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Smart horticulture: Integrating AI, IoT and precision farming

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Abstract

Smart horticulture employs Internet of Things (IoT) sensors, artificial intelligence (AI) and precision farming technology to maximize plant development. Growers employ networks of smart sensors in the field and greenhouse to capture real-time data streams (monitoring soil conditions, microclimate and crop health). This data is analyzed by AI algorithms and data analytics systems to identify illnesses, predict yields and offer decision-support insights. Precision agricultural solutions (variable-rate irrigation, targeted spraying, robotic harvesting) then provide inputs just where required, decreasing waste. The paper elaborates on the history of development of horticulture technology, critical AI and IoT approaches (machine learning models, computer vision, sensor networks, etc.) and common precision approaches (GPS guidance, controlled settings, etc.). We review current case studies and applications in diverse crop systems and locales and provide the results obtained. Finally, we discuss obstacles (cost, connection, data privacy) and ethical/sustainability issues (environmental footprint, equality, labor consequences). Smart horticulture is a promising approach to increase productivity and efficiency of resource use, but to realize its advantages it has to be carefully implemented and supported by enabling frameworks.

Keywords: Sensors, analysed, vision, labour, application, IOT

Introduction

Horticulture, the production of fruits, vegetables and ornamentals, is an important part of world agriculture. With people expanding and the environment becoming more variable, horticulture production will need to become more efficient and robust ^[1, 2]. The answer is Smart Technologies. Growers may combine Internet of Things (IoT) networks with artificial intelligence (AI) and precision farming techniques to monitor plant health in real-time and make data-driven choices. Moisture, nutrients, light and other characteristics are measured using soil and plant sensors ^[3]. Aerial observations of crop vitality are obtained via drone and satellite photography. The AI algorithms feed on this data to estimate yield, spot pests or illnesses at an early stage and prescribe the best course of action. Precision irrigation and fertilization systems then direct inputs to the zones that require them the most. This translates to increased yields and quality with less water, fertilizer and pesticides ^[4].

The notion of "smart horticulture" is based on the principles of precision agriculture and controlled-environment agriculture. These are extended to specialized high-value crops and the emphasis is on whole-system integration ^[5]. Instead of blanket applications of water or agrochemicals, inputs are customized according to plant demands, field by field. Digital solutions help farms plan crop rotations, manage labour and connect to supplier chains ^[6]. In recent years, smart agricultural experiments and deployments have been supported by governments and business. In our evaluation, we bring together the technical parts (AI algorithms, IoT hardware, precision tools) and the practical experiences of their use ^[7]. We discuss technical breakthroughs in horticulture, define the methodologies and structures used and provide illustrated case studies from throughout the globe. Finally, we discuss the limits, such as economic, social and ethical considerations, to present a holistic view of the smart horticulture scenario ^[8].

The modernization of horticulture has been a slow process throughout the ages. In the 19th century, the first glass greenhouses were built, allowing exact control of the environment (temperature, humidity) to enable exotic crops to be grown all year round [107, 9]. In general agricultural machinery (tractors, tillers) was introduced in the 20th century and in big commercial greenhouses temperature control systems were introduced by mid-century [108]. Early computer usage came into farm management (for record keeping and rudimentary automation) in the 1970s and 1980s [10]. Satellite remote sensing started in the 1970s with the introduction of Landsat and produced large-scale crop images. Accurate field mapping became possible with the invention of the Global Positioning System (GPS) in 1972 (first satellite) and its release for public usage in the 1990s. Farmers began utilizing GPS-guided tractors for straight-line ploughing and harvesting from 1995 [11, 105]. Precision agriculture arose in the 1990s and 2000s, targeting soil variability and yield mapping utilizing sensors coupled with GPS for site-specific management. Some inputs may be spatially adjusted with the use of yield monitors on combines and variable rate applicators [12]. However, these early devices were costly and were used only on big farms [106]. Automated climate controls in greenhouses became increasingly prevalent in Europe and Japan in the late 20th century [13]. Timers and basic feedback loops controlled temperature, ventilation and watering, especially in horticulture [14]. The integration of digital technology speeded up in the 21st century. Internet connectivity everywhere and inexpensive devices propelled IoT implementations in agriculture. Since 2010 crop scouting has been done using multi-spectral drones and machine learning [15]. Affordable microcontrollers (Arduino, Raspberry Pi) and wireless networks (Wi-Fi, LoRaWAN, cellular) made possible dense sensor networks even in rural regions. Meanwhile, AI methods (deep learning, computer vision) made achievements, enabling rapid detection of plant diseases and weeds from images. In the 2010s, all

these improvements were consolidated under the banner of “smart farming” [104, 16].

AI Methods in Horticulture

In horticulture, artificial intelligence (AI) provides the capacity to identify patterns and make predictions. In practice, machine learning algorithms may be trained on vast amounts of data on weather, soil and plants to recognize symptoms of illness, estimate yields or predict the need for resources. Image analysis [17]. Deep learning is a subfield of artificial intelligence that commonly uses neural networks, especially convolutional neural networks, or CNNs. For example, a CNN may be trained to distinguish between healthy plants and plants with fungal infections by employing thousands of labelled leaf images [18]. Another deep model is a recurrent neural network (RNN) or LSTM which may be used to predict crop growth or irrigation needs over time based on sequential data such as daily weather and soil moisture readings. These artificial intelligence systems can analyze far more information than human scouts and they do it with a high degree of accuracy. Vision is greatly supplemented by other algorithms [19, 100, 102]. The categorization of soil quality or plant stress levels may be done using support vector machines (SVMs) and random forest classifiers. These approaches investigate numerical sensor data, such nutrition levels, pH levels [20]. For guiding zone management, clustering methods like as k-means may be used to cluster parts of a field according to similarities in soil or yield data. Optimization approaches like as genetic algorithms are used to schedule irrigation and fertilization in order to get the best efficiency feasible [21]. Uncertain situations are commonly handled in greenhouses by embedding fuzzy logic controllers. For example, "if the humidity is high and the temperature is moderate, then open vents". Reinforcement learning, a kind of artificial intelligence in which agents learn by trial and error, is being explored for autonomous greenhouse temperature control or drone flight planning [103, 22].

Table 1: AI Methods and Horticulture Use-Cases [23, 24, 25, 26, 27, 28, 29]

AI Method/Algorithm	Horticulture Use-Case
Convolutional Neural Network (CNN)	Image-based disease and pest detection; fruit and flower recognition; weed identification
Recurrent Neural Network (RNN, LSTM)	Time-series forecasting of yield, weather and irrigation needs
Support Vector Machine (SVM)	Classification of plant health status or crop variety from sensor data
Random Forest (RF)	Crop yield and quality prediction; soil or disease classification
K-Nearest Neighbors (KNN)	Soil type classification; similarity-based detection of crop anomalies
K-Means Clustering	Grouping fields by soil or moisture zones; identifying clusters of disease outbreaks
Genetic Algorithm	Optimizing irrigation and fertilization schedules; resource allocation
Fuzzy Logic Control	Greenhouse climate and irrigation control under uncertain conditions
Reinforcement Learning	Adaptive irrigation control and autonomous navigation for field robots
Bayesian Network	Probabilistic risk assessment of disease or pest outbreaks
Principal Component Analysis (PCA)	Dimensionality reduction for hyperspectral image analysis

IoT Architectures and Sensors

In horticulture, artificial intelligence (AI) provides the capacity to identify patterns and make predictions. In practice, machine learning algorithms may be trained on vast amounts of data on weather, soil and plants to recognize symptoms of illness, estimate yields or predict the need for resources. Image analysis [100, 30]. Deep learning is a subfield of artificial intelligence that commonly uses neural networks, especially convolutional neural networks, or CNNs. For example, a CNN may be trained to distinguish between healthy plants and plants with fungal infections by employing thousands of labelled leaf images [31]. Another

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Table 2: Sensors and Specifications [36, 37, 38, 39, 40, 41, 42]

Sensor Type	Parameter Measured	Technology/Principle	Typical Range/Specs
Soil Moisture Sensor (Dielectric/TDR)	Volumetric water content	Capacitive dielectric or TDR probe	0-100% VWC; ± 1 -3% accuracy
Soil Temperature Sensor	Soil temperature	Thermistor or thermocouple	-40 °C to + 80 °C; ± 0.1 -0.5 °C
Soil pH Sensor	Soil acidity (pH)	Glass electrode or ISFET probe	pH 0-14; ± 0.1 -0.2 pH
Soil EC (Salinity) Sensor	Electrical conductivity	Conductivity probe	0-20 dS/m (0-20000 μ S/cm); ± 2 %
Soil Nutrient Sensor (N, P, K)	Soil nutrient levels	Ion-selective electrode or optical sensor	0-5000 mg/L; ± 5 -10%
Air Temperature Sensor	Ambient temperature	Digital thermistor/RTD	-40 °C to + 85 °C; ± 0.3 °C
Humidity Sensor	Relative humidity	Capacitive hygrometer	0-100% RH; ± 2 %
Barometric Pressure Sensor	Atmospheric pressure	MEMS pressure sensor	300-1100 hPa; ± 1 hPa
CO ₂ Sensor (NDIR)	CO ₂ concentration	Non-dispersive infrared (NDIR) sensor	0-5000 ppm; $\pm (30 \text{ ppm} + 3\%)$
VOC (Air Quality) Sensor	Volatile organic compounds	Metal-oxide semiconductor sensor	0-1000 ppb (approx. index)
PAR Light Sensor	Photosynthetically active radiation	Silicon photodiode (400-700 nm)	0-2000 $\mu\text{mol}\cdot\text{m}^{-2}\cdot\text{s}^{-1}$; ± 5 %
Lux (Illuminance) Sensor	Illuminance (light intensity)	Photodiode or light-dependent resistor	0-100, 000 lux
RGB Camera	Visible-spectrum imaging	CMOS/CCD camera module	~ 5 -20 MP resolution; color imagery
Multispectral Camera	Multi-band reflectance imaging	Multi-sensor array (e.g. Red, Green, Blue, NIR bands)	450-900 nm; 4-8 spectral bands
GNSS Receiver	Geolocation (GPS)	GNSS module (GPS/GLONASS)	± 2 -10 m (consumer); < 1 m (with RTK)
Rain Gauge	Rainfall (precipitation)	Tipping-bucket or optical sensor	0-300 mm; 0.2 mm resolution
Wind Sensor (Anemometer)	Wind speed/direction	Ultrasonic or cup anemometer	0-60 m/s; ± 0.5 m/s
Soil Tensiometer	Soil water tension (matric potential)	Porous ceramic tube with pressure transducer	0-100 kPa; measures matric potential

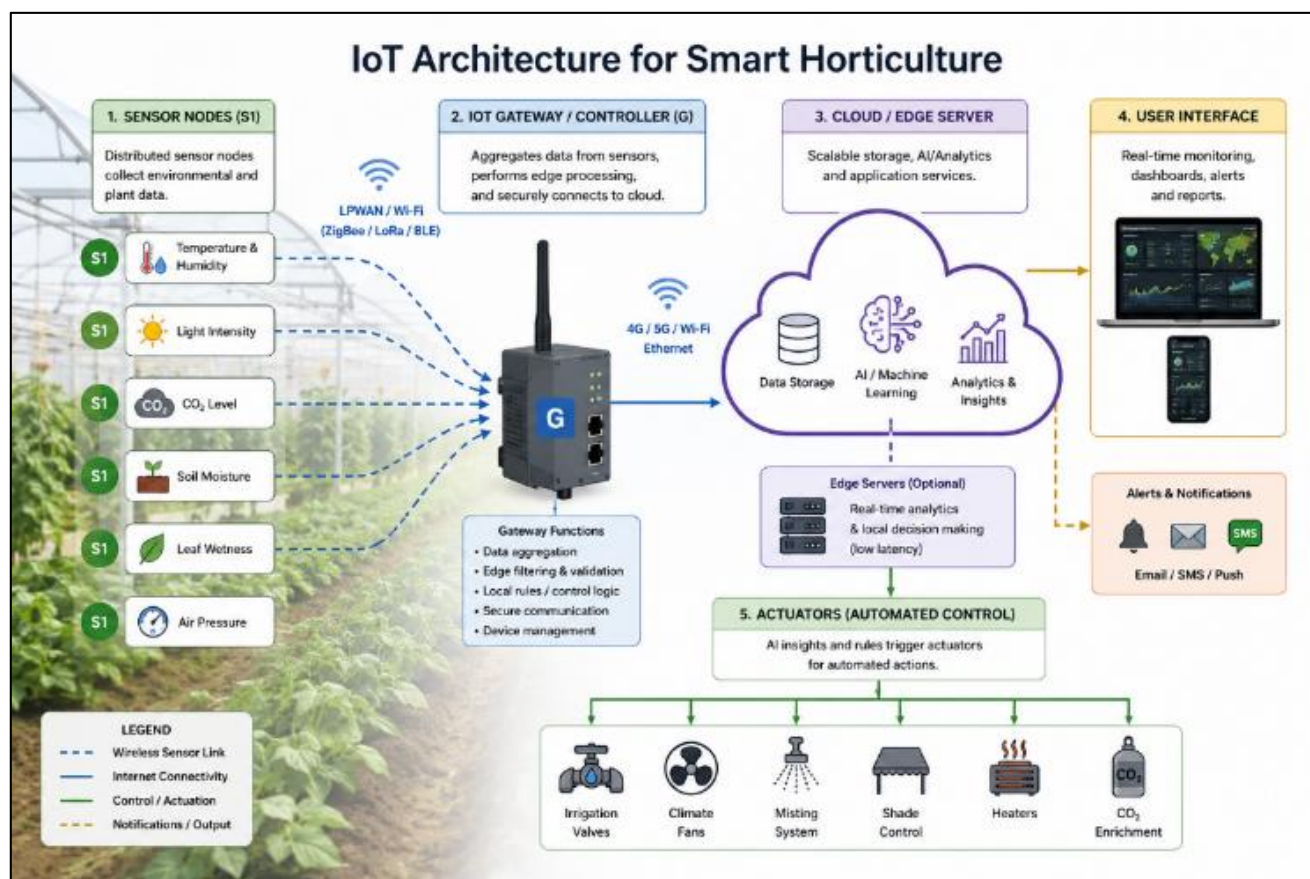


Fig 1: IOT architecture for smart horticulture

Precision Farming Techniques

In the actual world, precision farming approaches are used to control inputs on a very tiny scale for the purpose of experimenting with artificial intelligence and the Internet of Things. Precise treatments usually include irrigation, application of fertilizer and control of insects in horticulture. For example, the variable-rate irrigation approach uses information from soil moisture sensors or models to change flow rates on a zone-by-zone basis [96, 43]. A drip irrigation system disconnects itself automatically when sensors in the soil indicate that there is enough moisture and saves water. Another kind of fertilizing is called variable-rate fertilization, when the fertilizer is put on certain regions of the plant and is not equally spread throughout the whole plant [44]. The quantity of chemicals required may be decreased by 15-30% and yields can be maintained or even enhanced. Another approach is to spray pesticides accurately. Only the contaminated areas are dealt with, either using ground sensors or drone pictures. Vision systems may achieve substantial cuts in pesticide use with

the help of spot sprayers [45, 97]. The greenhouse temperature control system is a high precision technology which controls actuators (fans, vents, heaters and LED lights) precisely according to the sensor readings in real time. The system has precise actuator control. Modern greenhouses can maintain optimum levels of temperature, humidity, CO₂ levels and light cycles required for each stage of crop growth [46]. When this happens, the quantity of energy needed to create better quality food is less. Examples of the accuracy of architectural design include technologies that don't require soil such as hydroponics and aeroponics and vertical farming. In such tightly controlled and regulated conditions, every nutrient and water intake is tracked and saved for future use [48]. Further reduction of waste consumption is achieved in tuned-spectrum LED systems. In addition, a case study in Japan found that leafy greens had the ability to produce ten to twenty times more per square meter than open fields, using around ninety percent less water [98, 49].

Table 3: Precision Farming Interventions and Outcomes [50, 51, 52, 53, 54, 55, 56, 94, 95]

Intervention/Technique	Outcomes/Benefits
Sensor-driven Drip Irrigation	30-50% water savings; stable or increased yields; reduced plant stress
Variable-Rate Fertilizer Application	15-30% fertilizer savings; improved nutrient use efficiency; higher yields
Targeted Pesticide Spraying (Spot Spraying)	Up to 90% reduction in pesticide use; effective pest control; lower runoff
UAV Crop Monitoring & Spraying	Early stress/disease detection; timely intervention; ~10-15% yield boost
Autonomous Weeding Robots	50-80% reduction in herbicide use; labor savings; maintained yields
Automated Greenhouse Climate Control	Consistent high yields; 20-30% energy and water savings; uniform quality
Vertical Farming (Hydroponics/Aeroponics)	10-20× yield per area; ~90% less water use; year-round production
Satellite/NDVI-Guided Field Zoning	Optimized inputs by zone; 5-20% yield increase through site-specific management
Smart Fertigation Systems	10-30% fertilizer savings; more uniform nutrient delivery; healthier crops
Weather-Integrated Irrigation Scheduling	10-20% water savings; reduced disease risk; better timing of operations
Digital Twin Crop Modeling	Scenario planning; resource optimization; ~5-10% overall performance gains

Data Analytics and Decision Support

Collecting data is just half the battle. The aim is to make it actionable information. Horticulture data analytics is the filtering, storage and modelling of agricultural data. Time series databases hold sensor values (soil moisture, temperature, etc.) every minute, whereas image repositories are for pictures, multispectral images, etc. [92, 93, 57]. Some farms employ analytics pipelines operated on cloud services or even on premise computers, however big data solutions (like Hadoop or Spark) may be used for large scale analysis. These analytics rely on machine learning models (as described). Regression models might estimate tomato production as a function of cumulative heat units and water applied. Unsupervised learning might uncover new pest patterns [58]. Decision support systems may rate risks (eg. chance of frost occurrence) or recommend actions (best harvest timing). Usually all of this is supplied via a dashboard or mobile app. The farmer may examine maps of the moisture levels in his fields, graphs of the predicted yield and automatic notifications like 'pump failure identified at sensor' [59]. More advanced systems may use digital twins of farms, which are computer simulations that replicate plant development and the flow of resources. Growers may virtually tweak model inputs to predict results before real-world modifications are made [60]. The use of Geographic Information Systems (GIS) for visualisation of spatial data (e.g. yield maps) some systems provide collaborative tools that enable agronomists and farmers to exchange findings, for instance. Ultimately, the decision-support layer takes sensor noise and converts it into

suggestions about when to irrigate, when to sample or where to send a scout team [91, 61, 62]. In practical analytics, external data sources (weather predictions, market pricing, etc.) are commonly combined with field data for optimal planning. If a dry week is expected, for example, the system could irrigate deeper in anticipation [63]. If a vegetable exhibits an unexpected increase in market demand, AI may alter the fertilization towards more sugar. This degree of integration demands powerful software frameworks, which are already provided by many IoT platforms as part of their service (dashboards, machine learning toolkits, APIs for linking diverse data sources, etc.) [64, 65].

Case Studies and Applications

There are many of real-world instances of smart gardening. In a high-tech tomato greenhouse in the Netherlands, more than 3, 000 sensors are linked together via a fiber network. These inputs operate automated vents, blinds and LED light panels [66]. The outcome is constant harvests that utilize 20-30% less energy and water than conventional greenhouses. Dutch vegetable growers are also scouting fields using drone images and AI, allowing them to discover nutrient deficits or insect hotspots before they become a problem [90, 67]. Similarly, in California's wine area, sensors assess vine water stress and microclimate. Precision irrigation extends grape maturity and enhances quality that translates to higher-value wine [68]. Asia has experienced success with vertical farming and automated greenhouses. Singapore's lettuce vertical farm utilizes AI to modulate the LED spectrum and nutritional mixtures to grow consistent heads

all year round. These farms can produce up to 300 cycles of lettuce a year, compared to 12-15 cycles outdoors, reports reveal^[69]. Startups in India have fitted out orchards with IoT kits. Using soil-moisture and weather sensors, farmers can now irrigate mango trees just when required, halving their water use without losing any output. In Japan, there's an experimental smart orchard where robots pollinate and transport small sprayers, keeping the orchard organic with very little human effort^[70]. Agtech businesses have also created some remarkable initiatives. The Autonomous Greenhouse Challenge (Belgium) is a challenge where teams use AI to optimize agricultural productivity in greenhouses^[71]. Teams achieved 10 to 20 percent output increases using machine vision to monitor tomato blossom growth and alter inputs appropriately. Software systems like Microsoft Azure Farm Beats have aggregated IoT data from thousands of smallholder farms throughout Africa, helping to improve local crop recommendations. In the supply chain, corporations such as IBM and Walmart are trailing blockchain monitoring for product to ensure quality and reduce waste^[72].

Examples range from industrial farms worth many billions of dollars to greenhouses kept by hobbyists. A small vineyard may acquire a drone and an online analysis service for a total of \$5, 000, while a huge melon exporter would deploy a comprehensive temperature control and sensor network for hundreds of thousands of dollars. What they have in common is a quantifiable impact: case studies that have been documented generally claim reductions of 10-30% in water/pesticide consumption and corresponding percentage gains in yield or quality (depending on crop and context)^[73, 74].

Ethical and Sustainability Considerations

Smart horticulture raises new ethical and environmental concerns. Clearly, using water and chemicals precisely is good for the environment, since it decreases runoff and conserves resources. This is the good side of the issue^[75]. Smart farms include the use of renewable energy sources (e.g., solar powered sensors) and adoption of eco-friendly methods. It is feasible to avoid transforming natural ecosystems into new fields by increasing yields on farmland that is already in existence. On the opposite side of the coin, there are societal issues^[87, 89, 76]. Data of farmers including soil parameters, production records and financial data are integrated using cloud platforms. May it be that corporations or insurance firms may use it to their advantage for the farmer? To protect trust, establishing clear data governance and fair business models will be critical^[77, 78, 86]. There's also the problem of equity. Larger, more successful organizations are more likely to adopt clever technology, which might potentially widen the gap between them and smaller, more modest enterprises. This might have implications for the safety of the food supply. While work continues to develop low-cost, scalable Internet of Things solutions, equitable access remains a target^[79, 80]. And labour is affected. Automation (robots picking fruit, drones spraying fields) may help to ease labor shortages, but it may also lead to the displacement of some jobs. In horticulture the net effect is complex^[81]. Many systems are designed to deal with jobs that are difficult for human workers to perform (heavy lifting in greenhouses for example) but constant monitoring is necessary to ensure that workforce transitions (training in new skills) are supported^[82].

Considering the ethical implications of artificial intelligence, it is vital to eliminate biases in models, such as the propensity to misdiagnose diseases on certain crop types. AI assessments should be transparent and understandable, so that growers can trust the AI's ideas. Finally, the energy footprint of data centers and the consistent connectivity impact the environment; optimizing algorithms for energy efficiency is a growing focus of research^[83, 84, 85].

Conclusion

Smart horticulture is an attempt to blend digital technology with the study of plants in order to get the best potential results. Internet of Things (IoT) sensors, artificial intelligence analytics and precision farming equipment together may significantly increase the efficiency and sustainability of agricultural production. "This is a great opportunity for farmers. This study shows that these technologies have seen a quick maturity process in the recent decade, i.e. they have progressed from the level of experimental trials to the stage of commercial applications. There are several case studies that have shown the benefits of this approach, such as higher yields, lower inputs and improved resource conservation. These benefits are illustrated. Nevertheless, it is necessary to overcome non-technical challenges to achieve a successful deployment. This includes ensuring that the technology is priced fairly, putting in place digital infrastructure and training users. Dealing with ethical issues with data and equality is also an important aspect of the process. In the future, developments like as edge computing, 5G connectivity and more sophisticated robots are expected to provide further push to smart horticulture. There is potential for artificial intelligence to double advantages when utilized in conjunction with other technologies such as gene-edited crops or innovative phenotyping method. In conclusion, smart horticulture is well positioned to become an integral aspect of agriculture in the next years. Looking beyond the present state of the art, the history of agricultural technology development suggests a larger drive toward the development of technologically sophisticated and environmentally responsible food systems. If these systems become more prevalent, they have the potential to contribute in feeding a higher population while consuming fewer resources and having a lower effect to the environment. That would be good for environment. Continuing research, verifying it in the field and carefully deliberating on laws will be the most crucial stages to fully achieving its potential.

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