



REVIEW ARTICLE

Sustainable vegetable production through smart farming: Innovative technologies and practices

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Abstract

Smart farming is rapidly redefining agricultural practices by integrating modern technologies into conventional systems. In vegetable crop cultivation, these innovations offer context-specific solutions to improve productivity, resource-use efficiency and climate resilience. However, despite their proven potential, the adoption of smart farming in developing countries remains limited due to persistent infrastructural constraints, high initial investment costs, inadequate technical capacity, fragmented institutional support and policy gaps that hinder technology accessibility and scalability. Addressing these interconnected barriers forms the central problem addressed in this review. In contrast to studies that mainly address individual technologies or specific production systems, this review presents a comprehensive synthesis of smart farming applications across diverse vegetable cultivation systems, including greenhouse production, hydroponics, aeroponics, vertical farming and disease forecasting models. It uniquely integrates technological, socio-economic, infrastructural and policy perspectives to provide a holistic understanding of adoption challenges and opportunities. The study is organised into several key sections: it begins with an introduction to the relevance of smart farming, followed by a description of the review methodology. The core sections discuss available smart technologies and their practical applications in vegetable cultivation. Subsequent sections explore the ethical, environmental and socio-economic implications of these technologies, as well as the challenges hindering widespread adoption. The review concludes by identifying key research gaps and proposing future directions to support inclusive, scalable and sustainable implementation of smart farming practices.

Keywords: artificial intelligence; hydroponics; precision agriculture; smart farming; vegetable

Introduction

Agriculture has played a vital role, throughout history, by supplying humanity with food and raw materials. Agriculture has a major role in India's sustainable economic growth; a significant portion of the Indian population being fed by 52.3 % of available arable land (1). As reported by National Institution for Transforming India (NITI) Aayog, India's agricultural sector contributed 18.3 % to the country's Gross Domestic Product (GDP) in 2020, while also representing nearly 40 % of the total rural domestic income. Although the share of the GDP has decreased over time, agriculture's significance in India cannot be understated because two-thirds of the country's population still make their living from agriculture in rural areas (2). Even though India has achieved record production in food grains at 316 million metric tons, as per the Ministry of Agriculture's 2021–22 production estimate, the agriculture sector is facing numerous challenges. The population is growing exponentially each year,

which increases the demand for both quantity and quality of food. Rapid population growth intensifies competition for essential resources like land and water (3). The situation is exacerbated by the increased cost of cultivation, low per capita productivity, greenhouse gas emissions, inadequate soil maintenance, over usage of agrochemicals, pest and disease attacks, etc. Nowadays, climate change and natural calamities have been the biggest challenges faced by traditional farmers. Even though climate change affects all regions globally, agrarian economies such as India face more vulnerability due to their large agriculture-dependent populations (4). Another major factor of concern is the scarcity of farm labourers and limitation in the expansion of land. The Economic Survey 2017–18 revealed that by 2050, only 25.7 % of the workforce will be employed in agriculture. Consequently, modernising India's conventional agricultural systems has become imperative to enhance productivity and resource efficiency.

Smart farming has emerged as a transformative approach in agricultural practices, offering solutions to overcome limitations in conventional agricultural systems. This innovative approach operates on the principle of optimising output while minimising resource inputs. Technological integration in agricultural systems has demonstrated substantial improvements in yield per unit area of cultivated land (5). Contemporary research indicates that precision agriculture enhances occupational safety and market acceptance of agricultural products (6, 7). The implementation of smart farming methodologies presents opportunities for fundamental restructuring of farm management practices through cost reduction, operational efficiency enhancement and mitigation of environmental impacts (8–10). Modern agricultural systems employ integrated spatial technologies that generate farm-specific data, enabling analysis of agricultural operation disparities across regions. This data-driven approach facilitates informed decision-making, reduces agrochemical usage and promotes sustainable production practices (11–13). Cutting-edge agricultural technologies such as sensor networks, unmanned aerial vehicles (UAVs), geospatial information systems (GIS) and Internet of Things (IoT) platforms enable continuous monitoring of agronomic parameters, serving as data acquisition systems, while machine learning (ML) algorithms act as decision-support tools for informed farm management (14). Furthermore, these technological advancements contribute to climate change adaptation strategies and reduce the environmental footprint caused by agricultural activities (15).

This review was conducted to comprehensively analyse recent advancements in smart farming technologies as applied to vegetable crop production. A structured literature search and selection process was employed to ensure the inclusion of relevant, credible and up-to-date sources. The systematic literature review was performed by searching prominent academic databases, namely Scopus, Web of Science, Science Direct, IEEE Xplore, Springer Link and Google Scholar. The search encompassed publications from 2005 to 2025, with particular attention given to recent studies (published within the last 5 to 7 years) to capture contemporary technological advancements. The selection criteria included peer-reviewed journal articles, conference proceedings, comprehensive review papers and authoritative reports from international organisations. Full-text articles were thoroughly examined to extract pertinent data concerning smart farming technologies, including their operational mechanisms, deployment strategies, crop specific implementations and associated challenges. The extracted information was systematically categorized into key technological domains: sensor networks, IoT, GIS and Global Positioning Systems (GPS), UAVs, unmanned ground vehicles (UGVs), artificial intelligence (AI) and ML, big data analytics and decision support systems. Special emphasis was placed on technologies demonstrating potential to improve productivity, sustainability and resource use efficiency in vegetable production systems. To ensure methodological rigor, findings from primary research articles were cross-verified with data from review papers and technical reports, thereby enhancing the reliability and consistency of the synthesised information.

Technologies used in smart farming practices

The integration of advanced technologies and tools has brought about a tremendous transformation in smart farming and these technologies collectively enhance data-driven decision-making across all levels of farm management.

Sensors

A sensor constitutes an essential electrotechnical component that detects and quantifies environmental parameters, converting physical measurements into interpretable electrical signals for instrumentation systems (10). Various projections suggest that these devices will be deployed across approximately 525 million agricultural operations globally by 2050, reflecting their growing importance in modern farming (16). These operations include soil and nutrient monitoring, irrigation management, climate-controlled greenhouse production, crop health surveillance, precision fertilisation, pest and disease detection and post-harvest storage monitoring. Agricultural sensors provide critical capabilities for monitoring and optimising crop performance relative to dynamic environmental conditions. These systems are implemented across diverse platforms, including meteorological stations, autonomous harvesting equipment, robotic weeders, unmanned aerial vehicles and ground-based robotic systems.

Contemporary sensor technologies measure an extensive array of agronomic and environmental variables, encompassing atmospheric conditions (temperature, humidity, CO₂ concentration), edaphic factors (soil moisture patterns, mechanical stress), ambient parameters (light intensity, airflow, acoustic levels), spatial positioning data and plant water status indicators (17). This comprehensive monitoring capacity enables precise, data-driven agricultural management while supporting sustainable intensification of production systems. Advanced sensing methodologies, including photoelectric, electromagnetic, conductive and ultrasonic measurement techniques, are employed to quantitatively assess various soil characteristics, environmental conditions and plant growth parameters. The type of sensor selected depends on the specific parameter or change that needs to be monitored. The continuous monitoring capabilities of these sensors are crucial for informed decision-making in precision agriculture (18). An effective sensor for smart farming applications should be accurate, reliable and robust under agricultural conditions, particularly for vegetable cultivation (19). Other prominent sensor characteristics include precision, reliability, sensitivity and specificity. In contrast, low power consumption and wireless connectivity relate to system design features, while timely interventions and cost-effectiveness represent operational benefits derived from effective sensor deployment (20). Although sensor technologies have improved precision monitoring in vegetable production systems, challenges such as calibration errors, sensor drift, high maintenance requirements and limited standardisation continue to affect their reliability under diverse field conditions. In addition, concerns regarding the long-term accuracy and durability of low-cost sensors remain unresolved. Current research therefore focuses on developing robust, energy-efficient and interoperable sensor systems for sustainable field applications.

Types of sensors and its application: Specialised sensor arrays are strategically implemented to monitor agro-environmental variables based on crop-specific requirements. The acquired sensor data is subsequently archived in cloud computing platforms for advanced analytics, enabling automated regulation of agricultural operations with optimised human oversight. An overview of sensor types and their applications are summarised in Table 1.

Table 1. Sensor types and its application

Sensor types	Applications	References
Acoustic sensors	Detection of pests, categorising seed types and harvest index	(21)
Air flow sensors	Soil air permeability, soil moisture assessment and soil type compaction	(22)
Carbon dioxide sensor	Growth and yield monitoring	(23)
Chlorophyll sensor	Photosynthetic efficiency, yield	(24)
Colour sensors	NPK status of soil	(25)
Dielectric soil moisture sensors	Soil moisture estimation, irrigation management	(26)
Eddy covariance-based sensors	Quantifying exchange rates of carbon dioxide, water vapor and other trace gases	(27)
Electrochemical sensors	Soil nutrient and pH detection	(28)
Electromagnetic sensors	Soil electrical conductivity, nitrate residue and organic content detection	(29)
Floating sensors	Detect water level in well/water tank	(30)
Field programmable gate array (FAAA) based sensors	Real-time tracking of plant water uptake, irrigation scheduling and humidity conditions	(31)
Frequency domain reflectometry sensor	Detects moisture	(32)
Gas sensor	Identification of volatile organic components, storage studies	(33)
Humidity sensor	Relative humidity	(34)
Hyper spectral sensor	Disease forecasting	(35)
Light detection and ranging (LIDAR)	Geospatial mapping, soil characterisation, farm modelling and yield projection	(36)
Light sensor	Photoperiod requirement	(37)
Mass flow sensors	Precision yield monitoring	(38)
Mechanical sensors	Soil compaction or mechanical resistance	(38)
Multispectral sensor	Ground mapping, fruit quality assessment, environment monitoring	(39)
Optical sensors	Organic matter in soil, water retention and fruit maturity assessment	(36)
Optoelectronic sensors	Identification of crop as well as weed species	(40)
pH sensor	Measures hydrogen ion concentrations and pH	(41)
Pressure sensor	Pressure variation, water level detection	(42)
Radio frequency identification sensors (RFID)	Identification of objects, grading	(43)
Rain detection sensor	Detects water droplets	(37)
Remote sensor	Crop evaluation, yield prediction and harvest date estimation	(44)
Soft water level-based (SWLB) sensors	Used in catchments to characterise hydrological behaviours	(45)
Solar radiation sensor	Light intensity	(46)
Soil moisture sensor	Volumetric water content in soil	(47)
Telematics sensors	Geospatial position assessment, route optimisation algorithms and IoT-based farm activity logging	(36)
Temperature sensor	Variation in temperature	(25)
Time domain reflectometry (TDR)	Soil water estimation, irrigation and drought assessment	(48)
Ultrasonic ranging sensors	Tracking spray tank levels, optimising spray reach and scouting crop/weed growth	(49)
Water temperature sensor	Variation in water temperature	(50)
Wind speed and direction sensor	Environment parameters	(51)

E-sensing: Electronic sensing (E-sensing) involves the replication of human sensory functions through the integration of sensor arrays and advanced pattern recognition technologies (52). Among the various E-sensing systems, the electronic nose (E-nose), electronic tongue (E-tongue) and electronic eye (E-eye) are prominent examples, each designed to emulate specific human sensory capabilities (53).

Non-destructive quality assessment technologies, such as the electronic nose (E-nose) and electronic tongue (E-tongue), are increasingly being applied in postharvest monitoring of horticultural crops (54). The E-nose employs gas sensor arrays, while the E-tongue uses chemical sensors. E-nose technology supports optimal harvest scheduling, early disease intervention and reduced post-harvest losses. Its non-destructive nature allows repeated monitoring, improving produce quality, minimising unnecessary pesticide use and enhancing overall farm profitability (55). An E-nose comprising ten different metal oxide sensors was evaluated to monitor changes in volatile compound production during tomato ripening, classifying samples into ripe, fully ripe and overripe categories (56). Early identification of potato storage diseases was reported using an array

of metal-oxide-based gas sensors (57). The soil volatile organic compounds (VOC) fingerprint of soil can be useful for soil nutrient management in precision agriculture (58). Electronic tongue analysis was compared with sensory evaluation to assess whether grafted and non-grafted watermelon fruits differed in taste (59). Using an Alpha Astree II electronic tongue, the researchers concluded that fruit quality was influenced by the growing environment and production technologies rather than by the grafting method. A schematic diagram of the electronic sensing measurement process is given in Fig.1.

Geographic information system

A GIS is a computer-based framework designed to acquire, store, process, analyse and visualise spatially referenced data, enabling accurate cartographic representation of geographic features (60). It facilitates systematic management and spatial analysis of agricultural parameters such as soil properties, nutrient status, topography, irrigation networks, drainage patterns, fertiliser application and crop yield variability (61, 62). Common commercial GIS platforms include ArcGIS, MapInfo, GeoMedia and ArcView, while QGIS and GRASS GIS are widely used open-source alternatives.

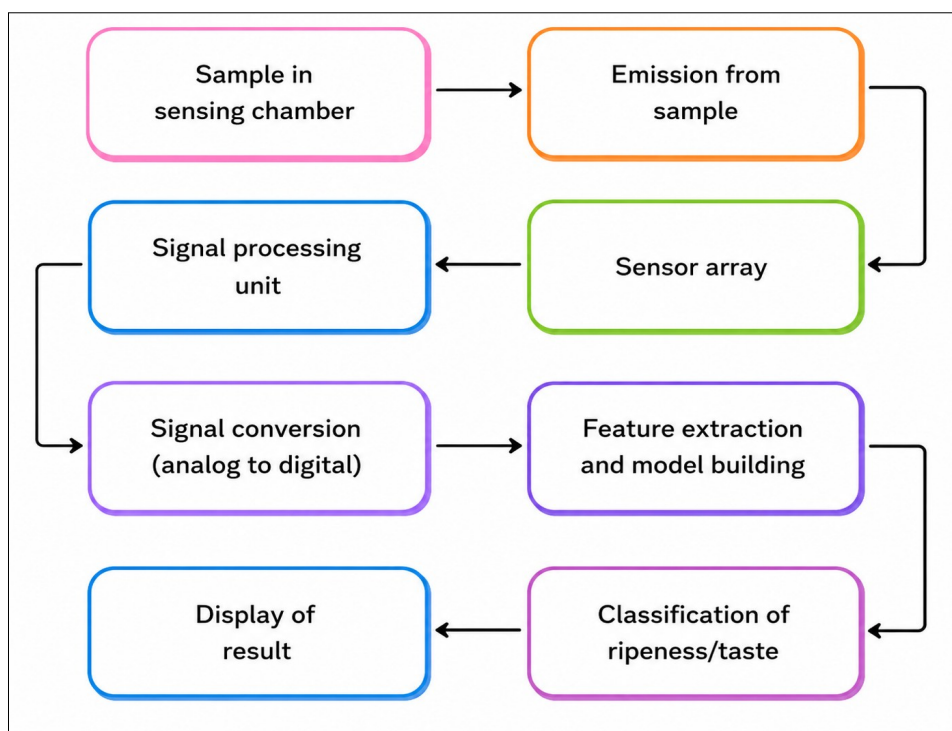


Fig. 1. Functioning of E-nose/E-tongue.

The GIS has been applied to identify suitable cultivation zones for specific crops. For instance, spatial analysis was used to generate maps delineating potential squash-growing areas within the Department of Bolivar (63). Such applications support land suitability assessment and region-specific crop planning.

The GIS enables detailed field mapping and delineation of management zones, supporting precision fertilisation and irrigation in vegetable crops such as carrots and onions (64). In open-field cucumber cultivation, vigour maps derived from soil nutrient status and canopy reflectance data were integrated with GPS-guided systems for variable-rate pesticide and fertiliser applications (65). The GIS was applied to track late blight in tomatoes and whitefly infestations in cucumber (66). Additionally, GIS-based nitrogen response mapping across vegetable production systems has demonstrated its effectiveness in optimising input use and improving economic returns (67).

Global positioning system

The GPS comprises a network of satellites that transmit encoded signals, enabling precise terrestrial positioning through satellite-based distance measurements. This technology provides accurate geospatial data, including latitude, longitude and elevation coordinates, which are essential for identifying specific field locations and implementing targeted agricultural interventions (68, 69). Yield mapping facilitated by GPS technology allows farmers to identify and analyse productivity-limiting factors within agricultural fields. Furthermore, GPS enables operators to navigate exact sampling points for grid or zone-based soil analysis, thereby improving the accuracy of nutrient requirement assessments for vegetable production systems (70). A fully automated GPS-based system was reported for intra-row weed control in tomato fields (71). The GPS-guided potato planting trials were conducted, enabling site-specific adjustments that significantly improved both overall yields and the proportion of marketable produce (72). The Air Surf-Lettuce Project integrated aerial NDVI imagery with GPS-tagged lettuce size data to generate high-resolution crop structure maps for management zone delineation (73). This system enabled

precision spraying and irrigation scheduling, reducing water and agrochemical inputs by targeting only high-need zones. A GPS-GIS precision farming model enabling real-time monitoring and input optimisation was implemented for small vegetable farms (74).

The integration of GPS with Variable Rate Technology (VRT) facilitates site-specific input applications through geospatial prescription maps, allowing for differential input distribution across agricultural fields (75). In Punjab, fertiliser spreaders were deployed in onion and garlic fields to achieve uniform nutrient distribution, reducing input costs by 18 % (76). The GPS-enabled systems reduce overlap during planting and spraying. Precision planting of vegetable seeds such as broccoli and cabbage with GPS-guided planters ensures optimal spacing and uniform crop establishment (77). The GPS-instrumented harvesting carts demonstrated potential for precision yield mapping in lettuce, enabling site-specific fertiliser applications and improved post-harvest logistics in high-value leafy vegetable production (78). Georeferenced mapping also provides a valuable tool for quantifying crop damage using satellite imagery and for forecasting pests and disease outbreaks. In a pioneering study in India, GIS and GPS technologies were used to track and analyse populations of cabbage butterfly (*Pieris brassicae*) infesting cole crops (79).

The GPS-based systems necessitate substantial initial investment and demand technical proficiency, which may limit adoption among smallholder farmers. Positional accuracy may fluctuate due to signal obstruction and atmospheric conditions, thereby affecting field-level precision. Moreover, successful implementation relies on the integration of GIS, sensors and reliable connectivity, which may not always be available in rural agricultural regions.

Unmanned aerial vehicles

A UAV (drone or flying robot) is a pilotless aircraft that navigates and operates in the air without a human operator on board (80). The UAVs are revolutionising remote sensing in agriculture by offering high-resolution, on-demand aerial imaging capabilities (81). A drone relies on sensors and the GPS for its operation.

The integration of autonomous flight systems in UAVs, combined with the innovation of highly efficient, lightweight hyperspectral imaging devices, marks a transformative milestone in remote sensing capabilities (82). A UAV operation relies on a combination of sensors, microprocessors and other technological components (83). Advances in UAV-based remote sensing have enabled the identification of weeds, disease symptoms, nutritional deficiencies and variations in plant growth and vigour (84). The UAVs are gaining prominence in vegetable cultivation for applications such as precision farming, crop surveillance and pest management (85). By capturing imagery with exceptional temporal and spatial resolution, UAVs facilitate detailed assessments of crop health and yield potential (86). When equipped with infrared cameras and GPS, drones further enhance agricultural decision-making and risk mitigation strategies (87).

Agricultural drones are equipped with multispectral or thermal imaging sensors to evaluate plant health, detect stress and disease outbreaks (88). For instance, changes in leaf colour or canopy temperature can be monitored to detect plant stress before visible symptoms appear. Sensors detect and record electromagnetic radiation, converting it into digital imagery that is subsequently framed to generate spectral reflectance bands. These bands serve as the foundation for deriving vegetation indices, including the leaf area index (LAI), photochemical reflectance index (PRI) and normalised difference vegetation index (NDVI) (89). The major applications of UAVs are summarised in Table 2.

Although UAV-based monitoring provides high-resolution information for crop surveillance and precision spraying, limitations such as restricted battery life, regulatory constraints and the need for skilled personnel hinder large-scale adoption. In addition, variations in environmental conditions and canopy structure can affect the accuracy of UAV-derived data. Current research focuses on autonomous navigation, AI-assisted image analysis and low-cost UAV systems to improve accessibility and scalability.

Unmanned ground vehicle

Unmanned ground vehicle (UGV) represents fully integrated intelligent systems that combine ecological sensing, positioning capabilities, decision-making algorithms, mobility control and navigation with path-planning functionality (94). Regarding market projections, recent analyses indicate that the global robotics sector will expand at a compound annual growth rate of 15 % during the 2017–25 period (95). The adoption of robotics in vegetable production has proven to be a game-changer, driven by the increasing demand for sustainable farming practices (96). Advances in sensor technology and artificial intelligence have led to the development of agribots.

The UGVs equipped with sensors can navigate fields to collect detailed data on individual plants and soil conditions. Research includes UGVs for continuous monitoring of sweet pepper plants in greenhouses for collecting data on growth and disease (97). Robotic systems are increasingly deployed for planting and transplanting, offering significant advantages over manual methods. Seeding robots ensure precise seed placement, improving uniformity and reducing labour. However, high capital costs, mechanical complexity, maintenance demands and navigation challenges in uneven or irregular plots may limit widespread adoption. Transplanting robots improve accuracy, stability and overall transplanting performance. Grafting robots enhance precision through real-time image analysis, ensuring better scion-rootstock alignment (98).

Robots equipped with computer vision and robotic arms precisely identify and remove weeds, reducing manual labour and chemical use. This is particularly relevant for high-value vegetable crops like lettuce and broccoli (99). FarmBot has facilitated automated polyculture gardening for over 7 years, supporting diverse crops like carrot, onion, leafy greens, squash, tomato and chilli (100). A robotic system for pollinating tomato flowers through hormone treatment in protected cultivation environments was proposed (101). A combination of image processing and robotic arms can be used to develop robotic harvesters. Robots can identify ripe fruits, thereby reducing post-harvest losses and significant research is now focused on developing robotic harvesters for delicate vegetables like tomatoes and cucumbers in greenhouses (102). Fraunhofer IPK's 'Catch' project focused on advanced automated cucumber harvesting using a two-arm robot prototype using vision-based systems for flexible gripper positioning and path planning (103). The UGVs facilitate phenotyping for breeding programs by collecting detailed plant data, thereby accelerating the development of improved vegetable varieties (104).

Variable rate technology and grid soil sampling

The VRT are used in farming to determine the input delivery rates based on a predetermined map generated from GIS data, enabling the placement of inputs in variable amounts at the right place and time (105). This approach facilitates site-specific input application, where grid soil sampling generates essential data for ideal resource management (75). Grid soil sampling involves collecting soil from a systematic grid to establish parameter-specific maps. These geospatial maps serve as the fundamental input for VRT systems and are subsequently programmed into variable-rate applicators. The computer and GPS receiver direct and control input delivery changes based on map features. This approach is fundamental for precise nutrient management in intensive vegetable cultivation, optimising nutrient allocation for mixed vegetable production (70).

Table 2. Applications of unmanned aerial vehicles (UAVs) in vegetable production systems

Application area	Sensor/Technology	Purpose	Example crops	References
Crop health and vigour monitoring	Multispectral / hyperspectral imaging	Detect stress, nutrient deficiencies, growth variability	Potato, cucumber	(81, 84, 88)
Vegetation index derivation (NDVI, LAI, PRI)	Spectral reflectance bands	Biomass and yield estimation	Leafy vegetables	(89)
Disease detection	Multispectral / thermal sensors	Early detection of powdery and downy mildew	Cucumber, spinach	(81)
Irrigation management	Thermal + NIR imagery	Crop water status estimation	Onion	(90)
Growth stage monitoring	RGB imaging, plant height detection	Identification of tuberisation stage	Potato	(91)
Precision spraying	GPS-guided spray nozzles	Targeted pesticide and fertiliser application	Cabbage, tomato	(92)
Pollination support	Autonomous drone systems	Mechanical pollination	Horticultural crops	(93)

Variable nitrogen application in potato fields improved nitrogen use efficiency and yield while reducing environmental impact (75). A GPS-guided VRT systems improve nutrient uniformity in lettuce beds, reducing nitrogen over-application by 22 % (106). A large-scale profitability analysis confirmed that VRT nitrogen recommendations based on satellite-derived vigour indices increased overall profits in leafy vegetable farms in California (67).

Internet of things

The IoT comprises an interconnected network of physical devices equipped with sensors and software, facilitating real-time agricultural data exchange and system control (107). Researchers suggested that IoT-based products must be developed and put into operation regularly and rapidly to implement smart farming in real-life situations (108). The IoT-based farming can target organic/inorganic farms and greenhouse farms as well as large- and small-scale farming. Based on sensor data, IoT systems can trigger automated actions, such as turning on irrigation pumps or controlling greenhouse climate. The integration of sensor technologies with IoT frameworks offers an efficient approach for monitoring seed germination and early plant growth. Such systems allow real-time data collection and analysis of critical environmental factors, including soil moisture, temperature, humidity and light intensity, enabling precise environmental regulation to improve germination success.

The IoT techniques can be used to monitor seeds and it was shown that IoT-monitored tomato seedbeds reduced the time of seed growing (109). Similarly, IoT-enabled smart irrigation systems based on soil moisture data in tomato beds guarantee the best possible irrigation (107). A smart algorithm was proposed based on open-source technology, developing a fully autonomous irrigation system that integrates real-time field parameters with weather forecast data for efficient water management (110). In another study, an IoT-based smart fertiliser management system was proposed, where a soil moisture sensor communicates with a controller via a global system for mobile communications (GSM) module to send short message service (SMS) alerts directly to the farmer's mobile device. Farmers can respond with alphanumeric commands to automate fertiliser application (34). However, system performance may be constrained by limited Wi-Fi coverage in rural areas, network instability affecting GSM reliability and dependence on cloud connectivity for data storage and processing, which may reduce functionality in regions with poor internet infrastructure.

The IoT platforms manage climate parameters (temperature, humidity, CO₂) in hydroponic greenhouses for leafy greens like lettuce, ensuring optimal conditions (111). On-site digital sensors are used for agronomic soil testing, providing crucial data on nutrient levels and pH. For crops like potatoes, precise data from these sensors allow farmers to tailor fertiliser applications to specific areas of a field, ensuring optimal nutrient availability for crop growth while reducing waste (112). The IoT applications have also been used for tracking the temperature and humidity of harvested vegetables (e.g., broccoli) during transportation to maintain freshness (113). The IoT-enabled smart farming systems have improved automation and real-time monitoring in vegetable cultivation. However, dependence on internet connectivity, uninterrupted power supply and cloud infrastructure limits system reliability. Additional challenges include data security concerns, device interoperability and high deployment costs. Consequently, current research is increasingly directed toward edge computing, energy-efficient communication protocols and decentralised systems to enhance practical applicability.

Information communication technology

Smart farming aims to transform traditional techniques into innovative solutions based on information and communication technology (ICT) (13). These technologies, which include tools and services for managing and exchanging information, serve as the foundation for data-driven decision-making in modern agriculture (114). By enabling the creation, collection, processing and dissemination of information in various formats (voice, text and images), ICT empowers farmers with critical real-time insights. These include market price trends, weather forecasts, pest alerts and guidance on seed selection and cultivation practices. Additionally, mobile applications and IoT-based platforms facilitate remote farm management, allowing farmers to adjust fertiliser applications based on online soil nutrient maps. Advanced decision support systems (DSS) further enhance precision farming by integrating weather predictions, soil analytics and crop modelling to provide tailored recommendations for planting schedules, fertilisation and pest management (114). Comparable ICT-enabled systems operating in India and globally include mKisan Portal, eNAM, Digital Green and Climate FieldView, which integrate mobile advisories, cloud-based analytics and remote decision-support tools for nutrient and crop management.

Artificial intelligence / machine learning / deep learning

An artificial intelligence (AI), ML and deep learning (DL) represent a suite of advanced technologies capable of autonomous problem-solving and task execution to accomplish specified goals. The study of artificial intelligence is crucial due to its rapid technological advancements and effectiveness in solving complex problems (14). AI enables robots to perceive their environment, navigate autonomously and perform complex tasks like selective harvesting or weeding (99). AI algorithms can optimise different cultural operations, including planting, irrigation, weeding, fertilisation and pesticide application. Two deep learning models, region-based convolutional network (R-CNN) and single shot detector (SSD), were implemented in tomato to detect flowers and fruits, thereby identifying maturity index for harvest (115).

Machine learning algorithms are capable of accurately analyse historical data on crop performance, weather patterns and soil conditions, in addition to predicting yield and the occurrence of pests and diseases. The ML algorithms trained on drone imagery and IoT soil sensors accurately predicted water stress and biomass accumulation in lettuce, enabling adaptive irrigation scheduling (116). An AI can be used to customise farming operations to specific farm requirements, crop varieties and geographical conditions (117). An AI-driven systems adjust nutrient delivery in hydroponic systems for lettuce and herbs, optimising growth while minimising waste (118). Recent advances in agricultural technology demonstrate how machine learning-based predictive models can accurately estimate yields for both greenhouse tomatoes and field-grown cabbage by analysing environmental parameters (119). Furthermore, modern AI-driven computer vision systems have shown remarkable capability in processing visual data captured by unmanned ground or aerial vehicles, enabling early identification and prediction of pest infestations and plant diseases. The DL models trained on image datasets have been used to detect early blight in potato (81). An AI- and ML-based approaches have improved disease prediction, yield forecasting and automated decision-making in vegetable production systems. However, their effectiveness depends on the availability of high-quality, region-

specific datasets and model accuracy often declines under diverse field conditions. In addition, the limited interpretability of deep learning models affects farmer trust and adoption. Current research therefore emphasises explainable AI and region-specific model development. A schematic representation of the use of AI in smart farming is presented in Fig. 2.

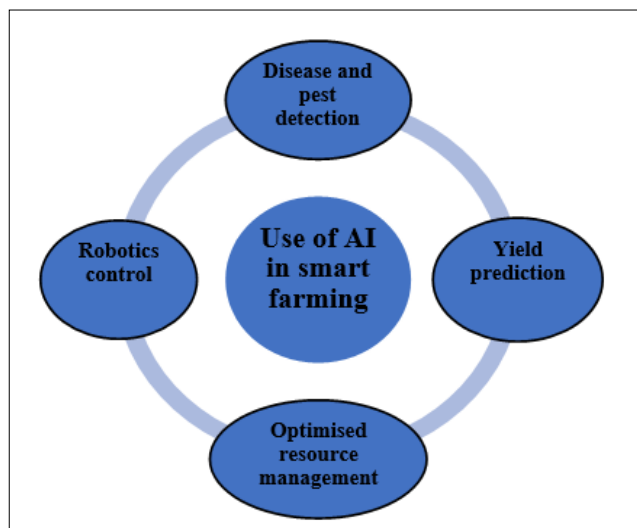


Fig. 2. Use of AI in smart farming.

Big data and real-time analytics

‘Big data’ refers to the rapid growth in data volume that traditional systems struggle to store, manage and analyse efficiently (120). In the context of precision vegetable cultivation, the synergistic combination of big data technologies, cloud computing platforms and advanced analytical tools facilitates optimised agricultural decision-making processes. Through sophisticated data mining techniques, these integrated systems can identify meaningful relationships within heterogeneous agricultural datasets, generating actionable insights regarding crop productivity, input use efficiency and agro-environmental optimisation. This facilitates optimised practices, cost reduction and improved profitability. Large datasets support more accurate yield forecasting and disease prediction models (119). Real-time analytics, which involves immediate data processing, enhances precision farming by enabling timely decisions on irrigation, fertilisation and pest control. Additionally, predictive analytics supports sustainable practices by analysing meteorological, soil and environmental data to recommend resource-efficient strategies that minimise ecological impact. Data analytics helps to predict the suitable crops by analysing meteorological data, soil sensor data and other relevant datasets. Farmers can implement techniques that lessen their ecological footprint, such as conserving soil, minimising chemical pesticide and fertiliser use and improving water-use efficiency.

Real-time moisture data streamed to cloud dashboards enabled remote irrigation scheduling in tomato farms, reducing labour requirements (121). In lettuce, UAV-based hyperspectral imaging combined with cloud-based ML predicted harvest timing and disease onset with 92 % accuracy (118). Big data-driven analytics optimised cold-chain logistics, reducing spoilage in spinach (122). Multi-season sweet corn datasets refined management strategies, while big data tracking minimised waste and improved logistics for perishable crops like broccoli (123).

Cloud computing

The on-demand availability of computer system resources, particularly data storage and processing power, without the need for

direct user supervision, is known as cloud computing. The resources are distributed online without the need for on-site setup or upkeep. Cloud computing architectures provide a comprehensive suite of service models that enable efficient data management in agricultural applications. The primary service offerings include Software-as-a-Service (SaaS), which delivers applications through cloud platforms; Platform-as-a-Service (PaaS), offering development environments for customised solutions; Infrastructure-as-a-Service (IaaS), providing fundamental computing resources; and Function-as-a-Service (FaaS), enabling event-driven serverless computing. These layered service models collectively address the critical challenges associated with storing, processing and analysing the voluminous data streams generated by IoT networks in precision agriculture. The elastic and scalable nature of cloud resources proves particularly valuable for handling the characteristic velocity, variety and volume of agricultural data, while simultaneously ensuring reliable access to advanced computational capabilities for data-driven decision making. In vegetable production systems, SaaS platforms enable real-time monitoring of greenhouse crops such as tomato and capsicum through dashboards displaying microclimate and fertigation data. PaaS supports the development of predictive models for diseases like early blight in tomato and powdery mildew in cucurbits. The IaaS facilitates storage of high-resolution drone imagery for crop health assessment, while FaaS enables automated irrigation in leafy vegetables based on soil moisture thresholds.

Greenhouse automation in tomato cultivation has been enhanced through the integration of fuzzy Proportional-Integral-derivative (PID) controllers with clustering-based preprocessing, allowing remote microclimate monitoring and control via cloud platforms (124). For pest management in cabbage and kale, the integration of GIS with cloud computing has enabled precise hotspot mapping, supporting targeted interventions and reduced pesticide application (66).

Applications of smart farming technologies in vegetable farming

Smart greenhouses enable self-regulating microclimates that enhance vegetable production by overcoming weather variability. Real time data on irrigation, temperature and lighting supports precision farming, improves yield and conserves resources. This data driven approach also enhances climate resilience through predictive forecasting (125).

Precision farming

Precision agriculture systems rely fundamentally on three key technological components viz, GPS guided controllers, advanced sensor networks and robust wireless communication infrastructure. These integrated systems play a particularly vital role in optimising irrigation management, which represents a critical determinant of crop productivity, especially in arid regions or areas prone to periodic water scarcity. Intelligent water management solutions constitute a cornerstone application of smart farming technologies, offering dual benefits of significant water conservation and reduction in agricultural runoff (126). The implementation of these precision irrigation systems enables data-driven decision making that accounts for crop water requirements at different phenological stages while minimising environmental impact through efficient resource utilisation. Since evapotranspiration (ET) plays a key role in regulating climate and hydrology, it must be accurately measured to support effective decision making in water resource management (127).

Remote sensing techniques can monitor large scale irrigation schemes, estimate evapotranspiration rates and create detailed maps of crop water stress indicators. Smart farming technologies help address spatial heterogeneities in fields and improve irrigation scheduling (128). The commonly used remote sensing-based techniques for estimating actual evapotranspiration (ETa) include the Surface Energy Balance Algorithm for Land (SEBAL) (129), Mapping Evapotranspiration at High Resolution with Internalized Calibration (METRIC) and the Surface Energy Balance System (SEBS) (130, 131). These techniques derive critical agronomic parameters including the Crop Water Stress Index (CWSI), Leaf Area Index (LAI) and surface temperature (Ts) through comprehensive analysis of surface energy balance components. By adopting new IoT-based approaches such as crop water stress index (CWSI) based irrigation management, the traditional crop watering scheme can be revolutionised (132). The CWSI framework quantitatively assesses plant water status by integrating multiple physiological indicators, notably canopy thermal properties, microclimatic conditions and temporal soil water content variations. This innovative approach enables real-time detection of water deficit stress, facilitating more responsive and efficient irrigation scheduling. Spatiotemporal analysis using Landsat 7 and 8 data found a high correlation between CWSI and LAI for lettuce ($r = 0.99$), confirming CWSI as a reliable water stress indicator. A moderate correlation was found for potatoes ($r = 0.44$), suggesting that additional environmental factors affect LAI during winter (133).

A multimodal precision farming system that consists of smart irrigation, smart fertiliser dose recommendation, crop disease detection system and a crop damage prediction system was proposed (134). The system architecture and component interactions of precision agriculture approach are visually depicted in Fig. 3.

Protected Crop Production

Greenhouse farming significantly optimises vegetable production by providing a controlled environment. The cloud server processes the collected data and applies automated control actions within the greenhouse. These systems integrate sensors for real-time data collection and actuators for automated climate adjustments, ensuring consistent yields and resource efficiency (118). In controlled environments like greenhouses, a network of smart

sensors (temperature, humidity, CO₂) provides continuous data for automated climate control systems. For example, in cucumber greenhouses, such systems have significantly reduced water use and ensured stable, year-round production, leading to increased yields and profitability (135). Using ZigBee communication technology and a variety of sensors, smart greenhouse systems have demonstrated that sensors and routers should be positioned at appropriate spacing to optimise plant growth (46).

An IoT platform based on edge and cloud computing using the MQTT protocol was developed for monitoring the greenhouse environment. The system sends alert SMS when water consumption is high and monitors water and nutrient consumption (136). Farm monitoring systems using MQTT protocols collect environment parameters via sensors, send the data to controllers and store it in databases, enabling farmers to remotely monitor and control agricultural operations (137). The IoT-based environment change monitoring in greenhouses has included sensors for temperature, humidity, soil moisture and light, combined with prediction analysis for optimal crop management (138). The IoT microclimate sensors integrated with GIS overlays allow spatial visualisation of temperature, humidity and pest incidence hotspots in cucumber and lettuce production systems (139).

Recent advances show that IoT-driven irrigation management has significantly optimised tomato production. Smart frameworks using soil moisture sensors linked to cloud dashboards can trigger irrigation automatically, improving yield by 15 % while saving water by 30 % (104). Arduino-based greenhouse sensor networks that maintained tomato root-zone moisture between 70–85 %, resulting in larger fruit size and uniform ripening compared to conventional watering were developed (140). The IoT-enabled soil probes were used in open-field trials on 10 hectares of tomato field in Bengaluru (121). Irrigation was only started when tension dropped below -23 kPa during the seedling stage and -30 kPa later in growth, reducing water use by almost 39 % without compromising yields. IoT, combined with machine learning, has been used to optimize fertigation in greenhouse-grown tomatoes by predicting essential nitrogen-phosphorous-potassium (NPK) requirements and enabling automated nutrient delivery to maintain

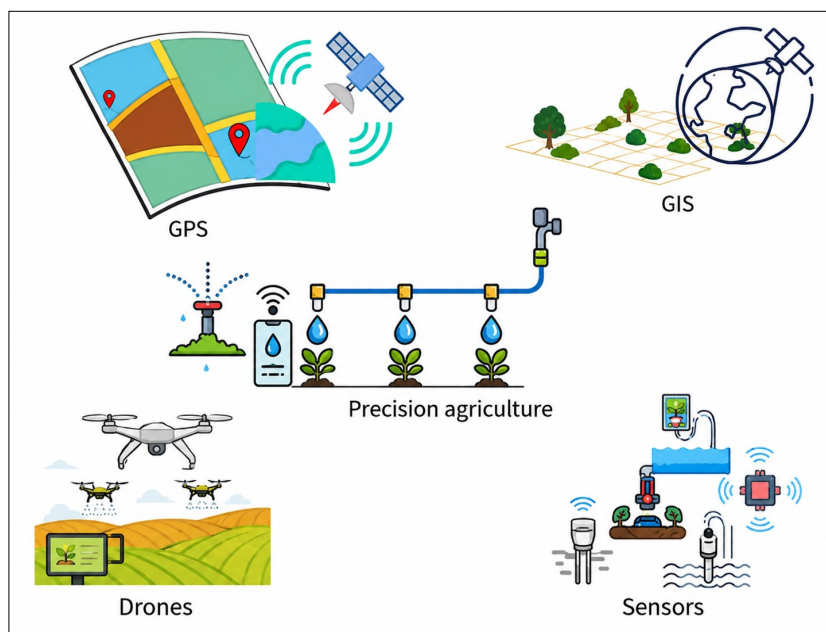


Fig. 3. Components of precision agriculture.

optimal growth conditions (141). The models proposed by them were able to predict essential NPK requirements for crops, enabling automated fertigation to maintain optimal growth conditions. The IoT-assisted nutrient delivery reduces fertiliser leaching by 25 % and improves nutrient use efficiency in tomatoes (142). An advanced AI fuzzy PID control system for greenhouse grown tomatoes, incorporating clustering algorithms for microclimate data processing and real-time cloud-based visualisation, resulted in an 18 % yield increase and reduced energy consumption (124). In a study focusing on optimising tomato growth, IoT-enabled soil pH and moisture sensors were deployed in a greenhouse. This system allowed for the continuous monitoring of soil conditions, enabling automated or manual (via mobile app) adjustments to drip irrigation systems based on real-time data (143). A model-based approach for the early warning detection of cucumber downy mildew in greenhouses was created (144). This system integrates climate and disease models, relying on real-time environmental data gathered by IoT sensors to provide timely predictions of disease outbreaks. Comprehensive software platforms like Farm Management Information Systems (FMIS) help in efficient planning, monitoring and execution of diverse agricultural operations and overall enhancement of farm productivity (145). The operational workflow of a smart farming system is illustrated in Fig. 4.

Hydroponics /aeroponics /vertical farming

Modern soilless cultivation methods, including hydroponics, aeroponics and vertical farming systems, are increasingly being employed through the integration of smart agriculture technologies. These advanced systems enable precise regulation of critical growth parameters, with automated hydroponic platforms demonstrating effectiveness in monitoring and adjusting nutrient composition, pH levels, temperature and humidity. A sensor-actuator network was implemented for environmental control in greenhouse hydroponics, with data logging and analysis performed through the Ubidots cloud platform (146). Further advancing this field, an IoT-based hydroponic system incorporating deep neural networks to optimise growth

conditions and improve yield in tomato cultivation was developed (147). Superior growth performance under controlled conditions was observed in plants grown within automated hydroponic systems compared to those cultivated outdoors (50). An indoor vertical hydroponic farming system was further advanced through IoT-based automation, where integrated sensors monitored system parameters and electromechanical relays controlled artificial lighting, water and nutrient dosing operations (148). An intelligent and manageable architecture for lettuce aeroponic cultivation was developed using an Arduino microcontroller integrated with electronic devices to monitor and control temperature, humidity and irrigation timing (149).

Vertical farming systems enable precise environmental control for plant growth while dramatically reducing spatial requirements and resource consumption through multi-layer cultivation architectures. Among critical monitoring parameters, carbon dioxide concentration plays a pivotal role, with non-dispersive infrared (NDIR) CO₂ sensors serving as essential components for maintaining optimal atmospheric conditions. Recent technological advancements have further enhanced vertical farming efficiency, whose cloud-integrated climate monitoring system achieved stabilised environmental parameters for lettuce cultivation, resulting in 20 % accelerated growth rates with reduced energy demands (150). Parallel developments have expanded the technological framework through their internet of everything (IoE) approach, which integrates nano sensor networks with blockchain technology and cloud-based analytics to optimise nutrient delivery in hydroponic spinach production (151). Controlled-environment farming systems such as hydroponics, aeroponics and vertical farming improve water-use efficiency, land utilisation and year-round production. However, their large-scale adoption is constrained by high energy demands, infrastructure expenses and technical management complexities. Ongoing research is therefore emphasising renewable energy integration and affordable automation strategies to enhance sustainability and

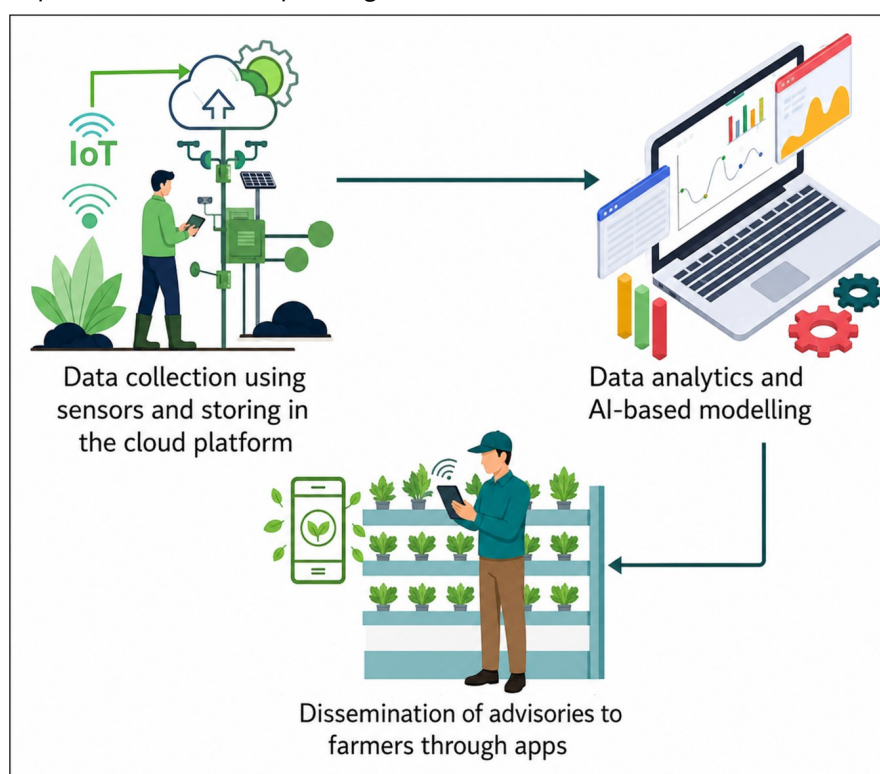


Fig. 4. Working of a smart farm.

economic viability.

Soil sampling and mapping, crop monitoring, quality monitoring, yield monitoring, forecasting and harvesting

For vegetable crop production, the combination of IoT and remote sensing is becoming crucial. Modern yield monitoring systems incorporate harvesters equipped with precision monitoring devices that transmit real-time data to mobile applications and web-based platforms. These integrated systems enable agronomists to access and disseminate high resolution yield maps, while providing farmers with the capability to export comprehensive agricultural data for detailed analysis and decision making. The IoT systems significantly enhance traditional soil sampling and mapping processes by providing real-time data on various soil parameters. An IoT-based system was developed incorporating multiple sensors, including pH, temperature and humidity sensors, along with a microcontroller, microprocessor and web camera. The WiFi enabled system transmits real-time soil sensor data to a central processor, providing farmers with crop suitability recommendations via mobile application for data-driven cultivation planning. The system also supported automatic irrigation when elevated soil temperature was detected (41). Additionally, RGB-D sensors were employed to extract colour and shape features of sweet peppers, allowing accurate localisation of the peduncle to enhance precision in automated harvesting (152). An automated clip type IoT camera system was designed to monitor tomato growth and predict harvest dates within greenhouse environments, enhancing precision agriculture practices (153). The UAV imagery integrated with GIS enabled the identification of crop health and yield variability in tomato fields, supporting site-specific nutrient application (154). Further advancements combined GIS, AI and drone data to improve water management in vegetable plots, resulting in a 25 % reduction in irrigation costs and facilitating real time, data-driven decision making (155).

By integrating IoT technology, smart vegetable storage systems can be efficiently controlled, allowing for real-time environmental condition monitoring. Real time quality assessment of vegetables was achieved using sensor-based hardware capable of detecting both physical and chemical attributes in selected crops. The system successfully quantified organic content and identified pesticide contamination in brinjal and okra samples (156). In a related advancement, a smart IoT-enabled storage system was designed for potatoes, allowing remote monitoring of warehouse conditions to preserve the quality of seed potatoes (157).

Crop pest and disease management

Contemporary IoT-based systems have significantly enhanced pest and disease management by enabling real-time monitoring, predictive modelling and precision-based interventions. These technologies can be broadly categorised into pest detection systems, sensor-based residue and infestation monitoring and disease prediction and forecasting platforms.

Pest detection and surveillance systems utilise automated smart traps and imaging technologies to quantify insect populations. For example, smart traps equipped with GPRS modules transmit pest data to centralised MySQL servers for real-time monitoring (158). Similarly, greenhouse insect monitoring systems employ image sensors and server-based processing to estimate pest density (159). Advanced approaches integrating video analytics, cloud computing and robotics have been applied

for early detection of tomato fruit borer (160).

Sensor-based detection technologies focus on identifying infestations and pesticide residues. Innovations include sensor-based detection of cowpea seed beetle (*Callosobruchus maculatus*) infestations in stored seeds (161) and portable molecular imprinting sensors for rapid on-site detection of imidacloprid residues in crops and water (162). These systems enhance residue monitoring and reduce excessive pesticide application (163).

Disease prediction and forecasting models integrate IoT sensors with wireless communication technologies to enable proactive management. An IoT-assisted decision-making system for potato late blight employs ZigBee-based wireless networks to detect suboptimal growing conditions and issue early alerts (164). Similarly, machine learning-based systems have been developed for the detection of *Septoria* disease, enabling timely preventive measures (165). Collectively, these structured IoT approaches improve surveillance accuracy, reduce chemical inputs and support data-driven pest and disease management in protected and open-field vegetable systems.

Challenges – ethical, economic and social implications

Despite rapid technological advancements, the widespread adoption of smart farming in vegetable production, particularly in resource-limited contexts such as India, remains constrained by economic, technical, social and ethical challenges. High initial investment costs, dependence on imported components and proprietary software platforms limit accessibility for small and marginal farmers. In addition, the development of smart agricultural technologies is hindered by the lack of affordable, adaptable and locally manufacturable solutions suitable for diverse farming systems and varying resource availability.

The effectiveness of AI and ML applications in agriculture is further restricted by the scarcity of geographically representative training datasets. Many existing models rely on datasets that inadequately capture diverse agro-climatic and ecological conditions, thereby limiting their practical applicability across regions. This highlights the need for publicly available, location-specific datasets to improve algorithmic performance in critical applications such as plant disease detection, crop yield prediction and resource management optimisation (14).

Technical barriers also include the absence of standardised frameworks for integrating heterogeneous technologies such as sensor networks, unmanned aerial systems, IoT platforms and artificial intelligence tools. This lack of interoperability restricts seamless data exchange and coordinated system functioning. Therefore, the development of cross-compatible, plug-and-play architectures is essential for effective smart farming implementation (166).

Social constraints further impede technology adoption. Digital illiteracy among farmers, inadequate technical training and limited extension support reduce the ability of farming communities to effectively utilise digital tools and interpret analytical outputs. User-centric approaches, including multilingual mobile applications, farmer-friendly interfaces and strengthened extension services, are necessary to bridge this gap. Moreover, many smart farming innovations remain confined to laboratory or pilot-scale experimentation, with limited large-scale field validation under diverse environmental and socio-economic conditions.

Infrastructure-related limitations, particularly unreliable electricity supply and poor internet connectivity in rural regions, continue to affect the operational efficiency of IoT-enabled and cloud-based agricultural systems. In such situations, edge computing technologies and renewable energy-powered off-grid solutions may provide practical alternatives for ensuring uninterrupted system performance.

Ethical and environmental dimensions of smart agriculture also remain insufficiently addressed. Major concerns include data ownership, privacy, access control, stakeholder trust and power asymmetries in agricultural data sharing. Furthermore, automation-driven labour displacement and the generation of electronic waste raise important sustainability concerns. Addressing these issues requires comprehensive governance mechanisms, ethical frameworks and life-cycle sustainability assessments to ensure equitable, responsible and environmentally sustainable technological integration. A summary of major challenges and proposed solutions is presented in Table 3.

Gaps in smart farming for vegetable crops

Smart farming, while rapidly advancing, presents several critical gaps when applied to vegetable crop production. One of the fundamental limitations is the lack of unification and scalability across systems, leading to difficulties in implementing comprehensive solutions in small scale and diverse vegetable farming settings. Many existing technologies are tailored for large scale monocultures, particularly cereals and do not accommodate the unique requirements of vegetable crops, which often involve shorter growth cycles and higher perishability. Furthermore, current smart farming systems frequently operate in silos, focusing on a single stress factor and lacking the capacity for real-time, multi factorial monitoring, an essential requirement for precision vegetable farming. The reliability of these systems is also a concern, as the failure of a single component can lead to the malfunction of the entire setup. Repeated monitoring and maintenance further add to operational burdens, especially in the absence of seamless integration among hardware, software and data platforms. These challenges are compounded by inadequate telecommunication infrastructure and limited internet coverage in many rural areas, impeding real time data transmission and system coordination. Moreover, difficulties in integrating data across heterogeneous equipment, machines and platforms restrict the ability to make informed decisions. The deployment of agricultural drones, although promising, is restricted by legal altitude limits (typically 400 feet) and short battery life and the raw images they capture require complex interpretation by trained professionals, which is an area still lacking in sufficient expertise and training (88). Additionally, the high initial investment and technical complexity of smart farming technologies act as major barriers to adoption by smallholder vegetable growers. There is also a notable lack of advanced systems for smart post-harvest handling of vegetables, including storage, grading and traceability, being an area of

particular importance due to the high perishability and market sensitivity of vegetable produce. Addressing these multifaceted gaps is essential for the effective integration of smart technologies into vegetable crop production.

Future scope

The integration of advanced technologies in vegetable farming is driving a paradigm shift towards more precise and adaptive management practices. Recent advancements in agricultural AI focus on integrating multisource data including meteorological trends, edaphic characteristics, pest population dynamics and crop growth stages to generate real time agronomic recommendations for optimal planting schedules, water management and harvest timing. These data driven models support improved resource use efficiency and yield prediction. Sensor fusion techniques are also gaining prominence, particularly those that combine hyperspectral imaging, biosensors and thermal cameras. This multi-modal sensing framework enables early detection of nutrient deficiencies, disease onset and water stress, thereby facilitating proactive interventions to mitigate crop losses. In regions with limited internet connectivity, edge computing devices offer a practical solution by enabling local data processing. These systems allow real time decision making without dependence on continuous cloud access, ensuring operational continuity even in remote agricultural settings.

Collectively, the literature indicates that smart farming technologies have progressed from isolated precision tools toward integrated digital agricultural ecosystems. However, a major trend emerging across studies is that technological sophistication alone does not guarantee successful adoption. Economic accessibility, interoperability, infrastructure availability, farmer literacy and policy support consistently determine real-world implementation success. Another recurring observation is that most technologies demonstrate strong performance under controlled experimental conditions but lack sufficient validation under heterogeneous smallholder farming systems. Therefore, future advancements in smart vegetable farming should prioritise integrated, scalable and farmer-centric solutions rather than isolated technological innovations alone.

Conclusion

Smart farming technologies have emerged as powerful tools for transforming vegetable production systems through improved precision, automation and data-driven decision-making. This review highlights the significant contributions of technologies such as internet of things (IoT), artificial intelligence (AI), geographic information systems (GIS), unmanned aerial vehicles (UAVs), sensor networks, cloud computing and automated cultivation systems in enhancing productivity, resource-use efficiency, crop monitoring and environmental sustainability. Applications in precision irrigation, protected cultivation, hydroponics, vertical farming and

Table 3. Summary of challenges and proposed solutions

Challenge	Proposed solution
High cost and proprietary systems	Promote low-cost, locally manufactured and open-source technologies
Limited AI training data (14)	Develop publicly available, location-specific agricultural datasets
Interoperability gaps	Establish standardised, plug-and-play integration frameworks
Poor rural infrastructure	Deploy edge computing and renewable-powered systems
Digital illiteracy	Multilingual interfaces and strengthened extension services
Ethical and environmental risks	Data governance policies and life-cycle assessments

disease forecasting demonstrate the potential of smart agriculture to address major challenges associated with conventional vegetable production. However, despite these advancements, several constraints continue to limit large-scale adoption, particularly in developing countries. High installation costs limited digital literacy, poor rural infrastructure, interoperability issues, lack of location-specific datasets and inadequate policy support remain major barriers. Ethical concerns related to data ownership, privacy, automation-driven labour displacement and electronic waste management also require careful consideration for responsible technological integration.

The review further identifies critical research gaps, including the need for scalable low-cost technologies suitable for smallholder farming systems, improved integration among heterogeneous smart farming platforms and the development of robust real-time decision-support systems tailored for vegetable crops. Future research should prioritise affordable open-source technologies, edge computing solutions, multisensor integration, AI-driven predictive analytics and farmer-centric extension strategies to ensure inclusive and sustainable adoption. Overall, smart farming has the potential to significantly enhance the resilience, profitability and sustainability of vegetable production systems. Achieving this transformation will require coordinated efforts among researchers, policymakers, technology developers and farming communities to bridge existing technological and socio-economic gaps and to ensure equitable access to digital agriculture innovations.

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Authors' contributions

RR conducted the survey, analysed the data and wrote the manuscript. GR analysed the data and reviewed the manuscript. SS reviewed the manuscript. All authors read and approved the final manuscript.

Compliance with ethical standards

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