Discover Food

REVIEW Open Access

Machine vision techniques for quality control in the wine industry

Elisa Verna[1*], Alberto Piovano[1] and Maurizio Galetto[1]

*Correspondence:
Elisa Verna
elisa.verna@polito.it
[1]Department of Management and Production Engineering, Politecnico di Torino, Corso Duca degli Abruzzi 24, Torino 10129, Italy

Abstract
The wine industry is undergoing a significant digital transformation with the integration of Machine Vision Systems (MVS) for automated, precise quality control across various production stages. Despite increasing interest in MVS applications, the literature lacks a comprehensive synthesis of how these technologies are integrated throughout the winemaking process. This systematic review addresses this gap by categorizing MVS applications according to their technological approach - Stereo Vision (SV), Remote Sensing (RS), Hyperspectral Imaging (HSI), X-ray Imaging (XRI), Thermal Imaging (TI), and Magnetic Resonance Imaging (MRI) - and mapping their deployment across distinct phases of wine production. A total of 77 studies published between 2013 and 2025 were selected based on PRISMA guidelines and clearly defined inclusion criteria. The findings reveal significant advances in vineyard monitoring, grape sorting, fermentation tracking, and bottling inspection, with MVS technologies enhancing operational efficiency, sustainability, and precision in quality assessment. Nonetheless, challenges persist, particularly in mid-stage processes such as crushing and filtration, and in transitioning laboratory innovations to industrial scales due to economic and infrastructural constraints. This review not only consolidates current knowledge but also outlines critical research gaps and future directions for the integration of MVS within a broader framework of smart and sustainable viticulture. The results are intended to inform researchers, technology developers, and policymakers engaged in the digital transformation of the agri-food sector.

Keywords Machine vision, Wine industry, Quality control

1 Introduction

The agri-food sector is a critical component of the global economy, integrating activities 'from field to fork' (F2F) and balancing growth with sustainability and evolving consumer demand [1].

Technological advancements have significantly transformed the agri-food industry, particularly through the implementation of digital solutions such as artificial intelligence (AI), the Internet of Things (IoT), and advanced systems [2]. Within this landscape, Machine Vision Systems (MVS) have emerged as a transformative tool for enhancing quality control and optimizing production efficiency. MVS combine imaging hardware with AI-based analytics to automate inspection and defect detection, enabling non-destructive, real-time evaluations that improve precision, consistency, and scalability [3, 4]. In winery settings, manual visual inspection is constrained by labour intensity, operator subjectivity, and limited sampling throughput, particularly at grape intake and high-speed packaging lines. These constraints are amplified by raw-material heterogeneity and line speeds typical of viticulture and winemaking.

Within wineries, the most frequent quality deviations are visually detectable and arise at high throughput: heterogeneous grape condition at intake (presence of stems/other materials, variable maturity, and rot) [5, 6], process-stage attributes such as foam formation and browning dynamics in sparkling wines [7], and end-of-line packaging/closure defects [8, 9]. These problem classes are naturally aligned with non-destructive imaging because they require rapid, objective, and in-line assessments that preserve product integrity while supporting traceable decisions. Representative applications reported in the literature include intake grading of harvest batches using conveyor imaging, early non-destructive detection of Botrytis cinerea for high-quality wines [6], computer-vision assessment of foam quality [10], smartphone-based monitoring of browning, and X-ray–based analysis of internal defects in cork stoppers that can influence oxygen ingress. In terms of unit operations, documented applications span grape harvesting, crushing and destemming, fermentation (alcoholic and malolactic) and clarification, pressing and filtration, racking and transfers, aging and maturation, and bottling and packaging; detailed in Sect. 2.

Across these use cases, imaging modalities span RGB/monochrome video for sorting and label/fill-level checks, hyperspectral/near-infrared sensing for compositional proxies and disease detection [11, 12], thermal views for process monitoring [13], and X-ray tomography for internal defect inspection [8]. In combination with established image-analysis and machine-learning pipelines, this non-destructive toolkit enables real-time decisions at industrial line speeds, reducing reliance on subjective inspection while maintaining scalability [14]. Despite clear advantages, MVS adoption can be constrained by capital costs, systems integration, and real-time performance in complex, heterogeneous environments [2, 14, 15].

Recent market analyses indicate a substantial increase in MVS adoption within the food and beverage industry [16]. Adoption of machine vision and process-analytical sensing in food and beverage manufacturing is accelerating, driven by throughput, traceability and automation requirements, creating a favourable context for winery applications [14]. Parallel trends are observed in viticulture with increasing deployment of non-invasive digital sensing [13]. Beyond improving quality, MVS technologies also contribute to sustainability by reducing unnecessary waste, optimizing processing conditions, and enhancing resource efficiency across the entire wine supply chain [13, 17].

Despite increasing academic attention to digital technologies in wine industry, there remains a lack of comprehensive synthesis that maps the use of MVS across all phases of wine production. Comparable syntheses in agri-food and viticulture either address digital sensing primarily at the vineyard stage or concentrate on specific products/unit operations (e.g., foam assessment in carbonated beverages), but do not map imaging-based MVS coherently across the vineyard-to-bottle chain [18, 19]. This review addresses this gap by examining the deployment of MVS across winemaking stages, categorizing applications by technological approach and production phase. To ensure transparency and reproducibility, the review was designed and reported in accordance with PRISMA method [20]. Specifically, the objectives of this study are to:

- Develop and apply a technology–process taxonomy aligning imaging modalities with wine unit operations and their control objectives.
- Evaluate the effectiveness and limitations of these technologies in addressing quality control challenges.
- Identify under-served stages and actionable priorities for translation to guide research and deployment in real winery contexts.

This framework serves as a conceptual thread throughout the paper and supports a systematic understanding of how different imaging solutions align with specific winemaking stages.

2 Background

2.1 The wine industry

The agri-food industry, which encompasses both primary production (raw materials) and secondary production (processed goods), plays a significant role in global economies, contributing substantially to employment and Gross Domestic Product (GDP) [9, 21]. Among its various subsectors, the wine industry holds unique importance due to its economic value, cultural heritage, and process complexity. These characteristics make it a compelling domain for applying advanced automation technologies in production and quality control. The global wine market has experienced steady growth in recent years; for instance, projections indicate a CAGR of about 3.4%, with worldwide revenues rising from approximately $155 billion in 2018 to $216 billion by 2028 [22]. Such growth, coupled with changing consumer preferences (e.g. interest in organic wines and wine tourism), underscores the wine sector's economic significance. Geographically, Europe remains the leading region in wine production and sales, followed by the Americas, while Asia's emerging markets are driving new demand.

Winemaking follows a well-defined sequence of steps, including grape harvesting, crushing/destemming, fermentation, pressing/filtration, and bottling [23]. At each of these stages, product quality is influenced by biological variability, environmental factors, and operational precision, necessitating rigorous quality control to ensure consistency, compliance with standards, and product differentiation in competitive markets. The vertically integrated wine supply chain, from vineyard cultivation to distribution, enables centralized quality control but also demands robust monitoring systems to maintain high standards throughout production. Figure 1 provides a schematic of common stages in wine production. Note that the exact sequence can vary by wine type: for example, red wines typically ferment with skins prior to pressing, whereas white and rosé wines are pressed before fermentation.

The production process consists of multiple interdependent stages, each posing distinct challenges in terms of precision and contamination risks. A brief overview of these stages is as follows:

1. *Grape Harvesting* The timing of grape picking is crucial, as the grape maturity directly influences wine quality. Key biochemical indicators (most commonly total soluble solids, titratable acidity, pH, and the relative abundance of glucose and

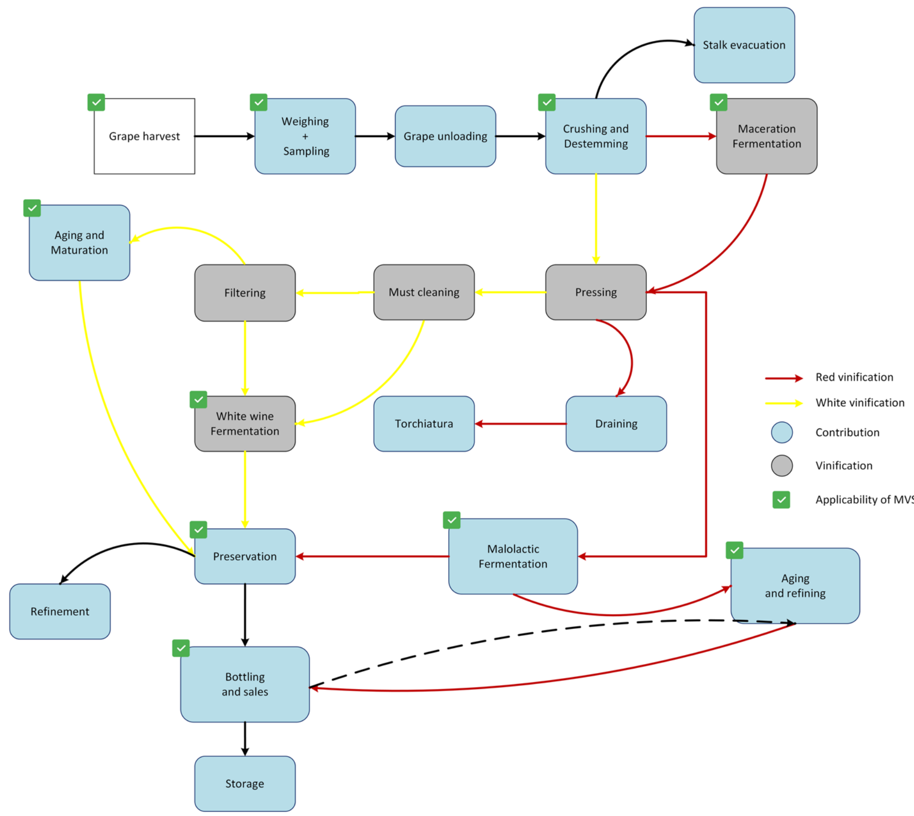

Fig. 1 Process flow of red and white wine production. The diagram distinguishes red (red arrows) and white (yellow arrows) vinification routes. Blue boxes indicate operational contributions, grey boxes represent vinification phases, and green check marks denote steps where Machine Vision Systems (MVS) can be applied

fructose) guide the harvest decision, but threshold ranges are variety- and region-specific. Practitioners often use sugar–acid balance or glucose–fructose profiles as decision cues, but recommended cut-offs vary by cultivar and climate. In addition to technological maturity, phenolic maturity, related to the concentration and extractability of tannins and anthocyanins, is also essential, particularly for red wines, as it influences colour stability, astringency, and mouthfeel [24]. Harvesting may be done manually, i.e., selective hand-picking of bunches (common for premium and sparkling wines), or mechanically using conventional specialised grape harvesters that increase throughput and reduce field labour. Unless otherwise specified, these refer to conventional tools; MVS-enabled solutions are addressed separately and include in-field, on-the-go imaging for early yield estimation to support harvest planning, and intake conveyor imaging at winery arrival for rapid raw-material grading and routing. Notably, the quality and composition of grapes at harvest are often the most determinative factors for the eventual wine quality – fruit composition at harvest is widely recognized as a primary contributor to wine quality.

2. *Crushing and Destemming* Once harvested, the grapes are transported to the winery, where they undergo crushing to extract juice. This step is usually combined with destemming to remove tannin-rich stems, that could impart undesirable bitterness or astringency. The crushing method (traditional press vs. modern mechanical crusher) affects the extraction of phenolic compounds that contribute to the wine's sensory attributes (colour, flavour, mouthfeel).

3. *Fermentation* Fermentation is a critical stage in winemaking during which sugars in the grape must are converted into alcohol and CO_2 by yeast. This biochemical process takes place in temperature-controlled vessels (stainless-steel tanks, wooden barrels, or concrete vats) to ensure optimal yeast activity [25]. Fermentation protocols differ significantly between red and white wines. In red wines, fermentation typically occurs in contact with grape skins, promoting colour and tannin extraction. In contrast, white wines are usually fermented after pressing to avoid phenolic over-extraction. Fermentation can be subdivided into:

- *Alcoholic Fermentation* Conducted by yeast strains, primarily *Saccharomyces cerevisiae*, which convert sugars into ethanol and carbon dioxide, alongside secondary metabolites such as glycerol and organic acids.
- *Malolactic Fermentation (MLF)* A secondary fermentation (usually after alcoholic fermentation) where lactic acid bacteria convert malic acid into softer lactic acid. MLF reduces acidity and enhances stability and mouthfeel, especially in many red and some white wines. MLF is particularly desirable in red wines and selected full-bodied whites (e.g., Chardonnay), as it softens acidity and contributes to mouthfeel and microbiological stability.

While fermentation is crucial for developing a wine's basic profile, the groundwork for quality is largely established by the incoming grape quality (stage 1). Selective hand-harvesting and grape sorting can be more critical to final quality than adjustments during fermentation.

4. *Pressing and Filtration* After fermentation, the liquid wine is separated from the solid grape matter (skins, seeds, pulp). In red wine production, grapes are fermented on their skins and then pressed post-fermentation to extract the remaining wine from the pomace. In contrast, white and rosé wines are typically pressed before fermentation, with only the juice undergoing fermentation. The pressing technique (e.g. gentle basket press vs. continuous press) can influence the level of tannin and phenolics extracted. Following pressing, filtration steps (such as cross-flow filtration or use of diatomaceous earth) are employed to clarify the wine by removing yeasts, bacteria, and particulates, ensuring stability and brilliance in the final product.
5. *Racking and Transfers* Throughout the fermentation and maturation process, wines are periodically transferred between containers (a process known as racking) to separate clear wine from sediments (lees) and to manage exposure to oxygen. These interim transfers are important for clarifying the wine and preventing off-flavors. Controlled oxygen exposure during transfers can benefit wine development and stability, but excessive oxidation must be avoided. Managing these movements between tanks or barrels is thus another critical operational step that contributes to product consistency and quality.
6. *Aging and Maturation* After initial fermentation and clarification, many wines undergo an aging period to develop complexity. Aging can take place in inert vessels (stainless steel or concrete for a "fresh" profile) or in oak barrels which impart additional flavour and allow slow oxygen ingress. The duration and conditions of aging (temperature,

humidity, and exposure to oxygen) are carefully managed. Limited, controlled oxygen contact during barrel aging can polymerize tannins and stabilize colour, enhancing complexity, whereas too much oxygen leads to oxidation and spoilage. Winemakers often perform periodic sensory and chemical analyses during aging to decide the optimal release time for each wine.

7. *Bottling and Packaging* The final stage involves stabilizing the wine (through fining and final filtration if needed), then bottling under sterile, inert conditions to prevent contamination [26]. Proper corking or capping, along with accurate labelling, is performed at this stage. Post-bottling, storage conditions (around 12–15 °C, and controlled humidity) are important to preserve wine quality. Even after bottling, many fine wines continue to evolve (bottle aging), but the packaging must protect the wine from excessive oxygen, light, and temperature fluctuations to maintain quality over its shelf life.

Each of these production stages faces challenges related to natural variability, precise control requirements, and risk of contamination. Traditional manual sampling and chemical analyses often cannot provide the real-time, high-resolution monitoring needed to address these challenges. This creates significant opportunities for technological integration in the wine industry [27].

2.2 Machine vision as an enabler of process innovation in wine production

MVS have become widely adopted in food and beverage processing due to their ability to automate quality control, continuously monitor product and process variables, and reduce reliance on human visual inspection [14]. These systems employ digital imaging hardware, advanced image-processing algorithms, and real-time decision-making to assess product quality at various production stages. In winemaking, the integration of MVS can enhance precision in grape sorting, fermentation monitoring, contamination detection, and packaging inspection. By providing consistent, objective evaluation, MVS helps overcome the limitations of manual methods (which can be slow, labour-intensive, and subjective), thereby improving efficiency and enhancing measurement repeatability and decision reproducibility across operators and batches. Moreover, the data collected by vision systems can contribute to traceability and inform adjustments in the process (for example, identifying a contaminated batch before it progresses further).

According to [2], a typical MVS workflow in production consists of two core phases:

- *Image acquisition* capturing images or video of the product or process using cameras with appropriate optics and lighting. In a winery context, this could mean imaging grapes on a sorting conveyor, monitoring fermentation tanks with cameras, or inspecting bottled wine on the line.
- *Image processing* applying image analysis algorithms to extract relevant features, evaluate product characteristics; modelling and decision-making are addressed in Sect. 2.2.3. This may involve measuring grape size and color to grade them, detecting defects or contaminants (like insects, stems, or particles), or reading labels and fill levels on bottles. The processing phase often includes automated decision triggers, for example, signalling a mechanical sorter to remove a defective grape, or halting a bottling line if a mislabelling is detected.

Figure 2 illustrates a generic workflow of MVS technologies, showing how image acquisition and processing components interact up to the decision-making stage (the figure focuses on the vision system itself; in practice, the final decision output would interface with physical equipment or alerts to implement the required action). This closed-loop approach, sensing, interpretation, and action, enables real-time process adjustments and rejects substandard products, thereby maintaining quality and efficiency. In industrial deployments, "real-time" implies that the combined acquisition–processing–actuation cycle time meets the line takt, for example continuous online cap inspection at ≥ 150 pieces min^{-1} (≈ 400 ms $item^{-1}$) or video-based process monitoring at ~ 2 frames s^{-1}, as reported in winery applications.

2.2.1 Image acquisition mechanisms

Various image acquisition techniques are employed in MVS, ranging from conventional 2D photography to advanced spectral and 3D imaging. According to the literature, MVS can acquire images in real time via standard photos, high-speed video, and even three-dimensional imaging modalities [11]. The captured images may be transmitted to the processing unit through different channels depending on the system architecture: wired connections (USB or Ethernet for industrial cameras), network links (industrial internet or LAN), or even wireless methods like radio frequency identification (RFID) tags and wireless sensor networks (WSN) for distributed sensing setup [2]. The choice of acquisition method and transmission channel depends on factors such as required resolution, speed, and the environment (for instance, a stable wired camera for a bottling line vs. a wireless network of cameras in a vineyard). Table 1 summarizes some of the most widely used image acquisition technologies in food processing with indicative technical specifications (spectral range, resolution/voxel, sensor type, scan mode) and typical uses. Each technology offers unique advantages for certain tasks in wine production.

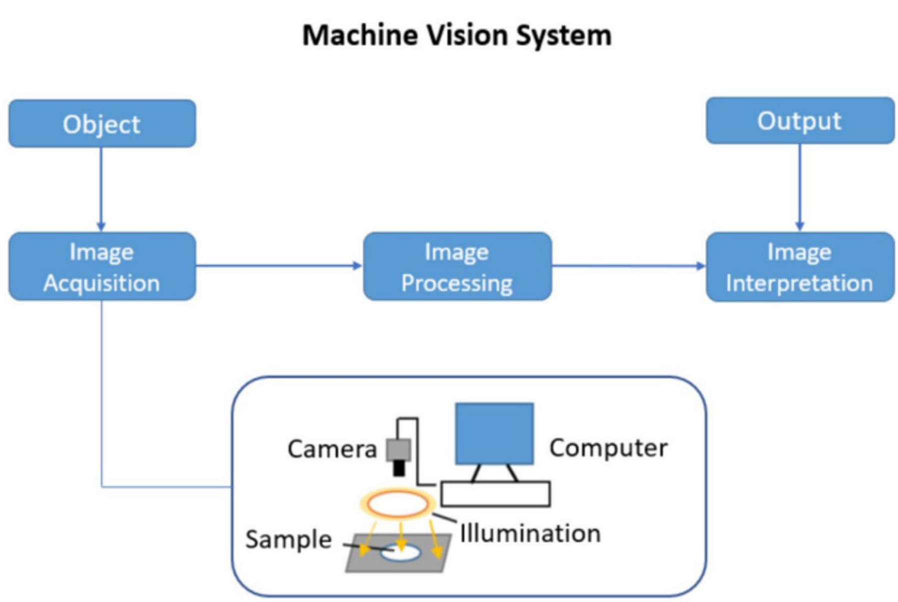

Fig. 2 Schematic of a machine-vision workflow (acquisition, processing, interpretation/decision). The diagram is generic; real-time operation is achieved when the loop closes within the process cycle time.
Source: [2]

Table 1 Most widely used image acquisition technologies in the food industry, with specific applications in wine production

Acquisition technology	Application in wine production	Description	Resolution	Sensor type	Wavelength range	Refs.
Stereo Vision (SV)	Precise classification of grape size and quality.	Captures paired views to recover depth, enabling 3D size/shape measurement for more accurate recognition than 2D imaging.	Video resolution depends on camera; example: 1024 × 768 px per view	Dual RGB cameras; disparity for depth	VIS ≈ 400–700 nm	[28]
Remote Sensing (RS)	Monitoring of grape composition, sugar levels, acidity, and polyphenol content, identification of grape defects and contamination.	Records reflectance in selected VIS–NIR–SWIR (and sometimes thermal) bands to derive canopy indices (e.g., vigor, water status) over large areas.	GSD spans sub-decimetre (UAV) to tens of metres (satellite)	Discrete VIS–NIR–SWIR (optionally LWIR) bands	Typical bands for vegetation indices (e.g., red, NIR; SWIR): ~400 nm to 2500 nm.	[29]
Hyperspectral Imaging (HSI)	Evaluation of grape ripeness, detects foreign substances, and ensuring product homogeneity.	Acquires hundreds of narrow bands to produce spatial–spectral cubes that reveal compositional and surface differences at pixel level.	Pixel-level cubes; effective spatial detail set by optics/working distance	Push-broom line scanner + spectrograph (CCD/CMOS)	Examples: 400–1000 nm (≈ 121 bands); 897–1752 nm (256 bands, ~ 3.34 nm sampling)	[13]
X-ray Imaging (XRI)	Identification of contaminants in bottled wine and assessment of cork integrity.	Uses X-ray attenuation/CT to reveal internal defects, foreign objects, and density variations non-destructively.	50–200 µm/pixel	X-ray tube + detector; attenuation contrast; (micro-)CT reconstruction	Specified by tube energy (kV), not optical λ	[30]
Thermal Imaging (TI)	Monitoring of temperature consistency during fermentation and detection of bacterial contamination in wine storage facilities.	Measures emitted infrared radiation to map temperature fields and detect hot/cold spots without contact.	Depends on optics/platform (e.g., 320 × 240 to 640 × 480 px in many systems)	Uncooled microbolometers (LWIR) or Photodetectors	LWIR ~ 8–14 µm (common)	[13]

Table 1 (continued)

Acquisition technology	Application in wine production	Description	Resolution	Sensor type	Wavelength range	Refs.
Magnetic Resonance Imaging (MRI)	Analysis of grape seed ripeness and evaluation of molecular changes (e.g., water distribution, sugar content) during fermentation.	Applies NMR principles to non-invasively image internal structure and distributions of water/solutes in 3D.	Application-dependent 3D resolution (coil/field limited). It can range from ~50 µm to 1 mm per pixel	Radiofrequency (RF) coils in magnetic field	No optical wavelength (RF excitation)	[31]

Each imaging technology above addresses different needs in the wine production process. Importantly, these acquisition mechanisms often must be combined with the right lighting, positioning, and calibration procedures to yield reliable data for subsequent analysis.

2.2.2 Image processing pipeline

Once images are acquired, analysis proceeds in hierarchical stages, from basic enhancement to task-oriented feature representation. This layered approach reflects increasing levels of computational complexity, abstraction, and interpretability:

- *Low-level processing* image enhancement operations to improve quality and prepare for analysis (e.g., noise reduction, contrast enhancement, colour calibration under variable lighting (reported as CIE Lab, hue angle, and chroma in vineyard and winery tasks)) [32].
- *Intermediate-level processing* object or region segmentation, shape description, and feature extraction (e.g., equivalent diameter, texture, colour indices) to quantify relevant characteristics of grapes, leaves, or packaged items [2].
- *High-level processing (feature representation)* aggregation and structuring of intermediate features (e.g., region statistics, shape descriptors, spectral indices) into compact, task-oriented representations suitable for downstream modelling and decision rules.

Continual improvements in in hardware and algorithms enable these steps to run in (near) real time. Figure 3 illustrates the layered structure from enhancement and segmentation to feature representation. The resulting feature matrices feed the chemometric and machine-learning models described in Sect. 2.2.3.

2.2.3 Chemometric and machine-learning modelling

Based on the features produced by the image analysis pipeline, chemometric and machine-learning models perform calibration, classification, prediction, and decision-making across winery tasks.

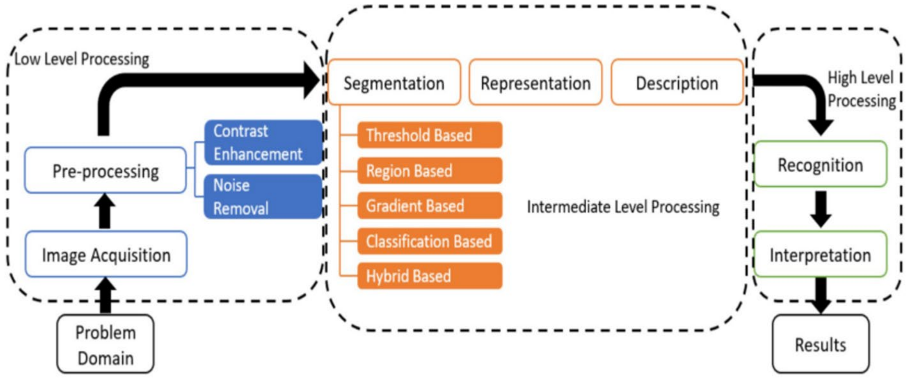

Fig. 3 Different levels of image processing in machine vision mechanisms.
Source: [2]

2.2.3.1 Chemometrics (feature-space modelling and calibration) Unsupervised methods such as principal component analysis (PCA) support dimensionality reduction and exploratory structure of spectral/colour features, while supervised approaches such as partial least squares (PLS) enable quantitative calibration of oenological parameters (e.g., soluble solids/Brix, phenolics) and authenticity tasks. Chemometric models are frequently used to transform high-dimensional spectral/colour representations into stable, interpretable predictors for process monitoring and quality assessment.

2.2.3.2 Machine learning and deep learning (decision models) Classical classifiers such as support vector machines (SVMs) and K-Nearest Neighbors (KNNs) have been widely applied to binary and multi-class tasks (e.g., disease detection, vine health assessment), often reporting accuracies exceeding 90% [28, 33]. PLS regression has achieved R^2 values above 0.90 for key targets such as Brix or tannins [34]. More recently, deep architectures—especially CNNs—have shown strong performance in segmentation and detection: for example, YOLOv5 distinguishing healthy vs. damaged grape clusters with F1 ≈ 0.92, and Mask R-CNN exceeding 92% accuracy for cluster segmentation and counting [35]. These models operationalize decisions ranging from “accept/reject” in sorting to automated alarms in packaging inspection, complementing chemometrics by handling complex, non-linear visual patterns.

3 Research methodology

The methodology of this systematic review follows the PRISMA framework [36], with the aim of ensuring transparency, replicability, and methodological rigour in the identification, selection, and analysis of relevant literature. PRISMA is particularly suitable for this study due to its systematic and structured approach to synthesizing fragmented and interdisciplinary knowledge, a key requirement given the complex nature of integrating emerging technologies like MVS into traditional sectors such as winemaking. The framework facilitates the identification of technological advancements, recognition of process-specific benefits and limitations, and exposure of underexplored research gaps, ultimately supporting evidence-based decision-making in the wine industry. The PRISMA-based approach for systematic literature review helps to guide future research and supporting evidence-based technology adoption in the wine sector. A PRISMA flow diagram (Fig. 4) summarises records identified, screened, assessed for eligibility, and included.

To ensure comprehensive coverage of relevant literature, searches were conducted across Scopus, Web of Science and Google Scholar (February 2025). Scopus was prioritized due to its broad indexing across engineering, food technology, and production management journals, combined with its rigorous source selection process. The search strategy was designed to capture the intersection of machine vision technologies, quality control processes, and wine production. A structured boolean query (provided in Appendix 6.) combined terms related to visual recognition, image analysis, automated inspection, and non-destructive testing, alongside terms specific to wine production and quality assurance. The search covered publications from 2013 to 2025, aligning with the rapid technological evolution and increased MVS adoption in the food and beverage sector over the past decade.

Inclusion and exclusion criteria were carefully defined to ensure scientific rigour and relevance to the study objectives. Studies included were peer-reviewed articles, conference proceedings and high-quality industry reports that explicitly focused on MVS applications related to wine production or viticulture. Selected papers described real-world implementations, experimental studies or validated prototypes, and explicitly addressed image acquisition, image processing or decision-making processes. Studies focusing on theoretical image processing algorithms without a clear practical application, sensor development without an explicit link to production, research from unrelated sectors and reviews without original empirical contributions were excluded.

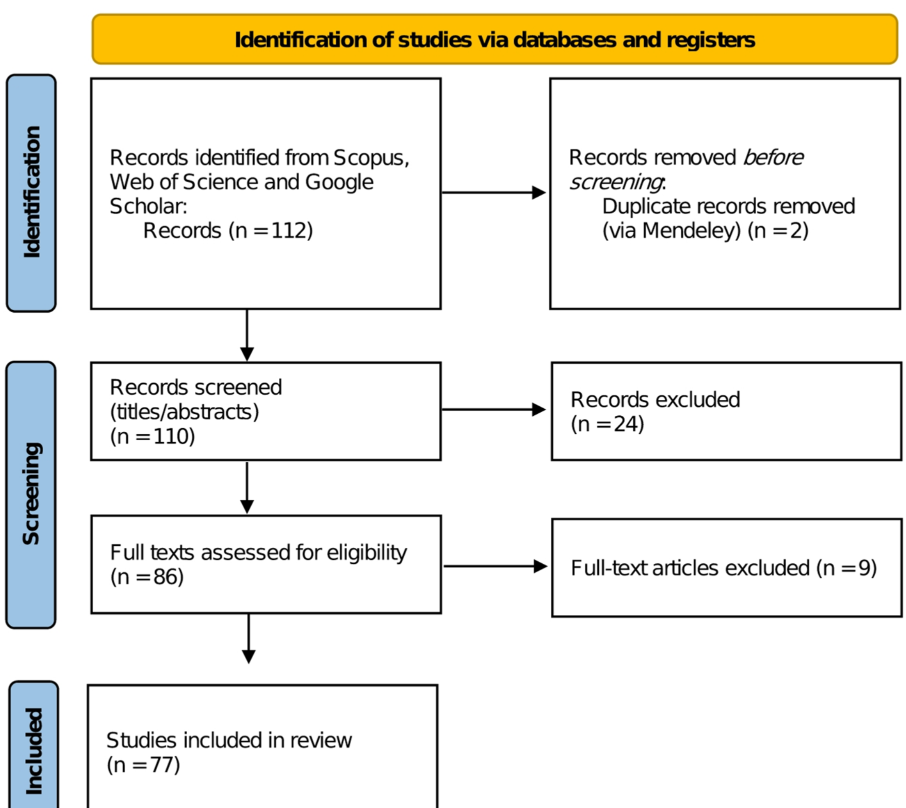

Fig. 4 Diagram prepared following PRISMA 2020 reporting guidance

PRISMA-guided study selection included duplicate removal (using Mendeley reference management), followed by title and abstract screening, and finally full-text availability checks. This systematic process reduced an initial set of 112 articles to 77 studies, which formed the basis for further analysis. A structured data extraction template was applied to each selected paper to capture bibliographic metadata, research focus, MVS configuration, image processing methods, performance metrics, benefits, limitations and recommendations for future research. This structured approach facilitated systematic comparison and supported the development of the taxonomy.

3.1 Bibliometric analysis

To complement the qualitative synthesis, a bibliometric analysis was conducted to provide a quantitative perspective on the research landscape. The VOSviewer software was used for its ability to effectively visualise and analyse bibliometric networks. This analysis mapped the geographic distribution of research activity, identifying leading research hubs and institutions and most-cited papers and authors to capture significant intellectual contributions and influential works. Keyword co-occurrence networks were also generated to uncover major research themes, interdisciplinary intersections, and emerging research directions, providing an essential overview of main actors and contributions within this research domain.

3.2 Taxonomy development

The extracted data, from papers, was synthesized into a two-dimensional taxonomy, mapping MVS applications across the wine production process. This taxonomy classifies the MVS applications according to:

- *Acquisition technology type* the specific image acquisition technology used (SV, RS, HSI, XRI, TI, MRI), according to the classification proposed in Table 1.
- *Process phase* the stage of the wine production process where MVS was applied (e.g., harvesting, fermentation, bottling), according to the classification proposed in Fig. 1.

This structured classification serves both academic and industrial purposes. For researchers, it offers a clear synthesis of existing work and identifies technology gaps. For industry practitioners, it serves as a benchmarking tool, helping wineries evaluate which MVS technologies align best with their specific process challenges.

To capture the progressive shift towards complexity in the image processing methods used in the reviewed studies, a three-level categorisation (low, medium and high complexity) was established. The complexity levels were defined based on the sophistication and type of image analysis techniques used: 'low' includes basic pre-processing or thresholding, 'intermediate' includes feature extraction and segmentation methods, and 'high' includes advanced machine learning algorithms (e.g., SVM, random forests) and deep learning-based models (e.g., CNNs), where the latter are characterized by multi-layered neural architectures capable of automatically learning hierarchical feature representations from large datasets. This dimension is crucial for understanding the technological maturity, practical feasibility and implementation challenges associated with the use of MVS in industrial settings.

4 Results

4.1 Bibliometric analysis

The systematic review identified 77 relevant studies after applying selection criteria, highlighting the increasing research interest in MVS for winemaking quality control. The journals and the number of citations for each journal can be found in Table 2. The most prolific journal in terms of publications and citations is *Computers and Electronics in Agriculture*, hosting 8 studies and accumulating 324 citations, indicating both substantial research activity and high impact within this specialized domain. Other journals that have published significant contributions include *Foods*, the *Journal of the Science of Food and Agriculture*, and *Molecules*, with each journal publishing five studies and accumulating between 51 and 121 citations. Beyond these, the remaining publications are

Table 2 List of journals examined in the review with the corresponding number of studies and citations

Name of journal	Studies	Citations
Computers and electronics in agriculture	8	324
Foods	5	100
Journal of the science of food and agriculture	5	121
Molecules	5	51
Biosystems engineering	4	99
Food control	4	196
Journal of agricultural and food chemistry	3	42
Remote sensing	3	111
Agricultural water management	2	44
Agronomy	2	19
Beverages	2	10
Food analytical methods	2	13
Food chemistry	2	44
Journal of food engineering	2	45
Microchemical journal	2	4
Oeno one	2	7
Artificial intelligence for digitising industry: applications	1	0
Carbohydrate polymers	1	15
Computers in industry	1	11
Electronic journal of biotechnology	1	5
Environmental science and pollution research	1	4
European food research and technology	1	3
Food and bioproducts processing	1	10
Food chemistry: X	1	39
Food research international	1	10
Frontiers in nutrition	1	6
Frontiers in plant science	1	12
Japan journal of food engineering	1	1
Journal of applied science and engineering (Taiwan)	1	5
Journal of field robotics	1	26
Journal of food composition and analysis	1	25
Journal of food process engineering	1	0
Membranes	1	23
Metabolites	1	17
PLoS one	1	2
Postharvest biology and technology	1	60
Precision agriculture	1	15
Scientia horticulturae	1	181
Smart agricultural technology	1	53

scattered across a wide range of journals, with each journal hosting one or two studies. This dispersion could reflect both the interdisciplinary nature of the topic and the fact that research on MVS in winemaking is not yet consolidated into a dedicated research stream, but rather embedded within broader fields such as precision agriculture, food technology, automation, and remote sensing.

The editorial distribution of the reviewed articles is presented in Fig. 5. A substantial share of publications is concentrated among three major publishers: Elsevier (42%), MDPI (19%), and John Wiley and Sons Ltd (10%). This distribution highlights the leading role of these publishers in disseminating research at the intersection of applied artificial intelligence, agriculture, and food science. The remaining contributions are spread across 13 other publishers, each accounting for less than 5% of the total, indicating a broader yet more fragmented editorial landscape.

The geographical distribution of research activity reveals a clear concentration in leading European wine-producing countries (Fig. 6). Spain contributes the highest number of articles (25), followed by Italy (13) and France (10). This reflects the economic importance of the wine industry in these countries and their strong tradition of research and innovation in winemaking, where quality is a recognized driver of competitiveness. Outside Europe, Australia and China emerge as the most active contributors, with seven and six studies respectively. The contrast between European and Asian research contributions is of particular interest. While European research tends to emerge directly from traditional wine regions, Asian contributions, especially those from China and Japan, may demonstrate a more strategic orientation. This strategic orientation is driven by

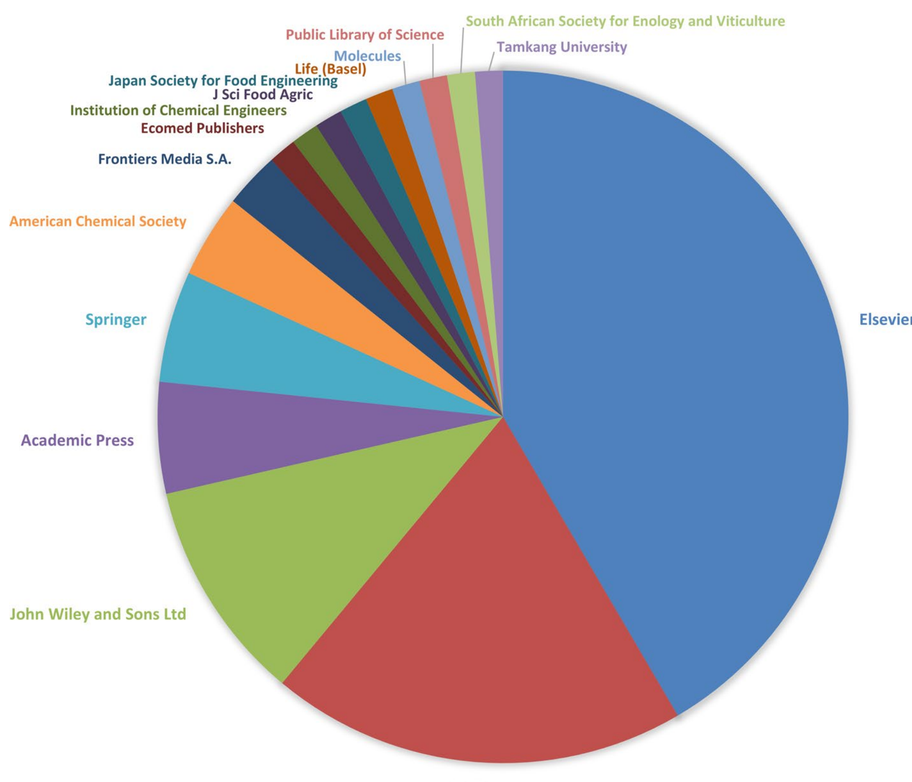

Fig. 5 Distribution of reviewed publications by publisher

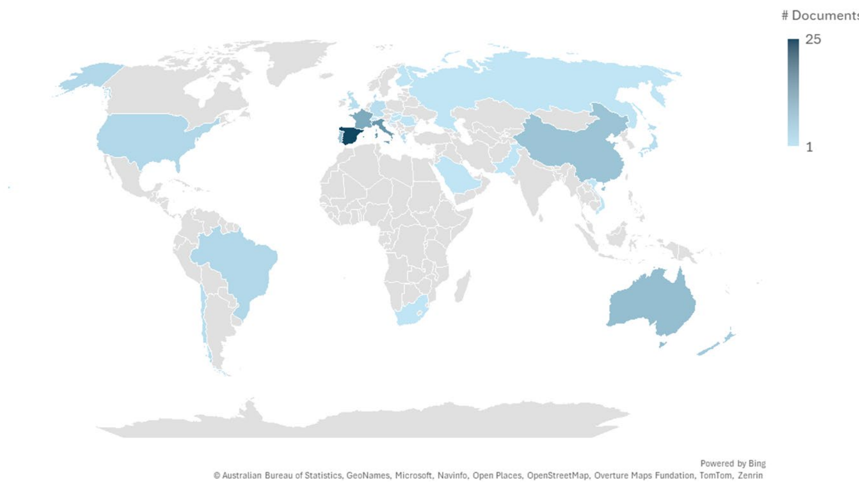

Fig. 6 Geographical distribution of studies by countries

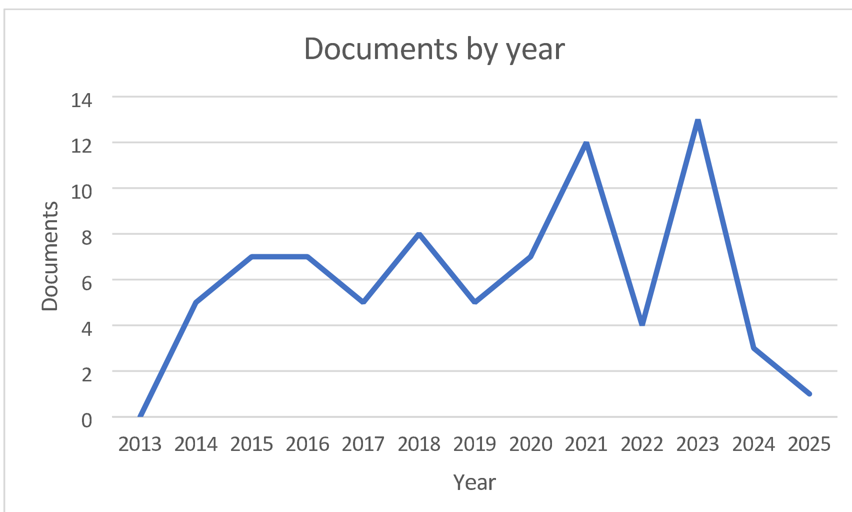

Fig. 7 Number of studies per year from 2013 to 2025

the need to improve product quality and global competitiveness in relatively new wine industries.

In addition to the geographic distribution, the temporal evolution of publications offers valuable insight into the growing research momentum on MVS in winemaking (Fig. 7). From 2013 to 2025, the number of studies has steadily increased, with two clear surges: the first in 2021, and a second in 2023. Initial years (2014–2018) reflect a stable foundation of research activity, with an average of 6–8 publications per year. The decline observed in 2024 is likely attributable to data incompleteness at the time of analysis. Overall, the trend demonstrates consistent and growing engagement with MVS applications in winemaking, confirming its relevance as an emerging research field.

In terms of the influence, the most frequently cited studies (Table 3) demonstrate an emphasis on the assessment of grape quality, vineyard monitoring, and the early detection of diseases. These studies focus on the primary stages of production (i.e. the primary industry) rather than stages of secondary industry (i.e., the processing industry).

Table 3 The most five cited publications from the considered studies

Title	Authors	Year	Journal	Citations	Refs.
Grapevine quality: A multiple-choice issue	Poni et al.	2018	Scientia Horticulturae	208	[38]
High Resolution Multispectral and Thermal Remote Sensing-Based Water Stress Assessment in Subsurface Irrigated Grapevines	Espinoza et al.	2017	Remote Sensing	105	[39]
Automatic detection of powdery mildew on grapevine leaves by image analysis: Optimal view-angle range to increase the sensitivity	Oberti et al.	2014	Computers and Electronics in Agriculture	90	[40]
Automated early yield prediction in vineyards from on-the-go image acquisition	Aquino et al.	2018	Computers and Electronics in Agriculture	78	[41]
NIR spectroscopy and chemometrics for the typification of Spanish wine vinegars with a protected designation of origin	Ríos-Reina et al.	2018	Food Control	68	[42]

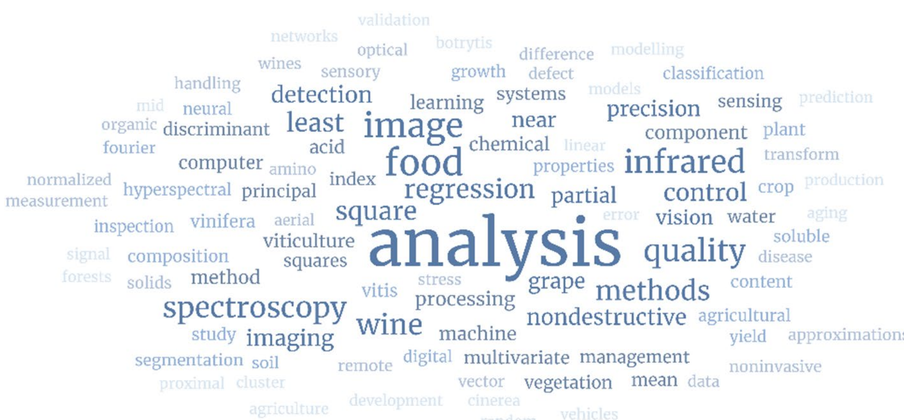

Fig. 8 Word-cloud of keywords after lower-casing and term harmonisation; font size reflects relative frequency. Dominant terms include analysis, image/computer vision, spectroscopy/infrared, and quality, indicating a methodological focus on analytical imaging for quality control

The most highly cited articles have been published in Scientia Horticulturae, Remote Sensing, and Computers and Electronics in Agriculture.

While citation patterns reveal a focus on vineyard-level applications published in specialized agricultural journals, a deeper linguistic analysis of the literature provides additional insights into methodological priorities across the wine production spectrum. Figure 8 shows the word cloud visualisation which highlights the most frequently occurring terms across the reviewed literature, with “analysis”, “image”, “spectroscopy”, and “quality” emerging as dominant keywords. This reflects a strong methodological focus on analytical techniques, especially spectroscopy-based imaging and quantitative quality control, reinforcing the central role of MVS in both compositional and visual assessment in wine production.

To further understand how these key terms relate to each other within the research landscape, a network analysis was conducted to identify distinct thematic clusters and their interconnections in the literature. The co-occurrence map, reported in Fig. 9 reveals three main thematic clusters, with the term “wine” which is the most frequently occurring keyword, occupying the central position within the network. The first cluster (green) focuses on terms such as “image analysis”, “viticulture” and “computer vision”, it represents technological development for vineyard monitoring and grape sorting. The

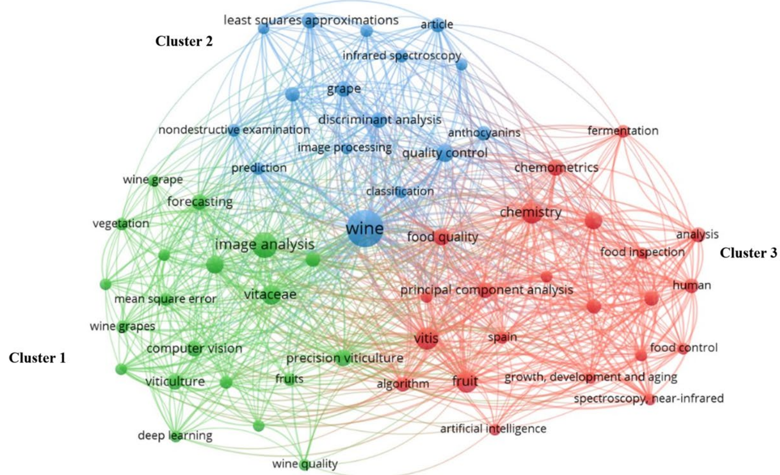

Fig. 9 Keyword co-occurrence network. Node size denotes frequency; edge thickness denotes link strength; colours denote clusters. Together, the map locates wine MVS at the intersection of image processing (green), spectral analysis (blue), and machine learning (red), with quality control as the common endpoint

cluster number 2 (blue) emphasizes “spectroscopy”, “quality control”, “classification” and “prediction” models, and aligns with analytical examinations in winemaking. The final cluster (red) combines terms such “chemistry”, “food inspection”, and “artificial intelligence”, reflecting the integration of machine learning in advanced quality control. The cluster analysis suggests that MVS research in winemaking operates at the intersection of image processing, spectral analysis, and machine learning, with a specific interest in quality control. Keyword maps were generated in VOSviewer using full counting, a minimum occurrence threshold of 5, lower-casing and simple term harmonisation, with generic stop-terms removed.

The keyword overview (Fig. 8) and co-occurrence structure (Fig. 9) together show a field anchored in image/computer vision and spectral–chemometric methods, converging on quality control across the wine chain. Terminology used in the clusters is mirrored in Sect. 4.2–4.4 (acquisition, analysis, and modelling), enabling direct cross-reference between themes and applications.

4.2 Taxonomy of MVS in winemaking process

The 77 papers selected have been classified according to the following dimensions: *i*) the specific acquisition technology used in the study, and *ii*) the stage of the wine production process where MVS was applied. This classification serves to address the disparity between the technical capabilities and practical industry applications, thereby highlighting the areas in which MVS contributes most effectively and the areas where research remains underdeveloped. Table 4 presents the proposed taxonomy, summarizing the alignment between technologies and process stages.

4.2.1 Heterogeneous distribution of research at various stages of production

The analysis reveals a significant imbalance in research efforts across different stages of wine production. As highlighted in Table 4, the Grape Harvesting stage is the focal point of most studies, particularly those that utilise SV, RS, and HSI. This pronounced research concentration mirrors the principal significance of precise grape quality assessment and

Table 4 Taxonomy of acquisition technologies and corresponding wine production process stages addressed in the reviewed studies

	Wine process stage					
Acquisition Technology	**Grape Harvesting**	**Crushing and Destemming**	**Fermentation**	**Pressing and Filtration**	**Aging and Maturation**	**Bottling and Packaging**
Stereo Vision (SV)	[5, 6, 28, 41, 43–47]	—	[7, 48–50]	[51]	[48, 49]	[5, 10, 50–53]
Remote Sensing (RS)	[5, 6, 12, 13, 29, 35, 39, 54–68]	[13]	[29, 50, 55, 57, 58, 62, 65, 67–73]	—	[29, 39, 55, 59, 69, 71–73]	[5, 50, 69, 74, 75]
Hyperspectral Imaging (HSI)	[5, 12, 13, 29, 35, 39–41, 55–57, 59, 60, 62, 64–68, 76–78]	[13]	[29, 50, 55, 57, 62, 65, 67–72, 77]	—	[29, 39, 55, 59, 69, 71, 72]	[5, 42, 50, 69, 74, 75]
X-ray Imaging (XRI)	—	—	—	—	[8, 30]	[8, 30, 79]
Thermal Imaging (TI)	[13, 39, 57, 58]	[13]	[57, 58]	—	[39]	—
Magnetic Resonance Imaging (MRI)	[59]	—	[31]	—	[31, 59]	[31, 75]

Cells with "—" indicate the absence of studies for the specific combination of image acquisition technology and wine production stage in the reviewed literature

early defect detection at this nascent stage, where determinations concerning harvest timing, sorting, and preliminary processing exert a direct influence on wine quality. A major motivation for applying MVS at this stage is the high intra-bunch variability in grape quality attributes such as ripeness, size, and colour. These heterogeneous characteristics make manual assessment inefficient and error-prone, whereas MVS offers the resolution and speed necessary for selective and accurate harvesting decisions. The primary advantages of MVS at this stage are threefold: real-time grape ripeness evaluation, non-destructive assessment of sugar content and acidity, and automated identification of diseased or damaged clusters. In contrast, the Crushing and Destemming stage is underrepresented, with only one study identified. The Fermentation phase, on the other hand, exhibits comparatively elevated research intensity, principally in studies employing HSI and TI technologies. This is propelled by the significance of continuous process monitoring during this chemically dynamic phase, wherein temperature, colour evolution, and microbial activity must be meticulously regulated to ensure fermentation stability and flavour profile development. MVS applied during fermentation have been demonstrated to provide real-time monitoring of fermentation kinetics and early detection of deviations, thereby enabling more precise process adjustments. The Pressing and Filtration stage is the only phase in wine production that currently lacks MVS's research in this analysis. This absence is likely attributable to the inherent characteristics of the processes involved, which predominantly encompass mechanical and chemical parameters (e.g. pressure control, particle size and clarity standards) as opposed to organoleptic inspections aspects. In contrast, the Aging and Maturation stages of the process demonstrate moderate research activity involving all the acquisition technologies examined, with HSI, RS and MRI being the most frequently employed. During these phases, MVS is predominantly utilised for the assessment of particle size distribution, turbidity, and chemical composition. This facilitates the refinement of optimisation of aging

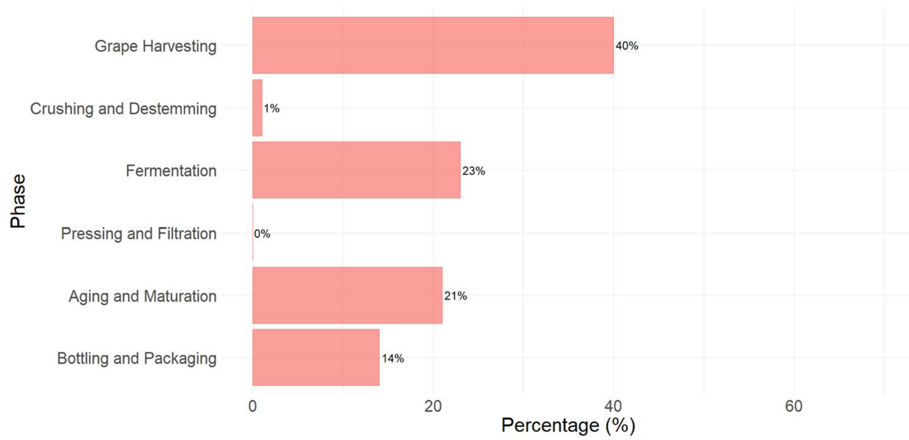

Fig. 10 Distribution of production phases addressed in the reviewed studies

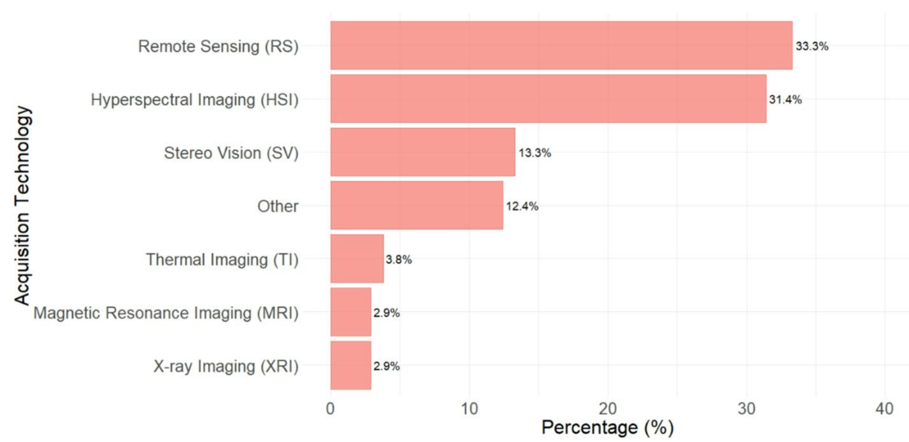

Fig. 11 Distribution of acquisition technologies addressed in the reviewed studies

conditions, informed by continuous non-destructive quality data. The final stage of the process, Bottling and Packaging, is of particular significance in ensuring the integrity of the final product. In this stage, all the acquisition technologies are present. The primary functions of these technologies are threefold: namely, the detection of foreign objects, the inspection of cork or cap integrity, and the assurance of label positioning and packaging compliance.

The technology-process taxonomy reveals a conspicuous imbalance in the intensity of research across various stages of production. This uneven distribution suggests that early-stage production and final packaging have attracted the most attention, while mid-stage processes remain less explored. As illustrated in Fig. 10, Grape Harvesting garnering the most research attention, featuring in 40% of the reviewed studies. This observation is not unexpected, given the critical role of raw material quality in determining the final characteristics of the product.

4.2.2 Technological trends in MVS applications

Among the six major MVS technologies, RS emerged as the most frequently applied, appearing in 33% of the selected studies (Fig. 11). Their dominance stems from their ability to provide detailed spectral and spatial data, making them highly effective for vineyard monitoring, disease detection, and real-time quality assessment. A similar reasoning applies to HSI technology, which accounts for 31.4% of the studies, thus confirming its critical role in the sector. In contrast, XRI and MRI are the least represented technologies, with each appearing in fewer than 3% of studies. The limited adoption of these technologies can be attributed to three main factors. Firstly, the high cost of implementation is a significant barrier, particularly for small-scale producers. Secondly, the applicability of these techniques within winemaking is restricted, as they require controlled environments, which are not always available. Finally, these techniques are primarily employed in bottling and final product inspection, rather than in the earlier stages of production where MVS is more extensively applied.

4.3 Image processing levels: shift towards complexity

As previously mentioned in Sect. 2.2.2, MVS systems rely on three levels of image processing. The reviewed studies revealed a strong preference for high-level processing (67%), followed by intermediate (19.6%) and low-level (13.4%) processing (Fig. 12). These methods are often combined, with processing levels adapted based on task complexity.

MVS in winemaking are increasingly reliant on AI-driven image processing, with Digital Image Analysis (DIA), deep learning, and statistical modelling playing crucial roles in quality assessment. DIA is extensively utilised for grape seed maturity classification, cork defect detection, and wine authentication, attaining accuracy rates exceeding 90% in various applications, including foam stability analysis in sparkling wines [46]. Deep learning models, such as CNNs and Mask R-CNN, have demonstrated high precision in grape cluster detection and wine disease classification, while machine learning classifiers like SVM and KNN have achieved over 89% accuracy in detecting vineyard diseases [35]. Furthermore, the employment of advanced statistical methods, such as PLS Regression and PCA, has been shown to enhance predictive modelling capabilities. In addition to these findings, the increasing utilisation of computer vision techniques in sparkling wine foam analysis and vineyard phenology monitoring serves to further illustrate the expanding role of AI-powered image processing in the automation and optimisation of winemaking operations.

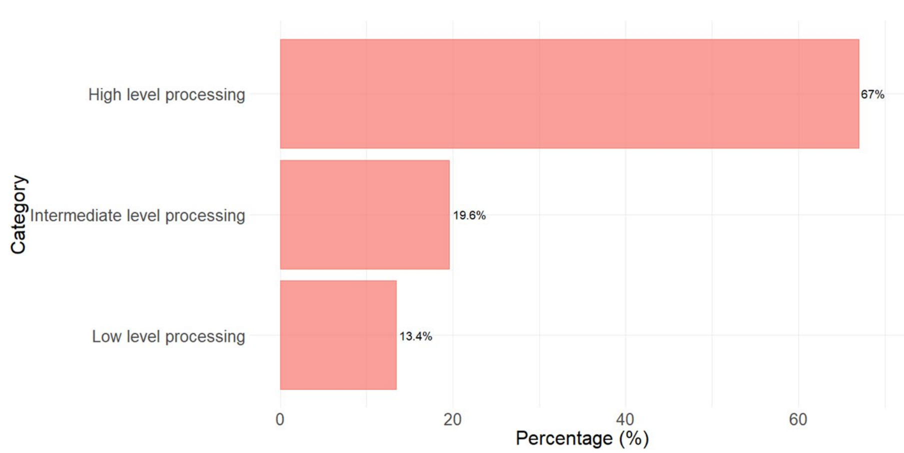

Fig. 12 Distribution of image processing levels addressed in the reviewed studies

4.4 Algorithmic landscape and control types

Table 5 consolidates the principal method families used across winery applications. Regression models (notably PLS-R, PCR, MLR, SVR) remain the default choice for quantitative estimation from spectral/colour features. Classification approaches (PLS-DA, SVM, CART, KNN) are prevalent in authentication/traceability and finished-product quality control, where decisions are dichotomous. Dimensionality reduction—chiefly PCA—is employed as a pre-processing step before calibration or classification and in process optimisation. Deep learning (e.g., CNN-based detection/segmentation) concentrates on visual inspection and process checks (defects, label/fill). Clustering (k-means, HCA) is used for exploratory grouping of varieties/batches, and classical image operations (thresholding, Hough transform) support pre-/mid-pipeline feature generation. Ensemble methods (Random Forest, Extra Trees, AdaBoost), feature-selection schemes

Table 5 Algorithmic methods by scope stage and application

Name of the technique	Stage scope	Algorithm used	Application	References
Regression	Process (must/wine)	PLS-Regression (PLS-R); Linear Regression; Multiple Linear Regression (MLR); Principal Components Regression (PCR); Random Forest Regression (RFR); Support Vector Regression (SVR)	Predict wine age from RGB image features (bottle images)	[7, 53, 61, 79]
Feature selection (chemometric)	Process (must/wine)	Hough transform, Thresholding, PLS, iSPA-PLS	Interval selection to improve image-based age prediction accuracy	[41, 79]
Classification	Finished product	PLS-Discriminant Analysis (PLS-DA); SVM; Classification and Regression Tree (CART), k-nearest neighbors (KNN):	Cork grade/defect classification from image features	[8, 63, 80]
Bayesian methods	Finished product	Bayesian classifier	Automated cork stopper grading/inspection	[8]
Dimensionality Reduction	Cross-stage	PCA	Pre-processing for classification/regression of quality attributes	[44, 62, 72]
Deep learning	Vineyard grapes	YOLOv5, CNNs, Artificial Neural Network (ANN)	Detect bunches and lesions on grape clusters	[35, 45]
Clustering	Vineyard grapes	K-means, Hierarchical Cluster Analysis (HCA);	Grouping lots/seed maturity with image descriptors	[10, 81]
Time-series	Process (must/wine)	Linear/zero-order kinetic models on RGB channel trajectories	Smartphone image sequences to model browning kinetics over time	[13]
Ensemble Methods	Cross-stage	Decision Trees, AdaBoost, Random Forest, Extra Trees	Supplemental baselines for quality classification/regression	[60]
Hybrid pipelines	Cross-stage	PCA→SVM/PLS-DA; Feature-selection→PLS;	End-to-end image analysis for QC	[33, 82]

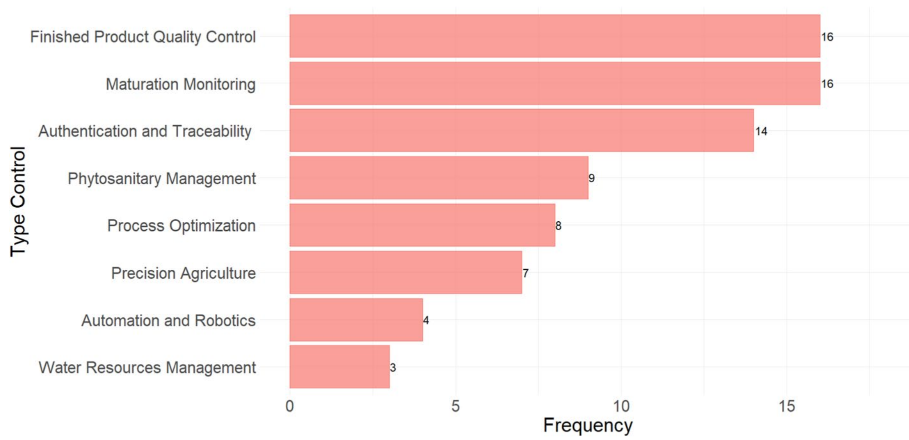

Fig. 13 Distribution of control types addressed

Algorithm family ↓ / Control type →	Maturation monitoring	Maturation monitoring	Authentication & traceability	Harvest decisions	Process optimization
Regression (PLS-R, MLR, PCR, SVR, RFR)	●	●	●	○	●
Classification (PLS-DA, SVM, CART, KNN)	○	●	●	○	○
Dimensionality reduction (PCA)	●	●	●	○	●
Deep learning (CNNs/segmentation/detection)	○	●	○	○	●
Clustering (k-means, HCA)	○	○	○		○
Ensemble methods (RF, Extra Trees, AdaBoost)	○	●	●		○
Classical image operations (thresholding, Hough)	○	●			○

Fig. 14 Concise map of algorithm families against control types in winery applications. Symbols indicate qualitative prominence consolidated from Table 5 (● primary; ○ secondary)

(e.g., iPLS, iSPA-PLS), time-series or kinetic models and Bayesian classifiers appear in targeted studies and are summarised by wine type, algorithm, and application in Table 5.

An examination of the various control types reveals that Fig. 13 accentuates the operational emphasis of the harvest stage. Figure 14 provides a concise algorithm-family × control-type map. The qualitative intensity confirms that: (i) regression dominates maturation monitoring, finished-product QC, and authentication/traceability; (ii) classification concentrates on authentication/traceability and finished-product QC; (iii) deep learning is concentrated in visual inspection tasks (defect/foreign-matter detection, label/fill checks) and process optimization; and (iv) PCA acts as a ubiquitous pre-processor that shifts emphasis toward process optimization when paired with regression.

Taken together, the distributions in Fig. 13 and the summary in Fig. 14 indicate that regression models (notably PLS-R, MLR, PCR) predominate in maturation monitoring, finished-product QC, and authentication/traceability, where quantitative relations between spectral/chemical attributes and targets are well described [29, 68]. PCA is used primarily as a pre-processor, often paired with regression, and is associated with process optimisation [61]. Classification algorithms (PLS-DA, SVM) concentrate on authentication/traceability and finished-product QC—tasks with dichotomous decisions [8, 80]. Deep learning appears in visual inspection/process checks (defect/foreign-matter, label/fill) and selected optimisation tasks.

5 Discussion

This section discusses the findings of the proposed systematic review, critically interpreting the application of MVS in winemaking through the lens of the proposed taxonomy. The adoption of MVS in winemaking represents a significant technological advancement in quality control. However, despite its demonstrated benefits, widespread adoption remains uneven across different production stages due to economic, technical, and practical constraints. Organizing the discussion by technological groupings, several patterns emerge. Beyond cataloguing techniques, the Discussion synthesizes cross-modal trade-offs (Table 6), links methods to control types (Figs. 13 and 14), and considers deployment and techno-economics (5.8) to guide stage-specific choices.

5.1 Stereo vision (SV)

Stereo Vision technologies, which typically employ dual-camera setups to reconstruct three-dimensional spatial data, operate primarily within the visible light range. These systems rely on spatial disparity between image pairs captured in the RGB spectrum to estimate depth and structure. While SV is not inherently limited to visible light, most practical implementations in viticulture and enology use standard RGB cameras due to cost, availability, and ease of deployment. Their primary applications include grape cluster counting, yield estimation and canopy morphology analysis, and robotic pruning [40, 42, 43]. SV is also used for the automation of field operations, such as robotic pruning of vine [28], improving operational efficiency and precision, reducing time and costs associated with vineyard management. Stereo systems have been shown to demonstrate a high degree of accuracy in the assessment of vegetative growth and the detection of early signs of disease or stress. Beyond qualitative cues, SV studies quantify cluster compactness and berry size with prediction $R^2 \geq 0.80$, and also estimate cluster volume ($R^2 \approx 0.82$), total berry weight ($R^2 \approx 0.83$) and number of berries ($R^2 \approx 0.71$) using 3D descriptors (e.g., concavity, berry–berry intersection) validated across ten cultivars [42]. Beyond vineyard operations, SV has been applied in the bottling phase for cork inspection and sparkling wine foam quality assessment [10]. While SV excel in spatial analysis and automation, simpler imaging technologies, such RGB, still maintain significant relevance in viticulture applications.

5.1.1 Red-green-blue (RGB) imaging

RGB imaging, despite being less technologically sophisticated than other modalities, remains a widely adopted and versatile tool in viticulture and winemaking due to its low cost and ease of integration [83]. Its applications range from grape maturity monitoring to quality classification and label inspection. To report colour in a reproducible way, studies use standard indices such as CIE L*a*b* (including hue angle and chroma) [84] and the HSV hue component [85]. Smartphone colourimetry for sparkling wines tracks browning via blue-channel decay and shows strong correlations with A_{420} and 5-HMF, offering a low-cost proxy of chemical markers. Beyond traditional use cases,

Table 6 Comparative view of acquisition technologies by analytics, advantages, and limits

Acquisition technology	Typical analytics	Control affordance	Key advantages	Main limitations
Stereo Vision (SV)	Classical CV (segmentation, 3D reconstruction), regression; DL detectors/classifiers (e.g., CNN/YOLO) for bunch detection, defect spotting	Finished product quality control; Automation & robotics; Precision agriculture;	Accurate geometry/counting in field; low-cost sensors; real-time feasible; proven for yield and canopy metrics, and for in-line foam/cork checks.	Occlusion and illumination sensitivity; calibration/rigidity of baselines; weak on chemical/phenolic traits (requires proxies).
Remote Sensing (RS)	Chemometrics (PCA, PLS-R/PLS-DA), feature selection; time-series updates	Maturation monitoring; Precision agriculture;	Fast, non-destructive quantification of °Brix/TSS, anthocyanins and even volatile families; on-vine/on-the-go feasible; strong for PDO/authentication.	Requires robust calibration/transfer; spectra are broad/overlapped—performance depends on chemometrics and population representativeness.
Hyperspectral Imaging (HSI)	Dimensionality reduction (PCA/iPCA), PLS, SVM/RF; emerging DL	Maturation monitoring; Phytosanitary management; Process optimization;	Joint spatial + spectral analysis; >90% class accuracies often reported for disease/trait mapping; precise sorting.	Sensor/compute cost; large data volumes; real-time deployment still challenging without model compression.
X-ray Imaging (XRI)	3D reconstruction/tomography; segmentation; defect classification	Finished product quality control; Authentication & traceability	Reveals internal defects (e.g., insect galleries, wetcork) and links them to oxygen ingress kinetics; non-destructive.	Capital/throughput constraints; radiation safety; integration effort for high-speed lines.
Thermal Imaging (TI)	Regression; time-series integration	Water resources management; Precision agriculture	Non-contact, ecology-friendly water-stress proxy; scalable from handheld to UAV; validated against plant water metrics.	Sensitive to environment (wind, solar load, emissivity); requires careful calibration and acquisition protocols.
Magnetic Resonance Imaging (MRI)	Pattern analysis; classification (lab)	Authentication & traceability (lab)	Molecular-level specificity; powerful research tool. (Evidence in this corpus is sparse and largely non-industrial.)	High cost/infrastructure; long acquisition times; rarely viable in-line.

This comparison moves from 'what each modality does' to when and why it should be preferred, given the required control function and the attainable analytics

recent studies have expanded its utility in more sophisticated analytical contexts [86]. RGB imaging has been successfully employed for wine authentication and adulteration detection through multivariate analysis of digital colour data, demonstrating predictive errors as low as 1.6% [83]. Similarly, it has shown promising results in estimating wine age using regression models based on colour histograms extracted from bottle images [79]. In vineyard applications, RGB systems have supported yield prediction by quantifying canopy density and vine structure, with accuracy rates exceeding 90% [40]. Smartphone-based RGB tools have also been developed for in-field monitoring of anthocyanin content in red grapes, offering a cost-effective solution aligned with laboratory standards [87]. These diverse applications typically rely on intermediate-level image processing. This confirms the continued relevance of RGB imaging as an accessible yet analytically robust modality in both precision viticulture and quality-oriented winemaking.

5.2 Remote sensing (RS)

RS dominate early-stage applications, especially in Grape Harvesting, where the capacity for high-resolution chemical and spectral analysis is leveraged for ripeness prediction, disease detection, and yield estimation.

5.2.1 Near infrared (NIR) spectroscopy

Among the various RS technologies, Near Infrared (NIR) spectroscopy has emerged as particularly valuable for its versatility and analytical precision. NIR spectroscopy has become one of the most versatile and widely used techniques in winemaking. Its main advantage is the rapid, non-destructive analysis of key compositional parameters, including soluble solids content, acidity and anthocyanins. NIR analysis was also combined with an e-nose for online monitoring of winemaking processes [29]. This approach has significantly improved quality control, allowing continuous and precise evaluation of critical parameters during wine production. NIR has proven particularly effective in the vineyard, where it enables real-time assessment of grape ripeness and soil variability, and in the winery, where it supports monitoring of fermentation kinetics and grape dehydration [55, 67]. When integrated with machine learning models - particularly PLS regression - NIR systems demonstrate levels of predictive accuracy that rival traditional chemical tests. This positions NIR as a valuable tool not only for quality control, but also for process optimisation and improved traceability throughout the supply chain [74]. Beyond wine, NIR plus chemometrics has proven effective for derived products, notably PDO wine vinegars, achieving >90% correct classification by category and origin using PLS-DA [70]. This rapid, non-destructive fingerprinting supports large-scale authenticity screening with minimal sample preparation.

5.2.2 Multispectral imaging

Complementing the point-specific analyses of NIR, Multispectral Imaging (MSI) extends similar principles to capture spatial variations across larger areas. MSI is a technique that operates across a limited set of discrete wavelengths, offering a balance between the simplicity of RGB and the complexity of HSI. The efficacy of MSI in predicting crop yield, classifying ripeness, and identifying water stress has been well-documented. Its deployment using UAVs or ground-based platforms facilitates large-scale monitoring. Despite its lack of spectral granularity when compared with HSI, MSI's computational efficiency and cost-effectiveness make it an attractive option for implementation in precision viticulture on a large scale [12].

5.3 Hyperspectral imaging (HSI)

HSI is distinguished by its capacity to integrate spatial and spectral data, facilitating pixel-level analysis of chemical and physical characteristics. The application of HSI has been successfully implemented across a range of stages in the production process, including the prediction of Brix content in grapes, the monitoring of tannin levels, and the detection of diseases such as grapevine leafroll-associated virus [33, 63, 77], Its classification accuracies of over 90% make it suitable for detailed mapping applications, such as phenolic profiling and quality sorting. Despite its data-intensive nature and relatively high computational demand, recent studies demonstrate growing integration of HSI with machine learning algorithms to enhance its real-time applicability and decision support functions.

5.3.1 Fourier transform infrared spectroscopy (FTIR)

Further extending the spectroscopic approaches in winemaking, Fourier Transform Infrared Spectroscopy (FTIR) provides additional molecular insights with distinct advantages. It is widely employed for authenticity verification, polysaccharide analysis, and monitoring of specific fermentation attributes [68, 74]. In wine vinegars, ATR-FTIR resolves category-specific changes in the fingerprint region enabling clear differentiation of PDO categories with unsupervised PCA. These spectra have been proposed for fast regulatory checks by PDO councils and producers. Studies have demonstrated its capability to detect unauthorised additives and dilution practices, particularly when combined with chemometric tools such as PCA and PLS. The FTIR method is characterised by its high speed, minimal sample preparation requirements, and compatibility with multivariate data analysis, which renders it a preferred method for rapid screening and regulatory compliance, particularly in protected designation of origin (PDO) contexts.

5.3.2 Raman spectroscopy

Raman spectroscopy is a technique that provides unique vibrational fingerprints of molecular compounds through inelastic light scattering, offering exceptional specificity. Its efficacy in the authentication of wine by variety, geographic origin, and vintage has been well-documented, with classification accuracies frequently exceeding 90%. Furthermore, Raman has been adopted for the monitoring of fermentation processes, enabling real-time chemical tracking of sugar, ethanol, and metabolite formation [74]. Its capacity to function without the need for extensive sample preparation or destructive analysis renders it a valuable adjunct to NIR and FTIR. However, limitations related to fluorescence interference and instrumentation cost continue to hinder its broader commercial deployment [73].

5.4 Thermal imaging (TI)

While spectroscopic methods reveal chemical composition, Thermal Imaging (TI) techniques shift focus to physiological parameters detectable through temperature variations. TI entails the discernment of variances in surface temperature. Its primary applications include the assessment of water stress in vineyards, the monitoring of fermentation processes, and the detection of diseases. The employment of UAV-mounted thermal cameras facilitates the spatial resolution of vine physiology analysis, thereby supporting the optimisation of irrigation practices and the promotion of sustainability [13]. Furthermore, TI has been integrated with multispectral and physiological data to enhance predictive models for grape quality. The non-contact nature and real-time feedback capabilities of TI are particularly well-suited to environmental control and microclimate analysis [76]. Recent applications have explored the use of TI in detecting temperature anomalies during fermentation and identifying microbial contamination risks, reinforcing its value as a diagnostic tool in critical production phases [56]. Despite its growing potential, TI remains less widespread than optical methods due to environmental sensitivity and calibration demands.

5.5 X-Ray technology (XRI) and magnetic resonance imaging (MRI)

XRI has been demonstrated to be a highly effective method of detecting internal defects in corks and packaging, thereby preventing oxygen ingress and contamination. Although less prevalent, MRI offers unparalleled resolution in molecular profiling and has been successfully utilised for wine authentication and adulteration detection. However, these advanced technologies are encumbered by substantial operational expenses and infrastructural demands, which restricts their utilisation to high-value production environments or laboratory settings [31, 78].

Taken together, these modality-specific findings suggest that adoption hinges on the analytical stack used and the type of control a system affords during each production phase; we therefore contrast the technologies along these dimensions (Table 6), building on the taxonomy in Table 4 and the analytics maps in Table 5.

5.6 Cross-technology comparison: analytics, control affordances, and trade-offs

Anchored to the acquisition taxonomy (Table 4) and the algorithmic landscape (Table 5), Table 6 contrasts machine vision modalities along five decision-relevant axes: typical analytics, control affordance key advantages, and main limits. Evidence is drawn from the reviewed corpus to avoid purely speculative trade-offs.

5.7 Implications for adoption and control

The cross-technology comparison explains the uneven adoption patterns discussed above: early-stage vineyard monitoring favours RS and TI for scalable, non-destructive proxies; midstream operations (e.g., Crushing & Destemming; Pressing & Filtration) still lack robust sensing under occlusion and multiphase flow; and late-stage bottling benefits from XRI's unique ability to expose internal defects. Crucially, the step up from classical CV/chemometrics to higher-complexity models (Table 5) only translates into stronger control affordances (Figs. 12 and 13) when data quality, calibration transfer, and deployment constraints are jointly addressed. Notably, these spectroscopic pipelines generalize to derived products: ATR-FTIR/NIR fingerprints enable PDO compliance and category verification in wine vinegars alongside winery quality control.

Building on these implications, the authors summarize deployment readiness and the techno-economic constraints that condition translation into practice.

5.8 Technological maturity and deployment considerations

The literature indicates three distinct bands of technological readiness (TRL) and deployment preparedness for machine vision in wine production.

- *Industrial and Near-Line Systems* the most mature solutions have extensive validation in operational settings (field and winery). These include portable spectrometers (NIR/FTIR) and conventional RGB/SV systems for surface inspection [29, 41, 83]. Use cases range from low-cost, smartphone-based browning monitoring to foam quality control with vision on robotic pourers. Integration costs are relatively modest, typically limited to controlled-illumination enclosures, simple mechanics, and routine upkeep of chemometric models.
- *Pilot and Controlled In-Line Systems* a second tier comprises in-line deployments under controlled conditions. Representative examples include deep-learning models

running on edge devices for real-time monitoring during pressing [19, 35]. These implementations demonstrate the feasibility of DL on the production line, albeit often with a small accuracy trade-off to meet latency constraints. In the same band, classical feature-based systems remain a pragmatic choice for high-speed packaging lines, where throughput can challenge non-optimized DL models.

- *Laboratory and Off-Line Systems* technologies largely confined to laboratory environments include hyperspectral imaging (HSI), X-ray computed tomography, and magnetic resonance imaging [33, 74]. Despite strong accuracy, HSI is hindered by high data rates and calibration-transfer complexity across instruments. X-ray and MRI systems are constrained by lengthy scan times, safety requirements (e.g., shielding), and high capital expenditure, making them more suitable for diagnostic analyses or control-system design than for high-speed inspection.

Importantly, maturity is highly use-case dependent. In contrast to HSI's constraints, targeted applications such as surface cork-stopper quality control already operate in real time with industrial line-scan cameras—illustrating that application complexity can be as decisive as technology complexity. Consequently, integration costs scale with optics and illumination, shielding requirements, robustness of calibration and model transfer, edge-compute demands, and safety infrastructure.

5.9 Research agenda and integration barriers

Despite this progress, this comparison also highlights persistent challenges that need to be addressed to fully realise the transformative potential of MVS in the wine industry. A notable imbalance is evident in the distribution of research efforts, with a pronounced concentration on early-stage applications, particularly vineyard monitoring, while mid-stream operations such as Crushing and Destemming and Pressing and Filtration remain underexplored. These stages pose unique challenges, including visual occlusion, high-speed throughput, and complex fluid-solid interactions, which may partially explain the limited application of imaging technologies. The development of imaging solutions that are resilient to environmental interference and capable of operating in opaque, heterogeneous media represents a significant research frontier. Moreover, a further limitation is that the transfer of laboratory innovations to industrial scale is hampered by high costs, lack of standardisation, and incompatibility with existing infrastructure, especially for advanced technologies such as XRI and MRI. Building on the comparison above, future research should focus on multimodal systems, real-time processing models, and interoperable facilities to foster integration in wineries.

6 Conclusions

This review systematises the application of MVS in the wine production, by mapping acquisition technologies to production stages and analytical roles, offering a taxonomy that consolidates fragmented evidence into an operational framework. The analysis shows that MVS contribute across the chain: RS/HSI/SV support vineyard monitoring and harvest planning; TI/MSI aid water-stress and ripeness assessment; and XRI/MRI address late-stage quality and authenticity (e.g., cork integrity, product verification). Beyond wine, the same toolchain extends to derived products—notably wine vinegars—where ATR-FTIR and NIR fingerprints enable rapid, non-destructive PDO/category checks suited to routine control.

Two cross-cutting insights emerge. First, effective adoption depends on matching sensing modalities to the control function required (monitoring, advisory, or in-line quality assurance), as reflected in the comparative view of technologies. Second, deployment readiness is uneven: industrial/near-line solutions (e.g., portable NIR/FTIR; RGB/SV inspection) are mature, while mid-stream operations (Crushing, Pressing/Filtration) remain constrained by occlusion, multiphase flow, and line-speed requirements. Addressing integration costs (optics/illumination, calibration transfer, edge compute, safety infrastructure) is therefore pivotal, especially for SMEs.

The taxonomy provides a scalable decision aid for stakeholders: producers can align investments with stage-specific needs; technology developers can benchmark performance and target gaps; and policymakers can prioritise digital enablers that strengthen traceability and sustainability. A methodological limitation should be noted: the synthesis relies primarily on English-language, indexed sources and may under-represent local or industry reports of deployment.

Future work should move beyond end-point quality checks towards real-time, in-situ monitoring across under-served mid-process stages, and deepen integration with IoT/AI/cloud analytics to close the loop from sensing to control. Advancing multimodal systems and interoperable architectures will accelerate scalable adoption. Taken together, these directions position MVS as a key lever for improving sustainability, precision, and efficiency in a progressively data-driven wine industry.

Appendix A

TITLE-ABS-KEY (((“Visual recognition” OR “Machine vision” OR “Image analysis” OR “Food inspection” OR “Optical inspection” OR “Automated inspection” OR “Computer vision” OR “Non-destructive”) AND (“Wine pro*” OR “Wine”) AND (“Quality” OR “control”))) AND PUBYEAR > 2013 AND PUBYEAR < 2026 AND PUBYEAR > 2013 AND PUBYEAR < 2026.

Acknowledgements
The authors would like to thank Mr. Fabio Viso for his valuable contributions to this work.

Author contributions
All authors jointly defined the scope and conceptualisation of this literature review study. E.V. and A.P. performed the systematic search and data analysis, and drafted the initial version of the manuscript. M.G. provided critical, substantive revisions that improved the intellectual content and clarity of the article. All authors read and approved the final manuscript.

Funding
This paper is part of the project NODES which has received funding from the MUR-M4C2 1.5 of PNRR funded by the European Union – NextGenerationEU (Grant agreement no. ECS00000036).

Data availability
No datasets were generated or analysed during the current study.

Declarations

Ethics approval and consent to participate
Not applicable.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

Received: 17 June 2025 / Accepted: 10 November 2025

Published online: 24 December 2025

References

1. Konfo TRC, Djouhou FMC, Hounhouigan MH, et al. Recent advances in the use of digital technologies in agri-food processing: a short review. Applied Food Research. 2023;3:100329. https://doi.org/10.1016/J.AFRES.2023.100329.
2. Zhu L, Spachos P, Pensini E, Plataniotis KN. Deep learning and machine vision for food processing: a survey. Curr Res Food Sci. 2021;4:233–49. https://doi.org/10.1016/J.CRFS.2021.03.009.
3. Blanco M, Villarroya I. NIR spectroscopy: a rapid-response analytical tool. TrAC Trends Anal Chem. 2002;21:240–50. https://doi.org/10.1016/S0165-9936(02)00404-1.
4. Seng KP, Ang LM, Schmidtke LM, Rogiers SY. Computer vision and machine learning for viticulture technology. IEEE Access. 2018;6:67494–510. https://doi.org/10.1109/ACCESS.2018.2875862.
5. Portalés C, Ribes-Gómez E. An image-based system to preliminary assess the quality of grape harvest batches on arrival at the winery. Comput Ind. 2015;68:105–15. https://doi.org/10.1016/j.compind.2014.12.010.
6. Modesti M, Alfieri G, Chieffo C, et al. Destructive and non-destructive early detection of postharvest noble rot (*Botrytis cinerea*) in wine grapes aimed at producing high-quality wines. J Sci Food Agric. 2024;104:2314–25. https://doi.org/10.1002/jsfa.13120.
7. Pérez-Bernal JL, Villar-Navarro M, Morales ML, et al. The smartphone as an economical and reliable tool for monitoring the browning process in sparkling wine. Comput Electron Agric. 2017;141:248–54. https://doi.org/10.1016/j.compag.2017.07.029.
8. Oliveira V, Knapic S, Pereira H. Classification modeling based on surface porosity for the grading of natural cork stoppers for quality wines. Food Bioprod Process. 2015;93:69–76. https://doi.org/10.1016/j.fbp.2013.11.004.
9. Bianchi A, Venturi F, Palermo C, et al. Primary and secondary shelf-life of bread as a function of formulation and MAP conditions: focus on physical-chemical and sensory markers. Food Packag Shelf Life. 2024. https://doi.org/10.1016/j.fpsl.2024.101241.
10. Condé BC, Fuentes S, Caron M, et al. Development of a robotic and computer vision method to assess foam quality in sparkling wines. Food Control. 2017;71:383–92. https://doi.org/10.1016/j.foodcont.2016.07.020.
11. ElMasry GM, Nakauchi S. Image analysis operations applied to hyperspectral images for non-invasive sensing of food quality - a comprehensive review. Biosyst Eng. 2016;142:53–82. https://doi.org/10.1016/j.biosystemseng.2015.11.009.
12. Benelli A, Cevoli C, Ragni L, Fabbri A. In-field and non-destructive monitoring of grapes maturity by hyperspectral imaging. Biosyst Eng. 2021;207:59–67. https://doi.org/10.1016/j.biosystemseng.2021.04.006.
13. Tardaguila J, Stoll M, Gutiérrez S, et al. Smart applications and digital technologies in viticulture: a review. Smart Agricultural Technology. 2021. https://doi.org/10.1016/j.atech.2021.100005.
14. Kakani V, Nguyen VH, Kumar BP, et al. A critical review on computer vision and artificial intelligence in food industry. J Agric Food Res. 2020;2:100033. https://doi.org/10.1016/j.jafr.2020.100033.
15. Palacios F, Bueno G, Salido J, et al. Automated grapevine flower detection and quantification method based on computer vision and deep learning from on-the-go imaging using a mobile sensing platform under field conditions. Comput Electron Agric. 2020;178:105796. https://doi.org/10.1016/J.COMPAG.2020.105796.
16. Market Insights | Statista. https://www.statista.com/outlook/. Accessed 13 Mar 2025.
17. Watson NJ, Bowler AL, Rady A, et al. Intelligent sensors for sustainable food and drink manufacturing. Front Sustain Food Syst. 2021;5:642786. https://doi.org/10.3389/FSUFS.2021.642786/BIBTEX.
18. Kang W, Lin H, Jiang H, et al. Advanced applications of chemo-responsive dyes based odor imaging technology for fast sensing food quality and safety: a review. Compr Rev Food Sci Food Saf. 2021;20:5145–72. https://doi.org/10.1111/1541-4337.12823.
19. Carneiro GA, Cunha A, Aubry TJ, Sousa J. Advancing grapevine variety identification: A systematic review of deep learning and machine learning approaches. AgriEngineering. 2024;6:4851–88. https://doi.org/10.3390/AGRIENGINEERING6040277/S1.
20. Page MJ, McKenzie JE, Bossuyt PM, et al. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. BMJ. 2021;372. https://doi.org/10.1136/BMJ.N71.
21. Food - Worldwide. | Statista Market Forecast. https://www.statista.com/outlook/cmo/food/worldwide. Accessed 28 Feb 2025.
22. Henning Vuo. (2023) Wine: market data & analysis | Statista.
23. Jackson RS. Introduction. Wine Sci. 2008;1–14. https://doi.org/10.1016/B978-012373646-8.50004-4.
24. International Code of Oenological Practices | OIV. https://www.oiv.int/standards/international-code-of-oenological-practices. Accessed 29 Sep 2025.
25. Jackson RS. Fermentation. Wine Sci. 2008;332–417. https://doi.org/10.1016/B978-012373646-8.50010-X.
26. Division IC. Agribusiness handbook. Grapes Wine; 2010.
27. Hitzmann B, Hauselmann R, Niemoeller A, et al. Process analytical technologies in food industry – challenges and benefits: a status report and recommendations. Biotechnol J. 2015;10:1095–100. https://doi.org/10.1002/BIOT.201400773.
28. Williams H, Smith D, Shahabi J, et al. Modelling wine grapevines for autonomous robotic cane pruning. Biosyst Eng. 2023;235:31–49. https://doi.org/10.1016/j.biosystemseng.2023.09.006.
29. Littarru E, Modesti M, Alfieri G, et al. Optimizing the winemaking process: NIR spectroscopy and e-nose analysis for the online monitoring of fermentation. J Sci Food Agric. 2025;105:1465–75. https://doi.org/10.1002/JSFA.13336.
30. Oliveira V, Lopes P, Cabral M, Pereira H. Influence of cork defects in the oxygen ingress through wine stoppers: insights with X-ray tomography. J Food Eng. 2015;165:66–73. https://doi.org/10.1016/J.JFOODENG.2015.05.019.
31. Viskić M, Bandić LM, Korenika AMJ, Jeromel A. (2021) NMR in the service of wine differentiation. Foods 10.
32. Senni L, Ricci M, Palazzi A. On-line automatic detection of foreign bodies in biscuits by infrared thermography and image processing. J Food Eng. 2014;128:146–56. https://doi.org/10.1016/J.JFOODENG.2013.12.016.
33. Zhang P, Wu Q, Wang Y, et al. Rapid detection of tannin content in wine grapes using hyperspectral technology. Life. 2024;14:416. https://doi.org/10.3390/LIFE14030416.

34. Swe KN, Takai S, Noguchi N. Novel approaches for a Brix prediction model in Rondo wine grapes using a hyperspectral camera: comparison between destructive and Non-destructive sensing methods. Comput Electron Agric. 2023;211. https://doi.org/10.1016/j.compag.2023.108037.
35. Pinheiro I, Moreira G, Queirós da Silva D, et al. Deep learning YOLO-Based solution for grape bunch detection and assessment of biophysical lesions. Agronomy. 2023;13. https://doi.org/10.3390/agronomy13041120.
36. Page MJ, Moher D, Bossuyt PM et al. (2021) PRISMA 2020 explanation and elaboration: updated guidance and exemplars for reporting systematic reviews. The BMJ 372.
37. Poni S, Gatti M, Palliotti A, et al. Grapevine quality: a multiple choice issue. Sci Hortic. 2018;234:445–62. https://doi.org/10.1016/J.SCIENTA.2017.12.035.
38. Espinoza CZ, Khot LR, Sankaran S, Jacoby PW. High resolution multispectral and thermal remote sensing-based water stress assessment in subsurface irrigated grapevines. Remote Sens. 2017;9(9):961. https://doi.org/10.3390/RS9090961.
39. Oberti R, Marchi M, Tirelli P, et al. Automatic detection of powdery mildew on grapevine leaves by image analysis: optimal view-angle range to increase the sensitivity. Comput Electron Agric. 2014;104:1–8. https://doi.org/10.1016/J.COMPAG.2014.03.001.
40. Aquino A, Millan B, Diago MP, Tardaguila J. Automated early yield prediction in vineyards from on-the-go image acquisition. Comput Electron Agric. 2018;144:26–36. https://doi.org/10.1016/j.compag.2017.11.026.
41. Ríos-Reina R, García-González DL, Callejón RM, Amigo JM. NIR spectroscopy and chemometrics for the typification of Spanish wine vinegars with a protected designation of origin. Food Control. 2018;89:108–16. https://doi.org/10.1016/j.foodcont.2018.01.031.
42. Ivorra E, Sánchez AJ, Camarasa JG, et al. Assessment of grape cluster yield components based on 3D descriptors using stereo vision. Food Control. 2015;50:273–82. https://doi.org/10.1016/j.foodcont.2014.09.004.
43. Tello J, Cubero S, Blasco J, et al. Application of 2D and 3D image technologies to characterise morphological attributes of grapevine clusters. J Sci Food Agric. 2016;96:4575–83. https://doi.org/10.1002/JSFA.7675.
44. Rabot A, Rousseau C, Li-Mallet A, et al. A combined approach using chemical and image analysis to estimate seed. maturity for Bordeaux area grapevine; 2017.
45. Majeed Y, Karkee M, Zhang Q, et al. Development and performance evaluation of a machine vision system and an integrated prototype for automated green shoot thinning in vineyards. J Field Robotics. 2021;38:898–916. https://doi.org/10.1002/rob.22013.
46. Cejudo-Bastante MJ, Rodríguez-Pulido FJ, Heredia FJ, González-Miret ML. Assessment of sensory and texture profiles of grape seeds at real maturity stages using image analysis. Foods. 2021;10:1098. https://doi.org/10.3390/FOODS10051098/S1.
47. Carmona L, Varela J, Godoy L, Ganga MA. Comparative proteome analysis of *Brettanomyces bruxellensis* under hydroxycinnamic acid growth. Electron J Biotechnol. 2016;23:37–43. https://doi.org/10.1016/J.EJBT.2016.07.005.
48. Prat-García S, Nevares I, Martínez-Martínez V, del Alamo-Sanza M. Customized oxygenation barrels as a new strategy for controlled wine aging. Food Res Int. 2020. https://doi.org/10.1016/j.foodres.2020.108982.
49. Viejo CG, Torrico DD, Dunshea FR, Fuentes S. Bubbles, foam formation, stability and consumer perception of carbonated drinks: a review of current, new and emerging technologies for rapid assessment and control. Foods. 2019. https://doi.org/10.3390/FOODS8120596.
50. Mohimont L, Roesler M, Steffenel A et al. AI-Based Quality Control System at the Pressing Stages of the Champagne Production.
51. Yang Q, Yu X, Chen Q. Design of drug and wine bottlecap defect detection system based on machine vision. J Appl Sci Eng. 2023;26:489–500. https://doi.org/10.6180/jase.202304_26(4).0005.
52. Crumpton M, Rice CJ, Atkinson A, et al. The effect of sucrose addition at dosage stage on the foam attributes of a bottle-fermented English sparkling wine. J Sci Food Agric. 2018;98:1171–8. https://doi.org/10.1002/jsfa.8570.
53. Marín-San Román S, Fernández-Novales J, Cebrián-Tarancón C, et al. Application of near-infrared spectroscopy for the estimation of volatile compounds in Tempranillo Blanco grape berries during ripening. J Sci Food Agric. 2023;103:6317–29. https://doi.org/10.1002/jsfa.12706.
54. Fernández-Novales J, Tardáguila J, Gutiérrez S, Paz Diago M. On-the-go VIS + SW - NIR spectroscopy as a reliable monitoring tool for grape composition within the vineyard. Molecules. 2019. https://doi.org/10.3390/MOLECULES24152795.
55. Lopo M, dos Teixeira Santos CA, Páscoa RNMJ, et al. Near infrared spectroscopy as a tool for intensive mapping of vineyards soil. Precis Agric. 2018;19:445–62. https://doi.org/10.1007/s11119-017-9529-2.
56. Lyu H, Grafton M, Ramilan T, et al. Using remote and proximal sensing data and vine vigor parameters for non-destructive and rapid prediction of grape quality. Remote Sens. 2023. https://doi.org/10.3390/RS15225412.
57. González-Fernández AB, Rodríguez-Pérez JR, Marcelo V, Valenciano JB. Using field spectrometry and a plant probe accessory to determine leaf water content in commercial vineyards. Agric Water Manag. 2015;156:43–50. https://doi.org/10.1016/j.agwat.2015.03.024.
58. Sanmartin C, Modesti M, Venturi F, et al. Postharvest water loss of wine grape: when, what and why. Metabolites. 2021. https://doi.org/10.3390/metabo11050318.
59. Trivella A, Richard C. New insights into pesticide photoprotection. Environ Sci Pollut Res. 2014;21:4828–36. https://doi.org/10.1007/s11356-013-1490-7.
60. Kasimati A, Espejo-Garcia B, Vali E, et al. Front Plant Sci. 2021;12. https://doi.org/10.3389/FPLS.2021.683078/PDF. Investigating a Selection of Methods for the Prediction of Total Soluble Solids Among Wine Grape Quality Characteristics Using Normalized Difference Vegetation Index Data From Proximal and Remote Sensing.
61. Beghi R, Giovenzana V, Marai S, Guidetti R. Rapid monitoring of grape withering using visible near-infrared spectroscopy. J Sci Food Agric. 2015;95:3144–9. https://doi.org/10.1002/jsfa.7053.
62. Urraca R, Sanz-Garcia A, Tardaguila J, Diago MP. Estimation of total soluble solids in grape berries using a hand-held NIR spectrometer under field conditions. J Sci Food Agric. 2016;96:3007–16. https://doi.org/10.1002/JSFA.7470.
63. MacDonald SL, Staid M, Staid M, Cooper ML. Remote hyperspectral imaging of grapevine leafroll-associated virus 3 in cabernet sauvignon vineyards. Comput Electron Agric. 2016;130:109–17. https://doi.org/10.1016/j.compag.2016.10.003.
64. Cancela JJ, Fandiño M, Rey BJ, et al. Discrimination of irrigation water management effects in pergola trellis system vineyards using a vegetation and soil index. Agric Water Manag. 2017;183:70–7. https://doi.org/10.1016/J.AGWAT.2016.11.003.

65. dos Santos Costa D, Oliveros Mesa NF, Santos Freire M, et al. Development of predictive models for quality and maturation stage attributes of wine grapes using vis-nir reflectance spectroscopy. Postharvest Biol Technol. 2019;150:166–78. https://doi.org/10.1016/J.POSTHARVBIO.2018.12.010.
66. Murru C, Chimeno-Trinchet C, Díaz-García ME, et al. Artificial neural network and attenuated total reflectance-Fourier transform infrared spectroscopy to identify the chemical variables related to ripeness and variety classification of grapes for protected. designation of origin wine production. Comput Electron Agric. 2019;164:104922. https://doi.org/10.1016/J.COMPAG.2019.104922.
67. Fuentes S, Tongson E, Chen J, Viejo CG. (2020) A Digital Approach to Evaluate the Effect of Berry Cell Death on Pinot Noir Wines' Quality Traits and Sensory Profiles Using Non-Destructive Near-Infrared Spectroscopy. Beverages 2020, Vol 6, Page 39 6:39. https://doi.org/10.3390/BEVERAGES6020039
68. Croce R, Malegori C, Oliveri P, et al. Prediction of quality parameters in straw wine by means of FT-IR spectroscopy combined with multivariate data processing. Food Chem. 2020;305:125512. https://doi.org/10.1016/J.FOODCHEM.2019.125512.
69. Baca-Bocanegra B, Nogales-Bueno J, Hernández-Hierro JM, Heredia FJ. Valorization of American barrel-shoot wastes: effect of post fermentative addition and readdition on phenolic composition and chromatic quality of Syrah red wines. Molecules. 2020. https://doi.org/10.3390/MOLECULES25040774.
70. Sánchez MT, Márquez R, Torres I, et al. Chemical characterization of wine vinegars belonging to the vinagre de Montilla-Moriles protected designation of Origin, using Near-Infrared spectroscopy. Food Anal Methods. 2020;13:802–10. https://doi.org/10.1007/S12161-019-01697-Z/FIGURES/1.
71. Suehara KI, Kameoka T, Hashimoto A. Spectral features characterizing rice wine sake variety using mid-infrared spectroscopy. Japan J Food Eng. 2016;16:279–89. https://doi.org/10.11301/JSFE.16.279.
72. Ríos-Reina R, Callejón RM, Oliver-Pozo C, et al. ATR-FTIR as a potential tool for controlling high quality vinegar categories. Food Control. 2017;78:230–7. https://doi.org/10.1016/j.foodcont.2017.02.065.
73. Wu Z, Long J, Xu E, et al. A feasibility study on the evaluation of quality properties of Chinese rice wine using Raman spectroscopy. Food Anal Methods. 2016;9:1210–9. https://doi.org/10.1007/S12161-015-0295-3.
74. Mac HX, Pham TT, Ha NTT, et al. Current techniques for fruit juice and wine adulterant detection and authentication. Beverages. 2023;9(4):84. https://doi.org/10.3390/BEVERAGES9040084.
75. Brink JC, Calitz FJ, Fourie PH. Spray deposition and control of *botrytis cinerea* on grape leaves and bunches: part 2 (Wine grapes). S Afr J Enol Vitic. 2016;37:157–68. https://doi.org/10.21548/37-2-1061.
76. Lyu H, Grafton M, Ramilan T, et al. Assessing the leaf blade nutrient status of Pinot Noir using hyperspectral reflectance and machine learning models. Remote Sens. 2023;15:1497. https://doi.org/10.3390/RS15061497.
77. Baca-Bocanegra B, Nogales-Bueno J, Heredia FJ, Hernández-Hierro JM. Influence of oak wood chips–grape mix maceration on the extraction of anthocyanins from low-extractable anthocyanin content red grapes. Eur Food Res Technol. 2018;244:729–34. https://doi.org/10.1007/S00217-017-2999-7/TABLES/1.
78. Lagorce-Tachon A, Karbowiak T, Loupiac C, et al. The cork viewed from the inside. J Food Eng. 2015;149:214–21. https://doi.org/10.1016/j.jfoodeng.2014.10.023.
79. Vyviurska O, Khvalbota L, Koljančić N, et al. Wine age prediction using digital images and multivariate calibration. Microchem J. 2023. https://doi.org/10.1016/j.microc.2023.108738.
80. Zhu H, Zhu D, Sun J. Application of GC-IMS coupled with chemometric analysis for the classification and authentication of geographical indication agricultural products and food. Front Nutr. 2023;10. https://doi.org/10.3389/FNUT.2023.1247695/PDF.
81. Agati G, Soudani K, Tuccio L, et al. Management zone delineation for winegrape selective harvesting based on fluorescence-sensor mapping of grape skin anthocyanins. J Agric Food Chem. 2018;66:5778–89. https://doi.org/10.1021/ACS.JAFC.8B01326.
82. Feng Skun, Yuan Lming, Ye H. Grading bunch tightness for grape by multiperspective imaging approach coupled with multivariate classification methods. J Food Process Eng. 2019;42:e13052. https://doi.org/10.1111/JFPE.13052.
83. Herrero-Latorre C, Barciela-García J, García-Martín S, Peña-Crecente RM. Detection and quantification of adulterations in aged wine using RGB digital images combined with multivariate chemometric techniques. Food Chem X. 2019;3:100046. https://doi.org/10.1016/J.FOCHX.2019.100046.
84. León K, Mery D, Pedreschi F, León J. Color measurement in L∗a∗b∗ units from RGB digital images. Food Res Int. 2006;39:1084–91. https://doi.org/10.1016/J.FOODRES.2006.03.006.
85. Flores-Vidal P, Gómez D, Castro J, Montero J. New aggregation approaches with HSV to color edge detection. Int J Comput Intell Syst. 2022;15:1–15. https://doi.org/10.1007/S44196-022-00137-X/TABLES/6.
86. Diago MP, Aquino A, Millan B, et al. On-the-go assessment of vineyard canopy porosity, bunch and leaf exposure by image analysis. Aust J Grape Wine Res. 2019;25:363–74. https://doi.org/10.1111/AJGW.12404.
87. Menozzi C, Calvini R, Nigro G, et al. Design and application of a smartphone-based device for in vineyard determination of anthocyanins content in red grapes. Microchem J. 2023;191:108811. https://doi.org/10.1016/J.MICROC.2023.108811.

Publisher's note