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# New developments and opportunities for AI in viticulture, pomology, and soft-fruit research: a mini-review and invitation to contribute articles

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Climate change constraints on horticultural production and emerging consumer requirements for fresh and processed horticultural products with an increased number of quality traits have pressured the industry to increase the efficiency, sustainability, productivity, and quality of horticultural products. The implementation of Agriculture 4.0 using new and emerging digital technologies has increased the amount of data available from the soil–plant–atmosphere continuum to support decision-making in these agrosystems. However, to date, there has not been a unified effort to work with these novel digital technologies and gather data for precision farming. In general, artificial intelligence (AI), including machine/deep learning for data modeling, is considered the best approach for analyzing big data within the horticulture and agrifood sectors. Hence, the terms Agriculture/AgriFood 5.0 are starting to be used to identify the integration of digital technologies from precision agriculture and data handling and analysis using AI for automation. This mini-review focuses on the latest published work with a soil–plant–atmosphere approach, especially those published works implementing AI technologies and modeling strategies.

KEYWORDS
**climate change, Agriculture 5.0, digital agriculture, remote sensing, machine/deep learning**

## 1 Introduction

In the past two decades, agriculture in general has been affected by market challenges driven by climate change adversities and global consumer pressures pertaining to the quality and sustainability of agricultural products, which have forced the horticulture and agrifood industries to be more sustainable and ethical to minimize their environmental footprints. Implementing Agriculture 4.0 using new and emerging digital technologies has enhanced the application of precision agriculture (PA) through technologies such as remote sensing, robotics, digital sensor networks, and the Internet of Things (IoT). The latest technologies have helped to increase the efficiency of and sustainability targets for horticultural production (Javaid et al., 2022; Maffezzoli et al., 2022). However, digital technologies have not been broadly implemented throughout all horticulture and agrifood production and supply chains. There is still a disconnect and lack of feedback/forward information among agricultural processes, food processing, packaging, and consumer appreciation/acceptability (Fuentes et al., 2021b).

New and emerging technologies, such as artificial intelligence (AI) and related disciplines, including machine/deep learning, robotics, computer vision, biometrics for sensory and consumer analysis, and digital twins, can help to fill the gaps within the agrifood sectors and production and supply chains. By implementing AI, a new agrifood revolution, or Agriculture 5.0, can be discussed. These advances reflect the latest figures reported on AI, which suggest that in nearly 98% of scientific fields, including agriculture and horticulture, AI has already been implemented in some capacity, with 5.7% of all peer-reviewed research papers published worldwide focused on AI applications (Hajkowicz et al., 2022). Furthermore, it is expected that AI implementation in agriculture, with the main objectives of monitoring crops, soil analysis, increasing crop yield, and, ultimately, reducing costs, will grow by 26% globally between 2019 and 2025 (Research Markets, 2020). Nowadays, some type of technology for precision agriculture is being used in 15%–40% of large farms in the United States, 20% of those in Australia and Canada, 85% of those in Scotland, 43% of those in Ireland, and 30% of those in Germany, along with 68% of small farms in Western Europe (Kinhal, 2022).

In line with findings from the aforementioned report, there has been a considerable increase in the number of publications related to digital agriculture/horticulture in the past 5 years that contain descriptions of new sensor technologies applied to the agrifood sector, from production to processing, and acceptability by consumers using sensory analysis and biometrics (Gonzalez Viejo et al., 2019). However, much of the research has been limited to digital technologies and model development for only one or two crops and specific research sites, with minimal or no deployment of AI models. Hence, there is a need for future research implementing AI to focus on the independent deployment options for the different applications and models developed.

This mini-review focuses on the latest published work based on a soil–plant–atmosphere approach, especially those published works implementing AI technologies and modeling strategies. It discusses the advantages and disadvantages of the methodologies proposed and how they should be tested, validated, and integrated throughout agrifood production and supply chains.

## 2 Digital technologies implemented for viticulture, pomology, and soft fruits

This mini-review was based on research papers published in the past 5 years. As mentioned before, due to the number of publications related to digital technologies in the previous 10 years, it would be impossible to cover all the research on crops and cultivars that has been conducted so far. Hence, this review focuses on the information from new and emerging technologies obtained from the latest papers related to the specific areas of viticulture (Table 1), pomology (Table 2), and soft fruits (Table 2).

## 3 Discussion

The research presented in this paper is a fair sample of the latest research on digital technologies including AI in horticulture. However, most of it did not report any attempt at deployment of the models developed, and the majority of the studies that did include it reported low performance ($R^2 < 0.52$; Tables 1, 2), with the exception of two studies with deployments on yield prediction ~85% (Table 2). These results reflect the main concern of and criticism articulated by AI scientists, who state that "even a system that appears to perform spectacularly in training can make terrible predictions when presented with novel data in the world" (Crawford, 2021). Therefore, deploying AI models in horticulture should be a must for future publications.

Creating a successful AI pilot model starts with identifying Goldilocks problems in horticulture that can be solved by the application of AI modeling techniques based on digital sensors and technologies (Rochwerger and Pang, 2021). Most research is focused on technologies that address problems at the block, orchard, or regional scales that do not offer significant advantages compared with other more established technologies from PA, remote sensing, or data analysis from meteorological stations (i.e., evapotranspiration estimation for irrigation scheduling or biotic stress management). On the other hand, AI models offering assessments of targets at the plant-by-plant scale or sub-meter scales offer little practical management information if the management is at a block, orchard, or regional scale. These Goldilocks problems can be identified for specific crops and environments. One of the most crucial resources in the production of horticultural crops that must be managed efficiently is water. Hence, an increased number of models have been developed to accurately estimate plant water consumption and increase water use efficiency, and this has direct implications for fruit yield and fruit quality traits (Tables 1, 2). The other common targets for AI modeling are fertilization, canopy management and vigor assessment, pest and disease detection and management, phenotyping for fruit quality estimations and crop improvement and yield, among other things. Moreover, as mentioned before, the management scale, in terms of temporal and spatial scales, should be similar to the one considered by the AI model development.

The most common and efficient inputs for AI modeling are based on data that is relatively easy to collect at the orchard level, either historically (i.e., management and phenology history, meteorological data, soil–plant–atmosphere-based sensor technologies) or through the implementation of new and emerging sensor technologies based on remote sensing employing long-range remote sensing via unmanned aerial vehicles (UAV) of short/proximal range, or manned or unmanned terrestrial vehicles (UTV) (Fuentes and Gago, 2022). In addition, growers should know

TABLE 1 Recent applications of digital technologies to viticulture displaying the technology used, the accuracy of the methods or models used, and details regarding deployment experiments (no = not conducted; % = deployment accuracy).

| Application | Technology | Assessment | Statistical method to assess accuracy | Accuracy | Deployment | Country | Reference |
|---|---|---|---|---|---|---|---|
| **Viticulture** | | | | | | | |
| **Soil** | Remote sensing imaging<br>Machine learning | Topsoil moisture area delimitation | Random forest —classification | 60%–85% | No | Portugal | (Mendes et al., 2021) |
| | Remote sensing imaging<br>Meteorological data<br>Machine learning | Root zone soil moisture | Random forest ensemble—regression | $R^2$ = 0.85 | No | United States | (Kisekka et al., 2022) |
| | Remote sensing imaging<br>Thermal infrared imaging | Soil moisture | Particle filtering | NR | No | United States | (Lei et al., 2020) |
| | Thermal infrared imaging | Soil surface temperature | None | NR | No | Portugal | (Frodella et al., 2020) |
| **Phenotyping** | RGB and NIR imaging | Drought phenotyping | Correlation analysis | $R^2$ = 0.71–0.86 | No | Italy | (Briglia et al., 2019) |
| | Computer vision<br>Near-infrared spectroscopy<br>Machine learning | Morphocolorimetry<br>Grapevine cultivar classification (16 cultivars) | ANN—classification | 92%–94% | No | Spain | (Fuentes et al., 2018) |
| | 3D-based phenotypic data | Quantitative Trait Locus Mapping | Linear correlation | R = 0.82–0.93 | No | Germany | (Rist et al., 2022) |
| | E-nose<br>Machine learning | Cultivar identification | DA—classification<br>QDA—classification<br>SVM—classification<br>ANN—classification | DA: 98%<br>QDA: 99%<br>SVM: 92%<br>ANN: 99% | No | Iran | (Khorramifar et al., 2022) |
| | RGB Imaging<br>Deep learning | Cultivar identification | CNN<br>AlexNet transfer learning | 77.30% | No | Portugal | (Pereira et al., 2019) |
| | Depth camera<br>Computational geometry<br>Deep learning | Grape bunch detection | VGG19 deep neural network | 92.52% | No | Switzerland | (Milella et al., 2019) |
| | UAV<br>Multispectral images | Canopy segmentation | Overestimation based on:<br>HSV-based algorithms<br>k-means algorithm<br>Digital elevation model | HSV most stable | No | Italy | (Cinat et al., 2019) |
| | Remote sensing imaging (optical and synthetic aperture radar) | $K_c$<br>Leaf Area Index | Correlation analysis and RMSE estimations | $K_c$: $R^2$ = 0.18–0.43<br>LAI: $R^2$ = 0.28–0.31 | No | Israel | (Beeri et al., 2020) |
| | 3D imaging | Phenotypic traits | SVM | $R^2$ = 0.70–0.91 | No | Germany | (Rist et al., 2019) |

*(Continued)*

TABLE 1 Continued

| Application | Technology | Assessment | Statistical method to assess accuracy | Accuracy | Deployment | Country | Reference |
|---|---|---|---|---|---|---|---|
| **Abiotic stress** | Robotics<br>Infrared thermal radiometry<br>Environmental sensor<br>Multispectral sensor | Water status monitoring and mapping | PLS—regression | $R^2$ = 0.42–0.57 | No | Portugal | (Fernández-Novales et al., 2021) |
| | Multispectral imagery<br>Environmental data<br>Infrared thermal thermography | Stem water potential<br>Spatial variability | PLS—regression<br>LDA—classification | PLS: $R^2$ = 0.63<br>LDA: 74% | No | Spain | (Diago et al., 2022) |
| | UAV<br>Aerial shortwave infrared<br>Multispectral imagery | Water stress geospatial mapping | Linear and exponential regression | General model: $R^2$<0.30<br>Model per variety: $R^2$>0.80 | No | Greece | (Kandylakis et al., 2020) |
| | VIS-NIR spectroscopy<br>Machine learning | Predawn leaf water potential | ANN-PCA | $R^2$ = 0.85 | No | Portugal | (Tosin et al., 2022) |
| | Satellite images | Stem water potential | Multivariable linear regression | $R^2$ = 0.84 | No | Israel | (Helman et al., 2018) |
| | Hyperspectral images<br>Machine learning | Drought | PLS-SVM<br>PLS-DA | >97% | No | Croatia | (Zovko et al., 2019) |
| | NIR<br>Viticanopy—RBG images<br>Machine learning | Berry cell death | ANN—regression | NIR: R = 0.87<br>Viticanopy: R = 0.98 | No | Australia | (Fuentes et al., 2021a) |
| | NIR<br>Machine learning | Berry cell death | ANN—regression | R = 0.94 | No | Australia | (Fuentes et al., 2020) |
| | NIR<br>Machine learning | Volatile phenols and glycoconjugates | ANN—regression | R = 0.98 | No | Australia | (Summerson et al., 2020) |
| | Thermal infrared imaging (TI)<br>NIR<br>Machine learning | Smoke contamination detection in leaves<br>Guaiacol glycoconjugates in berries and wine | TI: ANN—classification<br>NIR: ANN—regression | TI: 96%<br>NIR: R = 0.97 | No | Australia | (Fuentes et al., 2019) |
| **Biotic stress** | Thermal imaging<br>Machine learning | Downey mildew early detection | SVM—classification | 81.6% | No | Israel | (Cohen et al., 2022) |
| | Machine vision (MV)<br>Hyperspectral imaging (HI)<br>Machine learning | Downey mildew detection | MV: Linear correlation<br>HI: CNN | MV: $R^2$ = 0.76<br>HI: 81% | No | Spain | (Hernández et al., 2021) |
| | UAV<br>Computer vision<br>Machine learning | Mapping of *Cynodon dactylon* | Decision tree | 98% | No | Spain | (de Castro et al., 2019) |
| | UAV<br>Multispectral imaging<br>Machine learning | Detection of *Flavescence dorée* | SVM—classification<br>DA—classification | SVM: 88%–98%<br>DA: 88%–100% | No | France | (Al-Saddik et al., 2019) |

*(Continued)*

TABLE 1 Continued

| Application | Technology | Assessment | Statistical method to assess accuracy | Accuracy | Deployment | Country | Reference |
|---|---|---|---|---|---|---|---|
| | Computer vision<br>Deep learning | Differentiation between downy mildew and spider mite in leaves with visible signs | CNN | 0.94 | No | Spain | (Gutiérrez et al., 2021) |
| | RGB imaging<br>Deep learning | Detection of diseases | CNN | 67%–83% | No | Greece | (Morellos et al., 2022) |
| | Hyperspectral sensors | Detection of grapevine leaf stripe disease | NR | NR | NR | Brazil | (Junges et al., 2018) |
| | RGB imagery<br>Multispectral imaging<br>Thermal infrared imaging<br>Machine learning | Pest and disease detection | Multi-source data fusion | 96% | No | China | (Yang et al., 2021) |
| | Hyperspectral images<br>Machine learning | Red blotch virus and grapevine leafroll-associated viruses | CNN<br>Random forest (RF) | CNN = 77.7%<br>RF = 76.9% | No | United States | (Sawyer et al., 2023) |
| | UAV<br>Hyperspectral imaging<br>Multispectral imaging<br>RGB imaging | Detection of Phylloxera infestation | Digital vigor model<br>Digital surface model | NR—presented as a preliminary study | NR | Australia | (Vanegas et al., 2018) |
| **Fruit yield and quality** | UAV<br>Computer vision<br>Multispectral imaging<br>Machine learning | Yield estimation | ANN—regression | $R^2$ = 0.60–0.96 | $R^2$ = 0.32 | Spain | (Ballesteros et al., 2020) |
| | Robotic—imaging | Yield estimation | Pearson correlation | Low accuracy with higher coefficient of variation for image analysis | No | Portugal | (Victorino et al., 2020) |
| | Image analysis<br>Machine learning | Yield estimation | Boolean model | $R^2$ = 0.78–0.81 | No | Spain | (Millan et al., 2018) |
| | Hyperspectral imaging<br>Machine learning | Yield and quality traits | Extreme learning machine | Yield: $R^2$ = 0.68<br>Quality traits: $R^2$ = 0.52–0.68 | No | United States | (Maimaitiyiming et al., 2019) |
| | Remote sensing<br>Proximal sensing (canopy sensor) | Grape yield and quality | Correlation analysis | Remote sensing: R = 0.52–0.63<br>Proximal sensing: R = −0.56–0.68 | No | Greece | (Anastasiou et al., 2018) |

NR, not reported; R, correlation coefficient; $R^2$, determination coefficient; DA, discriminant analysis; LDA, linear discriminant analysis; QDA, quadratic discriminant analysis; SVM, support vector machine; ANN, artificial neural networks; e-nose, electronic nose; CNN, convolutional neural networks; UAV, unmanned aerial vehicle; HSV, hue saturation value; PLS, partial least squares; PCA, principal components analysis; NIR, near-infrared; RGB, red, green, and blue.

if they have the correct data to assess the targets of interest at the required temporal and spatial resolution. For example, the use of AI models based on Landsat multispectral data (30 m× 30 m pixel) to assess the incidence of water stress at the plant-per-plant level of a tomato crop would be ineffective, since at the spatial resolution scale the pixel footprint considers over 200 plants, and from the temporal resolution having an image every 15 days (satellite overpass) may not be appropriate for detecting water stress with daily fluctuations.

One of the main principles to consider when modeling using AI is the parsimony of input data compared with the targets considered. In other words, the inputs for AI modeling should be simpler to acquire than the targeted information. Furthermore, AI models developed should offer a certain level of automation in data acquisition, processing, and decision-making information to growers.

Many early criticisms of AI modeling were that they were “black boxes”, in the sense that there was no option to see how models treated the data that arrived at specific targets, especially in cases of unsupervised machine learning or deep learning, in which the machine automatically extracts parameters of importance from inputs to model target responses. However, the advances made in machine/deep learning have made this argument obsolete. The latter statement is less applicable in the case of supervised machine-learning modeling since an essential initial step is parameter engineering, in which the modeler decides which parameters/data are more relevant to model the patterns of behavior for a specific target (i.e., specific meteorological data for specific biotic/abiotic stress detection). Hence, modelers should

TABLE 2 Recent applications of digital technologies to pomology displaying the technology used accuracy of the methods or models and deployment (No = not conducted; % = deployment accuracy).

| Application | Crop | Technology | Assessment | Statistical method to assess accuracy | Accuracy | Deployment | Country | Reference |
|---|---|---|---|---|---|---|---|---|
| **Pomology** | | | | | | | | |
| **Soil** | Plum | Capacitive sensors Automatic irrigation | Automated irrigation schedule | ANOVA—Duncan's test | "Automatic irrigation avoided water stress." | No | Spain | (Millán et al., 2019) |
| | Mango | Wireless sensor network | Soil moisture monitoring | NR | NR | NR | Malaysia | (Nooriman et al., 2018) |
| | Apple | Moisture sensors Dendrometer Data transmitter Deep learning | Soil moisture and trunk diameter | Deep neural networks | R = 0.98 | No | NR | (Ionescu et al., 2019) |
| | Apple | Soil moisture sensors Long range wide area networks | Soil moisture monitoring | NR | NR | NR | Italy | (Wenter et al., 2021) |
| **Phenotyping** | Citrus | UAV Machine vision Machine learning | Tree segmentation | SVM | 76%–95% | No | China | (Chen et al., 2019a) |
| | Apple | UAV RGB imaging | Tree architecture | Pearson's correlation | R = 0.75–0.94 | No | United States | (Zhang et al., 2021) |
| | Apple | Robotics 3D light detection and ranging | Canopy | Pearson's correlation | R = 0.51–0.81 | No | United States | (Chakraborty et al., 2019) |
| | Apple | Multispectral dynamic imaging Machine learning | Apple recognition | SVM—classification | 72%–92% | No | United States | (Feng et al., 2019) |
| | Apple | Multispectral imaging Deep learning | Leaves segmentation | CNN | Precision: 0.70–0.72 | No | Russia | (Uryasheva et al., 2022) |
| | Apple | Image analysis Machine learning | Morphometric analysis | Random forest | 0.82–0.92 | No | Spain | (Dujak et al., 2023) |
| | Pomegranate | Aerial imaging Deep learning | Canopy segmentation | Mask Region-based CNN | 41%–97% | No | United States | (Zhao et al., 2018) |
| | Apricot | RGB imaging Machine learning | Variety classification | Adaptive network-based fuzzy inference system | 81%–89% | No | NR | (Mirnezami et al., 2020) |
| | Mango and avocado | UAV RGB imaging Multispectral imaging Satellite imaging | Height estimation | Linear regression | Mango: $R^2$ = 0.50–0.80 Avocado: $R^2$ = 0.45–0.81 | No | Australia | (Wu et al., 2020) |

*(Continued)*

TABLE 2 Continued

| Application | Crop | Technology | Assessment | Statistical method to assess accuracy | Accuracy | Deployment | Country | Reference |
|---|---|---|---|---|---|---|---|---|
| **Abiotic stress** | Olive | Thermal infrared sensors | Water status | Linear regression | $R^2 > 0.80$ | No | Portugal | (Noguera et al., 2020) |
| | Khasi mandarin orange | E-nose Machine learning | Water stress | SVM—bagging ensemble—classification | 85% | No | India | (Choudhury et al., 2019) |
| | Almond | Thermal infrared imaging | Water status | Linear correlation analysis | $R^2 = 0.76–0.95$ | No | Spain | (García-Tejero et al., 2018) |
| | Almond and pistachio | Satellite images Thermal infrared imaging | Evapotranspiration | Linear correlation | Almonds: $R^2 = 0.92$ Pistachios: $R^2 = 0.70$ | No | United States | (Bellvert et al., 2018) |
| | Mandarin | Thermal infrared imaging | Crop water stress index | Linear regression | $R^2 = 0.75$ | No | China | (Appiah et al., 2022) |
| | Cherry | Thermal infrared imaging | Water status | ANN—regression | R = 0.81–0.83 | No | Chile | (Carrasco-Benavides et al., 2022) |
| **Biotic stress** | Citrus fruits | Whole-cell-based biosensor | *Penicillium digitatum* detection | NR | NR | NR | NR | (Chalupowicz et al., 2020) |
| | Mandarin orange | E-nose Machine learning | Citrus tristeza virus detection | KNN—bootstrap ensemble—classification | 99% | No | India | (Hazarika et al., 2020) |
| | Pear | UAV Hyperspectral imaging | Fire blight monitoring | Logistic regression | 85% | 52% | Belgium | (Schoofs et al., 2020) |
| | Pear | UAV Multispectral imaging Machine learning | Fire blight detection | SVM—classification | 95% | No | Iran | (Bagheri, 2020) |
| | Apple | Multispectral imaging Thermal infrared imaging 3D imaging | Scab infections detection | NR | Reported as "accurate" | NR | United Kingdom | (Bleasdale et al., 2022) |
| | Avocado | RGB imaging Multispectral imaging Thermal infrared imaging Machine learning | White root rot detection | Logistic regression ANN | 82.5% | No | Spain | (Pérez-Bueno et al., 2019) |
| | Avocado | Multispectral imaging Machine learning | Laurel wilt detection | MLP | 99% | No | United States | (Abdulridha et al., 2019) |
| | Avocado | RGB imaging Satellite imaging Image analysis | Severity of Phytophthora root rot disease | Multivariate stepwise linear regression | RGB imaging: $R^2 = 0.89$ Satellite imaging: $R^2 = 0.96$ | No | Australia | (Salgadoe et al., 2018) |

*(Continued)*

TABLE 2 Continued

| Application | Crop | Technology | Assessment | Statistical method to assess accuracy | Accuracy | Deployment | Country | Reference |
|---|---|---|---|---|---|---|---|---|
| | Citrus fruits | E-nose<br>Machine learning | *Bactrocera dorsalis* infestation | LDA | 98.21% | No | China | (Wen et al., 2019) |
| **Fruit Yield and quality** | Sweet Cherry | UAV<br>Multispectral imaging<br>Machine learning | Yield estimation | ANN—regression | $R^2$ = 0.67 | No | Spain | (Blanco et al., 2020) |
| | Kaffir lime | E-nose | Aroma profile | NR | NR | NR | NR | (Ravi et al., 2020) |
| | Mango | Satellite imaging<br>Machine learning | Yield estimation<br>Number of fruits | ANN—regression | $R^2$ = 0.68–0.70 | No | Australia | (Rahman et al., 2018) |
| | Mango | IoT<br>Temperature and humidity sensor<br>Gas sensor | Quality traits | Pearson correlation (PC)<br>Spearman correlation (SC)<br>Kendall correlation (KC) | PC: 72%–98%<br>SC: 66%–99%<br>KC: 57%–91% | No | India | (Bardhan et al., 2020) |
| | Apple | Satellite imaging<br>Machine learning | Yield prediction | Backpropagation neural networks | 92%–95% | No | China | (Gao et al., 2023) |
| | Apple | UAV<br>Light detection and ranging imaging<br>Multispectral imaging<br>Machine learning | Yield prediction | Ensemble learning | $R^2$ = 0.81 | No | China | (Chen et al., 2022) |
| Soft fruits | | | | | | | | |
| **Soil** | Strawberry | IoT<br>Weather station<br>Moisture sensor<br>Machine learning | Automatic irrigation based on soil moisture | ANN—classification | 80% | No | Philippines | (Macabiog and Cruz, 2019) |
| **Phenotyping** | Strawberry | High spatial and temporal resolution imaging | Dry biomass and leaf area index (LAI) | Multiple regression | Dry biomass: $R^2$ = 0.84<br>LAI: $R^2$ = 0.79 | No | United States | (Guan et al., 2020) |
| | Strawberry | UAV<br>Multispectral imaging<br>Machine learning | Dry biomass | ANN—regression | $R^2$ = 0.89–0.93 | No | United States | (Zheng et al., 2022) |
| | Strawberry | High resolution imaging | Canopy delineation and metrics | Multiple linear regression | $R^2$ = 0.76–0.77 | No | United States | (Abd-Elrahman et al., 2020) |
| | Strawberry | Multispectral images<br>Machine learning | Crop productivity (fruit weight, number of fruits and leaves) | SVM | 84%–98% | No | Brazil | (Oliveira et al., 2023) |

*(Continued)*

TABLE 2 Continued

| Application | Crop | Technology | Assessment | Statistical method to assess accuracy | Accuracy | Deployment | Country | Reference |
|---|---|---|---|---|---|---|---|---|
| | Juniper | UAV<br>RGB imagery<br>Multispectral imagery<br>Machine learning | Density and canopy cover | SVM—classification | 77%–81% | No | United States | (Durfee et al., 2019) |
| **Abiotic stress** | Blueberry | UAV<br>Hyperspectral imaging<br>Machine learning | Water stress | Random forest—classification | $R^2$ = 0.62 | No | United States | (Chan et al., 2021) |
| | Blueberry | Hyperspectral imaging<br>Machine learning | Frost damage | PLS discriminant—classification | Sensitivity: >0.80<br>Specificity: >0.75 | No | United States | (Gao et al., 2019) |
| | Blueberry | Hyperspectral imaging | Frost damage | Linear regression | 64%–82% | No | United States | (Gao et al., 2021) |
| | Strawberry | Hyperspectral imaging<br>Machine learning | Heat stress<br>Water stress | Random forest—classification | 94% | No | Republic of Korea | (Poobalasubramanian et al., 2022) |
| **Biotic stress** | Strawberry | IoT<br>Proximal sensors<br>Computer vision<br>Deep learning | Disease detection | CNN | 92% | No | Brazil | (Cruz et al., 2022) |
| | Strawberry | RGB imaging<br>Deep learning | Disease detection | CNN | 98%–100% | No | Taiwan | (Xiao et al., 2020) |
| | Strawberry | RGB imaging<br>Deep learning | Disease detection | CNN | Precision: >0.68 | No | NR | (Lee et al., 2022) |
| | Strawberry | Machine vision<br>Machine learning | Powdery mildew detection | ANN | 85%–98% | 85%–88% | Canada | (Mahmud et al., 2020) |
| | Blueberry | RGB imaging<br>Machine learning | Septoria spot detection | SVM—classification | Precision: 0.95 | No | NR | (Latha and Jaya, 2019) |
| | Blueberry | Hyperspectral imaging | Disease detection | PLS discriminant—classification | 99%–100% | No | NR | (Huang et al., 2020) |
| **Fruit yield and quality** | Strawberry | UAV<br>High-resolution orthoimages<br>Deep learning | Yield prediction | Region-based CNN | Precision: 0.72–0.83 | 84.1% | United States | (Chen et al., 2019b) |
| | Strawberry | Hyperspectral imaging<br>Machine learning | Quality traits prediction | PLS—regression<br>SVM—regression<br>Locally weighted regression (LWR) | PLS: 0.72–0.92<br>SVM: 0.66–0.84<br>LWR: 0.78–0.94 | No | China | (Weng et al., 2020) |
| | Blueberry | 3D imaging<br>Computer vision | Number of fruits<br>Maturity | Mask Region-based CNN<br>Linear regression | Number of fruits: 97.3%<br>Maturity: R = 0.91 | No | United States | (Ni et al., 2021) |
| | Blueberry | Hyperspectral imaging<br>Machine learning | Maturity | Spectral angle mapping (SAM)<br>Multinomial logistic | SAM: 82.1%<br>MLR: 88.5%<br>CT: 89.8% | No | China | (Ma et al., 2019) |

*(Continued)*

TABLE 2 Continued

| Application | Crop | Technology | Assessment | Statistical method to assess accuracy | Accuracy | Deployment | Country | Reference |
|---|---|---|---|---|---|---|---|---|
| | | | | regression (MLR) Classification tree (CT) | | | | |
| | Raspberry | Satellite imaging Deep learning | Yield prediction | Voting regressor ensemble | $R^2$ = 0.78 | No | NR | (Chaudhary et al., 2021) |

NR, not reported; ANOVA, analysis of variance; R, correlation coefficient; $R^2$, determination coefficient; LDA, linear discriminant analysis; SVM, support vector machine; ANN, artificial neural networks; e-nose, electronic nose; KNN, k-nearest neighbors; CNN, convolutional neural networks; MLP, multilayer perceptron; UAV, unmanned aerial vehicle; HSV, hue saturation value; RGB, red, green, and blue; PLS, partial least squares; IoT, internet of things.

have detailed knowledge of the physical and biological processes affecting particular crops and their effects on the fruit yield and fruit quality traits required.

Growers should also be aware of the realistic steps involved in the production of AI models and the level of dependence for the maintenance and modification of the models implemented. Currently, these services are offered by several digital and AI agricultural companies, which makes access to specific models complex and accompanied by the risk that applicability may not be the most efficient for particular grower conditions. However, this last bottleneck could be solved in the next decade since high-ranking educational institutions and universities are offering more and more agricultural science and agronomy educational programs that incorporate digital agriculture principles and specific training on digital technologies, sensors, and remote sensing platforms, including data analysis using AI and decision-making automation through the use of digital twins (Ahmad et al., 2022).

Finally, one of the most common bottlenecks for AI technology adoption by growers has historically been the ownership of data. Even before full-scale research on AI modeling strategies for horticulture and other digital technologies was conducted, data ownership was a concern for PA from the mid-1980s. However, it has been proposed that this issue can be solved by treating data as currency through blockchain technology and implementing a digital ledger that will allow growers to know how the data obtained from their orchards have been used and who is using them, to grant permissions and relevant rights through licenses, and to obtain royalties (Fuentes and Gago, 2022).

There is a growing interest in the use of drones and computer vision as aids to monitor farm conditions and to support management strategies to increase the quality traits of produce. These have been developed and offered by either researchers or external companies such as Blue River Technology, Ilumina, and Trace Genomics based in California, United States, for famers, and these technologies have contributed to farmers obtaining higher yields and achieving higher-quality production (Walch, 2019; USM, 2022). The latter applications, using digital technologies and remote sensing, are collectively known as Agriculture 4.0. Currently, the implementation of AI in agriculture in the form of data handling and modeling using machine/deep learning has been successful in enabling farmers to handle large amounts of historical and real-time data (big data), such as those on weather information, soil conditions, and water usage (among other management strategies), which have aided in their timely decision-making. Farmers have also been using AI in Precision Agriculture for pests and diseases, nutrition needs detection, and management strategies. Precision Agriculture is considered an advancement on Agriculture 4.0, and combining AI with digital agriculture has advanced the terminology to Agriculture 5.0 (Fuentes et al., 2023).

The implementation of AI in the future could be ubiquitous and necessary to deal with an increased amount of data produced by new and emerging digital sensor technologies applied to the horticulture and agrifood sectors. This could be the case for producing horticultural crops using vertical farming systems, in which fully controlled conditions can be simulated using digital twins to manipulate the phenotype and genotype plasticity of different crops to vary fruit quality traits (Kugler, 2022; Siregar et al., 2022). These technologies and AI applications can not only decrease world hunger by increasing the efficiency needed to handle the growing demand for food based on the forecasted population growth (Revanth, 2019), maximizing fruit production efficiency and minimizing food waste and the environmental footprint associated with food production, but also be the basis for food production outside Earth. For long-term space missions, such as the NASA Artemis program from Earth to the Moon (by 2030) and from the Moon to Mars (by 2040), the use of advanced biological and genetic technologies will be required if plants are to be grown in space. Food, beverages, materials, and pharmaceuticals should then be produced using AI digital twins developed using research based on the experience of Agriculture 5.0. The latter plan may seem extremely futuristic; however, these are the current aims of the Australian Research Council (ARC) Centre of Excellence in Plants for Space with the University of Melbourne, Australia, as one of the five Australian universities with more than 38 additional partners, including international universities and space agencies (e.g., Australian Space Agency and NASA), and companies such as Axiom (ARC, 2022).

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