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# 3. Digital Agriculture: Technologies and Innovations

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***Abstract:***

*Digital Horticulture, technologies have significantly transformed horticulture, changing traditional crop management and monitoring methods. This chapter reviewed the substantial impact of these advancements on enhancing crop production, resource management, and monitoring practices. It covers a variety of innovative tools, including drones, satellites for remote sensing, IoT-based sensors, and sophisticated data analytics powered by artificial intelligence. These technologies facilitate precision irrigation, remote crop health monitoring, automated harvesting, and smart pest and disease detection. Their integration has led to better resource efficiency, increased crop yields, economic benefits, and more sustainable agricultural practices. Nevertheless, challenges such as technological barriers, costs, data security issues, and integration difficulties with traditional agricultural systems remain. Real-world case studies illustrate successful implementations, showcasing both the potential and the complexities of integrating digital farming into horticulture. The review also examines future prospects and emerging trends, indicating a major shift in agricultural practices.*

*The transformative potential of digital farming in horticulture is highlighted, along with its various impacts and policy implications. This study emphasizes the need for further research, adaptation, and regulatory frameworks to fully realize the benefits and address the challenges of incorporating digital technologies in horticultural practices. Ultimately, the paper envisions a technologically advanced agricultural landscape, leading to sustainable, efficient, and data-driven horticulture.*

***Keywords:***

*Artificial intelligence, Digital horticulture, Global Positioning System, Integrated Pest Management, Remote sensing.*

## 3.1 Introduction:

### 3.1.1 Digital Horticulture:

Horticulture is acknowledged as a sunrise sector, significantly contributing to doubling farmers' incomes and ensuring nutritional security. This sector has the potential to increase farm income, provide livelihood security, and generate foreign exchange through exports (Sunanda *et al.*, 2024). According to the Agriculture Ministry, the current Gross Value Added (GVA) is 33%, which marks a significant and notable impact on the Indian economy. The horticulture sector encompasses a variety of crops including fruits, vegetables, spices, medicinal plants, plantation crops, ornamental plants, mushrooms, and tuber crops. From the pre-independence period up until the Eighth Five-Year Plan, this sector did not receive significant attention, as the primary focus was on food security and poverty alleviation **(**Satisha *et al.*, 2023**).** In 2021-22, the total horticulture production was around 341.63 million tonnes, with fruit production at around 107.10 million tones and vegetable production at around 204.61 million tonnes. India's horticulture output is projected to reach an unprecedented 350.87 million tonnes in the current crop year (July 2022-June 2023), with notable increases in the production of fruits, vegetables, spices, and plantation crops (Singh et al., 2023). Historically, the growth rate of horticultural crop production has averaged 2.7% per year (Sengar et al., 2020). Currently, the global population exceeds 6 billion, with developing countries experiencing relatively rapid population growth at an annual rate of 1.2%. In contrast, populations in industrialized countries are expected to grow more slowly, at 0.3% annually until 2030 and 0.2% annually until 2050 (Motes et al., 2010).

Advancements in science and technology, along with global urbanization, are the primary drivers shaping the direction and development of agriculture. Agriculture has undergone significant changes over the years, and in 2024, both old and new systems exhibit notable differences in various aspects. These include advanced farming methods, the adoption of precision agriculture using GPS, drones, and IoT devices, and mechanization with modern machinery for efficient ploughing, planting, and harvesting. There is also the use of synthetic fertilizers and genetically modified crops for higher yields, crop diversification with an emphasis on high-value and cash crops, and integrated pest management (IPM) techniques. Additionally, the utility of farm machinery in cropping, harvesting, and storage strategies has improved. As time passes, digital agriculture has come into existence, taking the Indian agricultural system to a new era.

The rapid advancement of digital technology is causing revolutionary shifts in a number of fields, including horticultural sciences. Although shifting from old era to digital mode of application was not smooth, it was inevitable. Recent advancements in horticultural science technologies have established an ecosystem of digital innovations, including indoor vertical farming, remote sensing, drone sciences, embodied digital technologies, Internet of Things (IoT) interventions, artificial intelligence (AI) implementation, information and communication technologies, blockchain technology (BCT), big data analytics and nuclear technology. These technologies are transforming the field dramatically. They are now being utilized by commercial farms, small industrial units, and individual horticulture or nursery science enthusiasts, on both small and large scales, depending on the infrastructural facilities available in their regions. This chapter aims to provide mechanistic insights into various digital tools and techniques in horticultural sciences, stimulating scientific curiosity among researchers based on these observations.

### 3.1.2 Artificial intelligence (AI) in horticulture: Current approaches.

Artificial intelligence (AI) involves creating machines that mimic human intelligence and behavior, achieving human-like performance in cognitive tasks through logical reasoning. AI has broad applications in horticulture, such as disease detection, yield enhancement, weed control, nutrient detection, and fertilizer management. Machine learning, a subset of AI, uses data to make rapid, efficient decisions. An AI-based automatic method has been developed to determine the ripeness of fruits and vegetables using computer vision and machine learning algorithms. AI effectively tracks information and provides precise solutions to problems. The digital transformation in agriculture and horticulture offers significant potential for both producers and consumers, heralding a new era of digital agriculture, industrialization, mechanization, networking, and data management.

### 3.1.3 The development of Horticulture 1.0 to Horticulture 4.0.

Technological advancements in horticulture can be categorized into four main periods, much like those in industry. The first period, Horticulture 1.0, is the era of mechanization, marked by the introduction of tractors, which significantly boosted productivity. The second period, Horticulture 2.0, corresponds to the Green Revolution, characterized by the adoption of high-yielding varieties (HYVs), synthetic fertilizers, and pesticides, leading to rapid crop growth. Horticulture 3.0 saw the integration of computers and electronics, enhancing farm management efficiency. Currently, Horticulture 4.0 focuses on digital innovations such as sensor applications, drone technology, and real-time data analysis to optimize resource use (Ludwig-Ohm et al., 2023).

The concept of Horticulture 4.0 is not unique and can be paralleled with "Industry 4.0," which represents a transformative vision of future production. Industry 4.0 is characterized by digitized, optimized, and individualized production through automated processes, and interactions between humans and machines, as well as machine-to-machine communication, including automatic information exchange. This vision encompasses a shift from monolithic systems to more flexible and interconnected production models (Beier et al., 2023; BMBF, 2016; Kagermann et al., 2013; Lasi et al., 2014; Lucks, 2017; Vogel-Heuser et al., 2017; Horváth and Szabó, 2019; Posada et al., 2015; Roblek et al., 2016).

These technological advancements and principles are integral to the evolution of Horticulture 4.0. By viewing the field of horticulture as analogous to a factory, where plants are products and machines are production facilities, the transition becomes evident.

### 3.1.4 Digital Twins Concept in Fresh Horticultural Produce.

A digital twin of a product is a virtual representation of its real-world counterpart that (i) includes all essential elements, such as geometric components and material properties; (ii) accurately simulates all relevant processes and their kinetics throughout the product life cycle; and (iii) is connected to real product and process sensors, ideally updated continuously in real-time. This concept is also known by various other names, including digital shadow, digital mirror, virtual avatar, synchronized virtual prototype, and virtual ghost.

In the horticultural supply chain, the digital twin of horticultural products idealizes the shape, size, and structural components of the product (such as shell, seeds, and pulp). Prior to the digital age, this was referred to as virtual fruit. The digital twin also simulates, in silico, the physical, biochemical, microbiological, and physiological states of the product and its development within the cold chain, based on measured environmental conditions (such as air temperature, relative humidity, and concentration of metabolic gases).

**A Digital Twin Requires Three Elements to Function, Viz.**

i. A digital master model of the object includes the physical asset's outline, its properties, and related processes.
ii. Sensors monitor environmental parameters in real supply chains, such as air temperature, relative humidity, and the concentration of oxygen and ethylene (the ripening gaseous hormone).
iii. The connection of the digital master model to a physical asset using sensor data. This connection is crucial to the digital twin and sets it apart from standard computer models that operate independently of the real-world process. Ideally, this link is maintained in real-time, but it can also be established offline, in a sequential manner.

The connection of the digital model to the real world through identification allows the digital twin to evolve alongside its real-world counterpart throughout the post-harvest life cycle. This development varies for each individual "virtual" product, as the digital twin accounts for the unique boundary conditions faced by each product. As a result, it responds realistically to real-life changes.

Digital twins hold significant potential in post-harvest horticultural supply chains for several reasons. Each shipment experiences a unique temperature and atmospheric history due to unpredictable environmental, logistical, and socio-economic factors. Therefore, a "one-size-fits-all" approach is ineffective for maximizing shelf life. Ideally, future cold chains will enable interventions based on the quality development of fresh horticultural produce during transit. With current remote monitoring capabilities of cooling tanks (CP, 2020; Maersk, 2020), it will soon be possible to adjust inlet air temperature and ventilation settings during transportation. However, adapting to the specific needs of each shipment requires detailed, real-time information on the environmental, physical, biochemical, microbiological, and physiological conditions of the cargo. Digital twins can facilitate decision-making by evolving with each shipment, serving as an ideal tool for diagnosing potential problems and monitoring the cooling process and atmospheric conditions to prevent excessive quality degradation throughout the supply chain.

Second, sensors for real-time, wireless monitoring of environmental conditions, along with associated cloud-based software platforms for data acquisition, are already commercially available and used in fresh horticultural produce supply chains. With this essential component of digital twins already in place, the key development step is configuring the model and connecting it to the sensor data.

Third, the durations of global cold chains for fresh horticultural produce are relatively long, often taking days or weeks to transport fruits and vegetables from farm to table. This is because the processes that degrade the produce, such as cooling, moisture loss, temperature-dependent biochemical reactions, or ripening, occur slowly. This extended timeframe allows for the implementation of complex mechanical models that can be run in real time using finite elements on standard computer hardware.

Fourth, critical areas of cooling and associated quality degradation in commercial cold chains are often difficult to access with standard point sensors. For example, the center of a fruit stack or the core of an individual fruit, which typically cools the slowest, and breathing hot spots deep within the cargo are challenging to monitor. Digital twins provide the ability to remotely and unobtrusively monitor these locations, offering insights that would be difficult to obtain by examining the real-world counterpart in commercial cold chains.

## 3.2 Digital Farming Technologies in Horticulture:

### 3.2.1 Computer Vision of 2D and 3D Geometric Features:

Computer vision in horticulture is employed for various tasks, including plant classification, growth measurement, machinery inspection, pest and disease detection, and monitoring plants to assess geometric features and color attributes. Cameras are commonly used for these purposes. With the increasing availability of smartphone applications on iOS and Android operating systems, horticulture now benefits from apps that can record the location of pests or diseases (Röhrig, 2012). It is anticipated that, in the near future, software will be able to identify pests or diseases using computer vision directly from smartphones. Computer vision is advancing with the use of applications and surveillance camera systems on smartphones to manage agricultural production. Additionally, the horticultural industry is developing specialized machine applications with controlled lighting conditions. These setups often use preferred camera positions and custom software to measure manufacturing parameters for classification during production or at the point of sale. For instance, a typical sorting application might involve a two-camera system—one positioned above and the other in front of the plant—to capture up to 24 images as the plant rotates, enabling the tracking of flowers and other plant features. Parameters commonly detected by computer vision include flower count, plant volume, generative and vegetative height and width, leaf and flower color, and shoot number.

Driven by the manufacturing industry, Wageningen UR has developed a highly efficient 3D vision system (Koenderink *et al.*, 2012). The computer vision technique used is volume intersection. Techniques such as time of flight, laser triangulation or stereovision provide a depth image from only one perspective, called 2½D in computer vision. From one point of view, it is not possible to make a perfect 3D model with this technique. With volume intersection, images are taken from contrasting angles of the plant and merged into a 3D model.

Other 3D camera systems have also been implemented. Wageningen UR developed a stereovision application to detect the diameter of *Anthurium* cut flowers. This is implemented in the sorting engine. Another example is using laser triangulation to separate products on a dirty conveyor belt and using 3D data to improve quality. This is done in a chicory sorting line.

### 3.2.2 Hyper Spectral Imaging:

In addition to visible light, cameras can capture a broader spectrum, allowing for deeper insights into flowers and plants. Beyond traditional black and white or RGB (red, green, blue) cameras, multispectral cameras are equipped with sensors that detect wavelengths both within and beyond the visible spectrum. This expanded capability offers additional information about the internal properties of an object.

Multispectral cameras can have anywhere from four to 300 spectral bands, covering ranges from far infrared to far ultraviolet. In near-infrared (NIR) spectrometry, a white light beam is directed at the target, and the camera measures the transmitted or reflected light. By comparing the wavelength pattern of the product with those of known reference substances, one can determine the presence and concentration of various substances.

This can be achieved through point measurements or by assessing the entire product's characteristics. Each substance has a unique absorption pattern, enabling the determination of specific qualities such as lycopene content in tomatoes for sorting purposes. Other measurable substances include β-carotene, chlorophyll a, protein, and sugar content. Additionally, this technology can help assess the nutritional value of plants to optimize fertilization.

### 3.2.3 Fluorescence Techniques:

Chlorophyll fluorescence is measured by directing a red laser beam at the target, as chlorophyll reacts strongly to red light. A camera captures a fluorescent image, and by comparing an image taken with the red laser to one without it, you can assess the photosynthetic activity of the plant.

This method allows the sensor to detect various plant attributes, including photosynthetic capacity, maturity, shelf life, and quality of fruits, roots, and flowers. It can also identify plant stress and diseases. Technology is advancing from the use of laser beams to high-power LEDs (Jalink and van der Schoor, 2009), making measurements more affordable, faster, and more reliable.

### 3.2.4 Automated Guided Vehicles (AGVs):

Automated Guided Vehicles (AGVs) are commonly used in greenhouse farming to transport harvest wagons from central lanes to sorting and packing areas. In recent years, harvesting carts have been upgraded with motors, sensors, and advanced control systems to automate greenhouse operations. These systems are managed by central data processing, which tracks the exact location of all lifts.

Recent developments include integrating load cells with these automated carts to measure the weight of each fruit in a container, allowing for yield calculations per square meter. Workers can manually record pests and diseases using a small interface on the AGV, with this data automatically linked to the location and time of the observation. This information can be used to generate 2D maps of the greenhouse showing the distribution and evolution of pests and diseases. The next phase of development aims to include automatic detection of pests and diseases through sensors, along with their carriers, and to integrate automated spraying systems.

### 3.2.5 IoT (Internet of Things, Sensors) Devices in Horticulture:

IoT devices create interconnected systems that collect and transmit data across the farm. Devices such as weather stations and automated irrigation systems provide real-time information for efficient farm management. They optimise the use of resources such as water and energy by making decisions based on data.

### 3.2.6 Data Analytics and Artificial Intelligence in Crop Management:

Advanced algorithms process data from various sources and provide predictive models and algorithms for disease detection. AI-based tools enable informed decisions, optimise planting strategies, predict risks and improve overall crop productivity. These technologies give farmers practical knowledge to make informed decisions.

## 3.3 Research and Development Directions: Digital Horticulture.

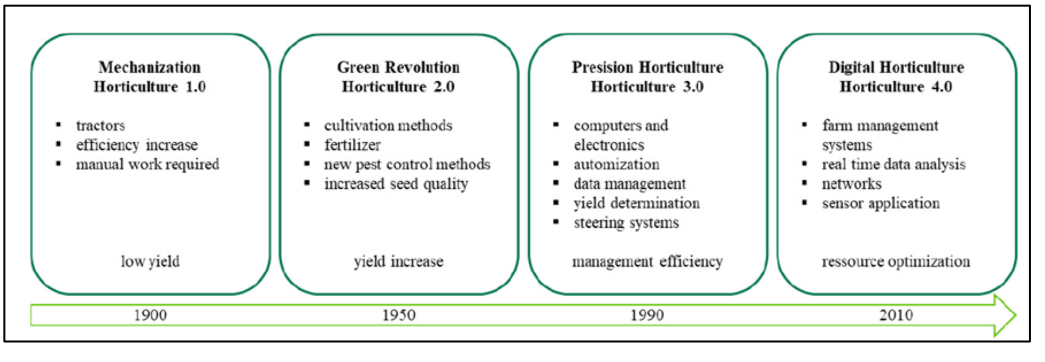


**Figure 3.1: Digital Horticulture**

**Table.3.1 Example of Some Databases Accessible and Useful for Horticultural Sector.**

| Database Name | Variables | Assessment Method | Spatial Resolution | Temporal Resolution | Remarks |
|---|---|---|---|---|---|
| **Horticultural cropping system:** | | | | | |
| Food and Agriculture Organization Corporate Statistical Database (FAOSTAT) | Production, prices, trade, harvested area etc. | One year survey | National | 1961-present | |
| Production, supply and distribution | Production and trade | One year survey | National | 1960-present | Only raisins, stone fruit and tree nuts |
| CountrySTAT and AgroMAPS | Production, prices, trade, harvested area etc. | One year survey | National and sub national | 1961-present | 31 countries data |
| Living Standards Measurement Study (LSMS) | Production, soil fertility, harvested area, labour etc. | Two to four years survey | Field to national | Irregular | 11 countries |
| Data Africa | Production, water supply, harvested area | Data compilation and model simulation | Sub national | Averaged | 13 countries |
| Global Agro-Ecological Zones (GAEZ) | Production, climate indices and yield gaps etc. | Data compilation and model simulation | 30 arc-seconds and 5 arc-minutes | Averaged | |
| EarthStat | Production, nutrient balance, harvested area | Data compilation and model simulation | ~10 km by 10 km | Averaged | 175 crops |
| **Crop species and cultivars:** | | | | | |
| HORTIVAR | Cultivar description, Production and seed sources | Observational | Points | Irregular | >70,000 technical sheets |

| Database Name | Variables | Assessment Method | Spatial Resolution | Temporal Resolution | Remarks |
|---|---|---|---|---|---|
| Agroforestry Species Switchboard (ASS) | Species description, genetics, management practices etc. | Observational | | | Repository of information to support tree research |

*Source: Sarron et al. 2021*

## 3.4 Tools for Controlling Smart Farms: The Current Problems and Prospects in Smart Horticulture.

**Current Tools Available for Smart Farming:**

### 3.4.1 Biological Sensors:

- **Water sensor:** These are integrated with wireless sensor networks (WSN) to optimize agricultural practices especially irrigation management. For sustainable farming practices, accurate soil moisture monitoring is necessary in the era of resource scarcity and climate change (Singh et al. 2011).
- **Meteorological sensors:** This plays a important role in providing timely and localized weather information. Using IoT, new system provides weather-based information to the farmers via alert through SMS or mail to the mobile, thereby enhancing the decision making and reducing the loss to the farmers making a way for the 4.0 agriculture revolution (Kumar et al. 2019).
- **Weed seekers:** This system differentiates the weeds and crops using mathematical algorithms and colour spectrum-based decision models. The advanced Trimble Weed Seeker 2, it has spot spray system that detects weeds and sprays herbicide, claiming about 90 % reduction in the herbicide application.

### 3.4.2 Optical Sensors:

- **Optical cameras:** Optical cameras, especially thermal remote sensors, they convert objects in to visible images and radiation patterns. They are mainly used for evaluating the fruit maturity, detection of pathogens, monitoring of green house and estimation of fruit yield (Ishimwe et al. 2014). Moverover, their use is increasing in drone technology to take aerial images of the large agriculture fields helping farmers in taking decision regarding irrigation, fertilization, pest and disease control, ultimately optimizing the productivity of the area. (López-Granados et al. 2016).
- **Light Detection and Ranging (LIDAR):** The use of this technology is increasing for monitoring aerosol emission, plant phenotyping and environment mapping. By integrating the LIDAR with Global Navigation Satellite System (GNSS) and Inertial Measurement Unit (IMU) sensors, environmental mapping is improved, helping agricultural operations by providing the precise data (Christiansen et al. 2017). It also

proven effective for plant phenotyping there by helping in identifying new varieties (Colaço et al. 2018).

- **Sensors for Detection of Microorganisms and Pest Management:** Agricultural production is influenced by both biotic and abiotic factors, necessitating an integrated crop management system to detect pests and diseases. This system comprises three main components: host response analysis with novel sensors, biophotonics and phage display using biosensors, and remote sensing techniques (Martinelli et al., 2015). Unmanned Aerial Vehicles (UAVs) equipped with RGB, multispectral, and advanced digital hyperspectral sensors are used for detecting and monitoring insect pests, such as grape phylloxera in vineyards. This integration supports new methodologies for remote sensing and plant pest surveillance (Vanegas et al., 2018).
- **Photometric Sensors:** These sensors use is increasing in plant monitoring and phenotyping. The PS-plant, a low cost portable 3-D platform for phenotyping was developed by using photometric sensors to increase the efficacy of plant phenotyping (Bernotas et al. 2019).
- **Soil Respiration or Moisture:** The factors like soil moisture, temperature, electrical conductivity, pH, and organic carbon, significantly impacts atmospheric $CO_2$ levels thereby influencing the soil respiration (Tona et al. 2019). Placing of sensor in optimal position is important for monitoring the soil moisture content in green house (Ryu et al. 2014). For the real time monitoring of soil moisture an IoT technology, ZigBee was invented (Zhang et al. 2017).
- **Photosynthesis Sensors:** Photosynthesis is an important physiological process that enhances the crop yield, solar energy conversion and is influenced by the climate change (Swift et al. 2018). Recent findings include the invention of FPGA based sensor. This sensor has been used to study the photosynthetic response of chilli pepper (*Capsicum annuum* L.), providing a new method to detect stress conditions and enable farmers to adjust strategies accordingly (Millan-Almaraz et al. 2013).
- **Leaf Area Index (LAI) Sensors:** Measuring the leaf area index (LAI) is valuable for projecting crop yields and making informed decisions. Ground-based laser distance sensors mounted on vehicles have proven effective for rapid LAI mapping in crops such as winter wheat, winter rye, and oilseed rape (Gebbers et al., 2011). The use of the LAINet observation system, combined with the Consistent Adjustment of the Climatology to Actual Observations (CACAO) method and Gaussian Process Regression (GPR), has demonstrated high accuracy in LAI retrievals, validated throughout an entire growing season at a cropland site in China (Yin et al., 2019).

### 3.4.3 Accelerometers

- **Rangefinders:** Laser Rangefinder sensors are useful for measuring the volume, height, biomass and optimizing the production process. The flight-time method, based on rangefinder experiments and technical data, has proven effective for specific crop management (Ehlert et al. 2009). By integrating rangefinders with a pan-tilt unit and inertial measurement unit enhances data analysis capabilities (Teng et al. 2016).
- **Dendrometers:** These are mainly used to measure the diameter of the tree, it also gives insights in to the tree growth including water status and response to environmental conditions (Drew and Downes, 2009). An IoT system, with low-cost optoelectronic sensors was developed to monitor radial growth in guava fruits, achieving a high data

transfer success rate of 97.54% and a maximum measurement error of 2 mm (Slamet et al., 2018). Additionally, the stem growth of 31 red maples in urban areas of the eastern United States was monitored using three dendrometers, confirming the utility of inexpensive band dendrometers for ecological research (Just and Frank, 2019).

- **Hygrometers:** These measure the air moisture content and can be used for detailed humidity readings like relative humidity and dew point. These sensors include relative humidity (RH) sensors, utilize various materials organic, inorganic, polymers, porous ceramics, and ceramic/polymer composites. Ceramic sensors, in particular, offer faster response times (Farahani et al., 2014). Fiber Bragg grating-based sensors for soil moisture show promise in landslide prevention (Leone et al., 2017). Furthermore, in India, the Arduino Uno board combined with FC28 Hygrometer and DHT11 sensors effectively collects and displays soil moisture, humidity, and temperature data (Bhadani and Vashisht, 2019).
- **Temperature Sensors:** These often combined with humidity sensors, are integrated into systems for real-time environmental data collection in agriculture, using IoT communication for data transfer (Kim and Oh, 2016). The new technology involves developing 3-D real time virtual sensors using computational fluid dynamics (CFD) to monitor and control greenhouse temperatures (Guzmán et al., 2018).
- **Gas Sensors:** These technologies play a major role in monitoring product quality. An electronic nose system (e-nose), equipped with a gas sensor array and gas channels, has been developed to assess product quality in agriculture, such as analyzing different fruit jams (Zhao et al., 2012). Additionally, smart packaging systems incorporate radio frequency identification (RFID) sensors, ripeness indicators, biosensors, and temperature indicators to maintain and monitor the quality and freshness of agricultural produce (Meng et al., 2014).
- **Chlorophyll Meters:** These include SPAD meters, which are essential tools for assessing the nitrogen status of crops and helps in deciding fertilizer application (Nguyen et al. 2019). The relationship between the SPAD meters readings and the nutrient content is influenced by the environmental factors and the specific crops (Xiong et al., 2015). Innovations like Google Glass applications have made chlorophyll measurement more efficient (Cortazar et al., 2015). The chlorophyll meters combined with non-destructive nitrogen estimation instruments offer information about crop health, productivity and increase the nitrogen use efficiency (Nguyen et al. 2019).

### 3.4.4 Image Sensors:

The use of Image sensors, including the thermal, RGB, and spectral sensors, play a critical role in modern agriculture for various applications such as monitoring plant health, irrigation scheduling, and yield estimation.

Thermal remote sensing can be used for greenhouse monitoring, disease detection and assessing fruits and vegetables (Ishimwe et al., 2014).

Non-destructive sensor-based methods, such as those using RGB cameras and deep convolution neural networks, have shown high accuracy in detecting plant diseases and classifying crop conditions (Mahlein, 2015; Ha et al., 2017).

### 3.5 Global Positioning System:

The use of GPS system has significantly improved the precision farming providing the site-specific information. Farmers leverage GPS to collect and map various data points such as slope, weed growth, nutrient levels, plant stress, and growth conditions using Geographical Information Systems (GIS) programs. This integration allows for the creation of comprehensive databases that benefit both farmers and scientists by enhancing data storage, management, and analysis capabilities, thereby improving decision-making and efficiency in agricultural practices (Goswami et al., 2012).

### 3.6 Current Problems and Prospects:

The integration of the advanced technologies to the agricultural practices faces many problems and opportunities. The main challenge is high initial investment required for adopting technologies like drones, sensors and automated systems, which is not feasible for farmers with small land holdings. Moreover, there is a significant knowledge gap, as many farmers are not having technical skills to use these technologies. Management and accessing of data are also important to make appropriate decisions.

On the other hand, the prospects of the digital horticulture are tremendous. These new technologies are helping farmers to take precise decisions thereby increasing the efficiency of resources. These will also help in addressing the labour shortages by automating the works. In addition, the smart horticulture will contribute to the sustainable farming practices by optimizing and reducing the wastage of the resources. As the technology continues to evolve, the adoption of these digitalized technologies may grow, offering significant benefit to the farming community by offering benefits to increase the productivity and sustainability**.**

### 3.7 Benefits and Impacts of Digital Farming in Horticulture:

1. **Automated Harvesting and Yield Estimation:** This offers as significant benefit by increasing the efficiency, precision and cost savings. Robotic harvesters, equipped with high-resolution cameras, sensors, and AI algorithms, identify and pick ripe fruits with precision, minimizing damage. The yield estimation relies on various sensors and models that effectively enhance the productivity and efficiency in horticulture.
2. **Improved Resource Efficiency:** By using the advanced technologies like IoT sensors, drones and GIS, farmers can monitor the field conditions on real time basis thereby increasing the efficiency of the resources. It reduces the water wastage and targeted application of fertilizers and insecticides reduces the impact on environment.
3. **Enhanced Crop Yield and Quality:** It is achieved by integration of advanced technologies with precise farming practices. Yields increased by data driven decision-making and remote monitoring of the crop preserves the quality and reduces the wastage of resources.
4. **Environmental Sustainability:** Digital farming conserves the soil health and minimizes the runoff and pollution by excess pesticides and fertilizers thereby, conserving the biodiversity (Vijayadeepika and Lakshmi, 2022).

## 3.8 Technological Barriers and Costs:

1. **Data Security and Privacy Concerns:** These are the important technological barriers in digital horticulture. Unauthorized access to the data may lead to the misuse such as competitive disadvantage and financial loss. Formulating the secure data sharing protocols is important.
2. **Integration and Adoption Challenges in Agriculture:** One major reason is initial investment cost to implement these technologies is very high and is not suitable for small-scale farmers. To address this barrier comprehensive approach is needed including the financial incentives, education and training (Vijayadeepika and Lakshmi, 2022).

## 3.9 Potential Impact on Future Agriculture Practices:

Digital farming holds a significant role in transforming the current agriculture system. It can increase the productivity and yields of crop by adopting the technologies like precision farming, automated machinery and data analytics. Real time monitoring of crop health and the application of inputs accordingly reduces the effective utilization of resources, reduces wastage and environmental pollution. In addition, crop quality also improves by optimal growing condition resulting in the better taste, appearance and nutritional value. Digital farming also reduces the dependency on labour, by automation and robotics. It also helps farmers to adapt to the climate change by providing advanced weather predictions. Digital platforms also bring transparency and enhance the market access thereby providing the better prices to the produce.

The integration of these digital technologies can bring innovations in the agricultural practices. Collaboration between the private sector, researchers and farmers leads to the development of new technologies that address the current problems in agriculture. Moreover, these technologies can help farmers with different size of land holdings like small farmers can adopt affordable and accessible tools like mobile apps and basic sensors and the large farmers can adopt the sophisticated technologies. Overall, digital farming helps to secure the food production and environmental health for future generations.

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