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REVIEW ARTICLE

The AI-viticulture nexus: Robotics and precision technologies for sustainable vineyards

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Abstract

Automation technologies, such as Artificial Intelligence (AI), robotics, IoT and remote sensing, are transforming viticulture by addressing labour shortages, climate resilience challenges and resource optimization. AI-driven machine learning models process data from multispectral drones and IoT sensors to monitor soil health, water stress and canopy dynamics, enabling precision agriculture practices like targeted irrigation and nutrient delivery. Autonomous robotic systems perform tasks such as selective harvesting, pruning and pest management, enhancing operational efficiency while reducing manual labour. IoT networks provide real-time insights into microclimatic conditions, empowering growers to adopt climate-smart strategies that minimize chemical inputs and improve yield stability. Despite progress, key barriers persist: AI models require terroir-specific adaptation, fragmented datasets hinder interoperability and field validation of autonomous systems under diverse conditions remains limited. Future research must prioritize accessible solutions: low-cost sensor networks for smallholders, adaptive AI frameworks for climate volatility (e.g., drought or flood prediction) and edge computing for real-time analytics. Ethical concerns data privacy, algorithmic bias and technology access disparities demand inclusive governance. Additionally, user-friendly interfaces are essential for broad adoption. Addressing these gaps will unlock automation's full potential in advancing sustainable viticulture: optimizing water/energy use, reducing agrochemical reliance, enhancing biodiversity and ensuring economic resilience for growers. Ultimately, integrated automation promises a balance between ecological stewardship, resource efficiency and sector-wide viability in a climate-constrained future.

Keywords: autonomous systems; climate resilience; machine learning; precision agriculture; resource optimization

Introduction

The rising global temperatures and erratic rainfall are disrupting phenological cycles, increasing disease risks and disrupting traditional vineyard practices, compelling the adoption of AI, robotics and sensor networks. These technologies address climate driven challenges while aligning with consumer demands for sustainability and efficiency (1). Labor shortages, aggravated by aged workforces and seasonal labour dependencies, further accelerate automation. Robotic harvesters and pruners now perform tasks with human level precision using computer vision and machine learning, mitigating workforce gaps (2). The vineyards are adopting data driven platforms to reduce chemical use and carbon footprints (3). Real time monitoring of soil health, microclimates and vine vigour enables precise irrigation and resource management. AI-driven innovations are central to this shift, with Convolutional Neural Networks (CNNs) analysing drone-captured imagery for early pest detection, thereby reducing pesticide reliance (4). There are advancements in robotics, such as LiDAR equipped systems for canopy management and IoT-enabled autonomous vehicles that optimize soil moisture and nutrient delivery through variable rate applications (5). Together, these technologies create a feedback loop of resilience. AI and robotics not only counter climate and labour pressures but also meet eco-friendly consumer expectations. However, their success hinges on seamless integration sensor networks must inform robotic actions and predictive models require real time environmental data. By unifying these tools, viticulture can achieve precision agriculture at scale with balancing productivity with ecological sustainability. Widespread automation adoption in viticulture remains hindered by high costs, limited grower expertise and compatibility issues between proprietary systems (6).

Regulatory frameworks, especially in regions with strict agricultural policies, struggle to keep pace with technological advances, creating gaps between innovation and governance. Concurrently, concerns over data privacy and algorithmic bias reduce trust in AI tools, further slowing adoption (7). Hybrid human AI systems combining machine learning with growers' expertise could improve adaptability across diverse vineyards (8). Advances in edge computing and 5G may decentralize data processing, enabling real time responses to environmental shifts, while blockchain could enhance supply chain transparency (9). CRISPR-based biomarkers integrated with AI might revolutionize vine breeding, tailoring crops for climate resilience and merging genomics with precision agriculture (10). Yet it needs scalable sustainability demands and systemic change. Interdisciplinary collaboration, policy updates and subsidies are vital to democratize access to automation, preventing small-scale producers from being sidelined in viticulture's digital transformation (11). Without reasonable solutions, the sector risks deepening differences even as it follows innovation. The historical timeline of automation in viticulture is conceptualized in Fig. 1.

AI and machine learning

AI and machine learning are revolutionizing vineyard management by addressing critical challenges in disease detection and yield optimization. The biotic stressors like powdery mildew and pest infestations which causes the loss of 10 billion dollars annually in wine industry, which drives demand for AI solutions (12). Hyperspectral imaging, which enables non-destructive vine health monitoring by capturing spectral images linked to chlorophyll loss, cellular damage and pest activity across visible, NIR and thermal wavelengths (13). The CNNs trained on multispectral data now identify mildew outbreaks 7-10 days before symptoms appear with >90 % accuracy, enabling targeted fungicide use that reduces chemical applications by 25 % (14). Integrating drone-collected hyperspectral imagery with IoT microclimate sensors (e.g., soil moisture monitors) strengthens disease prediction by correlating risks with environmental factors like leaf wetness duration (15). Privacy concerns are being addressed through collaborative AI training across vineyards, which enhances predictive accuracy without sharing sensitive data, while AI-trained systems have also advanced yield forecasting (16). Vision Transformers (ViTs) a breakthrough in deep learning which outperform CNNs by using self-attention mechanisms to analyse spatial relationships between grape clusters and canopy structures, achieving <5 % error in yield predictions (17). For example, as detailed in a 2023 study which uses ViT systems trained on drone captured RGB and NIR images to predict Cabernet Sauvignon yields with 93 % accuracy by assessing berry size, colour consistency and occlusion patterns (18). Additionally, Reinforcement Learning (RL) algorithms are used to simulate vineyard responses to pruning and climatic conditions, enabling dynamic adjustments to yield forecasts as conditions change (19). Together, these innovations go with AI's transformative potential by merging hyperspectral imaging, IoT networks and advanced algorithms, viticulture can achieve precision agriculture that balances economic viability with environmental sustainability. Table 1 depicts the comparison of AI models for disease detection.

AI driven irrigation and fertilization systems now reduce water and chemical use by 20-30 % while maintaining grape quality, balancing sustainability and cost-efficiency (27). Machine learning models like random forests which integrate soil moisture sensors, weather forecasts and evapotranspiration rates to create real time irrigation schedules that prevent over watering and nutrient loss (28). For example, in Napa Valley, AI powered drip systems reduce water use by 28 % during droughts by aligning irrigation with vine growth stages and soil conditions. AI guided fertilization systems use electromagnetic soil maps and sap flow sensors to deliver precise nutrient doses, reducing nitrogen use by 22 % without any reduction in yields (29). Edge computing enables on device AI processing, overcoming latency and bandwidth issues in remote vineyards (30). Robotic platforms are also addressing labour shortages with well-equipped knowledge in it. Autonomous harvesters equipped with LiDAR and stereo vision navigate vines with centimetre precision, while soft grippers minimize berry damage (31).

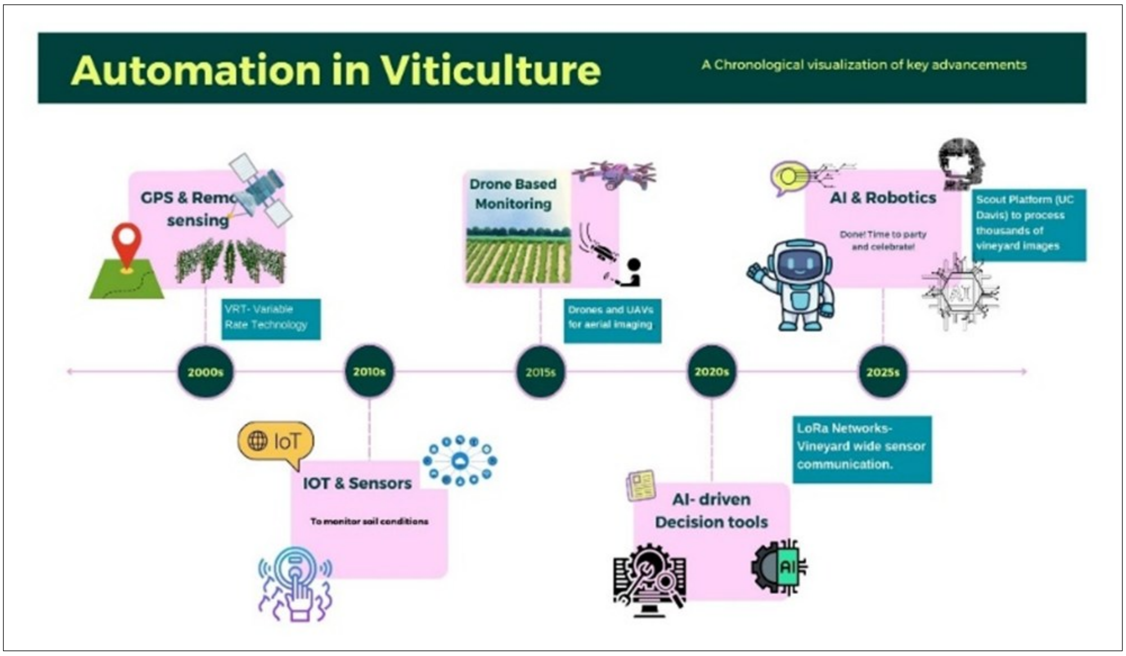

Fig.1. Historical timeline of automation in viticulture.

Table 1. Comparison of AI models for disease detection

Model	Accuracy	Deployment Scalability	Key Features	Disease Detected	References
ResNet-50	98.2 %	High (cloud/edge hybrid)	Residual blocks prevent overfitting; integrates with vineyard IoT sensors.	Black Rot, Powdery Mildew	(20)
YOLOv4	97.5 %	High (drone-based)	Real-time detection (25 sec/ha); processes RGB + thermal imagery for canopy analysis.	Downy Mildew, Esca	(21)
MobileNet-V2	95.8 %	High (smartphone/edge)	Lightweight design for field use; depth-wise convolutions reduce compute needs.	Powdery Mildew, Leaf Spot	(22)
Vision Transformer (ViT)	96.7 %	Low (GPU-dependent)	Self-attention detects subtle symptoms; requires high-res imagery (>10MP).	Early-stage Powdery Mildew	(23)
Faster R-CNN	94.3 %	Moderate (server-based)	Region Proposal Network (RPN) for precise lesion localization.	Black Rot, Botrytis Bunch Rot	(24)
Federated Learning (ResNet-34)	97.1 %	High (privacy-focused)	Decentralized training across vineyards; preserves grower data confidentiality.	Downy Mildew	(25)
Agrinet (Hybrid CNN)	99.0 %	Moderate (IoT-enabled)	Combines multispectral imaging + CNN; detects asymptomatic infections.	Esca, Pierce's Disease	(26)

Pruning robots, such as the EU funded Vine Robot, mimic expert decision-making through deep RL, achieving 85 % accuracy in identifying optimal pruning sites (32).

Emerging approaches like swarm robotics, deploy fleets of small robots with CNN-based weed detection to apply micro doses of herbicides (33). Wireless Sensor Networks (WSNs) and IoT platforms support these advances (34). Low-power networks such as LoRaWAN transmit data from soil probes to enable real-time difference detection, while blockchain platforms ensure data integrity for certifications, including organic labelling (35). The high costs (€20000-50000 per hectare for sensor-robot systems) and technical complexity limit small-scale adoption (36). Interoperability gaps between proprietary AI platforms and legacy equipment complicate integration (37). Neuromorphic computing could democratize automation by enabling energy efficient AI models for edge devices, while these innovations promise transformative efficiency, equitable adoption hinges on lowering costs and simplifying systems for diverse vineyard operations (38). Fig. 2 shows the integrated architecture of advancement in automation for sustainable viticulture.

Robotics and autonomous systems

Autonomous tractors like John Deere's 8R series are revolutionizing vineyard operations. Equipped with six stereo camera pairs and AI driven neural networks, these machines detect obstacles in 360° and operate with precision within one inch, enabling fully automated tillage and soil management (39). The system's neural network processes visualize the data in under 100 milli second which distinguish terrain from hazards like rocks or workers (40). Farmers manage these tractors through the John Deere Operations Centre, where preloaded tillage plans and real-time adjustments maximize efficiency during critical weather conditions (41). Deer's autonomy 2.0 system helps in precision spraying of chemicals to the orchard and it is monitored with the help of stereoscopic cameras for spray depth perception and it also increases the speed of application by 40 % (42). The robotic harvesters are overcoming precision challenges (43).

Jiangsu University's dual arm robot achieves an 83 % success rate using depth-sensing cameras and a "sequential mirroring method" to map grape clusters spatially, harvesting bunches in just 9 sec. A prototype developed by Extend Robotics and Queen Mary University that uses AI sensors and pressure-sensitive grippers to assess grape ripeness via sugar levels, enabling 24/7 harvesting through remote VR operators (44). These innovations address labour shortages in regions like Napa Valley and Essex, where manual harvesting costs exceed $6480 per tonne for premium grapes. Steep slope vineyards, comprising 30 % of Europe's wine growing land, require

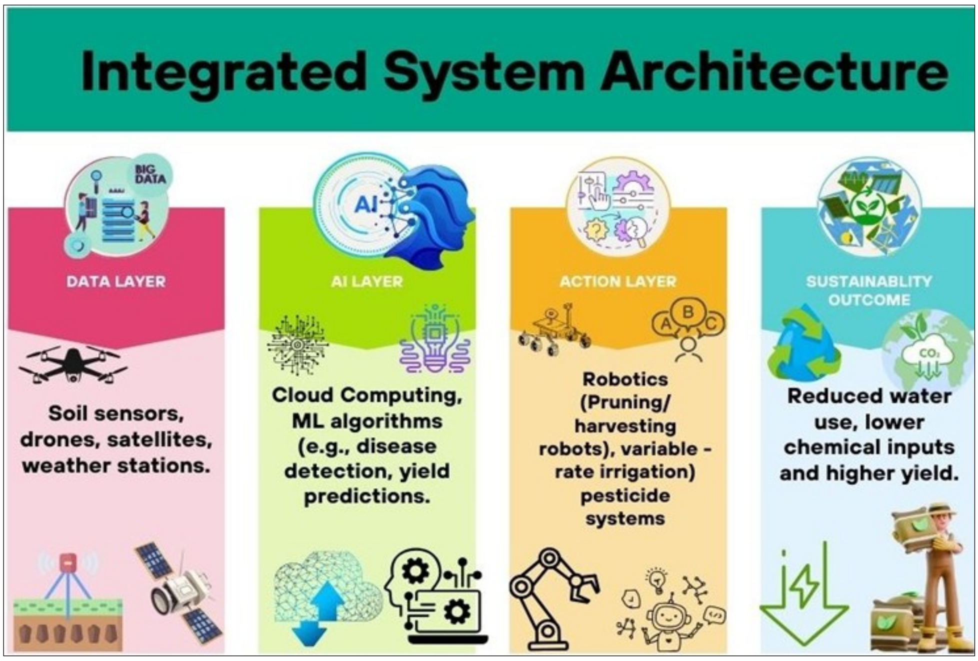

Fig. 2. Integrated system architecture for viticulture.

specialized automation. Projects like HEKTOR's LAAR combine aerial and ground robots with LiDAR and multispectral sensors to navigate slopes over 30°, performing precision spraying while reducing soil compaction which is critical for preserving terroir (45). For example, Westside equipment's VMECH Chariot pruner adapts to complex trellis systems, covering 3 acres/hr with AI vision that cuts pruning costs by $600 per acre. Such systems are vital in regions like Germany's Mosel Valley, where steep terrain makes manual labour extraordinarily expensive. These advancements illustrate automation's transformative role, merging AI, robotics and real time data to address labour, terrain and efficiency challenges. However, scalability hinges on cost reduction and adaptability to diverse vineyard architectures.

Postharvest automation is transforming winemaking through enhanced uniformity and efficiency. Recent studies demonstrate that AI controlled fermenters use IoT sensors to monitor temperature, pH and sugar levels in real time, dynamically optimizing fermentation to replicate ideal microbial conditions (1). For example, Prospero equipment's UNICA Electro Pneumatic filling valve, deployed in GAI Monoblock bottling systems, maintains volumetric precision of ± 0.5 % under pressures ranging from 0 - 6 BAR. This allows wineries to package both still and sparkling wines on a single line while minimizing oxidation risks. Blockchain integration further boosts transparency, as shown by platforms enabling consumers to scan QR codes for verified organic certification and carbon footprint data a feature increasingly prioritized by eco-conscious markets (46). Despite these innovations, adoption barriers also persist. Autonomous systems such as the 8R tractor require investments of $20000-50000 per hectare, excluding retrofitting costs, which strains small-scale growers who lack the technical expertise to merge AI platforms with older machinery (47). Regulatory frameworks also lag behind technological progress; EU policies, for instance, lack clear guidelines for AI liability and data privacy (48). The shift toward AI, robotics and precision tools are redefining viticulture as a sustainable, data centric industry. While costs and technical complexity remain challenges, interdisciplinary collaboration and updated policies are critical to democratize access and strengthen ecological resilience. As climate pressures escalate, these advancements promise not only to safeguard wine production but also to model sustainable practices for broader agriculture.

IoT and sensor networks in viticulture

IoT networks equipped with soil moisture, temperature and humidity sensors provide real-time data essential for precision irrigation and disease prevention. As demonstrated in recent studies, Time-Domain Reflectometry (TDR) and capacitance-based sensors are widely adopted for soil moisture monitoring due to their accuracy and durability (49). For example, IoT - guided irrigation reduce water use by 20-30 % in Cabernet Sauvignon vineyards without affecting yield (50). WSNs further enhance microclimate monitoring by tracking canopy-level humidity and temperature, which are critical for predicting fungal outbreaks like powdery mildew. A study in Tuscany revealed that hyperlocal humidity data from IoT nodes improved disease prediction accuracy by 40 % compared to regional weather stations (51). To address power limitations in rural vineyards, Low Power Wide-Area Network (LPWAN) protocols such as LoRaWAN and NB IoT enable energy efficient, long range data transmission (52). Sensor fusion combines data from ground sensors, drones and satellites to create comprehensive vineyard health models. Ground based IoT nodes deliver frequent updates, while drones equipped with multispectral cameras capture spatial variability in chlorophyll content (e.g., NDVI) at resolutions up to 5 cm/pixel (53). Satellite platforms like Sentinel-2 complement these datasets with thermal and spectral imagery, enabling water stress detection across large estates (54). Machine learning algorithms, such as CNNs, integrate these inputs to generate 3D health maps. A hybrid model combining soil moisture data, drone derived NDVI and satellite thermal imagery achieved 92 % accuracy in predicting grapevine water stress during a Napa Valley trial (55). Kalman screens Bayesian networks further refine data reliability by reconciling discrepancies between sensor types (56). Emerging solutions like solar powered IoT nodes and energy harvesting sensors are extending deployment longevity (57), while standardized data formats (e.g., ISO 11783 for agricultural machinery) ensure system scalability (58). Modular, open-source hardware, such as Raspberry Pi based sensors, could democratize access for small scale growers, bridging the gap between advanced technology and practical implementation. Table 2 indicates the regional adoption trends

Table 2. Regional adoption trends for viticulture

Region	Leading Technology	Adoption Rate	Key Driver (Policy/ Climate)	Sustainability Priority	References
Napa Valley, USA	AI-driven harvest robots	85 % large estates	Labor shortages	Water conservation	(59)
Bordeaux, France	Satellite NDVI monitoring	70 % cooperatives	EU subsidy programs	Carbon neutrality	(60)
Mendoza, Argentina	UAV-based disease detection	50 % mid-sized	Drought resilience	Soil health	(61)
Barossa Valley, Australia	Autonomous pruning systems	65 %	Heatwave adaptation	Energy efficiency	(62)
Maharashtra (Nashik, Pune, Sangili)	IoT soil sensors, solar-powered wineries, automated irrigation systems	IoT: 40 % Solar: 65 %	State subsidies, wine tourism	Water conservation and organic certification	-
Karnataka (Nandi Hills, Bengaluru Rural)	GPS-guided harvesters, blockchain traceability, AI-driven analytics	Blockchain: 25 % (premium wineries); AI: Pilot stage	Progressive excise policies	Carbon footprint tracking	-
Himachal Pradesh	Drone-based NDVI imaging,	Low (<10 %); experimental vineyards	Government grants for "sparkling wine hub,"	Biodiversity conservation	-
Telangana/Andhra Pradesh	Satellite yield monitoring, drought-resistant rootstocks	Very low (<15 %); state-supported pilots	State subsidies, corporate expansions	Rainwater harvesting, soil health management	-

for grape growing.

Remote sensing and imaging

Recent advancements in remote sensing which have transformed vineyard sustainability by enabling precise, data driven management. Hyperspectral Imaging (HSI), a non-destructive tool which analyses grape quality by capturing spectral data across 350-2500 nm wavelengths which detect biochemical variations linked to maturity. As shown in recent studies Partial Least Squares-Discriminant Analysis (PLS-DA) models effectively process these datasets, achieving over 90 % accuracy in predicting Total Soluble Solids content (TSS) for cultivars like Cabernet Sauvignon (63). For instance, HSI-trained PLS-DA models non-destructively predict SSC with a Root Mean Square Error (RMSE) of 0.8°Brix which outperform traditional destructive methods. This approach also quantifies anthocyanins and pH levels and offers growers appropriate idea about grape quality. By analysing hundreds of spectral bands, HSI identifies suitable biochemical shifts which enables targeted harvesting and reduction of waste. Such innovations highlight the spectral technologies are replacing labour intensive practices, advancing both precision viticulture and ecological sustainability. Fig. 3 depicts the AI driven decision makings systems in viticulture.

Precision technologies enable growers to optimize harvest timing, reduce waste and improve resource efficiency. Building on ground-based methods, Unmanned Aerial Vehicles (UAVs) equipped with LiDAR and multispectral cameras offer scalable vineyard monitoring. Studies highlight LiDAR's role in canopy management: its high resolution 3D mapping quantifies Leaf Area Index (LAI) and identifies areas require pruning or leaf removal, improving sunlight penetration and air circulation which is a critical strategy for mitigating fungal diseases like powdery mildew (64). Meanwhile, multispectral cameras detect early pest and environmental stresses using vegetation indices such as the Normalized Difference Vegetation Index (NDVI), which measures plant health and the Photochemical Reflectance Index (PRI), which tracks photosynthetic activity. For example, a previous study used UAV-derived NDVI to map vine vigour variability, linking it to *Botrytis cinerea* susceptibility and reducing fungicide use by 30 % through targeted spraying (65). Integrating LiDAR and multispectral data further enhances precision. Recent trials in Bordeaux vineyards demonstrated that machine learning algorithms combining these data sets and predict yield variability with less than 5 % error (66). By combining hyperspectral, LiDAR and multispectral insights, growers gain a multi-layered understanding of vineyard health, enabling interventions that minimize chemical inputs and conserve water. These advancements not only refine agricultural practices but also strengthen ecological resilience for sustainable viticulture.

Data-driven decision support systems

The integration of digital twins and blockchain technology is revolutionizing sustainable viticulture by enhancing precision, transparency and climate resilience. Digital twins' dynamic virtual models of vineyards leverage real-time data from IoT sensors, weather stations and remote sensing to simulate vineyard responses to environmental and management variables. For example, a Napa Valley case study demonstrated that digital twins integrating soil moisture, microclimate and canopy data predicted irrigation needs and disease risks (e.g., *Plasmopara viticola*) with 92 % accuracy, reducing water use by 25 % and fungicide applications by 18 %. These systems employ machine learning algorithms, such as Recurrent Neural Networks (RNNs), to forecast yield variability and nutrient deficiencies weeks in advance, enabling proactive interventions (67). Concurrently, blockchain technology ensures supply chain transparency by immutably recording data from grape maturity to distribution. Smart contracts automate compliance with sustainability certifications (e.g., ISO 14001) by validating practices like organic pest control or carbon-neutral harvesting. A 2023 Bordeaux pilot study illustrated blockchain's potential: tracking grape quality metrics (e.g., sugar content, pH) and pesticide residues allowed consumers to verify authenticity via QR codes, cutting wine fraud by 40 %. Furthermore, blockchain data combined with digital twins enhances predictive analytics. For instance, a

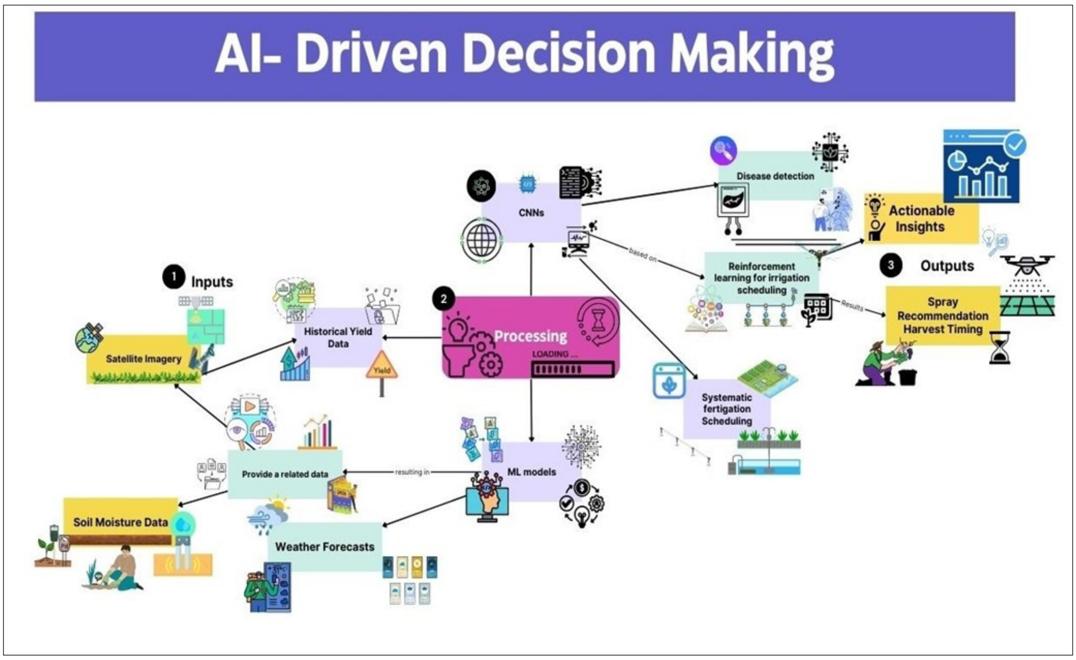

Fig. 3. AI-Driven decision making in viticulture.

hybrid model linking historical blockchain records (e.g., harvest dates, fermentation conditions) with real-time sensor inputs improved vintage forecasts and predicted terroir-driven flavour profiles with 89 % accuracy compared to some earlier assessments (68). This synergy minimizes resource waste while increasing market accountability. Digital twins optimize irrigation and disease management, directly supporting water conservation and chemical reduction. Blockchain's traceability re-assures consumers about sustainable practices, from organic farming to carbon-neutral logistics. Together, these technologies create auditable, climate-resilient supply chains, aligning viticulture with global sustainability goals. By merging predictive analytics with immutable records, stakeholders gain actionable insights while fostering trust a critical advantage in an industry increasingly pressured by ecological and regulatory demands.

Sustainability and resource efficiency

The convergence of automation and precision technologies is reshaping viticulture's ecological footprint by advancing water conservation, carbon neutrality and circular resource systems. Precision irrigation systems, for instance, combine IoT soil moisture sensors with AI-driven predictive models to reduce water use by 15-25 % in arid regions like California and Spain. A recent study demonstrated this in Tempranillo vineyards, where Variable-Rate Irrigation (VRI) systems using real time evapotranspiration data and HSI reduce water consumption by 22 % without compromising yield and grape quality (69). These systems dynamically adjust irrigation schedules using machine learning, responding to microclimatic shifts detected by in canopy sensors (70). Meanwhile, solar-powered robotics are reducing carbon emissions by replacing fossil fuel-dependent equipment. Autonomous platforms like the Vinbot, powered by photovoltaic energy, perform tasks such as weeding and pruning.

Trials in Bordeaux vineyards showed such robots reduce CO_2 emissions by 1.2 tonnes per hectare annually (71). Regenerative practices further enhance sustainability with AI guided cover cropping and no till farming, tested in Tuscany, which increased soil organic carbon by 30 % over five years by using drones to seed nitrogen fixing legumes between vine rows (72). Circular economy principles are also gaining traction through AI driven waste reduction. Computer vision equipped robotic harvesters, for example, limit grape spillage to less than 3 % far below the 15 % typical of manual harvesting. In Napa Valley, AI algorithms repurpose pruning waste into biochar or compost, diverting 90 % of organic waste from landfills (73). Deep learning models like CNNs analyse drone imagery to identify underutilized biomass for conversion into biofertilizers, reducing synthetic fertilizer use by 40 % (74). Together, these innovations precision irrigation, decarbonized robotics and AI-driven circularity show how automation can align viticulture with planetary boundaries. By optimizing water use, cutting emissions and stopping resource loops, the sector achieves resource efficiency without sacrificing productivity. This integration of technology not only addresses immediate environmental challenges but also builds a framework for long term ecological resilience, proving that sustainability and productivity can coexist in modern agriculture. Table 3 describes the cost benefit analysis of robotic systems in Indian viticulture.

Challenges and limitations

Despite the transformative potential of automation in viticulture, its widespread adoption faces significant barriers rooted in cost, technical complexity and cultural resistance. Cost barriers remain a critical hurdle, particularly for small and medium sized vineyards. For instance, AI driven robotic systems, such as autonomous harvesters with advanced computer vision, can exceed $150000 per unit, while precision irrigation systems integrating IoT sensors and machine learning models require high investments in hardware and software infrastructure (83). While long term savings in labour, water and pesticide use are well documented, the initial capital outlay often strains budgets, especially in regions with fragmented land ownership or limited access to financing. Even solar powered solutions, though reducing operational costs by 40-70 % over time, demand significant upfront expenditures, with payback periods of 5-7 years posing risks for cash - flow - sensitive operations.

Technical complexity further complicates implementation, as integrating heterogeneous data streams from HSI, LiDAR and IoT sensors into unified AI models requires robust and alternate standards and scalable cloud architectures. For example, deep learning models for yield prediction must harmonize real time drone imagery with historical climate data and soil health metrics, yet inconsistencies in data formats and sampling frequencies often degrade model accuracy (84). Additionally, scaling AI solutions across diverse terroirs remains challenging; neural networks trained on Tempranillo vineyards in Spain may fail to generalize to Pinot Noir crops in Oregon due to variations in canopy structure and microclimates. Adoption hesitancy, driven by the tension between tradition and innovation, further hinders the progress. Many small scale winemakers view automation as a threat to artisanal practices and the concept of terroir, with

Table 3. Cost-benefit analysis of robotic systems in Indian vineyards

Factor	Large Vineyards	Small Vineyards	References
Initial Investment	₹1.35-1.8 crore per robot (high upfront cost), but lower per-acre amortization.	₹18-90 lakh per robot; leasing/shared ownership models preferred.	(75)
Labor Cost Reduction	Saves ₹6-10 lakh/year per 100 acres by replacing 3-5 seasonal workers.	Saves ₹1.5-3 lakh/year; robots assist but rarely replace labour.	(76)
Scalability	High: Modular systems (e.g., **Agribot**) manage tasks across 500+ acres.	Limited by terrain; smaller robots (e.g., **Krishibot**) suit <10-acre plots.	(77)
Precision & Yield Impact	AI-driven irrigation boosts yield by 15 - 20 % (₹25-40 lakh/year added revenue).	Moderate yield gains (5-10 %); ROI hinges on premium grape prices (e.g., Nashik vineyards).	(78)
Environmental Benefits	30-50 % herbicide reduction (saves ₹2-4 lakh/ year); lower soil compaction.	20-30 % water savings via IoT-guided systems (saves ₹50000 - 1.5 lakh/year).	(79)
Maintenance & Training	Annual upkeep: ₹13.5-27 lakh (10-15 % of robot cost); dedicated IT staff required.	Training challenges; ₹1.8-13.5 lakh/year upkeep strains small budgets.	(80)
Regulatory Challenges	Compliance with state drone/autonomous vehicle laws adds ₹2-5 lakh/year in fees.	Fewer regulations but limited subsidies (e.g., Maharashtra's Agri-Tech Fund excludes small farms).	(81)
ROI Timeline	3-5 years (labour + yield savings offset costs).	7-10 years (dependent on subsidies or shared leasing).	(82)

surveys indicating that 60 % of family owned European vineyards prioritize manual methods to preserve heritage (85). This cultural resistance is compounded by workforce with reduced skills in operators often lack training in AI analytics or robotics maintenance, leading to underutilization of advanced systems (86). However, hybrid approaches such as Italy's Antinori vineyard, which combines robotic harvesters with manual quality checks demonstrate that tradition and technology can coexist. Similarly, phased implementation strategies, as seen in North Carolina solar adoption programs, allow gradual integration of automation while preserving legacy workflows. Addressing these challenges demands collaborative frameworks, which incentivizing research and development tax credits, standardizing data protocols and fostering partnerships between tech developers and viticultural communities to ensure solutions align with ecological and cultural priorities (87). Table 4 explains the AI enabled institutes in globe and in India for viticulture.

Conclusion

Automation is transforming viticulture by combining precision, efficiency and environmental conditions which sets a new standard for sustainable farming. Technologies like advanced imaging, AI powered irrigation and solar robots have already shown impressive results which reduce water use by 15-25 %, lower carbon emissions by 1.2 tonnes per hectare and reuse 90 % of vineyard waste. However, success depends on experts from different fields like agronomy, technology and engineering working together to solve challenges like incompatible sensors or overly complex AI models. For example, AI tools designed for vineyards must be adjusted by local growers to match unique soil and climate conditions. Moving forward, efforts should focus on making these technologies affordable for small farms and ensuring they are used ethically, protecting both workers and ecosystems. Programs like the EU's ClimateViti, which encourages sharing data openly, show how fair innovation can thrive. The future of viticulture lies in combining smart robots, climate-ready digital tools and supportive policies like grants for eco-friendly technology. By implementing innovation and accepting tradition and nature, the wine industry can meet global sustainability goals and keep its rich heritage alive in a greener world.

Future directions

The integration of AI, robotics and precision technologies in viticulture is poised to accelerate, driven by evolving climate challenges, technological democratization and collaborative innovation. The democratization of AI is essential to empower small and medium sized vineyards, which constitute over 70 % of global wine production. Recent advancements focus on reducing cost and complexity through tools like Microsoft's FarmVibes.AI enable growers to build custom models without coding expertise, using drag-and-drop interfaces to predict yield or disease risks. Cornell's *PhytoPatholoBot* (PPB) now offers a subscription model at $50 per month, providing small vineyards with hyperspectral disease alerts via SMS, cutting fungicide costs by 40 % (92). Next generation robotics will leverage decentralized coordination to enhance efficiency. Italy's *VitiSwarm* project uses 50+ drones with YOLOv7 vision to map 100 hectare vineyards in <2 hours, sharing data via mesh networks to optimize pruning routes (93). California's *VineCoord* system pairs ground robots for soil sampling with aerial drones for NDVI mapping, synchronized via federated learning. Trials in Napa achieved 95 % yield prediction accuracy (94). Bordeaux's *WineChain* platform automates payment to robot fleets using smart contracts, validated by IoT data on task completion (e.g., canopy density <0.8 LAI) (95). Latency in multi-robot communication remains a bottleneck. Recent advances in 6G based Digital Twin networks, however, cut latency to <5 ms, enabling real-time replanning during harvest (92). The EU's *GreenViti* program offers €15000 per hectare grants for solar-powered robots, contingent on achieving 30 % pesticide reduction. Similarly, California's *SAFE Viticulture* initiative funds 50 % of AI tool costs for organic-certified vineyards (96).

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Table 4. AI enabled institutes in globe and in India for viticulture

S. No	Institution	Technology	Application	References
1.	**University of Cádiz (Spain)**	AI-driven disease prediction models and automated harvesting systems	Implements computer vision for early disease detection and robotic harvesters with real-time quality grading.	(88)
2.	**University of Melbourne (Australia)**	IoT sensor networks + ML algorithms	Monitors vine water status using hyperspectral drones and detects smoke taint via e-noses.	(89)
3.	**INRAE & VINITECH (France)**	Big data analytics integrated with vineyard DSS	Processes multi-year agronomic data for disease forecasting (e.g., powdery mildew) and resource allocation	(90)
4.	**Wine Tech Israel**	Autonomous vineyard robots	Deploys AI-guided robots for precision pruning and targeted spraying, cutting chemical usage by 35 %	(91)
5.	**ICAR-National Research Centre for Grapes (Pune)**	Image-based AI disease detection	Mobile systems diagnosing powdery mildew/pests with 89 % accuracy, reducing yield losses by 22 %.	(91)
6.	**Tamil Nadu Agricultural University (Coimbatore)**	Satellite remote sensing + AI	Analyzes Sentinel-2 imagery for vigor mapping and yield prediction in Tamil Nadu vineyards.	(61)
7.	**VIT Vellore & IIT Bombay**	ML-based irrigation models	Predictive algorithms using soil moisture/temperature sensors to optimize water use in Nashik vineyards.	(90)

Authors' contributions

All authors contributed to the study's conception and design. The first draft of the manuscript was written by BM. PSK, IM, AS, DB and PPM provided corrections and valuable input. All authors commented on previous versions of the manuscript and approved the final version.

Compliance with ethical standards

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Grammarly was employed while preparation of the manuscript for grammar verification. All suggested changes were reviewed and approved by the author(s) and the scientific content, analysis and conclusions were developed independently.

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