Journal of Electrical Engineering, Vol. 77, No. 4, 2026, pp. 444-459
https://reference-global.com/journal/JEE

Automatic vineyard health control: A review of existing systems and datasets for disease identification

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In recent years, computer vision and machine learning technologies have enabled new approaches to automatic vineyard health monitoring. This review synthesizes findings from 30 highly relevant studies covering automatic vineyard disease identification systems, examining system architectures ranging from ground-based robots and unmanned aerial vehicles (UAVs) to IoT-integrated platforms, mobile applications, and embedded devices. We analyse the computer vision and machine learning methods employed, including convolutional neural networks for classification, semantic segmentation, object detection, and multimodal sensor fusion techniques. We identify and describe publicly available and custom datasets used for model training and validation, highlighting important differences between controlled laboratory datasets and field-acquired imagery that affect model generalizability. The restricted generalizability is documented by training an EfficientNet-B2 classifier on controlled-background PlantVillage images and testing it on an independent dataset of field-acquired images. Although the model achieved 99.61 ± 0.17% accuracy on the internal test set, its accuracy decreased to 66.80 ± 8.38% and its mean F1-score to 58.33 ± 5.90% on the external field dataset, demonstrating a substantial domain shift between laboratory and vineyard conditions. Our analysis reveals that, while many systems achieve classification accuracy above 90%, significant challenges remain in the early detection of pre-symptomatic infections, robust multi-disease differentiation, and practical deployment across diverse real-world vineyard conditions. We discuss current limitations and outline priority directions for future research, including the need for standardized benchmarks, that require large annotated and balanced datasets, integration of emerging deep learning architectures such as Vision Transformers and foundation models, and development of low-cost, accessible solutions for widespread adoption.

Keywords: vineyard, grapevine, computer vision, deep learning, imaging/monitoring systems, robotic platforms, plant pathology

1 Introduction

Grapevine diseases represent a critical threat to global viticulture, causing substantial economic losses and requiring intensive management interventions. Traditional disease monitoring relies on manual scouting, a process that is time-consuming, labor-intensive, and often detects infections only after significant damage has occurred. The advent of computer vision, machine learning, and robotics has opened new possibilities for automated vineyard health management, enabling early detection, continuous monitoring, and precision treatments.

This review synthesizes recent advances in automatic vineyard disease detection and identification systems, examining the technological approaches, datasets, and performance characteristics reported in the literature. Throughout this paper, the term disease identification systems or methods refers collectively to computational approaches designed for disease detection, localization, classification, segmentation, and other related image analysis tasks. We focus on systems that leverage digital imaging combined with artificial intelligence to identify and quantify disease symptoms in vineyard settings. Our analysis includes diverse platform types – from ground robots and UAVs to mobile applications and embedded devices – and evaluates their suitability for practical deployment in commercial vineyards.

The primary objectives of this review are threefold: (1) to characterize the range of system architectures and sensing modalities employed for automatic vineyard health monitoring, (2) to identify and describe existing datasets for training and validating disease identification models, and (3) to assess the current state of performance and readiness for field deployment. By synthesizing findings from 30 highly relevant studies, we aim to provide researchers and practitioners with a comprehensive understanding of available technologies and guide future development efforts.

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https://doi.org/10.2478/jee-2026-0043, Print (till 2015) ISSN 1335-3632, On-line ISSN 1339-309X

1.1 Literature selection methodology

To ensure a systematic and reproducible review, we conducted a structured literature search across multiple academic databases including IEEE Xplore, Scopus, Web of Science, and Google Scholar. The search was performed using combinations of keywords such as "vineyard disease detection", "grapevine disease classification", "vine health monitoring", "precision viticulture deep learning" and "UAV vineyard disease". We limited the search to publications from 2017 to 2025 to capture the most recent advances in deep learning-based approaches.

Inclusion criteria required that studies: (a) present a system, method, or dataset specifically targeting grapevine disease detection or monitoring, (b) employ computational methods including machine learning, deep learning, or computer vision, and (c) provide a quantitative evaluation of detection and classification performance. Studies focusing exclusively on non-disease vineyard tasks (e.g., yield estimation without disease context) or generic plant disease identification without vineyard-specific validation were excluded. From an initial pool of over 120 candidate publications, we selected 30 highly relevant studies that collectively represent the diversity of platforms, methods, diseases, and datasets in the field.

2 Theoretical foundations and existing solutions

Vineyard diseases can be broadly categorized into fungal, bacterial, and viral infections, each presenting distinct visual symptoms on leaves, stems, and berries. Fungal diseases such as downy mildew (Plasmopara viticola), powdery mildew (Erysiphe necator), and esca are among the most economically damaging, causing leaf discoloration, necrosis, and reduced photosynthetic capacity [1, 2]. Bacterial diseases like bacterial cancer and viral infections such as grapevine leafroll-associated virus and grapevine yellows (including Flavescence dorée) further complicate disease management [3-6].

Early detection is crucial for effective disease management. Visual symptoms often appear only after pathogens have established significant populations, limiting treatment potency. Computer vision offers the potential to detect subtle changes in leaf color, texture, and morphology that precede visible symptoms or enable identification at early stages [7]. Deep learning, particularly convolutional neural networks (CNNs), has revolutionized image-based plant disease detection by automatically learning hierarchical feature representations from raw pixel data [8-10].

The application of automatic disease detection and identification in vineyards faces several unique challenges. Vineyard environments present high variability in lighting conditions, leaf orientations, and background clutter. Diseases may manifest with overlapping symptoms, and multiple diseases can co-occur on the same plant [11]. Furthermore, practical deployment requires systems that can operate autonomously under field conditions, process data in near-real time and integrate with existing vineyard management workflows [9, 12].

2.1 Identification platforms and system architectures

The choice of platform fundamentally shapes the capabilities, limitations, and deployment scenarios of vineyard health monitoring systems. Each platform type offers distinct trade-offs between spatial coverage, image resolution, operational autonomy, and cost. In this section, we categorize and analyze the main platform types reported in the literature: ground-based robotic systems for close-range high-resolution imaging, UAVs for rapid large-scale surveys, IoT-integrated sensor networks for continuous environmental monitoring, and mobile or embedded devices for accessible on-demand assessment.

2.1.1 Ground-based robotic systems

Ground-based robotic platforms offer several advantages for vineyard disease monitoring, including close-range imaging, consistent data acquisition geometry, and the ability to operate under canopy cover.

Based on their design, ground robotic platforms can be divided into two basic types. The most commonly used platforms are those designed as wheeled autonomous rover that moves along vineyard rows between vines. Such wheeled platforms include the autonomous robot PhytoPatholoBot (PPB) developed by Liu et al. [7], the autonomous robot Frasky developed by IIT-Istituto Italiano di Tecnologia [13], and the robotic manipulator RoMu4o developed by Mortazavi et al. [14].

The PhytoPatholoBot (PPB), developed by Liu et al., represents a state-of-the-art autonomous ground robot specifically designed for near real-time disease scouting [7]. This system uses a custom imaging setup with active illumination to ensure consistent image quality regardless of ambient lighting. The robot integrates RTK-GPS for precise localization and runs custom segmentation models on low-power edge computing devices, enabling autonomous traversal of vineyard rows while detecting and quantifying disease severity [15].

The PPB system has been validated for multiple diseases, including downy mildew and grapevine leafroll disease, demonstrating performance comparable to experienced human scouts [1, 7, 15]. The use of active illumination and near-range imaging allows for high-resolution capture of leaf-level symptoms, while the autonomous navigation capability enables systematic coverage of large vineyard areas. The system's ability to map disease progression over the growing season provides valuable temporal data for understanding disease dynamics and treatment potency.

Frasky is a prototype robot designed to move and interact in agricultural environments [13]. It is equipped with a robotic arm with an integrated camera and a hand for manipulating plants and fruits. The integrated camera in the arm allows the system to map the surroundings and the condition of the crops, accurately detecting obstacles and specific objects, such as grapes. The entire Frasky robot system is modular and flexible in terms of both hardware and software, which allows the integration of tools according to the needs of farmers. For example, Frasky's robotic arm includes a nozzle for applying selective treatments to the vineyard.

RoMu4o is a robotic manipulation unit designed for orchard work, which aims to autonomously collect hyperspectral data from leaf samples [14]. It has a built-in deep learning-based perception system for leaf detection and segmentation, and provides an algorithmic procedure for leaf structure extraction, point cloud processing, and 6D position estimation. Furthermore, a robotic manipulation workflow is created for leaf gripping and hyperspectral data collection.

The next robotic platform is an autonomous over-the-row robotic platform featuring a gantry-style (tunnel-type) architecture that enables traversal above crop rows. Such platforms include the autonomous Thorvald robot from Saga Robotics [16]. One of the main tasks of the Thorvald robot is to control mold (e.g. powdery mildew) using UV-C light, and also provides data collection and crop monitoring (e.g. yield prediction, growth analysis).

Ground robots offer the additional advantage of integration with treatment systems, enabling a closed-loop approach in which system immediately informs targeted intervention. However, challenges remain in navigating complex vineyard terrain, managing power consumption for extended operation, and ensuring robust performance across diverse vineyard layouts and training systems.

2.1.2 UAV and aerial imaging systems

Unmanned aerial vehicles (UAVs) have emerged as a popular platform for vineyard disease identification due to their ability to rapidly survey large areas and capture overhead imagery of entire vineyard blocks [9, 17, 18]. UAV-based systems typically employ RGB cameras, multispectral sensors, or combinations to capture canopy-level disease symptoms.

Kerkech et al. [19] developed multiple UAV-based approaches, including the VddNet architecture that integrates visible, infrared, and depth information for vine disease detection. Their work demonstrated that combining multispectral data with depth maps extracted from 3D processing significantly improves segmentation accuracy compared to using RGB imagery alone [19, 20]. The VddNet architecture, based on three parallel auto-encoders, achieved superior performance compared to baseline methods including SegNet, U-Net, DeepLabv3+, and PSPNet.

Musci et al. [6] applied Faster R-CNN to UAV imagery for detecting Flavescence dorée disease, achieving 82% average precision on a custom dataset of 522 high-resolution images. Their approach demonstrated the feasibility of quasi-real-time disease identification using object detection networks, which can localize diseased spots more effectively than pixel-wise classification methods.

UAV systems excel at providing rapid, large-scale assessments and can detect spatial patterns of disease spread across vineyard blocks. However, they face limitations in detecting early-stage or subtle symptoms due to the distance from the canopy and potential occlusion by upper leaves. Weather conditions, particularly wind, can also constrain UAV operations. Additionally, the overhead perspective may miss symptoms on lower leaf surfaces or within the canopy interior.

2.1.3 IoT and sensor-based approaches

Internet of Things (IoT) technologies enable continuous environmental monitoring and can complement image-based disease identification.

Roscaneanu et al. [5] developed a dual-method approach combining IoT sensors measuring air temperature, humidity, soil temperature, and rainfall with UAV imaging analyzed by neural networks. Their statistical prediction method using sensor data achieved 90.9% accuracy with a Hidden Markov Model for predicting diseases: downy mildew, powdery mildew, and grey rot.

Xiao et al. [4] developed an intelligent monitoring system integrating photoelectric sensors with YOLOv5 for disease detection, 82.4% precision, 83.6% recall, and 85.0% mAP@0.5. This system supports real-time environmental regulation in addition to disease identification, demonstrating the potential for integrated vineyard management platforms.

The integration of environmental sensors with image-based identification offers several advantages. Environmental conditions are key drivers of disease development, and sensor data can predict infection risk before symptoms appear. This predictive capability enables proactive treatment decisions. Furthermore, IoT systems can operate continuously with minimal power consumption, providing temporal resolution that complements periodic imaging surveys.

2.1.4 Mobile and embedded systems

Mobile applications and embedded devices bring disease identification and detection capabilities directly to vineyard managers and workers, often enabling on-demand assessment with limited or no specialised equipment. Rudenko et al. [2] developed an intelligent vineyard monitoring system integrating a vehicle-mounted software–hardware platform with a mobile application for real-time disease monitoring. Based on YOLOv5, their system achieved 97.5% accuracy on a custom dataset of 4,845 grape disease images covering eight disease categories while maintaining a compact model size of only 14.85 MB, making it suitable for mobile deployment. Designed for installation on virtually any agricultural vehicle, the system performs real-time vineyard monitoring and visualizes disease locations on a map, facilitating practical field use by growers.

Falaschetti et al. [21] addressed the challenge of deploying CNNs on resource-constrained embedded devices by developing LR-Net, a compressed CNN architecture based on tensor decomposition. Implemented on a low-cost OpenMV Cam STM32H7 Plus with a 480 MHz ARM Cortex-M7 microcontroller and programmed using MicroPython, their system achieved Esca disease identification with superior inference time and memory occupancy compared to standard networks. Designed for installation on agricultural vehicles, the edge device performs on-board inference without cloud connectivity, enabling real-time disease detection (target inference time ≈68 ms per image) during field traversal while reducing storage requirements and supporting autonomous precision viticulture operations.

The trend toward edge computing and mobile deployment is critical for practical adoption. Field-deployable systems must operate reliably without constant internet connectivity, process data with minimal latency, and integrate seamlessly into existing workflows. Embedded systems also offer advantages in terms of cost, power consumption, and ease of deployment compared to larger robotic platforms.

2.2 Computer vision and machine learning methods

The choice of computer vision and machine learning method determines the granularity, speed, and accuracy of disease identification. Methods in the reviewed literature span a spectrum from image-level classifycation, which assigns a single disease label to an entire image, through object detection that localizes disease instances with bounding boxes, to pixel-level semantic segmentation that enables precise quantification of affected area. In addition, multimodal approaches combining data from different sensor types have shown promise for improving robustness. This section reviews the main methodological categories and highlights representative implementations.

2.2.1 Classification approaches

Convolutional neural networks have become the dominant approach for grape disease classification, with numerous architectures demonstrating high accuracy across diverse datasets. Transfer learning from pre-trained networks has proven particularly effective, allowing models to leverage features learned on large-scale image datasets and adapt them to the specific characteristics of grape disease symptoms.

Elsherbiny et al. [22] developed AI GrapeCare, a hybrid deep network combining CNNs, LSTMs, and DNNs with transfer learning from VGG16, VGG19, ResNet50, and ResNet101V2. Their combined CNNRGB-LSTMGLCM network achieved 96.6% validation accuracy, precision, recall, and F-measure, with an IoU of 93.4%. The software reportedly processed and diagnosed an input image in a few seconds, with the diagnosis time not exceeding one minute.

Rajan et al. [23] introduced VitiNet, based on EfficientNetB7, for identifying five major grapevine diseases: Powdery Mildew, Downy Mildew, Anthracnose, Black Rot, and Esca. The model was fine-tuned by unfreezing the last five layers to extract disease-specific features while maintaining computational efficiency. EfficientNet architectures are particularly attractive for disease identification due to their scalability and strong performance-to-parameter ratio.

Oprea et al. [24] compared VGG16 with a modified version (Avert-CNN) for grapevine disease classify-cation, achieving over 94% prediction accuracy with their novel architecture, surpassing the classic VGG16 (90.21%), Random Forest (72.87%), and Support Vector Machine (85.82%). Research addressees the identify-cation of health status of grapevine leaves using specialised classification algorithms on images from PlantVillage dataset and images acquired in vineyard in the South-East of Romania. The outcome of these classifications consists in predictions based on one of the 5 classes. Their work demonstrates that architectural modifications tailored to the specific characteristics of grape disease imagery can yield meaningful performance improvements.

2.2.2 Semantic segmentation approaches

While classification networks assign a single label to an entire image, semantic segmentation assigns a class label to each pixel, enabling precise localization and quantification of disease symptoms. This capability is essential for severity estimation and targeted treatment planning.

Liu et al. [1] developed a modified DeepLabv3 network for near real-time downy mildew segmentation on robotic platforms. Their model achieved the best efficiency-accuracy balance compared to state-of-the-art real-time segmentation models when deployed on embedded computing devices. Importantly, the severity estimation pipeline based on this model showed comparable measurement accuracy and statistical power in differentiating fungicide treatments as offline models, validating its utility for practical disease management.

Kerkech et al. [9] used separate SegNet encoder-decoder models for visible and infrared UAV imagery and fused their outputs, achieving an F1/Dice score of 92.81% for symptomatic-vine detection at the grapevine level and 87.12% at the pixel-wise leaf level. Their approach classified each pixel into four categories: shadow, ground, healthy vegetation and symptomatic vegetation. It then generated detailed disease maps by fusing the visible and infrared segmentation outputs, supporting spatially targeted vineyard treatment.

Hernández et al. [25] combined computer vision with fuzzy logic to assess downy mildew severity on grapevine leaf discs by assigning each pixel a degree of infection according to sporulation intensity. Their method achieved R^2 = 0.87 and RMSE = 7.61% when compared with the mean visual severity ratings of eleven trained experts, who estimated the percentage of leaf-disc area covered by sporulation on a 0 to 100% scale. The method also achieved 86% accuracy when classifying infection severity as low, medium or high. By assigning continuous membership values between 0 and 1, fuzzy logic represented gradual differences in sporulation intensity more precisely than a binary infected versus non-infected classification.

2.2.3 Object detection methods

Object detection networks, which simultaneously localize and classify objects within images, offer advantages for detecting discrete disease lesions or symptommatic leaves within complex vineyard scenes.

Rançon et al. [26] employed RetinaNet for plant-scale esca detection in Bordeaux vineyards, achieving 90% precision at 40% recall with approximately 70% average precision. Their system operated at approximately six frames per second on GPU, enabling near real-time processing. Importantly, they observed good correlation between annotated and detected symptommatic surface per plant, allowing efficient separation of slightly symptomatic from severely attacked plants.

Kuznetsov et al. [12] utilized YOLOv7 for intelligent vineyard monitoring, achieving 90% detection accuracy on a dataset of 6,320 grape leaf images. YOLO architectures are particularly attractive for real-time applications due to their single-stage design and efficient inference.

2.2.4 Multimodal and sensor fusion techniques

The integration of multiple sensor modalities – RGB, multispectral, thermal, and depth – has emerged as a promising approach for improving disease identify-cation accuracy and robustness. Different spectral bands capture complementary information about plant physiology and stress responses.

Kerkech et al.'s [19] VddNet architecture exemplifies effective sensor fusion, integrating visible, infrared, and depth information through three parallel autoencoders (Kerkech, Hafiane, and R. Canals 2020). The depth information, extracted from 3D processing of UAV imagery, helps distinguish disease symptoms from shadows and other artifacts that can confound RGB-only analysis. Their results demonstrated that this multimodal approach achieves higher accuracy than methods using any single modality.

The combination of environmental sensor data with image analysis, as demonstrated by Roscaneanu et al. [5], represents another form of multimodal fusion. In their framework, microclimatic data (air and soil temperature, air and soil humidity, rainfall, and atmospheric pressure) collected via a Smart Agriculture Xtreme station were fused with UAV aerial RGB imagery. While parameter thresholds and statistical analysis were applied to the sensor stream for real-time risk assessment, the drone footage was processed using neural networks for visual leaf classification. Environmental conditions provide context for interpreting visual symptoms and enable predictive modeling of disease risk.

Future developments in sensor fusion may incorporate hyperspectral imaging, which captures hundreds of narrow spectral bands and can detect subtle changes in leaf reflectance associated with early-stage infections. Thermal imaging can reveal changes in leaf temperature associated with reduced transpiration in diseased tissue. The challenge lies in developing efficient fusion architectures that can process high-dimensional multimodal data in real-time on resource-constrained platforms.

2.2.5 Emerging architectures and methods

While CNNs remain the dominant paradigm in the reviewed literature, several emerging architectural trends show significant potential for vineyard disease identification. Vision Transformers (ViT) [27] and their variants, such as Swin Transformer [28] and DeiT [29], have achieved state-of-the-art results on general image classification benchmarks and are increasingly being explored for agricultural applications. Unlike CNNs, which rely on local receptive fields, Transformers capture global dependencies through self-attention mechanisms, which may prove advantageous for recognizing disease patterns that manifest across different spatial scales on leaves.

Foundation models represent another emerging paradigm with potential impact. Models such as Segment Anything (SAM) [30] and DINO [31], pre-trained on massive and diverse image corpora, offer strong zero-shot and few-shot generalization capabilities. These models could be particularly valuable for vineyard disease identification, where annotated training data is scarce for rare or newly emerging diseases. Fine-tuning foundation models on small domain-specific datasets may enable rapid development of identification systems for new diseases or geographic regions without requiring large-scale data collection efforts.

Generative approaches, including Generative Adversarial Networks (GANs) [32] and diffusion models [33], are being explored for synthetic data augmentation to address class imbalance and data scarcity. By generating realistic synthetic images of diseased leaves, these methods can expand training datasets and improve model robustness. Few-shot [34] and zero-shot [35] learning methods also address the annotation bottleneck by enabling models to recognize new disease categories from very few or even no labeled examples, leveraging learned representations from related tasks.

Unsupervised, semi-supervised and self-supervised learning methods offer promising opportunities to reduce dependence on large manually annotated datasets, which remain difficult and costly to produce for vineyard disease identification. Although some studies have explored these approaches, vineyard-specific research remains limited and has not yet been sufficiently validated across different diseases, cultivars, imaging conditions and field environments. Their rapid development in the broader computer vision community nevertheless suggests that they may play an increasingly important role in future vineyard disease identification systems, particularly where labelled data are scarce.

2.3 Datasets

High-quality annotated datasets are the foundation upon which machine learning-based systems are built. The availability, resolution, diversity, and annotation quality of training data directly influence model performance and generalizability. In field of vineyard disease identification, datasets vary considerably in their acquisition conditions, annotation granularity, disease coverage, and public availability. A critical distinction exists between datasets acquired under controlled laboratory conditions where individual leaves are photographed against uniform backgrounds and field-acquired datasets capturing leaves in their natural canopy environment with variable lighting, occlusion, and background clutter. This distinction has profound implications for model generalizability, as models trained exclusively on controlled-background imagery often fail to maintain their performance when deployed in real vineyard conditions [36]. The reviewed datasets are summarized in Tables 1 and 2, which distinguish publicly accessible datasets from custom datasets developed for individual studies and compare their annotation type, size, disease coverage, acquisition conditions and access status.

2.3.1 Publicly available datasets

The availability of high-quality datasets is crucial for developing and evaluating disease identification models. While supervised learning relies on well-annotated training data, unsupervised and self-supervised approaches can reduce this requirement, although annotated reference data remain necessary for validation and benchmarking. Several publicly available datasets have been developed specifically for grape disease identification, though the field still lacks the large-scale, standardized benchmarks common in other computer vision domains.

The Esca dataset [37] from the Polytechnic University of Marche, Ancona, Italy, has been used in multiple studies [3, 21]. This dataset originally contained 882 images of healthy grapevine leaves and 888 images of leaves affected by Esca disease. Margariti et al. applied data augmentation techniques to expand the dataset to 23,010 images. This expanded dataset was then split into 13,806 training (60%), 3,452 validation (15%), and 5,752 testing images (25%) [3].

The PlantVillage dataset [38], while not vineyard-specific, includes grape disease images and has been used for training and transfer learning in several studies. Oprea et al. [24] supplemented PlantVillage images with field-acquired images from vineyards in South-East Romania to improve model generalization to real-world conditions.

Rajan et al. curated two custom datasets. GrapeVine Dataset and VineHealthDataset [23] for training their VitiNet model on five major grapevine diseases: Esca, Powdery mildew, Downy mildew, Anthracnose, Black

Rot. The creation of multiple datasets with diverse environmental conditions and disease manifestations is essential for developing robust models that generalize across different vineyard settings.

2.3.2 Custom and domain-specific datasets

Many research groups have developed custom datasets tailored to specific diseases, geographic regions or imaging platforms. These domain-specific datasets often provide greater ecological validity than generic collections, but their accessibility varies. Some are publicly available online, others can be obtained only upon request and some remain unavailable to the broader research community. To support reproducibility and facilitate reuse, the access status of each dataset is therefore indicated in the accompanying table.

Rudenko et al. [2] created a dataset of 4,845 grape disease images covering eight disease categories common to the Black Sea region: Mildew, Oidium, Anthracnose, Esca, Gray rot, Black rot, White rot, and bacterial cancer. This dataset includes healthy plant images and was specifically designed for training YOLOv5 models for real-time mobile deployment.

Musci et al. [6] developed a custom dataset for Flavescence dorée detection comprising 522 high-resolution UAV images (4000×3000 pixels), with 3,660 and 915 polygons annotated as diseased areas for training and testing. The dataset captures images from different UAV platforms under varying field conditions, providing realistic variability for model training.

Rançon et al. [26] created a custom database from two Bordeaux vineyards, acquiring pictures of diseased and healthy vine plants in summer 2017. Their patch database contains 6253 images (224×224 pixels) labeled at the leaf scale, with differentiation between esca and other foliar symptoms including Powdery Mildew/Black Rot, Flavescence Dorée, wilted leaves and deficiencies.

Liu et al. [15] collected custom datasets using their robotic platforms in California vineyards for downy mildew and grapevine leafroll disease [1, 7]. These datasets include high-resolution images acquired under controlled illumination conditions, along with human expert assessments for validation.

Table 1 provides a structured comparison of the main datasets used across the reviewed studies. Notably, datasets differ substantially in their acquisition setting: laboratory or controlled-background datasets (e.g., PlantVillage, Esca dataset) photograph individual leaves against uniform backgrounds, greatly simplifying the segmentation task. In contrast, field-acquired datasets (e.g., UAV imagery from Kerkech et al. [9, 19] and Musci et al. [6], robotic imagery from Liu et al. [1, 7, 15]) capture leaves within the natural canopy, introducing challenges such as overlapping foliage, shadows, variable illumination, and background clutter.

Table 1. Publicly accessible datasets relevant to grapevine disease identification

Dataset	**Task and annotation**	**Dataset size and image resolution**	**Classes or diseases**	**Acquisition conditions**	**Access**
Esca dataset [37]	Image classification, image-level labels	1,770 images; 1,920 × 1,080 or 1,280 × 720 px	Healthy, Esca	Individual grapevine leaves acquired under controlled imaging conditions	Online
PlantVillage grape subset [38]	Image classification, image-level labels	4,062 images; 256 × 256 px	Healthy, black rot, Esca or black measles, leaf blight	Detached leaves photographed against a uniform background	Online
PDD grapevine dataset [22]	Image classification, image-level labels	295 images reported; 256 × 256 px	Healthy, black rot, chlorosis, Esca, powdery mildew	Field-acquired leaf images with variable backgrounds and viewing conditions	Online
Downy mildew on Merlot dataset [39]	Semantic segmentation, pixel-level masks	99 RGB images; 2,592 × 2,048 px; 95 images annotated	Healthy leaf, healthy berries, stems, leaf edges, foliar mildew, berry mildew, other anomalies	Whole grapevine canopies acquired in situ from a tractor-mounted RGB camera with flash	Online
GVLiD [40]	Image classification, image-level labels	3,477 images; 1,080 × 1,080 px	Healthy, black rot, Esca, leaf blight	High-resolution in situ vineyard images with natural backgrounds	Online

Table 2. Custom vineyard datasets used in the reviewed disease identification studies

Study or dataset	Task and annotation	Dataset size and image resolution	Target classes	Acquisition platform and setting	Access
Rudenko et al. [2]	Object detection, bounding boxes	4,845 images; native resolution not reported	Eight grapevine diseases	Field images, Black Sea region	Not publicly available
Musci et al. [6]	Object detection, bounding boxes	200 selected from 522 acquired images; 4,000 × 3,000 px; 4,575 bounding-box annotations 4,575 annotated disease regions	Flavescence dorée	UAV RGB imagery, vineyard in Piedmont, Italy	Not reported
Rançon et al. [26]	Image classification and object detection, bounding boxes	6,253 leaf patches at 224 × 224 px; 1,274 whole-plant images at 2,592 × 2,048 px	Control, Esca and confounding factors	Proximal RGB imaging, Bordeaux vineyards, France	Not reported
Kerkech et al. [9]	Semantic segmentation, pixel-wise masks	480 visible and 480 infrared UAV images at 4,608 × 3,456 px; augmented into 105,515 visible and 98,895 infrared vineyard-scene patches at 360 × 480 px	Shadow, ground, healthy vine vegetation, symptomatic vine vegetation	UAV visible and near-infrared imagery, Centre-Val de Loire, France	Not reported
Liu et al., downy mildew [1]	Semantic segmentation, pixel-wise masks	687 annotated tiles at 1,352 × 1,125 px, extracted from 2,704 × 3,376 px stereo images	Downy mildew infection, healthy canopy/background	Ground vehicle, stereo RGB camera with active illumination, vineyard in Geneva, New York	On request
Liu et al., leafroll [7]	Semantic segmentation, pixel-wise masks	10,588 acquired images; 100 annotated images; 4,096 × 3,000 px, split into four 2,048 × 1,500 px tiles	Grapevine leafroll symptoms and background	Ground robot, RGB imaging with active illumination, California vineyards	On request
Kuznetsov et al. [12]	Object detection, bounding boxes	6,320 images extracted from 1,920 × 1,080 px UAV video; model input 640 × 640 px	Healthy and diseased grape leaves	UAV RGB imagery, vineyard monitoring system in Crimea	Not reported

2.3.3 Data augmentation and annotation strategies

Given the labor-intensive nature of collecting and annotating disease images, data augmentation has become a standard practice for expanding training datasets and improving model generalization. Common augmentation techniques include rotation, flipping, scaling, color modification, and adding noise to simulate variations in lighting and imaging conditions.

Margariti et al. [3] demonstrated the effectiveness of augmentation by expanding the Esca dataset from 1,770 original images to 23,010 augmented images, significantly improving model performance. Elsherbiny et al. showed that their combined deep network with data augmentation achieved 96.6% accuracy compared to lower performance without augmentation [22].

Annotation strategies vary depending on the identification task. Classification tasks require only image-level labels, while object detection requires bounding boxes around diseased regions, and semantic segmentation requires pixel-level annotations. Tardif et al. [41] employed a two-step annotation approach, first detecting individual symptoms with a CNN-based box detector and deep segmentation algorithm, then using these symptom detections for disease diagnosis.

The development of semi-supervised and self-supervised learning approaches may help address the annotation bottleneck. Miranda et al. explored variational autoencoders for anomaly detection in grapevine berries, achieving 92.3% accuracy with their FPL-VAE model [11]. Anomaly detection approaches require only healthy samples for training, potentially reducing annotation requirements for rare or emerging diseases.

3 Key findings and comparative analysis

This section synthesizes the key findings from the reviewed literature, providing a comparative analysis of system performance, disease coverage, and computational efficiency. We highlight both the strengths of current approaches and the gaps that limit their practical deployment. The performance metrics are drawn from the original publications and should be interpreted with caution, as evaluation conditions, dataset sizes, and splitting strategies vary considerably across studies.

3.1 Performance metrics across systems

The reviewed systems demonstrate consistently high performance across diverse platforms and methodologies, with most achieving accuracy above 90%. Table 3 summarizes key performance metrics from representative studies.

Table 3. Performance metrics of representative grapevine disease identification systems reported in the reviewed literature

System	Platform	Method	Diseases	Accuracy/Performance
PhytoPatholoBot [7]	Ground robot	Modified segmentation	Downy mildew, Leafroll	83.07% mIoU
Rudenko et al. [2]	Mobile/Vehicle	YOLOv5	8 diseases	97.5% accuracy
Margariti et al. [3]	UAV	CNN (5 layers)	Esca	94.94% accuracy, 94.03% F1
Xiao et al. [4]	IoT + Vision	YOLOv5	Black rot, measles, blight	0.824 precision, 0.85 mAP
Musci et al. [6]	UAV	Faster R-CNN	Flavescence dorée	82% average precision
Kerkech et al. [9]	UAV	FCN	General vine diseases	92% grapevine-level, 87% leaf-level
Kuznetsov et al. [12]	Automated	YOLOv7	General diseases	91% accuracy
Rançon et al. [26]	Ground proximal	RetinaNet + MobileNet	Esca	91% leaf accuracy, 70% AP
Elsherbiny et al. [22]	Software	VGG16 + LSTM	General diseases	96.6% accuracy
Oprea et al. [24]	Image-based	Modified VGG16	4 diseases	94% accuracy
Hernández et al. [25]	Laboratory	Computer vision + fuzzy logic	Downy mildew	R^2=0.87, 86% severity classification
Falaschetti et al. [21]	Embedded	LR-Net (compressed CNN)	Esca	Superior inference time, real-time

The consistently high performance across diverse approaches suggests that grape disease identification is a relatively mature application of computer vision, with multiple viable technical pathways. However, as noted earlier, reported accuracies should be interpreted cautiously, as they are often evaluated on custom datasets that may not reflect the full complexity of real-world vineyard conditions.

3.2 Disease coverage and specificity

The reviewed systems address a wide range of economically important vineyard diseases, with some focusing on single diseases and others targeting multiple disease types. The most addressed diseases are summarized in Table 4.

Table 4. Diseases addressed by the reviewed automatic vineyard disease identification systems, grouped by pathogen category

Category	Disease	Pathogen / Type	Data collection approaches
Fungal [1, 5, 23, 25, 42]	Downy mildew	Plasmopara viticola	Robotic platforms, UAV-based imaging
Fungal [2, 5, 23, 24]	Powdery mildew	Erysiphe necator	Multi-disease classification systems
Fungal [2, 3, 11, 21, 23, 24, 26]	Esca	Fungal trunk disease complex	Foliar symptom analysis, classification models
Fungal [2, 4, 5, 23, 24]	Black rot	Guignardia bidwellii	Multi-disease identification systems
Fungal [2, 5]	Anthracnose	Elsinoë ampelina	Comprehensive disease identification systems
Fungal [2, 5]	Gray rot	Botrytis cinerea	Multi-disease identification systems
Fungal [2, 5]	White rot	Coniella diplodiella	Multi-disease identification systems
Viral [7, 15]	Leafroll disease	Grapevine leafroll-associated viruses (GLRaVs)	Robotic scouting systems
Viral / Phytoplasma [6, 41, 43]	Grapevine yellows (Flavescence dorée)	Candidatus Phytoplasma vitis	UAV imagery, proximal sensing
Bacterial [2]	Bacterial cancer	Agrobacterium tumefaciens	Multi-disease datasets

Systems targeting single diseases often achieve higher specificity and can be optimized for the particular visual characteristics of that disease. For example, Liu et al.'s specialized downy mildew identification system achieved performance comparable to offline models while operating in near real-time [1]. Multi-disease systems offer broader utility but face the challenge of distinguishing between diseases with overlapping symptoms [11, 41].

3.3 Real-time processing and edge computing

The ability to process images in real-time or near real-time is critical for practical deployment, particularly for autonomous robotic systems and mobile applications. Several studies have specifically addressed the computational efficiency required for field deployment.

Liu et al. [1] demonstrated that their modified DeepLabv3, incorporating an efficient multiscale feature extraction and fusion module, a TensorRT-compatible ASPP head, and TensorRT optimization, achieves an excellent efficiency–accuracy balance on an NVIDIA Jetson AGX Xavier embedded platform suitable for integration with commercial robotic systems. Their approach enabled near real-time downy mildew segmentation of 2704×3376 px vineyard images, requiring only 0.151 s per frame (≈6.6 FPS), making semantic segmentation feasible for on-board field deployment.

Falaschetti et al. [21] addressed edge deployment through model compression, developing LR-Net based on CANDECOMP/PARAFAC (CP) tensor decomposition and post-training 8-bit quantization. By compressing the model 13-fold (from 48 KB to 25 KB), their compressed CNN achieved real-time Esca detection on an ARM Cortex-M7-based OpenMV Cam STM32H7 Plus, demonstrating that sophisticated deep learning can be deployed on severely resource-constrained devices.

Rançon et al. [26] RetinaNet-based system achieved approximately six frames per second on GPU, enabling processing 6 frames per second for ground-based proximal sensing and Rudenko et al. [2] achieved real-time performance with a compact 14.85 MB YOLOv5 model suitable for mobile devices.

The trend toward edge computing reflects practical requirements for vineyard deployment. Many vineyards lack reliable internet connectivity, making cloud-based processing impractical. Edge processing also reduces latency, enables offline operation and addresses data privacy concerns. However, real-time inference is not always essential, since image or video data can be collected together with GPS and camera-orientation metadata and processed offline after the survey, for example once per day. Edge deployment requires careful optimization of model architectures and often involves trade-offs between accuracy and computational efficiency.

3.4 Generalization ability of models

The question of the generalizability of classification models of diseased grapevine leaf images is crucial for the good functioning of the models. The most common way to solve image classification problems in the vast majority of domains uses a deep neural network trained on a large dataset with further fine-tuning of the chosen classifier on your dataset. To verify the generalization ability of the classification model, we used the publicly available Grape Plant dataset from PlantVillage Dataset [38] containing images of grapevine leaves in four classes: Black rot, Esca, Leaf blight and Healthy, which are captured under controlled laboratory conditions, to train the model. To address class imbalance, offline augmentation was applied exclusively to the training subsets after data splitting to prevent data leakage. The augmentation comprised random rotations, horizontal and vertical flips, moderate zoom and brightness adjustments, with each class expanded to 1,400 training images. EfficientNet-B2, proposed by Tan and Le [44], was selected as the classification model because the EfficientNet family achieved the best performance among the architectures compared by Mathew [45], while the native input resolution of the B2 variant closely matched the resolution of the source images. The model was initialized with ImageNet-pretrained weights and evaluated using 5-fold stratified cross-validation with a separate test set. An external PDD dataset consisting of real field images [46, 47] was used to test the model and verify the generalization.

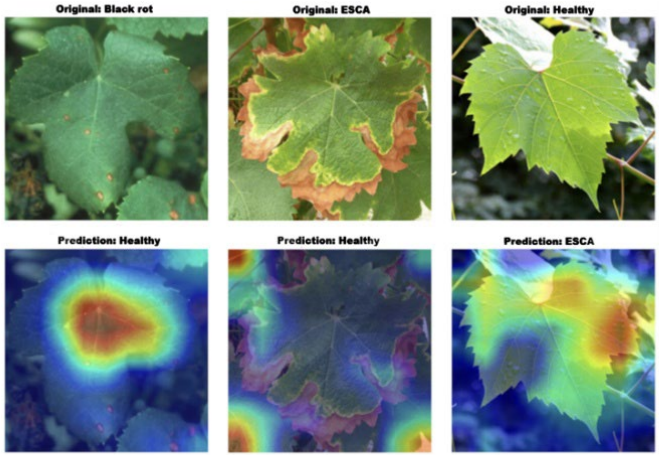

Fig. 1. Grad-CAM visualization of a three-class model on the PDD dataset (incorrect classifications)

Table 5. Results of the three-class EfficientNet-B2 model on the external PDD dataset. A necessary condition for extensive research in the field of identifying vineyard health is the existence of a publicly available, sufficiently large, annotated database of grapevine leaves photographed under real vineyard conditions.

Class	Precision (%)	Recall (%)	F1-score (%)	Num. images
Black rot	27.00 ± 5.10	34.20 ± 6.65	29.20 ± 2.04	31
Esca	64.40 ± 9.52	86.60 ± 4.88	73.40 ± 4.96	73
Healthy	90.60 ± 4.88	63.60 ± 19.19	72.40 ± 14.29	133
All classes	60.67 ± 3.22	61.47 ± 2.91	58.33 ± 5.90	237

To interpret the model's decisions, we applied Grad-CAM, which showed that the model often focused on biologically relevant regions of the leaves. Grad-CAM analysis identified the visual similarity of the symptoms of the Black rot and Esca classes as the main cause of consistent misclassifications across all cross-validation folds, confirming that these errors do not stem from training process deficiencies (Fig. 1). The four-class model achieved a testing ACC of 99.61 ± 0.17% and an average F1-score of 99.66 ± 0.13%. Since the PPD dataset did not contain the Leaf blight disease class, we used only the three-class classification model for testing. When testing the three-class model on the external PDD dataset, we achieved an ACC of 66.80 ± 8.38% and an average F1-score of 58.33 ± 5.90%, which points to a fundamental limitation of models trained exclusively on laboratory images (Table 5). Their generalization to real field conditions is significantly worse than the ACC achieved on the Grape Plant from Plant Village Dataset would suggest. The high standard deviation of the ACC ± 8.38% compared to the internal results ± 0.17% confirmed the instability of the model on real field images.

To improve the generalization ability of the model, it would be helpful in the future to expand the training data to include real field images from vineyards, or to use domain adaptation techniques to bridge the gap between laboratory and field conditions [48]. Another direction could be to test on a larger and more diverse dataset, as well as to investigate the robustness of the model to adversarial perturbations, similar to the study by Alam and Ahmed [49].

4 Discussion

The preceding analysis reveals a field that has achieved substantial technical maturity, with multiple systems demonstrating impressive performance under experimental conditions. However, a critical assessment of the reviewed literature also reveals significant gaps between research demonstrations and practical, widespread deployment. In this section, we discuss the current capabilities and limitations of automatic vineyard disease identification, examine practical deployment challenges, and consider the integration of these technologies within the broader framework of precision viticulture.

4.1 Current capabilities and limitations

The reviewed literature demonstrates that automatic vineyard disease identification has reached a level of maturity where multiple systems achieve accuracy comparable to or exceeding human experts under controlled conditions. Deep learning approaches, particularly CNNs, have proven highly effective for learning discriminative features from disease imagery without requiring manual feature engineering.

However, several limitations remain. Most systems are evaluated on relatively small, custom datasets that may not capture the full variability of real-world vineyard conditions. Disease symptoms can vary significantly depending on cultivar, disease stage, environmental conditions, and co-occurring stresses. Models trained on data from one region or growing season may not generalize well to different contexts.

The challenge of early detection remains largely unresolved. Most systems identify diseases from visible symptoms, by which point substantial infection or damage may already have occurred. Pre-symptomatic detection can be supported by multispectral, hyperspectral or thermal imaging, as well as by combining image data with environmental risk models. Although such methods have already been investigated and can be deployed in practice, they generally require more expensive sensors, more complex calibration and greater computational and operational resources than conventional RGB-based systems.

Multi-disease detection and differentiation of diseases with overlapping symptoms present ongoing challenges. Tardif et al. [41] addressed this through a two-step approach combining symptom identification with symptom-based diagnosis using Graph Neural Networks, achieving (0.88, 0.88) precision and recall. However, more work is needed to develop robust multi-disease systems that can handle the complexity of real vineyard environments where multiple diseases and abiotic stresses co-occur.

4.2 Practical deployment challenges

Despite impressive laboratory and field trial results, widespread commercial deployment of automatic disease identification systems remains limited. Several practical challenges must be addressed:

Cost and accessibility: Robotic platforms and UAV systems with advanced sensors represent significant capital investments that may be prohibitive for small and medium-sized vineyard operations. Mobile and embedded solutions offer more accessible entry points but may sacrifice some detection capabilities.

Integration with management workflows: Disease identification is only valuable if it informs timely management decisions. Systems must integrate with existing vineyard management software, provide actionable recommendations, and fit within the operational constraints of vineyard labor and equipment scheduling.

Robustness and reliability: Commercial deployment requires systems that operate reliably across diverse weather conditions, vineyard layouts, and training systems. Many research prototypes have been validated in limited settings and may require additional development to achieve the robustness needed for commercial use.

Regulatory and training considerations: Vineyard managers and workers need training to effectively use new technologies. In some regions, regulatory frameworks for autonomous vehicles and UAV operations may constrain deployment options.

Data management and privacy: Systems that collect detailed imagery of vineyard blocks raise questions about data ownership, privacy, and security. Clear frameworks for data management and sharing are needed to build trust and enable adoption.

4.3 Integration with precision viticulture

Automatic disease identification represents one component of broader precision viticulture systems that aim to optimize vineyard management through data-driven decision making. The full potential of disease identification technologies will be realized through integration with other precision viticulture tools including:

- Variable rate treatment systems: Disease maps generated by identification systems can guide variable rate application of fungicides, reducing chemical use in healthy areas while ensuring adequate protection in diseased zones. This integration requires spatial registration between identification and treatment systems and real-time data transfer.
- Yield prediction and quality assessment: Disease incidence affects both yield and fruit quality. Integrating disease data with yield prediction models and quality assessment systems can improve harvest planning and enable targeted quality management interventions.
- Environmental monitoring and disease risk modeling: Combining image-based disease identification with environmental sensor networks enables validation and refinement of disease risk models. This integration can improve predictive capabilities and enable proactive rather than reactive management.
- Long-term vineyard health monitoring: Systematic disease monitoring over multiple growing seasons can reveal spatial patterns of disease pressure, identify problem areas requiring remediation, and quantify the effectiveness of management interventions. This longitudinal perspective is essential for continuous improvement of vineyard health management.
- The development of integrated platforms that combine disease identification with other precision viticulture capabilities represents an important direction for future research and commercial development. Such platforms must balance sophistication with usability, providing vineyard managers with clear, actionable information without overwhelming them with data.

5 Future directions and recommendations

Based on this review, we identify several priority areas for future research and development.

5.1 Standardized benchmarks and datasets

The field would benefit from large-scale, standardized datasets that capture disease variability across regions, cultivars, and growing conditions. Public benchmarks would enable more rigorous comparison of methods and accelerate progress. Efforts to create and maintain such resources should be prioritized and supported by the research community and industry stakeholders.

5.2 Early identification and pre-symptomatic identification

Advancing beyond identification of visible symptoms to identify infections at earlier stages represents a key frontier. This may require hyperspectral imaging, fluorescence imaging, or other advanced sensing modalities combined with sophisticated analysis methods. Integration with environmental risk models and pathogen monitoring could enable truly predictive disease management. Early detection would also facilitate targeted interventions, allowing treatment to be applied only where necessary, thereby reducing pesticide use, lowering production costs, minimizing environmental impact, and supporting more sustainable vineyard management

5.3 Robust multi-disease systems

Developing systems that can reliably detect and differentiate multiple diseases under real-world conditions remains a challenge. Approaches that combine symptom-level identification with disease-level diagnosis, as demonstrated by Tardif et al., show promise [41]. Incorporating temporal information and disease progression patterns may improve the differentiation of diseases with similar symptoms.

5.4 Explainable AI and decision support

As disease identification systems become more sophisticated, ensuring that their outputs are interpretable and actionable becomes increasingly important. Explainable AI methods that highlight which image regions contribute to disease classifications can build user trust and facilitate learning. Integration with decision support systems that recommend specific management actions based on detected diseases, severity levels, and other contextual factors would enhance practical utility.

5.5 Low-cost and accessible solutions

Reducing the cost and complexity of disease identification systems is essential for widespread adoption. Continued development of mobile applications, embedded devices and cloud-based analysis services can democratize access to these technologies. Exploring alternative imaging platforms such as smartphone cameras may enable very low-cost solutions suitable for small-scale producers. This direction is also supported by studies showing that some disease identification methods can achieve useful performance with relatively low-resolution images, reducing the need for expensive high-resolution imaging equipment.

5.6 Validation in diverse contexts

More extensive field validation across diverse vineyard settings, cultivars, and management systems is needed to establish the generalizability and robustness of identification methods. Multi-site trials involving commercial vineyards would provide valuable data on real-world performance and identify remaining technical and practical barriers to adoption.

5.7 Integration and interoperability

Developing standards for data formats, communication protocols, and system interfaces would facilitate integration of disease identification with other precision viticulture tools. Open-source software frameworks and modular system architectures can accelerate innovation and reduce barriers to entry for new developers.

6 Conclusion

Automatic vineyard health control through computer vision and machine learning has advanced significantly in recent years, with multiple systems demonstrating high accuracy for detecting major grapevine diseases. The field has progressed from laboratory proof-of-concept studies to field-deployable systems including autonomous robots, UAV platforms, IoT-integrated solutions, and mobile applications. Deep learning approaches, particularly convolutional neural networks, have proven highly effective, with many systems achieving accuracy above 90% and some approaching or exceeding human expert performance.

Several publicly available and custom datasets have been developed to support model training and validation, though the field would benefit from larger, more standardized benchmarks. The most commonly addressed diseases include downy mildew, powdery mildew, esca, black rot, and various viral diseases, with systems ranging from single-disease specialists to multi-disease classifiers.

Key technological trends include the move toward edge computing and real-time processing, the integration of multiple sensor modalities, and the development of semantic segmentation approaches for precise disease localization and severity estimation. Robotic platforms with active illumination and autonomous navigation capabilities represent the state-of-the-art for ground-based monitoring, while UAV systems excel at rapid, large-scale assessment.

Despite impressive technical achievements, practical deployment challenges remain, including cost, integration with existing workflows, robustness across diverse conditions, and the need for user training and support. The full potential of automatic disease identification will be realized through integration with broader precision viticulture systems that enable data-driven, site-specific management.

However, the generalization experiment conducted in this study demonstrates that high internal test performance can substantially overestimate practical field performance. The EfficientNet-B2 classifier achieved $99.61 \pm 0.17\%$ accuracy on an internal test set derived from controlled-background images, but only $66.80 \pm 8.38\%$ accuracy and a mean F1-score of $58.33 \pm 5.90\%$ on an independent field dataset. This result confirms that domain shift caused by natural backgrounds, variable illumination, leaf orientation, occlusion and symptom variability remains one of the principal barriers to reliable vineyard deployment.

Future research should prioritize the development of standardized benchmarks, early detection capabilities, robust multi-disease systems, and low-cost accessible solutions. Continued field validation in diverse commercial settings and attention to explainability and decision support will be essential for translating research advances into practical tools that improve vineyard health management and sustainability.

Acknowledgment

This work was funded by the EU NextGenerationEU through the Recovery and Resilience Plan for Slovakia under the project No. 09I04-03-V02-00034.

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Received 31 May 2026