarios are considered. The models are pre-trained with *ImageNet* (Deng et al. 2009) or with *PlantVillage* (Hughes et al. 2015), which is followed by a fine-tuning phase mainly using *PlantVillage*, but later with proprietary images. These proprietary images differ from open source datasets since while the *PlantVillage* images are single leaves on a neutral surface, their proprietary images represent vines in the field with often multiple leaves in the images. This difference in data does not hinder the performance of the architectures, of which the *Inception v3* architecture provides the best overall classification accuracy.

Oprea et al. (2023) prune the *VGG* (Simonyan and Zisserman 2015) to achieve a lighter, but better-performing model named *Avert-CNN*. This model detects and classifies disease from close-up images of grapevine leaves. Although its main dataset is the *PlantVillage* (Hughes et al. 2015) dataset, the authors also include several images cropped from field images.

Roşcăneanu et al. (2022) present a vineyard monitoring system, where various sensors *Iot* (temperature, humidity, radiation, etc.) help to estimate disease, while images based on *UAV* provide a means of assessing current vineyard condition and the presence of the three diseases in focus (*powdery mildew*, *downy mildew* and *gray rot*). Unfortunately, the image processing part, based on machine learning, requires a large amount of manual labor for the preprocessing; furthermore, the authors do not include the used architecture, while the focus on *Iot* sensors is so high that the model description is missing.

Rudenko et al. (2023) improve the performance of a *YOLOv5* (Jocher 2020) architecture in disease detection by extending a selective search algorithm. The method is suitable for mobile deployment for in-field disease detection, although the images must be taken from a close range.

Tockova et al. (2022) base their disease detection method on the *ResNet* architecture (Du and Li 2018). Furthermore, the main curiosity of this method is the cloud-based implementation using *Amazon SageMaker* (AWS 2023). Although the model was trained on the *PlantVillage* (Hughes et al. 2015) dataset, which consists of individual leaves with an unnatural background, the method detects disease for leaves grown from other sources with a natural background. However, for real-world deployment, this method needs a cropping tool as a preprocessing step to detect black rot, black measles, or leaf blight disease.

Wang et al. (2022a) start their presentation by comparing the *MobileNetV2* (Sandler et al. 2018) architecture with the *YOLOX_s* (Ge et al. 2021) architecture. According to their results, *YOLOX_s* performs better on the *PlantVillage* (Hughes et al. 2015) dataset. Therefore, it is used for further processing. This *YOLOX_s* architecture is an enhanced *YOLOv5* (Jocher 2020), with the addition of *FPN* (Lin et al. 2017) and two attention modules: *Squeeze-and-Excitation Network* (Hu et al. 2018) and *Convolutional Block Attention Module* (Woo et al. 2018). After optimizing this network on a custom dataset containing about 30K images, the authors deploy this disease detection algorithm on the web using an embedded platform. It is important to mention that since the *PlantVillage* (Hughes et al. 2015) dataset is a laboratory environment, the customs data are similar, meaning that this method requires close-up images of leaves.

Wang et al. (2023a) use a handheld hyperspectral camera to detect *grapevine leafroll* disease in a proximal sensing situation. The data collected are first preprocessed using the *Savitzky-Golay* filter (Savitzky and Golay 1964), *standard normal variate* method (Barnes et al. 1989), and the *mean center* method (Hofer 2017). For outlier identification,

Hotelling's T^2 and *Q residuals plot* are proposed (Miller 2010).

Yang et al. (2021) use *ShuffleNet V2* (Ma et al. 2018) for disease detection (*anthracnose*, *downy mildew*, *mites*, *leafhopper*, and *viral*). The inputs are close-up images acquired with three cameras: *RGB*, multispectral, and *TIR*. The given data types are evaluated separately and also in combination with each other. The authors conclude that the processing of individual *RGB* images yields the best performance. All other combinations are inferior, especially if the multispectral image is involved, which has too many channels. Although *TIR* does not provide significant results, its inclusion in a group could improve the results (Table 2).

Zhang et al. (2022) improve the precision of *YOLOv5* (Jocher 2020) with *path aggregation network* (Liu et al. 2018) and *coordinate attention mechanisms* (Hou et al. 2021) in detecting *downy mildew* spots in leaves. Although the increase in accuracy is only around 1 2%, the decrease in runtime is almost 40%. Although the images are close-ups, containing almost only one leaf each, the authors implement a unique data augmentation technique when they alter only the diseased spots previously marked manually, and not all of them.

Proximal sensing

This section includes papers that detect a disease from a distance, familiar to a person walking through the vine rows while surveying the plants without closer inspection. This means that the camera is between 0.5 to 5 m from the subject.

Abdelghafour et al. (2020) tackle the problem of *downy mildew* detection by first converting the *RGB* images into *HSV* (Rittner et al. 2010). This is important to create structural information from colourimetric data and to filter out non-vegetation pixels by applying *Otsu's thresholding* (Otsu 1979). Subsequently, a *local structure tensor* (Knutsson et al. 2011) is created to extract geometric information and trends from local features, with the addition of mapping the tensors to the *log-euclidean* space using *Riemannian manifold* (Arsigny et al. 2006). The resulting representation is called the *tensorial colour log-euclidean structure tensor* based on their previous work (Abdelghafour et al. 2018, 2019), which are similar in the description of the method, but more focused on the detection of grape bunches. Later, the authors publish an article about the used dataset (Abdelghafour et al. 2021), containing *RGB* images about vine foliage, specifically in the case of *Merlot* grapes. The acquisition camera is mounted on a ground robot, in this case, a tractor, oriented directly toward the leaves; therefore, this dataset is appropriate for both *leaf segmentation* and *disease detection* on the leaves. Grape berries are immature; therefore, their usefulness is relatively low. In addition to healthy leaves, this dataset also contains leaves that show symptoms of *downy mildew*, making it ideal for future researchers focusing on this specific disease. The dataset is available; more information is available in Sect. 3.5.

Barjaktarović et al. (2022) base their work on the method of Garcia et al. (2021) and extend it to process hyperspectral and multispectral images simultaneously. Another contribution of this work is the introduction of a low-cost multispectral camera system for embedded computers, which is based on the works of Themelis et al. (2008) and Fawzy et al. (2015). The spectral camera is mounted on a ground structure and focuses on *flavescence dorée* detection.

Barjaktarović et al. (2023b) propose a low-cost multispectral camera system for proximal in-row *flavescence dorée* detection. This camera system is based on *Raspberry Pi 4* and *Arducam Quad-Camera Bundle Kit*. The total cost is around 2K euros. The system is evaluated by detecting diseases, for which the authors start applying *standard normalize variate* (Asaari et al. 2018) to reduce the effects of the slope and distance of the leaf from the camera. The detection itself is a *linear discriminant analysis* application (Peller et al. 2021). This assembly appears again in Barjaktarović et al. (2023a), where the authors continue their quest for proximal spectral detection of *flavescence dorée*. The multispectral camera mentioned above is combined with a consumer-grade hyperspectral camera, while the *standard normalize variate* (Asaari et al. 2018) mechanism is still present to filter the signals. To improve detection and classification, *k-fold cross-validation* (Srinivasan et al. 2019) with the *MLP* network is used, the same as by Al-Saddik et al. (2019).

Boulent et al. (2020) focus on the detection of *flavescence dorée* symptoms mainly in white grapevines, such as *Chardonnay*. They propose a *fully convolutional network* (Shelhamer et al. 2017), such as *ResNet* architecture (He et al. 2016), pre-trained in *ImageNet* (Deng et al. 2009). The class activations are finely detailed and discriminative due to *guided gradient-weighted class activation mapping* (Selvaraju et al. 2020). Furthermore, the authors preserve the global structure with reduced dimensionality using *uniform manifold approximation and projection* (McInnes and Healy 2018).

Falaschetti et al. (2021) focus on *esca* disease detection. Their main contribution to *state of the art* is creating an architecture that can be run on a low-cost, low-performance device. Firstly, a *full-rank* network is created and trained using the dataset by Alessandrini et al. (2021). Secondly, the network is optimized and pruned to be as small as possible using *CANDECOMP/PARAFAC decomposition* (Cichocki et al. 2015) and *Tensorly* (Kossaifi et al. 2019). The small model achieves a compression rate of 13 Hz while barely losing the accuracy of competing methods. This approach is called knowledge distillation (Hinton et al. 2015). However, the authors do not mention this notion.

Table 2 List of the extreme proximal sensing methods

Method	Data type	Description	Based on
Bendel et al. (2020a)	Spectral	Evaluating proximal and remote sensing using hyperspectral and multispectral data, captured from a tractor and a *UAV*	Asaari et al. (2018), Backhaus et al. (2011), Hearst et al. (1998), Cybenko (1989), Martinetz et al. (1993)
Gutiérrez et al. (2021)	*RGB*	Detects *downy mildew* and *spider mite* on handheld device-acquired *RGB* images	Smith (1978), Hamuda et al. (2017), Siogkas and Dermatas (2006), Kamilaris and Prenafeta-Boldú (2018)
Jovanovska et al. (2022)	*RGB*	Using static camera and *ResNet*	Broome et al. (1995), He et al. (2016)
Liu et al. (2020)	*RGB*	Detecting *anthracnose*, *brown spot*, *mites*, *black rot*, *downy mildew*, and *leaf blight* using *RGB* images	Szegedy et al. (2015), Simonyan and Zisserman (2015), He et al. (2016), Huang et al. (2017), Szegedy et al. (2016)
Math and Dharwadkar (2022)	*RGB*	Processing and classifying individual grape leaves	Bhatia et al. (2020), Lin et al. (2014), Trivedi et al. (2020)
Miranda et al. (2022)	*RGB*	*Variational autoencoder*-based berry anomaly detection	Chen et al. (2018), Kingma and Welling (2014), Sandler et al. (2018), Simonyan and Zisserman (2015), Zabawa et al. (2020)
Molnár et al. (2023)	*RGB*	Evaluate multiple methods on cross-domain validation	Badrinarayanan et al. (2017), He et al. (2017), Howard et al. (2019), Lin et al. (2017), Otsu (1979)
Morellos et al. (2022)	*RGB*	Classifying diseased vine leaves using transfer learning	Krizhevsky et al. (2012), Simonyan and Zisserman (2015), Szegedy et al. (2016)
Oprea et al. (2023)	*RGB*	Lightweight *VGG* architecture for close-up disease detection and classification	Simonyan and Zisserman (2015)
Roşcăneanu et al. (2022)	*RGB*	Disease estimation using *Iot* sensors, and disease detection using preprocessed images from a *UAV*	not specified
Rudenko et al. (2023)	*RGB*	Expanding the base *YOLOv5* method with selective search algorithm for a light-weight disease detection application	Jocher (2020)
Strothmann et al. (2019)	*RGB*	Detecting diseased grapevines using *autoencoders*	Vincent et al. (2010)
Tockova et al. (2022)	*RGB*	Individual leaf disease detection using *Amazon SageMaker*	AWS (2023), Du and Li (2018)
Wang et al. (2022a)	*RGB*	*YOLOv5* customization with attention modules and *FPN* for embedded disease detection	Ge et al. (2021), Hu et al. (2018), Lin et al. (2017), Woo et al. (2018)
Wang et al. (2023a)	spectral	Handheld hyperspectral data processing for *grapevine leafroll* assessment	Barnes et al. (1989), Hofer (2017), Miller (2010), Savitzky and Golay (1964)
Yang et al. (2021)	*RGB*spectral	Comparing the different combinations of *RGB*, multispectral, and *TIR* images for disease detection using *ShuffleNet*	Ma et al. (2018)
Zhang et al. (2022)	*RGB*	*Downy mildew* spot detection on close range images based on *YOLOv5*	Hou et al. (2021), Liu et al. (2018), Jocher (2020)

Farahani et al. (2022) combine the methods *Faster-RCNN* (Ren et al. 2017) and *VGG* (Simonyan and Zisserman 2015) to propose a proximal disease detection algorithm, named *Enhanced VGG*. The architecture achieves almost perfect detections on 10,000 proximal images *RGB* (manually annotated by the authors but not publicly available), focusing on (*downey mildew*, *anthracnose* and *powdery mildew*).

Liu et al. (2022) describe their observations of *disease detection* based on a tractor-mounted vertical stereo camera accompanied by a high-power flash, similar to the work of Abdelghafour et al. (2020), but with a faster exposure time (Mueller-Sim et al. 2017). The flashlight makes the *canopy segmentation* possible after converting the images into *HSV* colour space. The photos are split into six regions to reduce the loss of resolution during resizing. The overlap of objects between different images is omitted using the *GNSS* information combined with the depth information computed using the *stereo semi-global block matching* method (Hirschmüller 2008). For the *disease detection* itself *hierarchical multiscale attention for semantic segmentation (HMASS)* (Tao et al. 2020) is used. The authors experiment with different levels of severity, which is the relationship between the infected canopy and the overall canopy based on *Horsfall-Barratt scale* (Horsfall 1945). The mean *intersection over-union (IoU)* of *downy mildew* is above 0.8, while for *powdery mildew* is above 0.75.

Liu et al. (2022a) aims to create an algorithm to detect and segment *downy mildew* diseases in images from a tractor-mounted camera near real-time instead of conventional offline data processing. To achieve this, the authors combine *ResNet* (Du and Li 2018) and *atrous spatial pyramid pooling*, and use the *DeepLabv3* architecture (Chen et al. 2017). Further inspiration was drawn from the *holistically-nested* architecture (Xie and Tu 2015). This method segments the diseased spots in the images acquired from a tractor-mounted camera. Masks are automatically generated using *colour gating* method (Liu et al. 2021).

The work of Mendes et al. (2022), called *VineInspector*, describes a product which detects *downy mildew* and counts moths in a trap by cloud processing using the environment *mySense*[2] (Morais et al. 2019). Although the environment is customized for the *PA* and *PV* applications, and the *Scaled-YOLOv4* method (Wang et al. 2021a) provides good detection accuracy, the system uses three fixed cameras per unit, which reduces vineyard coverage.

Mousavi and Farahani (2022) modify the basic *VGG* (Simonyan and Zisserman 2015) architecture, and mix it with *Faster-RCNN* (Ren et al. 2017) to obtain *disease detection* on vine leaves. The architecture processes images of cropped leaves, although the method used to crop the leaves from an image of an entire vine plant is unclear. The proposed method outperforms other methods, such as *AlexNet* (Krizhevsky et al. 2012), *GoogLeNet* (Szegedy et al. 2015), *VGG* (Simonyan and Zisserman 2015), and *ResNet* (He et al. 2016). Despite insufficient details, the authors propose that a smaller drone that wanders the vineyard photographing the vines sends these images with the location *GNSS* to a central server. The server detects possible diseases and sends a larger drone to spray the problematic plant.

Nguyen et al. (2021) focus on *grapevine vein-clearing virus* detection using proximal hyperspectral imagery. The first step is to segment the canopy. This process is carried out using *SVM* (Hearst et al. 1998) and *RBF* (Buhmann 2000). Furthermore, the *random forest* (Ali et al. 2012) algorithm provides image classification. The architecture is doubled, where one instance is responsible for 2D feature extraction while the other extracts 3D features. Different vegetation indices are responsible for further optimization.

Rançon et al. (2019) approach the problem of detecting *esca* disease by finding the appropriate features, based on *scale-invariant feature transforms (SIFTs)* (Lowe 2004). Due to the use of a keypoint detection method, it is often referred to as *difference of Gaussian*—SIFT. Using this encoding, they generate sets of features that describe the images and, thus, the grapevines in a compact fashion. The extraction of features is extended with *unsupervised clusterings*, such as the *bag of visual word* method (Sivic and Zisserman 2003). During training, *vector of locally aggregated descriptors* (Jégou et al. 2010) is proposed to eliminate insufficient weighing. The search for features is further completed with *Fisher vectors* (Perronnin et al. 2010) and *L2 normalization* (van Laarhoven 2017). To conclude the architecture, the authors use *MobileNet* (Howard et al. 2017) as the basis of their neural network. Across these lines, the authors compare popular methods of *content-based image retrieval* (Zheng et al. 2017), other methods based on *SIFT*, such as *dense scale-invariant feature transform* and *pyramid histogram of visual words-SIFT* (Bosch et al. 2007), on difficult plant *disease detection* and classification problems. The main focus is to discriminate *esca* disease samples from other leaf diseases and classify them into three severity groups. The authors achieve a slight increase in accuracy while keeping the parameterization cost low.

Tang et al. (2023) develop an application to detect and assess the severity of *grapevine trunk* diseases. The basis of their method is the *YOLOv5* (Jocher 2020) architecture, by which a smartphone application is presented in this article. The smartphone is mounted on a trailer, and each detection is geotagged for later verification.

The focus of Tardif et al. (2023) is the *flavescence dorée* disease. This paper is the follow-up of other works of (Abdelghafour et al. 2020; Tardif et al. 2022, 2023). Furthermore, the dataset presented is published by Tardif et al.

[2] https://mysenseapi.utad.pt/.

(2023). The authors realized that simple leaf detection algorithms are incapable of high-accuracy disease identification due to the complex nature of a vine canopy, but also because similarities between *flavescence dorée* and other diseases are too high at the leaf level. To prove this, the authors compare traditional detectors of one-stage *CNNs* and two-stage detectors. The *CNNs* are represented by *Xception* (Chollet 2017), *VGG* (Simonyan and Zisserman 2015), or *YOLOv4* (Bochkovskiy et al. 2020); while the two-stage detectors are based on these *CNNs*, but other post-processing modules are added. The first option for such a module is a *random forest* classifier (Ho 1995; Ali et al. 2012), which predicts the results using feature vectors. The second option uses *graph neural network* (Scarselli et al. 2009). Both options are designed to detect the disease by the structure and relations of the detected leaves, bunches, and segmented green shoots. For the shoot, segmentation is done with two different methods: *structure tensor* (Budde and Frank 2012) with *hysteresis thresholding operations* (Pridmore 2001) and *ResUnet* (Diakogiannis et al. 2020). This latter method operates on small image crops that work like a *sliding window* method, with *pixel reduction* (every second row and column is removed). This means that instead of processing an image with a pixel count of 2048×2448, 20 images with 256×256 pixels are processed and reassembled. In this case, the loss used is the *Tversky* loss, Eq. 1, which penalizes false positives and negatives while not being affected by unbalanced data. Although the focus of this paper is on the detection of *flavescence dorée*, an improvement in precision is observed when adding classes *esca* and *confounding*. Both options for the second stage increase the precision and recall by at least 10%. This shows that the diseases appear on the plant somewhat structurally, and analyzing the image as a whole, or even more images together, leads to a better disease estimation.

$$Tversky_{\text{loss}} = 1 - \frac{\text{TP}}{\text{TP} + \alpha\text{FN} + \beta\text{FP}} \tag{1}$$

where TP, FP, and FN are true positive, false positive, and false negative, respectively, while the roles of α and β are balanced (Table 3).

Remote sensing

This section presents the methods that base their work on data captured from a remote distance, in this case greater than 5 m. These methods are generally based on *UAV* s, such as drones, aeroplanes, or satellites. Although the sensor used in the previous two sections is most commonly an *RGB* camera, in remote sensing, the spectral cameras are optimal, which is reflected in the increase in these sensors in this section.

Albetis et al. (2019) compare different indices and variables based on *UAV*, collected using *multispectral* imaging to detect *flavescence dorée* and *grapevine trunk diseases* such as *esca*. 24 variables are tested in general, including *biophysical parameters*, and *vegetation indices*. After training *SVM* (Hearst et al. 1998) with *RBF* (Buhmann 2000) for classification, the precision is calculated with *receiver operator characteristic* (Fawcett 2006), *area under curve*, *Welch's t-test* (Welch 1947), and *root-mean-square error (RMSE)*. The authors conclude that none of the variables analyzed at the berry level offers adequate discrimination of diseases. For leaf level detection, the best variables are: overall—*red green index* (Gamon and Surfus 1999), for red grape cultivars—*GRVI* (Gitelson et al. 2002), for white grape cultivars—*normalized difference red-edge index (NDREI)* (Patrick et al. 2017). The biophysical parameters are generated by inverting *canopy reflectance model* based on the works of Féret et al. (2017) and Jacquemoud et al. (2009). As such, the *carotenoid* content analysis is the most optimal.

The work of del-Campo-Sanchez et al. (2019) presents an experiment with the idea of *UAV*-based *Jacobiasca lybica-impact detection*. These leafhoppers, even if they are not necessarily defined as diseases, cause leaf discolouration and drying, visible from a high altitude. From the *RGB* images, taken from 80 m above ground and converted to the *L*a*b* colour space, point clouds are generated, and the *infection rate* is computed based on the *LAI* (Córcoles et al. 2013), for optimal image capture, different flight plannings are applied (Hernandez-Lopez et al. 2013; Ribeiro-Gomes et al. 2016).

Galvan et al. (2023) estimate the occurrence of *grapevine leafroll-associated virus complex 3* disease using remote sensing. The airborne vehicle is about 1000 m from the ground. Using a ground-level assessment, the authors create a dataset that contains grapevine plants without visible symptoms. Therefore, three classes are considered: noninfected, symptomatic, and asymptomatic. Some important steps in the detection pipeline are: *bidirectional reflectance distribution function and a topographic correction* (Queally et al. 2022) and *spectral mixture residuals* (Sousa et al. 2022). The latter is important to estimate the fractional areas and to quantify the wavelength-explicit errors. The source code is available at[3]; however, access requires a login.

The work of Kerkech et al. (2020b) is based on the work of Kerkech et al. (2018), and besides the green channel of an *RGB* image, it adds an *IR* signal from the camera of a *UAV* flying about 110 m of altitude. The backbone of this method is the *Accelerated-KAZE* algorithm (Alcantarilla et al. 2013), which extracts points of interest from the two normalized channels and then filters out the outliers with *random*

[3] https://github.coecis.cornell.edu/GoldLab-GrapeSPEC.

Table 3 List of the proximal sensing methods

Method	Data type	Description	Based on
Abdelghafour et al. (2020)	*RGB*	Detecting *downy mildew* using ground-based *RGB* images	Abdelghafour et al. (2018), Abdelghafour et al. (2019), Rittner et al. (2010), Otsu (1979), Knutsson et al. (2011), Arsigny et al. (2006), Abdelghafour et al. (2021)
Barjaktarović et al. (2022)	Spectral	Spectral camera-based low-cost system for *flavescence dorée* detection	Fawzy et al. (2015), Garcia et al. (2021), Themelis et al. (2008)
Barjaktarović et al. (2023b)	spectral	Low-cost multispectral camera system evaluated with *flavescence dorée* detection	Asaari et al. (2018), Peller et al. (2021)
Barjaktarović et al. (2023a)	Spectral	Multispectral and hyperspectral-based proximal *flavescence dorée* detection	Al-Saddik et al. (2019), Asaari et al. (2018), Srinivasan et al. (2019)
Boulent et al. (2020)	*RGB*	*Flavescence dorée* symptom detector on Chardonnay grapevines	Shelhamer et al. (2017), He et al. (2016), Selvaraju et al. (2020), McInnes and Healy (2018)
Falaschetti et al. (2021)	*RGB*	Implementing a complex architecture, which is later decomposed into a significantly smaller model	Cichocki et al. (2015), Kossaifi et al. (2019)
Farahani et al. (2022)	*RGB*	Proximal disease detection using the *Faster-RCNN* and the *Enhanced VGG*	Ren et al. (2017), Simonyan and Zisserman (2015)
Liu et al. (2022)	*RGB*	*Mildew* detection using *HMASS* architecture with *HSV* color space, and severity analysis	Abdelghafour et al. (2020), Hirschmüller (2008), Horsfall (1945), Mueller-Sim et al. (2017), Tao et al. (2020)
Liu et al. (2022a)	*RGB*	Near real-time *downy mildew* detection using *DeepLabv3* architecture for proximal imagery	Chen et al. (2017), Du and Li (2018), Liu et al. (2021), Xie and Tu (2015)
Mendes et al. (2022)	*RGB*	Cloud-based disease detection and moth counting	Morais et al. (2019), Wang et al. (2021a)
Mousavi and Farahani (2022)	*RGB*	detecting diseases by combining *VGG*, *GoogLeNet*, and *Faster-RCNN*, for drone-centered application	Ren et al. (2017), Simonyan and Zisserman (2015), Szegedy et al. (2015)
Nguyen et al. (2021)	spectral	Proximal hyperspectral *grapevine vein-clearing virus* detection	Ali et al. (2012), Buhmann (2000), Hearst et al. (1998)
Rançon et al. (2019)	*RGB*	*Esca* disease detector and severity classifier	Lowe (2004), Sivic and Zisserman (2003), Jégou et al. (2010), Perronnin et al. (2010), van Laarhoven (2017), Zheng et al. (2017), Bosch et al. (2007)
Tang et al. (2023)	*RGB*	Mobile application for *grapevine trunk* diseases	Jocher (2020)
Tardif et al. (2022)	*RGB*	Disease detection with a two-stage network	Bochkovskiy et al. (2020), Ho (1995), Ali et al. (2012), Budde and Frank (2012), Pridmore (2001), Diakogiannis et al. (2020)
Tardif et al. (2023)	*RGB*	Disease detection using *Random Forest* algorithm and *YOLOv4*	Bochkovskiy et al. (2020), Ho (1995), Ali et al. (2012)
Tardif et al. (2023)	*RGB*	Analyzing the structure of detected leaves and segmented disease shoots and bunches using feature vectors and graphs	Abdelghafour et al. (2020), Ali et al. (2012), Bochkovskiy et al. (2020), Budde and Frank (2012), Chollet (2017), Diakogiannis et al. (2020), Ho (1995), Pridmore (2001), Scarselli et al. (2009), Simonyan and Zisserman (2015), Tardif et al. (2022), Tardif et al. (2023)

sample consensus (RANSAC) (Fischler and Bolles 1981). Segmentation is performed using *SegNet* (Badrinarayanan et al. 2017). The authors conclude that the *NIR* data contribute to increased detection accuracy. The *SegNet* method (Kerkech et al. 2020b) is further improved by Kerkech et al. (2020c) with 3D data processing. The *UAV* flies at an altitude of 20 to 25 m and acquires *RGB* and spectral images. These images are later used to create a depth map following the pipeline described by Burgos et al. (2015). Kerkech et al. (2020a) significantly rethink their approach described as follows: while creating a depth map is still a vital part of disease detection, the underlying architecture is more complex than in previous articles. Three different encoders are implemented for each data type (*RGB*, *NIR*, and depth map), for whom the output is merged; then, a decoder creates the segmentation map visualizing the diseased plants. For this architecture, inspiration was drawn from other architectures such as *VGG* (Sermanet et al. 2014), *SegNet* (Badrinarayanan et al. 2017), and *UNet* (Ronneberger et al. 2015).

Musci et al. (2020) tackle the problem of *flavescence dorée* by using *UAV* s, 20 to 25 m above the ground. Their chosen architecture is *Faster-RCNN* (Ren et al. 2017). In the validation phase, the authors compute *out-of-bag score* (Zhang and Ma 2012), *average precision* (Everingham et al. 2010), and *IoU* (Liu et al. 2020), which prove the superiority of using *Faster-RCNN* instead of pixel-wise methods, such as *random forest* (Breiman 2001).

Ouhami et al. (2022) combine meteorological data with *UAV* imagery, which consists of *RGB*, *NIR*, and depth images; however, the authors state that depth information is not essential to increase the accuracy of disease detection (*downy mildew*). The architecture used is an autoencoder-like architecture, with elements from other architectures: *DeepLab* (Chen et al. 2018), *UNet* (Ronneberger et al. 2015), *ResNet* (He et al. 2016), *recurrent neural network* (Pineda 1987), *long short-term memory* (Hochreiter and Schmidhuber 1997), and *gated recurrent unit* (Cho et al. 2014).

Wang et al. (2023b) evaluate the performance of remote sensing in detecting *grapevine leafroll-associated viruses* and *grapevine virus A*. The average height of *UAV* is about 45 m. Each plant was previously geotagged in the dormant period to improve individual plant detection when the lack of a canopy made this step easier. Further processing was performed using *Agisoft*[4] software, where the *random forest* (Breiman 2001) classifier and *projected leaf area* were calculated for each plant to assign the disease.

Zottele et al. (2022) evaluate the usefulness of the deployment of *GNSS-RTK* in *grapevine yellow* detection (mainly *flavescence dorée* and *bois noir*) in aerial imagery. The authors conclude that the more precise location helps to create a more precise orthomozaic of the vineyard, thus increasing the accuracy of the *Stan* method used (Baudart et al. 2021) while also helping to map the infected plants. A disease specialist helped with data acquisition through virtual reality glasses to achieve more targeted image capture of both *RGB* and multispectral information (Table 4).

Vélez et al. (2023b) search for *botrytis* disease using *UAV*-based *multispectral* images. Their method not only detects already sick plants with an accuracy of more than 70% but also shows vulnerable regions with a high risk of disease occurrence. The main steps to achieve this are the computation of *DTM*, *NDVI*, *canopy height model*, and *LAI*, following the method described by Vélez et al. (2021), based on shadow measurement (Baeza et al. 2010), which also requires tight flight scheduling (Vélez et al. 2020). The authors made their dataset publicly available; more information is provided in Sect. 3.5.

Vineyard related datasets

One common thing in the surveyed papers is the description of the dataset acquisition system. This is due to the lack of publicly available datasets. Therefore, the authors usually create a dataset for each application. On one hand, these applications contain only a few images. On the other hand, these datasets are rarely published. This means, that the proposed methods do not reach their full potential, they are not evaluated properly, and precious time is spent on image capturing. On this note, we provide an overview of the found datasets in Table 5 containing the data type, targeted application, a brief description, and a link where the dataset is available (at the end of 2023). The order of the applications is first the year of publication, then the authors/dataset name (if exist) in alphabetical order.

Summary

This section offers an overview of the algorithms and datasets analyzed, including a few generalizations and observations.

A common approach is to capture *RGB* images and then convert them into *L*a*b*, *HSV* colour spaces. Although a benefit could occur in certain cases, most of the methods stuck to the simple *RGB* colour spaces and obtained excellent results. In this regard, we would consider this kind of conversion a possibility to slightly increase accuracy; however, it is not an obligation.

For *proximal sensing* applications (including extreme proximal), some architectures are often used, such as *YOLO*, *VGG*, *Random Forest*, or *SegNet*. These are commonly used architectures across all computer vision domains, showing that disease detection in vineyards is similar to other

[4] http://www.agisoft.com.

Table 4 List of the remote sensing methods

Method	Data type	Description	Based on
Albetis et al. (2019)	Spectral	Comparing multiple remote sensing variables on classifying diseases	Hearst et al. (1998), Buhmann (2000), Fawcett (2006), Welch (1947), Gamon and Surfus (1999), Gitelson et al. (2002), Patrick et al. (2017), Féret et al. (2017), Jacquemoud et al. (2009)
del-Campo-Sanchez et al. (2019)	*RGB*	*UAV*-based *Jacobiasca lybica* infection detector	Liu et al. (2012), Córcoles et al. (2013), Hernandez-Lopez et al. (2013), Ribeiro-Gomes et al. (2016)
Galvan et al. (2023)	spectral	High altitude remote sensing for disease detection	Queally et al. (2022), Sousa et al. (2022)
Kerkech et al. (2020a)	*RGB*spectral	Autoencoder architecture with three encoders for each data type (*RGB*, *NIR*, and depth map)	Badrinarayanan et al. (2017), Burgos et al. (2015), Kerkech et al. (2020b), Ronneberger et al. (2015), Sermanet et al. (2014)
Kerkech et al. (2020b)	*RGB*spectral	*UAV*-based *mildew* disease detector	Kerkech et al. (2018), Alcantarilla et al. (2013), Fischler and Bolles (1981), Badrinarayanan et al. (2017)
Kerkech et al. (2020c)	*RGB*spectral	Disease detection using *SegNet* and depth map estimation	Burgos et al. (2015), Kerkech et al. (2020b)
Musci et al. (2020)	*RGB*	*Flavescence dorée* detection using *UAV* s and *Faster-RCNN*	Ren et al. (2017), Zhang and Ma (2012), Everingham et al. (2010), Liu et al. (2020)
Ouhami et al. (2022)	*RGB*spectral	Combining aerial imagery with meteorological data to detect *downy mildew*	Chen et al. (2018), Cho et al. (2014), He et al. (2016), Hochreiter and Schmidhuber (1997), Pineda (1987), Ronneberger et al. (2015)
Vélez et al. (2023b)	spectral	*UAV*-based *botrytis* detection and risk estimation using remote sensing methods	Baeza et al. (2010), Vélez et al. (2020), Vélez et al. (2021)
Wang et al. (2023b)	*RGB*	Remote sensing-based disease detection	Breiman (2001)
Zottele et al. (2022)	*RGB*spectral	*Grapevine yellow* detection using aerial imagery and a high-accuracy positioning system (*GNSS-RTK*)	Baudart et al. (2021)

Table 5 A listing of the available datasets for grapevine analysis

Description, Year, Data type, Quantity, and Application			
Liu et al. (2015) Images of grape clusters (only clusters with wall background). For berry counts, a manually counted berry number is associated with each of the 112 images. The authors use this dataset for 3D bunch reconstruction. http://www.robotics.unsw.edu.au/srv/dataset/liu2015lightweight.html			
2015	*RGB*	112 images	grape berry count
PlantVillage—Hughes et al. (2015), Mohanty et al. (2016) This dataset contains images of individual plant leaves on a table surface. Various plant species are included (pepper, tomato, etc), but most importantly, grape leaves are in different categories: *healthy*, *black rot*, *esca*, and *leaf blight*. https://www.kaggle.com/datasets/abdallahalidev/plantvillage-dataset			
2015	*RGB*	50000 total images 4000 grape images	disease detection classification
Škrabánek and Runarsson (2015) Few 1936×1288-pixel images of grapevine canopy, from a tractor, with a perpendicular view. The vineyard is located in the Czech Republic, with *Welschriesling* planted. The dataset also contains cropped images. https://www.researchgate.net/publication/279195591_Detection_of_grapes_in_natural_environment_using_support_vector_machine_classifier_-_datasets			
2015	*RGB*	5 images	detection
GrapeCS-ML—Seng et al. (2018) Proximal *RGB* images about grape clusters in different stages, containing multiple species (*Merlot*, *Shiraz*, *Cabernet Sauvignon*, *Pinot Noir*, *Sauvignon Blanc*). Various images might contain references with size or color charts, in addition to images about the segmented berries for a subset of the images. https://researchoutput.csu.edu.au/en/datasets/grape-image-database			
2018	*RGB*	2300 images	segmentation yield estimation
Salento Grapevine Yellows dataset—Cruz et al. (2019); Ampatzidis et al. (2018) Similar to *PlantVillage* dataset, but with more images and categories (*powdery mildew*, *grapevine yellow*, *stictocephala bisonia*, *leafroll*, *healthy*, *black rot*, *esca*, and *leaf blight*). https://github.com/DrAlbertCruz/Salento-Grapevine-Yellows-Dataset			
2018	*RGB*	4700 images	disease detection classification
del-Campo-Sanchez et al. (2019) Orthoimage compiled from aerial (80 ms above ground) images of vineyards in Spain. The dataset is focused on detecting *Jacobiasca lybica*. https://osf.io/mv9bh/			
2019	*RGB*	1 orthoimage	disease detection
CR2 Dataset—Coviello et al. (2020) Part of a dataset (rest is not publicly sharable) for yield estimation, containing images captured with an 8-megapixel smartphone (with density maps). The images are close to the canopy (*Teroldego* variety) from a distance of about 1 m, focusing on the bunches at the time of veraison, but many leaves are present in the 17 images. The dataset includes manual annotations for more than 18000 berries. https://github.com/MPBA/CR2/			
2020	*RGB*	17 images	yield estimation
***Embrapa* wine grape instance segmentation dataset (WGISD)**—Santos et al. (2020) This dataset contains grapevine plants viewed perpendicularly from the side. The contained grape species are *Chardonnay*, *Cabernet Franc*, *Cabernet Sauvignon*, *Sauvignon Blanc*, and *Syrah*. The berry clusters are annotated with masks and bounding boxes. https://github.com/thsant/wgisd			
2020	*RGB*	300 images	detection instance segmentation
Abdelghafour et al. (2021) This dataset contains images of *Merlot* grapevines, perpendicularly to the vine rows, from a tractor. A high-power flashlight ensures that the illumination is even and distinct, while the background vanishes into the darkness. Not for all images, but for a handful of them, a segmentation mask is created to differentiate the leaves, clusters, and branches, while the mask for *downy mildew* is also included. https://ars.els-cdn.com/content/image/1-s2.0-S2352340921005345-mmc1.zip			
2021	*RGB*	99 images	disease detection segmentation
Aghi et al. (2021) Dataset for vine canopy segmentation. The viewpoint is from half the height of the vines, parallel to the rows (the center of the image looks toward the end of the current row, while the vine plants are on the left and right side of the image). A binary mask is included for canopy segmentation. The images are from at least 14 different video sequences, however, they are ordered randomly, therefore object tracking is only possible after manual reordering. Only a third of the original dataset is publicly available. https://github.com/MrD1360/deep_segmentation_vineyards_navigation			
2021	*RGB*	500 images	segmentation
ESCA-dataset—Alessandrini et al. (2021) The dataset contains grapevine leaves, captured relatively closely (30 cm) in the field. The leaves are either *healthy* or infected with *esca* disease, for which annotation files are included, along with *Jupyter notebooks* for image augmentation and classification. https://data.mendeley.com/datasets/89cnxc58kj/1			
2021	*RGB*	1700 images	disease detection classification

Table 5 (continued)

Description, Year, Data type, Quantity, and Application			
AI4Agriculture Grape Dataset—Morros et al. (2021) Side-view of the grape canopy, captured using a smartphone camera, from Ribera de Duero, Spain. Images for grape detection are suitable for yield estimation, fruit counting, and field robotics. The annotations are available in both *Pascal VOC* and *YOLO* types. Additional *Aruco* codes are also present on the images. https://zenodo.org/record/5660081			
2021	*RGB*	250 images	grape detection
Grapevine Leaves—Vlah (2021) Proximity vine leaves (the majority of an image is one leaf), with the vine canopy as the background. 11 vine species are collected (*Auxerrois*, *Cabernet Franc*, *Cabernet Sauvignon*, *Chardonnay*, *Merlot*, *Müller Thurgau*, *Pinot Noir*, *Riesling*, *Sauvignon Blanc*, *Syrah*, and *Tempranillo*), each of them containing 60–120 images. https://www.kaggle.com/datasets/maximvlah/grapevine-leaves			
2021	*RGB*	1000 images	classification
Zabawa et al. (2019, 2020, 2019, 2020) The images contain grapevines of *Riesling*, *Felicia*, and *Regent* varieties before and after thinning. For each image, a binary mask is included for berry segmentation. The images represent the sides of the vine rows, using artificial light and a white diffuse cloth as the background. https://www.openagrar.de/receive/openagrar_mods_00067631			
2021	*RGB*	42 images	berry detection
Buds-Dataset—Apostolidis et al. (2022) 1080x1920 images about dormant grapevines. Each of the 100 images has a masked pair, which contains the segmentation information about the trunk, cordon, and crane of the plants. This dataset is useful for automatic pruning applications. https://github.com/humain-lab/Buds-Dataset			
2022	*RGB*	100 images	segmentation pruning
GrapevineLeaves ImageDataset —Koklu et al. (2022) Classifying 5 vine species (*Ak*, *Ala Idris*, *Büzgülü*, *Dimnit*, *Nazli*) by their leaves. The dataset contains 500 512×512-pixel images, captured in a laboratory environment, in a black box, blocking any outside light, that would cause shadows on the flat-pressed leaves. http://www.muratkoklu.com/datasets/Grapevine_Leaves_Image_Dataset.rar			
2022	*RGB*	500 images	classification
GreenAI—Barros et al. (2022) Aerial drone footage of three vineyards in Portugal. The dataset contains multispectral images, high-definition orthomosaics, and *DSMs* acquired from an altitude of 60–120 ms. https://github.com/Cybonic/DL_vineyard_segmentation_study			
2022	multispectral	3 multispectral 3 orthoimage + *DSM*	remote sensing
S3CavVineyardDataset—Casado-García et al. (2022) The dataset contains consecutive images of 0.3 megapixels from a vineyard in Switzerland, from a tractor, perpendicular to the vine row. *Bunch/leaves-detection-oriented* and *object-segmentation-oriented* labels are included as masks for a subset of the images, marking bunches of poles, branches, leaves, and the background. The images are consecutive, therefore this dataset has the potential for object tracking purposes. https://github.com/ispstiima/S3CavVineyardDataset			
2022	*RGB*	400 images	segmentation
wGrapeUNIPD-DL—Sozzi et al. (2022) The dataset aims for variety classification (*Chardonnay, Glera, Trebbiano*) and yield estimation. The labeling of the bunches is provided using bounding boxes. The images are between the rows, perpendicularly to them from a distance of 1.5–3 m. Macbeth color reference is included in the images. https://zenodo.org/records/4066730			
2022	*RGB*	373 images	yield estimation
VitiVisor Vineyard Datasets—Collins et al. (2022) Dataset created in a vineyard in Australia, containing images captured from the ground, showing the bottom of the grapevines, with the sky as the background. The vine species are *Shiraz*, *Chardonnay*, *Cabernet Sauvignon*, *Mataro*, and *Pinot Gris*. The data gatherings cover the whole life cycle of the plants, from the bud appearance, through the harvestable bunches, to the fallen leaves, including the annotation for a subset of images. Separated images are provided before and after the pruning procedure. https://figshare.com/projects/VitiVisor_Vineyard_Datasets/137388			
2022	*RGB*	many	segmentation
Ariza-Sentís et al. (2023) Using the camera of a *DJI Matrice 210 RTK UAV*, the creators offer videos of vine rows, from side-view and low altitude (about 1-2 ms above the canopy, with a slightly inclined camera angle). This dataset is destined for detecting grape bunches (mask labels included) and training object tracking. https://zenodo.org/record/7330951			
2023	*RGB*	40 videos	object detection object tracking

Table 5 (continued)

Description, Year, Data type, Quantity, and Application			
GrapeNet—Barbole and Jadhav (2023) Concentrating on images of grape clusters in Indian vineyards, which tend to be more complex than European vineyards. The dataset includes more than 11K images depicting multiple scenarios: single or multiple grape bunches in natural or artificial environments (grape bunches on a sheet of paper). Additionally, the depth information is also available. https://data.mendeley.com/datasets/mhzmzd5cwx/1			
2023	*RGB-D*	11000 images	yield estimation
3D2Cut—Gentilhomme et al. (2023) The dataset contains 1511 images of around 4000×3000 pixels, captured with smartphones and professional camera equipment. The images show the plants from a perpendicular angle, with an artificial white or blue background. Each image is annotated, specifying the nodes and terminations. The authors stated that they have another dataset, which contains images without artificial backgrounds, named *RealGuyot*, however, as of the time of writing, this dataset is not published. https://zenodo.org/records/7679898			
2023	*RGB*	1511 images	structure estimation
Grapevine Bunch Condition Detection Dataset—Pinheiro et al. (2023) Proximal images for bunch detection captured with a smartphone. The image size is 720×540 pixels. The annotation is bounding boxes described with the *YOLO* format. Included varieties: *Touriga National*, *Barroca*, *Tinta Roriz*, *Cabernet Sauvignon*, *Viosinho*, *Trajadura*. The annotation makes a difference between optimal bunches and damaged bunches. https://zenodo.org/records/7717014			
2023	*RGB*	968 images	bunch detection
Grapevine Bunch Detection Dataset—Pinheiro et al. (2023) Proximal images for bunch detection captured with a smartphone. The image size is 720×540 pixels. The annotation is bounding boxes described with the *YOLO* format. Included varieties: *Touriga National*, *Barroca*, *Tinta Roriz*, *Cabernet Sauvignon*, *Viosinho*, *Trajadura*. The annotation has only one class, which is the bunch class. https://zenodo.org/records/7717055			
2023	*RGB*	968 images	bunch detection
Tardif et al. (2023) Disease detection on *Cabernet Sauvignon*, *Cabernet Franc*, *Merlot*, *Ugni Blanc*, and *Sauvignon Blanc* varieties, marking the *esca*, the *flavescence dorée*, and confounding classes, resulting in 744 annotated images. On 110 images the bunches were also annotated with bounding boxes, while symptomatic shoots with broken lines. Additionally, 128 images have a pixel-wise mask for bunches and shoots. The equipment is the same as in Abdelghafour et al. (2021), where the most important factor is the usage of a high-powered flash. https://data.mendeley.com/datasets/3dr9r3w3jn/2			
2023	*RGB*	1483 images	disease detection
Vélez et al. (2023a) Multispectral imagery for estimating disease risks and detecting *botrytis*. The images originate from three vine rows from a vineyard in Spain, on the day of harvest at a specific solar time (16:00-16:30) with a *Micasense RedEdge 3* sensor. The flight height is 30 ms. The dataset includes a shapefile with the *GNSS* location of *botrytis* and *ground control points*. https://zenodo.org/record/7064895			
2023	multispectral	16500 multispectral	remote sensing disease detection
Székely et al. (2024) This dataset contains 10000 images with markings of the diseased leaves and also of the grape bunches. The images were captured using a DJI Mini 2 flying at low altitudes across many vineyards (from different countries). Available on request from the authors.			
2024	*RGB*	10000 images	disease detection
Roboflow Universe This is a special entry in the table from Roboflow Universe containing many datasets from numerous users of the platform. We propose to search with the terms: "grape" or "vine", etc. As they are semi-official datasets, we do not want to specify any datasets on the platform. Despite not being a professional source, we think it is beneficial to survey this website, regardless of the task or the domain for data collection. https://universe.roboflow.com/			
–	*RGB*	Many	Many

domains. Another common approach (more so for extreme proximal sensing) is to use transfer learning when the architectures are trained on a large general dataset and then fine-tuned on a small vineyard-related dataset.

In *remote sensing* applications, the method gravitates toward calculating certain vegetation indices or constructing a 3D structure such as an orthomozaic image. For this step *Agisoft* (Agisoft LLC, St. Petersburg, Russia),[5] *Pix4D* (Pix4D SA, Switzerland),[6] and *MatLab* (The MathWorks Inc., Natick, MA, USA) are widely used.

[5] http://www.agisoft.com.

[6] https://pix4d.com/.

Conclusion

In this survey, we presented several papers in the domain of disease detection in *PV* in the last four years, focusing on visual-assisted methods, especially the use of autonomous devices. In addition, we briefly describe other surveys related to this topic and list 30 sources of vineyard-related datasets. A taxonomy based on remote distances was considered for building up different categories of papers. The methods were classified into three categories according to the type of environment: extreme proximal, proximal, and remote sensing. During the search procedure, we follow the *PRISMA* guideline (Page et al. 2021) among a large number of available papers to select the most relevant and cited works from this domain.

In general, Agriculture 4.0 is now popular, generating a considerable amount of paper each year. Although this process seems to continue in the future, surveys are extremely helpful in summarizing the state of the art at a given moment. With a particular focus on publicly available datasets and methods, this survey focuses on the most relevant works in the domain *PV*, ensuring the reader a usable map for navigation in the digital era of agriculture.

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Data availability The datasets generated during and/or analyzed during the current study are available from the corresponding author upon request.

Declarations

Conflict of interest The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

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