Pak. J. Bot., 58(5): 1176-1191, May 2026.

ARTICLE | DOI: http://dx.doi.org/10.30848/PJB2026-5(8)

THE TRANSFORMATIVE IMPACT OF ARTIFICIAL INTELLIGENCE ON AGRICULTURE AND NANOBOTANY

SUMERA JAVAD*, NADIA GHAFFAR, AINA INAM, IQRA NASEER, IQRA AKHTAR, SADIA AFZAL AND SAIMA BASHIR

Department of Botany, LCWU, Lahore, Pakistan

*Corresponding author's email: Zif_4@yahoo.com

Abstract

Technological advances laid the foundation for an emerging field in the form of nanotechnology, playing a role in every discipline of life, from material, chemistry to computational and life sciences. This emerging field transformed the agricultural sector by integrating nanobotany and nanoagronomy with artificial intelligence (AI). As AI can handle large datasets and can accomplish complicated tasks independently, it has the potential to transform future agricultural practices with better yield and sustainability. AI can incorporate nanobotany by improving the efficiency, accuracy, and versatility of nanobots to interact with plant systems. AI tools can make satellite imaging, monitoring, and crop data analysis more accurate than traditional methods. The integration of machine learning (ML) and deep learning (DL) algorithms with mobile detection algorithms could facilitate early disease detection, optimization, prediction of plant status, and breeding processes. The production of AI-aided nanosensors, nanobots, nanomedicines, nanocarriers, nanomaterials (nanoparticles, nano-fertilizers, and nano-pesticides, etc.), and their transformative roles in nanoscale imaging, phyto-mining, nanotoxicity analysis, NPs optimization, pest management, early disease detection, genetic manipulation, precision farming, environmental monitoring, targeted delivery of pesticides, and biocontrol agents are briefly described in the present study. The challenges, ethical concerns about use of AI in nanobotany, and their possible solutions are also discussed here. This study reflects an integrative approach of nanotechnology, AI, and plant sciences, which will pave the way for innovation by assisting policymakers, scientists, and farmers to address sustainability challenges. In conclusion, AI-based nanotechnology holds promise as the future of sustainable agriculture.

Key words: AI tools; Nanoparticles (NPs) optimization; Pest management; Nanosensors; Nanobots; Precision farming; IoT

Introduction

In the recent era of technological revolution, nanotechnology has shown a promising role in the field of plant sciences, and other interdisciplinary fields have evolved like Nanobotany or nanoagronomy. Nanobotany includes the use and role of NPs in plant life, whereas nano-agronomy is the use of NPs in the field of agronomy. Furthermore, AI is considered as the future of agriculture at a global level. It is a dynamic area of research at present where we see the combination of nanotechnology, computer science, data science, agriculture, and plant science. AI is a powerful set of techniques that has improved scientific research and applications in a very different way. This review article explains the role of the triangle of nanotechnology, AI, and botany shaping the future of agriculture. Developed countries are already getting benefits from this fruitful combination of technologies. There is a dire need for acceptance of AI and nanotechnology in solving botanical and agricultural problems particularly, in developing countries.

This review includes the study of the impact of nanotechnology and AI on scientific advancements carefully. This topic covers the synthesis of NPs and their use in smart agriculture, precision agriculture, genetic manipulation, disease management, and weather forecast etc. There is a potential for AI in transforming each of the above fields by integrating supercomputers and nanorobots with them. The scope of using AI for the plant sciences and agriculture extends beyond a simple exploration of advancements in technology. AI is revolutionizing agriculture by optimizing current practices such as using AI-powered drones for precision spraying and crop monitoring, optimizing NP synthesis, and analyzing complex biological data. It is also paving the way for future advancements like predictive models for climate-resilient farming and autonomous farming systems that can sustainably feed a growing population. It directly links the Sustainable Development Goals (SDGs) with the use of AI in all the above-mentioned fields. There is also a need for ethical considerations for transparency, privacy, accountability, and responsibility etc. Therefore, it needs proper navigation of all efforts and possibilities of transformations related to the use of AI in agriculture and nanobotany. It can help us to understand scientifically the sustainable and possible coexistence of human race and plants with all the environmental parameters. Therefore, the present study suggests the understanding of role for scientists and policy makers to embark on the transformative character of AI in agriculture and plant science. This review article, therefore, addresses the gap in research about integration of AI in nanobotany that is still unexplored in the literature. It will help to establish foundational understanding and research directions at the intersection of three cutting-edge fields: AI,

Received: 13-05-2025 | Revised: 21-07-2025 | Accepted: 30-07-2025 | Online: 14-01-2026

nanotechnology and botany, particularly in developing countries like Pakistan. It can serve as a source for researchers and students and guide policy makers on AI-enabled sustainable technologies.

Fundamentals of Nanobotany: A key perspective of nanobotany is the use of instruments and tools that are designed to work at nanoscale. In doing so, they have a precise interaction with the plants at the cellular and molecular level. These tools are specifically designed for plants with their specific roles in plant biology, and these include nano-carriers, nanosensors, and other NPs. Here is a brief overview of some main definitions of tools and technologies related to nanobotany (Nazir, 2018).

Nanotechnology: A branch of science that deals with materials whose size is in the range of 1-100 nm in at least one dimension.

Nanosensors: These highly sensitive tools can detect changes in plants and their environment at the nanoscale. These may be equally active in determining the nutrient level of plants. Some nanosensors can also detect plant stress level. These can be used to detect minor changes in the physical and chemical environment of plants and the resultant consequences on the plant. Nanosensors can detect the endogenous growth regulator levels of plants, pathogen and disease level, heavy metals, and gaseous composition of air as well (Presti *et al*., 2023).

Nanomedicine: The use of nanotechnology and development of therapeutic agents of nano-range in size are included in this field. NPs synthesized from plant material are included in nanobotany and are used to develop various medicines as they have plant metabolites on their surface and often show synergistic medicinal effects.

Nanocarriers: These are the NPs used for the targeted delivery of other molecules and substances to the specific locations inside the plant or plant cells for gene editing, nutrient status improvement, or disease treatment, etc. (Zhi *et al*., 2022).

Nanoparticles (NPs): These are engineered materials that show a size ranging from 1 to 100 nm. These NPs may be organic, inorganic, or biological in nature, and their use is also dependent on their nature and size. These NPs can be used as plant nutrients (fertilizers at the nanoscale), agrochemicals (pesticides, etc.), and for targeted delivery of genes, etc. (Prasad *et al*., 2017).

Phytomining: Extracting the metals from the soil with the help of plants is often termed as phytomining. An attempt to enhance the ability of plants to extract metals from the soil by using NPs can be named nano-phytomining and can be a useful future tool.

Nanotoxicity: It is also an important term related to the use of nanobotany. It covers the harmful effects of NPs on the plants and the environment. NPs are very active in their actions due to their small size and higher surface to volume ratio. However, it may have many toxic aspects other than advantages.

Historical progress in nano-botany: The idea of nanotechnology started from a lecture by Richard Feyman in 1959. But it was confined to material sciences only. It coincided with plant sciences in the late 90s. Positive impact of NPs on plants was discovered that led to the efficient use of resources like fertilizers and lesser impact on the environment. It provided the idea of nano nutrients, and the use of nanofertilizer was coined in the early 2000s. Effects of various NPs including metallic, organic, and polymeric NPs were analyzed on plant health. Their toxic studies were also conducted in relation to plants (Liu & Lal, 2005). The concept of nano-pesticide (nano-fungicide, and nano-insecticide, etc.) was introduced. In this era, a lot of work was done on the effects of NPs on plant growth and yield in relation to their cross talks with various plant growth regulators and signaling molecules (Yan *et al.,* 2006).

In 2010-2020, the term "Nanobotany" was introduced, when extensive studies were started on the interaction of plants and NPs at the cellular and molecular levels. This era mainly included the study of NPs' absorption by plants, their translocation through the vascular system, and then their deposition in various plant parts. Thus, the focus was on targeted delivery of nutrients to plants, crop improvement, stress mitigation, nutrient-enriched food, etc. Thereafter, nanosensors emerged paving way for real-time monitoring of plant requirements, plant health, and its disease response (Bhagat *et al*., 2023; Javad and Butt, 2018). This suggested the potential applications of nanobotany in improving crop resilience and yield. Some of the earlier applications of nanotechnology in the field of plant sciences included the use of NPs for imaging the plant structure. It helped to study and to understand the plant parts at nanoscale (Zhang *et al*., 2023).

Whereas era of 2020-present is considered as the era of integration of nanobotany and omics, where researchers are using genetic editing with nanoscale tools for modification of plants (Yan *et al*., 2022).

Integration of AI in nanobotany: AI is playing a significant role in all fields of life, and its importance is increasing with each passing day. We can't deny its importance as it is going to make a large difference in everyone's life. AI is a part of every discipline of life including healthcare, agriculture, communication, navigation, transportation, in homes and lifestyles, entertainment, and education, etc. (Talati *et al*., 2024). AI has an astonishing capability of handling larger amounts of information and difficult tasks on its own. In nanobotany, it helps to improve the efficiency, accuracy, and versatility of the nanobots in interaction with plants. The interaction between plants and nanobots opens new horizons for interdisciplinary approaches, enhancing the accuracy and efficiency of methods and techniques in plant sciences. Interaction of nanobotany with AI offers a forefront of innovation, leaving behind the conventional scientific methodologies (Dong *et al*., 2024). AI plays a vital role in nanobotany, offering innovative agricultural practices through a synergistic integration that enhances crop production, protection, and sustainability (Fig. 1).

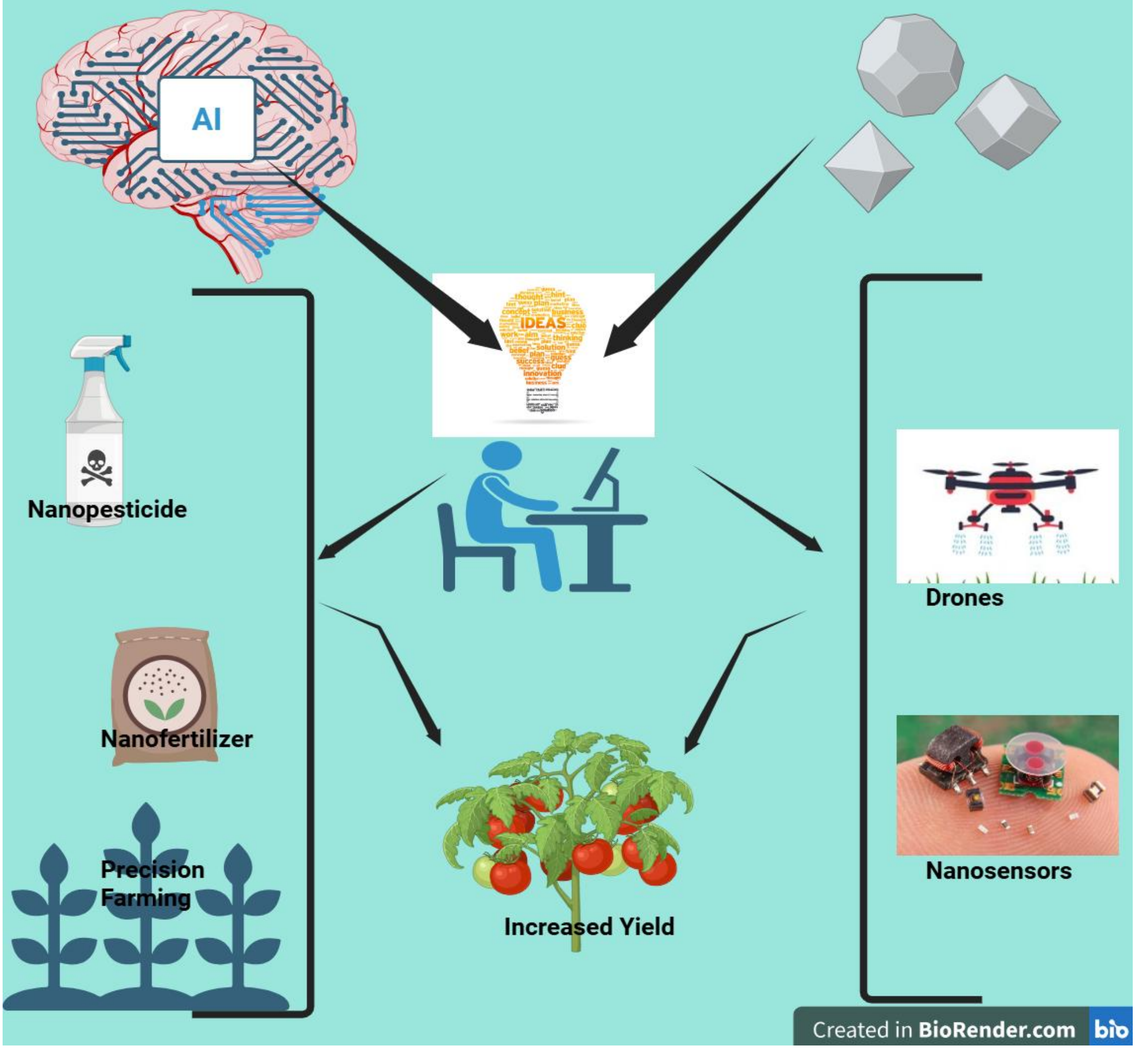

Fig. 1. A synergistic behavior of AI for nanobotany to increase plant production created in Biorenders.com.

There are various horizons, including nanoscale imaging, data analysis, predictive modelling, precision agriculture, environmental impact assessment, multiomics integration, and sustainable business integration, where AI impact is already visible. In botany, for example, when we take high-resolution images of plant structures by nanoscale imaging. Then AI tools are used to process these images in an accurate way and to identify anomalies and patterns of these images. AI tools increase the efficiency and accuracy of data interpretation compared to traditional methods. AI models can also explain the effects of the environment or other stresses in plants, in less time with more ease and accuracy (Flores *et al*., 2023; Agunuru, 2025). Such AI models are crucial for nanobotany as they can detect potential toxicity and ecological effects of NPs in advance. Thus, they can help to mitigate the probable negative effects of NPs on plants and soil ecosystems (Zhang *et al*., 2021). AI models can work smartly to enhance the impact. They decrease the cost of the project and increase its efficiency. AI can integrate genomics, metabolomics, and proteomics (Multiomics concept) for use in nanobotany. This gives more detail of the interaction of plants with NPs, thus helping to establish a more targeted and effective approach for the use of NPs in botany (Flores *et al*., 2023). Nanosensors also play an important role in nanobotany. When they are integrated with AI tools and models, they enable the researchers and farmers to monitor the plants' nutrient requirements, irrigation needs, and fertilizer adjustments, etc. This leads towards precision agriculture and food security. This idea of sustainable agriculture by use of AI also gives rise to the idea of sustainable business models where a precise and accurate use of NPs according to the requirement of the system can generate more business and profit with lesser input (Jankovic & Curovic, 2023).

AI-driven optimization of NPs: The 21st century can be named as "The century of nanotechnology". Today the production of NPs has increased due to their enhanced applications in every field of life. Medicines, agriculture, optics, electronics, conservation biology, meteorology, criminology, cosmetics, and more are involved with NPs.

However, it is not an easy task to synthesize NPs with desired characteristics. It is a time-consuming and difficult task that needs a real investment of time, funds, and resources. Green synthesis of NPs also has its importance (Ghaffar *et al*., 2024) as it uses plants, fungi, bacteria, and algae as raw material which represent renewable resources.

NPs can be synthesized with various shapes, sizes, surface charges, colors, appearances, surface morphologies, and stability depending upon their method of synthesis and other physical factors involved. The practical application of any NP is directly related to its characteristics as described above. If these characteristics of NPs are not properly controlled and understood, their application may not be successful. Therefore, their application in the field may be prohibited by the regulatory authorities even if they have shown promising effects on plant growth and yield. The investment of money and time is wasted for such projects. Here, AI plays its role by effectively predicting the characteristics of NPs on the targeted application with smart tools and modeling. These tools inform which method with which conditions and with which raw materials can be used to get the NPs of desired characteristics.

AI tools and ML tools can efficiently tune the parameters of the synthesis process for NPs. AI algorithms can also predict the interactions of these parameters. AI can suggest new materials and chemicals for NP synthesis and can present high-throughput experimentation for an optimized method out of a thousand possible testing combinations. This can minimize waste and save time and resources. Real-time data acquisition system of AI can find the faulty step of synthesis at once and can further modulate the process to achieve accuracy. Even properties of NPs can be tailored by pattern recognition and predictive modeling of the NPs synthesis methods (Reineck *et al.*, 2019; Desai *et al*., 2023). Furthermore, AI-based tools can analyze experimental data to optimize synthesis parameters (temperature, pressure, and reactant concentrations) quickly (Mikolajczyk & Falkowski, 2022), thereby ensuring the production of precise NPs with effective interactions in plant systems. Some of the AI tools that have applications in nanobotany are summarized (Table 1).

AI-driven control of NP **characteristics for targeted delivery:** Plants are of different types according to their environment including halophytes, mesophytes, xerophytes, and hydrophytes. They have specific characteristics, metabolism, and physiology depending upon the type of plants. They have their pattern of stomatal opening, leaf structure, stem morphology, and root development, etc. They also need a varied amount of water, nutrients, and other things. Plants need nutrients that are supplied in the form of fertilizers (Pandey, 2018). Owing to the health hazards of chemical fertilizers, the use of nano-fertilizers in the form of NPs is considered a better and economic option for farmers. As plants have various morphologies, the compatibility of NPs with plant morphologies and uptake mechanisms is crucial for the desired outcomes (Colipano & Cagasan, 2022). The mode of application of NPs should determine the interaction between plant receptor sites and NPs. This interaction should be strong enough that NPs are not released into the environment unnecessarily (Khan *et al*., 2019). For example, the smallest size NPs can have more efficient access to the targeted sites in plants (Gaumet *et al*., 2008). Sometimes, individual NPs can’t perform targeted functions, like providing nitrogen to plants nanohybrid of urea and hydroxyapatite was prepared (Kottegoda *et al*., 2017). For some NPs, proper encapsulation can guarantee the controlled release of the NPs at targeted sites at required time intervals. NPs furnished with nanobarcodes and nanosensors can work more precisely to identify the target and ensure the precise delivery of nano-emulsions, i.e., also a type of nanoencapsulation (Periakaruppan *et al*., 2023; Zain *et al*., 2023). This compatibility can only be achieved with the required characteristics of NPs including, shape, surface charge, and size, etc. Adaptive feedback systems can adjust nanoparticle characteristics dynamically, ensuring optimal performance in response to changing conditions. AI tools with real-time monitoring can enable us to understand the behavior of NPs outside and inside the plants and can make the technology more viable for large-scale agricultural use. Even AI modelling can predict different encapsulation for NPs (Grillo *et al*., 2021; Zhang *et al.*, 2021; Mikolajczyk & Falkowski, 2022).

Table 1. Use of AI algorithms in nanobotany.

Sr. #	AI Algorithms	Main usage	Reference
1.	Quantitative Structure-Property/Characteristic relationship (QSPCR)	Used to predict the optimized method for the synthesis of nanotubes of titanium oxide	Mikolajczyk and Falkowski, (2022)
2.	Decision Trees	ML tools that can be used to determine the possible physical characteristics of formed NPs	Desai *et al*., 2023
3.	Random Forests	ML tools that can be used to determine the possible physical characteristics of formed NPs	Desai *et al*., 2023
4.	Variational Autoencoders (VAE)	Are used to analyze TEM datasets	Wen *et al.,* 2021; Wang *et al*., 2024
5.	Convolutional Neural Networks (CNN):	This algorithm is used to analyze electron microscopy images and nanoscale pattern	Zheng *et al*., 2023
6.	Recurrent Neural Networks (RNN)	This is used in molecular simulations or to analyze the time-series data from nanosensors	Loukil *et al*., 2024
7.	Generative Adversarial Networks (GANs)	Help generate synthetic nanoscale images	Pronin & Volosova, 2023
8.	Particle Swarm Optimization (PSO)	These are used in nanoscale circuit optimization for nanophotonic design	Yan *et al*., 2020
9.	K-Means Clustering	Applied to study features of size and shape of NPs	Khan *et al*., 2024

Furthermore, AI algorithms can analyze a vaster dataset to correlate the characteristics of NPs and their delivery efficiencies. Plant scientists and nano-botanists can anticipate the structure and function of NPs and predict the required modifications at the surface of NPs to make their delivery to the plant surface more efficiently (Grillo *et al.*, 2021). AI can well predict the optimal ligands for NPs to improve their interaction with plants. These AI tools may include molecular modeling, molecular simulation, and data-driven ligand selection. Very unconventional ligands can be predicted by AI tools that may not be possible for the human mind. These tools can even learn with time and improve the NPs-ligand interactions (Di Filippo & Cavasotto, 2022.).

Case studies and real-world applications: A significant work was reported by Ji *et al.*, (2021) in which they prepared a nano-conjugate of pesticide and fertilizer (named PFAC). Their main aim was to decrease the weeds from fields and to increase the production of the main crop. The application of this PFAC material in the fields was monitored by NIR (Near Infrared radiation). Results showed that weeds suppression started just two hours after application of PFAC. It is a good example of combining nanobotany, agriculture, and AI tools. AI tools made it possible to get feedback in real-time.

Another example of customized use of NPs and AI for optimizing the NPs' interaction with plants was reported by Kottegoda *et al.*, (2017) a nanohybrid of urea-HA was applied to rice fields, and a comparison was made with simple urea in providing nitrogen to rice plants. Real-time data proved that the nanohybrid of urea was more efficient. Varsou *et al.*, (2019) developed a safe-by-design computational system for the characterization of NPs. This computational system is economical, robust, and user-friendly for constructing and categorizing NPs. Li *et al.*, (2024) employed an artificial neural network program to monitor the benefits and drawbacks of Se NPs on *Oryza sativa*. Their study detected the bioavailability and adaptive adjustments in nanoparticle properties to ensure optimal performance and responsiveness towards the plant environment. Deng *et al.* (2023) tested these models and successfully forecasted responses in beans, *Triticum aestivum*, and corn by applying NPs at different topographies. This predictive capability can aid in designing NPs that align with the physiological and biochemical features of plants, improving their overall effectiveness. TiO_2 nanotubes can transform carbon dioxide (a contributor to the greenhouse effect) into harmless components, ensuring environmental safety (Mikolajczyk & Falkowski, 2022).

Environmental and health considerations: AI-driven optimization minimizes the quantity of NPs required for effective delivery. This reduction not only enhances efficiency but also contributes in minimizing the potential environmental impact associated with nanoparticle applications in agriculture. All these points are important to consider as these NPs may not be compatible with the environment and food chain for a longer duration. These NPs may not be good for soil microbes, thus disturbing the soil biome (Tian *et al.,* 2019; Hofmann *et al.,* 2020). If NPs are sustained by plant parts, these may cause health hazards to humans and other consumers. Therefore, comprehensive programming is needed to determine the quantitative and qualitative attributes of NPs before they can be used in the field applications to increase their reliability (Tian *et al.*, 2019). AI and ML facilitate the integration of nanoparticle-based solutions with existing agricultural practices. This includes considerations of application methods, timing, and dosage to maximize the benefits of nanoparticle delivery in plants (Mani *et al.*, 2025).

AI-Driven use of NPs in disease and pest management: AI is incorporated into precision farming by providing digital elucidations of crop-related issues to decrease disease risk. AI-based tools (satellites, aircraft, drones, nanobots) facilitate precision farming via disease detection at very early stages. Nanobots contain sensors and GPS (Global Positioning System) and GIS (Geographic Information System) facilitated with data collection, monitoring, and analysis software. These systems aid in risk management of diseases and pests. The sensors and software assist in visualizing data in the form of pictures, plots, and graphs. The extent of the graphical plots represents the intensity and severity of various environmental factors, soil conditions, and pest attack.

AI-Enhanced early detection of plant diseases via nanobots: Aerial photographs of field crops by satellites and aircraft are quite expensive, and the quality of pictures can be affected by unpredictable weather conditions (Dawod & Dobre, 2022). The use of AI-based drones and nanobots (~ 1--100 nm) is a feasible and economical approach for the early detection of plant diseases. This approach involves taking, monitoring, and evaluating photographs to detect stress and chance of disease spread (Radoglou *et al.*, 2020).

Nutrient content and soil topography vary from region to region. Imbalanced soil nutrient levels can induce abiotic stress and cause various symptoms. For example, nutrient deficiency of nitrogen and magnesium may decrease the chlorophyll content and cause yellowing of leaves, contributing to a decrease in crop yield. Similarly, plant pathogens (fungi, bacteria, viruses, insects, and weeds) also destroy crops. Nanobots equipped with thermal, multispectral, and hyperspectral sensors can detect soil edaphic factors (type, structure, texture, pH, salt, water, nutrient, and heavy metal contents), thereby facilitating the detection of possible risks of plant health and diseases. Sensors establish temporal, spatial, and spectral evidence and can differentiate between pest attacks or nutrient deficiency (Xue & Su, 2017). Sensors should contain high-resolution cameras for clear images (Kiobia *et al.*, 2023). There are also thermal sensors which perceive weather conditions, including cold, warm, precipitation, dampness, and air flow. The spectral sensors employed by the NDVI (Normalized Difference Vegetation Index) indices can detect crop cover, health, disease and pest vulnerability (Dawod & Dobre, 2022).

Targeted delivery of pesticides and biocontrol agents: Sensors in nanobots can detect environmental parameters (temperature, humidity, light, and pollutants), as well as soil water and nutrient contents. The GPS provides the exact location of the affected area. The GIS system is accompanied by versatile software to process data in numerical form. The NDVI system is based on remote sensing and satellite imagery to determine health and plant biomass in certain zones (Dawod & Dobre, 2022). The NDVI provides a graphical representation of the vegetation cover of a particular region. This method aids in the calculation of the desired number of pesticides, fertilizers, or other biocontrol agents along with their targeted delivery to affected areas. VRA (variable rate application) is a commonly used technology to detect the presence of pests or plant diseases as well as edaphic factors by incorporating maps, and GPS, or sensors (Radoglou *et al*., 2020). Sensors detect information, process and analyze the information via algorithm software. Then they make decisions about suitable types and quantities of pest and disease control agents, depending upon plant and soil needs. VRA technology (equipped with spraying machinery) contributes to the target delivery of chemical and biocontrol agents to susceptible zones. Targeted delivery systems are restricted to affected regions, thereby decreasing the use of pesticide. Therefore, an AI-assisted targeted delivery system for synthetic and biocontrol agents is an eco-friendly approach with minimal health hazards.

AI-based data-driven strategies involve combinations of various technologies for optimal pest management. Among AI-based strategies, sensor networks involve the installation of sensors in agricultural fields to monitor environmental conditions and the presence of pests. CNN (Convolutional Neural Network) algorithms can process, analyze, and classify data to provide real-time insights, helping farmers make informed decisions. Customized versions of CNNs, including ResNet34, Signets, FSL, and SSD, can precisely identify and classify cotton pathogens (Kiobia *et al*., 2023).

Satellite imagery and remote sensing detect changes in crop health and identify potential pest infestations based on vegetation indices like NDVI, SR (Simple Ratio), NLI (Non-Linear Index), RDVI (Renormalized Difference Vegetation Index), and MSR (Modified Simple Ratio). Satellite sensors obtain data as spectral images (depending upon wavelengths absorbed and reflected by crops). Remote sensing considers three light spectra, i.e., UV, visible, and NIR. AI algorithms can process large datasets to calculate vegetation indices quickly. Then these calculated vegetation indices are used to determine specific vegetation properties (Xue & Su, 2017), enabling early disease detection by pathogens and targeted interventions.

Machine learning models utilize historical and real-time data to forecast pest outbreaks. These models can consider various factors, including weather patterns, crop types, and pest life cycles. Therefore, they can make accurate predictions for vegetation status. Plant nutritional deficiencies and the impact of abiotic stressors can also be analyzed via machine learning models. The Densenet-201 model provides the optimum results (96% perfection rate) concerning nutrient status in corn (Ramos *et al*., 2023). Another study used the GoogLeNet cellphone app. It is a suitable tool for pest identification with **a** 94% perfection rate (Yulita *et al*., 2023). Remote sensing combined with machine learning can identify pathogens and monitor vegetation. In this context, the 12-band model furnished better results than did the NDVI-based satellite imagery system (Lozano *et al*., 2023). Robotic and drone technologies equipped with AI algorithms and spraying machinery ensure the monitoring and targeted delivery of pest control agents (Radoglou *et al*., 2020). These technologies can cover large areas quickly and precisely to intervene when needed.

Research has revealed the development and applications of nanosensors in precision farming (Romanovski *et al*., 2023). Sensors are extensively used as smart traps and monitoring devices in agriculture to identify and quantify pest populations. Data from these sensors can guide farmers to apply control measures where and when needed. Hyperspectral and multispectral imagery, along with machine learning algorithms, e.g., PLSR (Partial Least Squares Regression) and SVR (Support Vector Regression), are used to quantify the compositional parameters of stored apples against pest attack (Khaled *et al*., 2023). AI, along with IoT (Internet of things) tools, identifies pathogens with 98% precision (Kiobia *et al*., 2023). Nanobarcodes are used to detect health and disease status as well as the productivity of vegetation. Coupling barcodes with Global Positioning Systems (GPS) is under investigation for the detection of pathogens and screening of crops (Periakaruppan *et al*., 2023).

There is another study, where nanosensors are used to monitor the response of plants to hydrogen peroxide application. Nanosensors were sensitive to changes in foliage cells. Plants secrete some defensive metabolites, helping plants to avoid pests that can be detected (Johnson *et al*., 2021). In such situations, AI tools gather data from soil sensors, weather stations, and pest monitoring devices and then process the integrated data for integrated pest management (IPM) (Ivezic *et al*., 2023). One example is automated Decision Support Systems (DSSs), including a machine learning system, that robustly recommended specific pest management strategies (Yulita *et al*., 2023).

Genetic manipulation and engineering: Advancements in biotechnology have led to various treatments for human diseases. One suitable option is gene therapy. Commonly utilized gene therapy techniques include nucleases (activators), zinc nucleases, and certain short sequences associated with protein systems known as CRISPR. However, the successful delivery of edited sequences to targeted cells is quite challenging. In this context, nanotechnology provides an efficient solution for effective drug delivery to target sites. These NPs improve gene therapy, protect target genes from degradation and stabilize DNA. Moreover, porous NPs, gold NPs, lipid-based, and polymer NPs are commonly utilized for gene therapy (Hu *et al*., 2023).

AI-optimized gene delivery and editing through nanobots: The introduction of normal genetic material to diseased cells is known as gene therapy to improve their health. This approach is essential for genetic modification, although it is a difficult task in medical research. The techniques of gene editing can modify genomes by inserting, deleting, or replacing a DNA sequence at the position of interest. Gene editing can precisely alter the DNA sequences targeted in the living cells (Khalil 2020). The most advanced types of gene editing are CRISPR/Cas-associated nuclease (CRISPR/Cas9), Transcription activator-like effector nucleases, and zinc finger nucleases. These can be employed to address mutations that are disease-causing, can knock out genes, and can insert new genes, thus helping cells fight against disease, or get rid of it. Integration of AI with gene editing techniques like CRISPR/Cas9 can revolutionize healthcare. For example, AI models can identify the cancer subtypes, and Gene editing can disrupt those oncogenes. AI models can also be used to design guide ribonucleic acid (gRNAs) for CRISPR/Cas systems. AI tools not only design gRNA but also predict the effects of gene editing on the function of the gene and the resultant cell phenotype. Moreover, as the understanding of the genetic process evolves, the model can be updated with more continuous feedback loops (Dixit *et al*., 2024). In plants, this combination of AI and gene editing tools can produce better crops with desired traits in less time. For example, in tomato, AI models have optimized and predicted mutations in fruit ripening genes, leading to improved shelf life and taste (Liu *et al*., 2024). Similarly in rice, salt tolerance genes have been predicted by AI models. Thus, guiding the gene editing to improve rice yield in saline soils (Sheng *et al.,* 2023).

Ethical considerations in genetic nanobotany enhanced by AI: Although NPs play many beneficial roles in medicine, agriculture, and other fields, but there are certain limitations. The efficacy of NPs mainly depends on engineering methodologies and NP formation. In agroecosystems, NP bioconjugation, design, and surface variation are also important factors. All these properties of NPs are essential for determining their behavior in genetic nanotechnology. There are still many problems faced in this regard. As an example, regardless of the current developments in the bioconjugation of NPs, better techniques are required to attain reasonable reproducibility, robust surface coatings, and functionalization and bioconjugation techniques due to the complex surface chemistry of NPs. Furthermore, the precise gene editing tool in crops, CRISPR-Cas9 has the potential to improve nutritional quality, yield, and stress tolerance. Nevertheless, it has several drawbacks and moral dilemmas. In theory, off-target effects from CRISPR could result in unexpected mutations that alter other characteristics or impair plant function. Inconsistent phenotypes can also arise from mosaicism, in which all plant cells are not altered uniformly. Regenerating entire plants from modified cells is frequently ineffective, and delivering CRISPR components into plant cells is still difficult, particularly in complex or resistant crops like wheat and maize.

The ethical classification of CRISPR-edited crops as genetically modified organisms (GMOs) is a topic of continuous discussion because it affects both public and regulatory acceptance. Concern is increased by the possible ecological hazards, such as decreased biodiversity or the unintentional flow of genes to wild relatives. Furthermore, smallholder farmers' access to CRISPR technology may be restricted by intellectual property rights, leading to disparities in agricultural innovation. The sustainable use of CRISPR in crop improvement depends on careful evaluation and responsible use because the long-term effects on ecosystems and food systems are still unknown (Ahmad *et al*., 2021).

Advancements in precision agriculture through genetic nanobotany applications: Traditional methods of genetic engineering have many drawbacks in agriculture, such as ineffectiveness, damage to the plant cell wall, and nonsignificant gene expression. Various techniques, such as microprojection, Agrobacterium-mediated transformation, and vectors, are typical methods for gene delivery. Furthermore, these conventional techniques of genetic engineering cause problems after integration into the host cell. These may include a narrow range of hosts, fertility problems in plants, and post-modification regeneration (Demirer *et al*., 2017; Nandy *et al*., 2020). Additionally, they are not versatile for utilization. However, NPs have remarkable properties in precision agriculture because of their versatility, small size, easy-to-use nature, and high success rate. The NPs are bound with genomes and transferred to the host cells with minimal loss or problems in the plants. NPs also act as genetic carriers by crossing barriers such as the cell wall owing to their small size. NPs as nanocarriers effectively protect DNA from nucleases. Additionally, it efficiently transfers genetic material to the nuclease without disturbing the cell. For example, silica and gold NPs actively transfer genetic material inside plant cells (Torney *et al*., 2007). Moreover, titanium NPs are also taken up by plant cells, and genetic material is transferred to the plants.

Modern techniques involving visualization, cellular differentiation, and gene delivery are utilized for NP applications. Due to the visualization factors (fluorescence) of the NPs, the genes delivered to the plant cell can be detected. Furthermore, many inorganic NPs act as synthetic vectors that offer various advantages over conventional lipid-based vehicles, including tunable size and surface characteristics, multifunctional abilities, and the ability to translate the physical characteristics of the metal core to the delivery vector (Arsianti *et al*., 2010).

Precision farming and environmental monitoring: Currently, we find ourselves at the initial phase of a burgeoning agricultural revolution marked by data-intensive methodologies (Jonathan *et al.*, 2023). This revolution employs machinery at every stage of the agricultural process, encompassing diagnosis, decision-making, and execution. Human involvement is relegated primarily to monitoring and maintenance only. In addition to the evolutionary changes brought about by past industrial revolutions in agriculture, the ongoing fourth industrial revolution is playing a pivotal role, giving rise to what is now termed Agriculture 4.0. This emerging discipline is distinguished by data-centric management, the integration of new tool-based production methods, an emphasis on sustainability and professionalization, and a concerted effort to reduce the environmental impact of farming through the incorporation of modern smart technologies (Walter *et al.*, 2017). These technologies include robot technology, drones, big data, AI, computer vision, 5G, cloud computing, the IoT, and blockchain technology (Javaid *et al*., 2022), collectively contributing to more autonomous and intelligent agricultural production systems (Shaikh *et al*., 2022). Consequently, new trends, such as precision agriculture, are evolving, introducing enhanced capabilities to smart farming practices.

Version 3.0 and 4.0 of agriculture are the two phases of agricultural evolution, each having its specific technology, practices, data, and innovations. These two phases can be differentiated from the mentioned (Table 2).

Table 2. Comparison of Agriculture revolution version 3.0 and 4.0.

Feature	Agriculture 3.0	Agriculture 4.0	References
Time period	Late 20th to early 21st century, also known as precision agriculture	Mid 2010 to present also called as digital agriculture or smart agriculture	Rahmann *et al*., 2017; Liu *et al*., 2020; Silva *et al*., 2020; Araújo *et al*., 2021; Aggarwal & Verma, 2022
Data techniques	Limited data Mainly depend upon local information and machines	Extensive data Cloud based, integrated from many sources, and real time data	
Key technologies	GIS, VRT, GPS, mechanization	Big data, robotics, blockchain, IOT, AI	
Automation level (AL) and Decision making (DM)	AL is partial DM is based on experience	AL is high DM is AI-driven, predictive	
Farm management	Site specific	Fully integrated	
Internet involvement	Minimal	Critical	
Human involvement	Main Factor	Minimal	

Big data: Precision agriculture relies on extensive data and information, akin to the datasets used by major industries for predicting customer behavior. In agriculture, big data analytics, which employs tools such as data mining, AI, and predictive analytics, plays a pivotal role in decoding data-intensive processes for informed decision-making. These analytics operate on vast datasets, utilizing technologies such as machine learning, cloud computing, image processing, and GIS to identify patterns and trends. Such insights assist farmers in navigating risks and challenges. The integration of data in agricultural production enhances traceability and elevates product quality, meeting the rising consumer demand for ecologically mindful products. However, challenges persist, including data updating, device security, accuracy, availability, and encryption. Addressing these issues is crucial, as invalid data can lead to costly and disruptive decisions for farmers (Bhat & Huang, 2021).

But in the case of developing countries like Pakistan, there are many limitations regarding the use of Big Data. One of the main reasons is the low literacy levels in digital data. Small-level farmers don't have the finance and literacy abilities to effectively use data-driven insights. They also don't have access to digital infrastructure due to the higher cost of precision agriculture tools and services. In the real world, there are many institutional issues in making farming policies. These include inadequate policy support, weak extension services, and limited public-private collaborations. It is crucial to address these constraints for equitable technological advancements in agriculture across the globe (Kamilaris *et al*., 2017; Wolfert *et al*., 2017; Soto *et al*., 2019).

Machine vision technology: Precise and accurate data are fundamental to the success of precision agriculture. For example, a recent shift towards more reliable data sources, such as image analysis, compared with labor-intensive methods (Jang *et al*., 2023). Machine vision (MV), also known as agro-vision or the 'eyes' of robots, uses pixel images to provide nondestructive, robust, and rapid monitoring of cultivation processes. MV systems empower machines with vision and judgment capabilities in image processing and data extraction. While MV technologies have been successful in various applications, such as crop species identification, stress detection, seed quality assessment, and weed and disease detection, but they are still in the prototype stage. Emerging deep learning (DL) techniques are now being integrated with machine learning (ML) technologies to develop intelligent robots capable of multispectral imagery analysis and real-time field variable rate applications (Punithavathi *et al.*, 2023). Even commercial smartphones are becoming valuable tools for monitoring crop health and stress via MV systems, leveraging their widespread accessibility among the human population.

But it also faces many challenges in its application in developing countries. These challenges include higher initial investment costs (for imaging software and hardware), lack of local technical expertise, lack of high-quality data, limited access to high-speed internet, and lack of cloud computing infrastructure, etc. Without considering these barriers, it is impossible to accept and apply agriculture 4.0 (Kamilaris & Prenafetaboldu, 2018; Zhang & Kovacs, 2018; Shahhosseini *et al*., 2020).

Internet of things (IOT): The Internet of Things (IoT) is a network of interconnected items and technologies, representing a crucial advancement in precision agriculture and smart farming. In agriculture, IoT architecture, including agricultural sensors with ICT (Information and Communication Technology), and UAVs (Unmanned Aerial Vehicles) facilitate data collection for precision agriculture. With advancements in communication technologies and wireless networks (5G, LoRaWAN, NB-IoT, Sigfox, ZigBee, and Wi-Fi), the IoT's application has expanded to diverse fields, enabling real-time remote control, high-throughput phenotyping, and better coverage, bandwidth, connection density, and end-to-end latency (Shin *et al.*, 2022). When integrated with cloud computing, the IoT contributes to smart farming across livestock monitoring, smart greenhouses, fishery management, and weather tracking.

Precision agriculture benefits from various IoT sensors for collecting data on temperature, humidity, light intensity, and other factors, which are uploaded to cloud information support systems for management. The IoT also enhances ground and underground cognition through agricultural sensor nodes, autonomous farm vehicles, and mobile crowd sensing.

In developing countries, there is a lack of Govt policies, experts, and digital infrastructure that hinders the conversion of IOT solutions to the local contexts.

Therefore, it ends in performance in diverse agro-climatic conditions (Ayaz *et al*., 2019; Boursianis *et al*., 2022).

Despite these challenges, the IoT continues to play a pivotal role in revolutionizing agricultural operations, extending to areas such as cattle monitoring and weed detection through machine vision. Edge computing further facilitates real-time data transmission in IoT precision agriculture, reducing the data package size and leveraging smart technologies for improved convergence speed and task completion rates. Pioneering companies such as Cisco and Huawei contribute to shaping the landscape of edge computing within the IoT (Karunathilake *et al.*, 2023).

Artificial intelligence (AI), Machine learning (ML), and Deep learning (DL): AI plays a pivotal role in robotics and autonomous systems (RASs) and has seen significant development in the Internet of Things (IoT), contributing to continuous data streams in agriculture. Employing mining techniques, AI transforms agricultural data into meaningful information crucial for decision-making, especially in pest identification, disease detection, yield prediction, and fertilization plans. The potential of AI extends to reducing food wastage; improving production hygiene; and monitoring machines in various stages of agriculture, including the supply chain, production patterns, and soil, crops, and water management, as well as disease and pest control, to overcome challenges in conventional farming (Saranya *et al.*, 2023).

Machine learning (ML) and deep learning (DL) are sub-concepts of AI, with ML focusing on learning systems and algorithms for understanding data-intensive farming processes. DL, with its layers and nonlinear functions, addresses limitations in the practical implementation of robots, mobile terminals, and intelligent devices in modern agriculture. Machine learning algorithms integrated into mobile detection algorithms have improved detection methods, overcoming challenges in technology adaptation. These advancements have wide-ranging applications, including accurate fruit and pest detection, optimization, and prediction of complex conditions in plant tissue cultures and breeding processes. Despite challenges in processing speed and efficient information visualization systems for farmers dealing with big data, continuous research on big data, the IoT, ML, and DL holds great potential in providing accurate predictions for agriculture and identifying new opportunities (Alfred *et al.*, 2021).

AI applications in smart farming include soil management, crop management, disease management, weed control, and mobile expert systems for disease diagnosis and soil health analysis. The integration of AI with precision agriculture has formalized this approach, making it more scientifically grounded for optimal agricultural outputs. However, addressing experience gaps between AI specialists and farmers, ensuring accessibility, and addressing privacy protection issues with large datasets are essential for the further development of AI in agriculture (Liu *et al.*, 2020).

Guidance systems: Guidance systems leverage GPS technology to offer farmers real-time information on equipment and herd-grazing locations, facilitating optimized field operations such as planting, harvesting, and herding. Overcoming challenges such as limited satellites and poor signal strength, the introduction of the GNSS (Global Navigation Satellite System) has replaced labor-intensive farm operations with more efficient methods such as VRA (Variable Rate Application). GNSSs are pivotal for optimizing the effectiveness and efficiency of agricultural machinery, contributing to the emergence of commercialized agricultural machinery services. The trend of GNSS-enabled devices in fully automated steering of traction saves time, labor costs, and money, whereas precision agricultural robots and rovers rely on high-resolution navigation solutions. Studies integrating DL propagation models in GNSS with inertial navigation datasets have enhanced precision agriculture, exemplified by successful tests of electric seeders with optical fiber detection technology. The development of software-based farm management solutions for GIS encourages automation in data collection, analysis, supervision, storage, decision-making, and overall farm management (Du *et al.*, 2023).

But inconsistent satellite signal coverage, high-cost maintenance, lack of skilled operators, and weaker Govt supports are the main reasons for poor or nil adaptations of Guidance systems by farmers for precision agriculture (Mulla, 2013; Jat *et al.*, 2016).

Blockchain technology: Blockchain originally employed in cryptocurrency, is a decentralized and distributed database that maintains an ever-growing list of ordered records or blocks. This technology enhances data transparency, immutability, and reliability, fostering mutual trust in the supply chain. Introduced to precision agriculture, blockchain facilitates the integration of digital technologies, addressing challenges in smart farming, such as insufficient and insecure data-sharing infrastructure.

It proves valuable in the "IoT applied Greenhouse Monitoring System," enabling remote monitoring and control of farm equipment. The nature of Blockchain is decentralized, anonymous, and secure systems that can provide security and privacy to address the issues of IOT. It’s the start of using Blockchain technology in agriculture, but it shows a promising future in providing a reliable, faster, and secure platform for monitoring agricultural fields. When we use it in the food supply chain, it becomes crucial for food safety concerns and fragmented information in the supply. Its programming can be useful in agricultural processes like energy consumption, irrigational water sharing, robot coalitions, autonomous UAVs, and labor integration (Kamilaris *et al*., 2021).

Robotics and self-sustained autonomous systems (RASs): In natural farming practices, there are different sources of variation that make them quite uncertain. These variations and uncertainties can be well handled by the RASs, which are equipped with various sensors, actuators, and machine learning algorithms. RASs can promote autonomous farming which is an integration of robotics, drones, sensors, and remote sensing. These all facilitate planting, watering, spraying, harvesting, plucking, and weeding, etc. Thus, overall cost and labor is reduced (Liu *et al*., 2020; Monterio & Santos, 2022).

Further improvements in RAS systems can make it more efficient, accurate, autonomous, and precise in a dynamic agricultural environment. Present key uses of RASs in agriculture include 3D food printing, autonomous farming, automated husbandry, aerial monitoring, plant phenotyping, leaf peeling, selective spraying, and fruit counting, etc. Other than these, the use of auto-steered agricultural vehicles also uses RAS as these vehicles perform various field applications including planting, chemical applications, harvesting, tilling, and equipment positions. While doing so, these vehicles must avoid overlaps and skips (Liu *et al*., 2020; Hundal *et al*., 2023).

This is a new system, but there are many limitations with its application in agriculture 4.0. These issues include scalability. Infrastructure and connectivity requirements, privacy concerns, integration challenges, and data immutability (Casino *et al.*, 2019; Tripoli & Scmidhuber, 2018; Duan *et al.*, 2021).

Artificial satellites, Unmanned aerial vehicles (UAVs), and Unmanned ground vehicles (UGVs): Artificial satellites, including American Landsat satellites, the European Sentinel-2 System, RapidEye constellation satellites, the GeoEye-1 system, and WorldView-3, contribute to remote sensing by generating multispectral data accessible from a distance. The deployment of intelligent remote-sensing satellites ensures comprehensive coverage for collecting agricultural information (Berger *et al.*, 2023). Recent advancements in ubiquitous and affordable technologies such as drones, crews, and aircraft have allowed closer and more frequent ground-level image capture, enhancing detail and functionality (Fragassa *et al.*, 2023). Unmanned ground vehicles (UGVs) play a role in acquiring high-resolution data for weed identification, selective pesticide spraying, soil analysis, and crop scouting. Scoring robots, including the Oz robot for mechanical weeding; the GUSS autonomous sprayer for spraying; the RowBot system for fertilization, mapping, and seeding; and VineRobots for vineyard management, achieve specific targets (Berger *et al.*, 2023). Information derived from satellite, UAV, and UGV imagery is crucial in precision agriculture. They support vegetation patch identification, weed recognition, pest attack detection, environmental stress observation, and accurate classification via variable rate technology (VRT). In various agricultural disciplines, such as aquaculture, agroforestry, and forestry, imagery data plays a significant role, covering large areas for information gathering and reproducibility. Data from satellites, UAVs, and UGVs are complemented by detailed ground survey data processed with machine learning (ML) and deep learning (DL) algorithms to provide usable and meaningful information.

Deforestation is monitored by remote sensing satellites and drones, where they can accurately and precisely classify plant types and species, thus surpassing other UAV and LiDAR data. Densities of forests and distribution of various tree types can be studied by using UAV data (Sentinel-2 NDV1 and RGB images). To monitor the large farmlands, use of drones, and other automated aircraft is increasing day by day as it is costeffective and quite helpful for providing precise information using multispectral cameras, hyperspectral sensors, and other advanced technologies (Ma et al., 2021; Tomaszewski & Kolakowski, 2023).

Data collection and analysis: In the field of nanobotany, dynamic synergy exists with data collection and AI tools. This has become a very significant relationship with the passing days due to the increased research and increased data. AI tools can increase data credibility in several ways, including:

A) Handling large and complex data sets
B) Development of predictive models
C) Optimization of experimental conditions
D) Automated image analysis
E) Enhancing precision in the synthesis and characterization of NPs
F) Accelerating research through AI-driven simulations
G) Integration of multiscale data

Data collected by nanobots from plant systems are usually vast and complex datasets. It includes various studies, like the use of gold NPs for sensing arsenic accumulation in plant leaves, giving real-time data of plant responses. This dataset may include absorption, translocation, and storage of arsenic in plant tissues at different timings with different temperatures and soil conditions (Ulhassan *et al.*, 2022). This approach can change how we understand plant biology and open new ways to explore and to study plants using nanobots.

Challenges and ethical considerations for use of AI in NanoBotany: After looking into the details of positive impacts and uses of AI tools and algorithms, this fascinating world leads us to frontiers of promising results in plant sciences, nanobotany, and agriculture. This convergence of AI tools and nanobotany seems to be really promising to resolve the issue of food security and environmental concerns in the future. But this convergence has issues and challenges. Integration of AI tools into every system encompasses technical, ethical, and regulatory dimensions. This review article critically investigates both aspects of the picture, i.e., advantages and disadvantages (Fig. 2), and we can take advantage of these synergies only if we consider both aspects in designing and using AI techniques. Public acceptance of these AI tools is another problem related to the complex interaction of AI in life (Jha *et al*., 2019).

Main ethical concerns regarding use of nanobots could be invasive surveillance. Thus, the privacy of individuals is compromised. AI-enabled nanobots can gather detailed information at nanoscale, thus raising concerns about unauthorized access to personal data (Schulte & Salamanca-Buentello, 2022). There may be some unintended results of nanobots usage, so how much autonomy should be granted to AI tools? It is a basic question of the scenario. Therefore, Human control and oversight are critical for its crucial use. Then there are environmental issues and concerns related to the life cycle, age, and sustainability of nanobots. There are ethical concerns in minimizing the environmental impact of AI and using sustainable approaches for AI-based technologies. Addressing these ethical challenges is imperative to ensure the responsible development and deployment of AI-enhanced nanobots in various fields (Munoko *et al*., 2020; Brendel *et al*., 2021). Researchers and ethicists continue to explore and address these ethical concerns as the fields of nanotechnology and AI advance (Schicktanz *et al*., 2023). When such new technologies are introduced in society, there are several ethical, legal, and societal concerns. Therefore, there is a dire need to balance the advantages and concerns/limitations related to the use of AI tools in nanobotany and nanoagronomy. It's the responsibility of the scientific community, policy makers, and the regulatory bodies to have a check and balance system for AI tools, including a regulatory framework, ethical deployment, etc. (Adefemi *et al.*, 2023; Cheng *et al*., 2021) to address the challenges faced due to the use of AI (Table 3).

Limitations of AI in nanobotany: AI in combination with nanobotany can revolutionize agriculture. It enables the complex and intelligent design of the NPs, offers predictive modelling and decision making in plant systems based on databases. But several limitations still exist, one of the main challenges is the lack of large and high-quality datasets. Such data sets are the basic requirement of AI to make accurate predictions. In nanobotany, NP-plant interaction experimental data is still limited and inconsistent, reducing model reliability. Responses of plant systems are quite complex, and they variably respond to the applied NPs, making it difficult for AI models to predict accurately. Many AI models act as black boxes for nanobotany, having multiple roles but lacking main explanations.

Additionally, integrating multidisciplinary data from plant physiology, genetics, biochemistry, and nanotechnology is also a computational and technical hurdle, making a wide gap between AI and real-world validation. It especially happens when lab-based models are shifted to field models. Various ethical issues also arise while using AI in controlling and manipulating plant systems at the intersection of AI, nanotechnology, and plant biology. It limits the progress and implementation of these emerging fields.

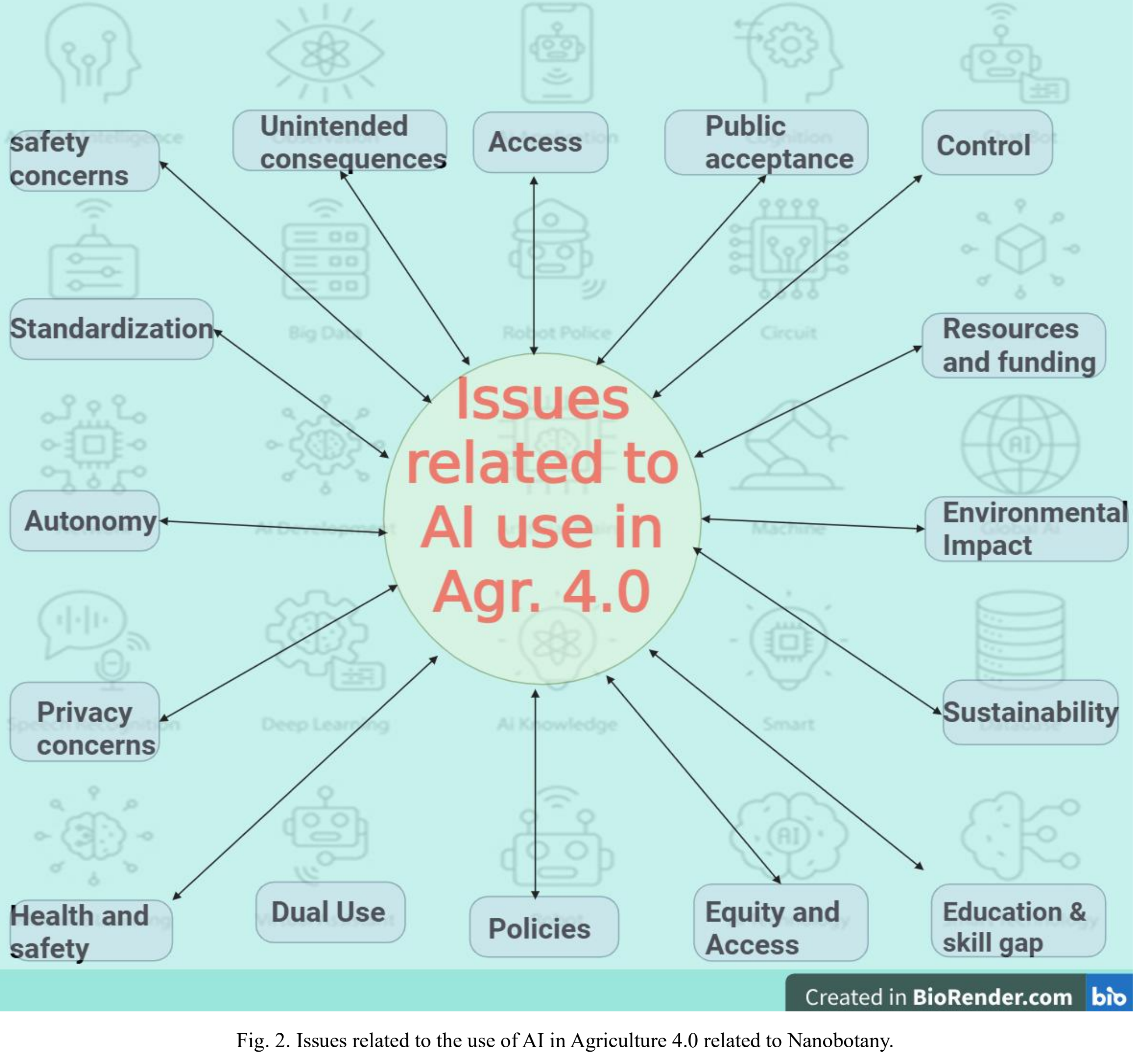

Fig. 2. Issues related to the use of AI in Agriculture 4.0 related to Nanobotany.

Table 2. Addressing the AI challenges in the field of Nanobotany and Nano agronomy.

	Addressing the concerns
1) Regulatory frameworks 2) Privacy safeguards in data collection	Botanists, nanotechnologists, and AI experts: teams that include botanists, nanotechnologists, computer scientists, and AI specialists to bring together expertise in plant biology, nanotechnology, and AI Educational programs for policymakers, industry professionals, and other stakeholders should be developed to enhance their understanding of the interdisciplinary nature of nano-botany and its potential impact (Kusters *et al*., 2020) Privacy-preserving technologies such as differential privacy or homomorphic encryption. Establishing clear guidelines for data storage, access, and sharing, along with obtaining informed consent from stakeholders, will contribute to building trust and mitigating privacy risks
Secure communication protocols	The implementation of encrypted communication protocols protects information from unauthorized access and potential cyber threats. Employing state-of-the-art encryption algorithms and regularly updating security protocols will fortify the integrity of communication channels, assuring stakeholders that the data exchange in nanobotanies remains confidential and protected against external interference (Cheng *et al*., 2021).
Ethical data usage and transparency	Rules and policies about how data will be obtained, utilized, shared, and retained. Regular auditing and accountability standards can enhance the transparency of AI systems in nanobotany
1) Environmental impact assessment 2) Energy-efficient designs	Evaluating the potential ecological consequences of deploying nanobots in plant systems ensures that any adverse effects on soil health, nontarget organisms, or broader ecosystems are identified and mitigated
Good governess and sustainability	Facilitate partnerships between academic researchers, industry players in nanotechnology and AI, and government agencies to combine resources and expertise Sustained funding models that support long-term interdisciplinary research in nanobotany, are advocated, recognizing that breakthroughs may require time and continuity
Stakeholder engagement and education	Engaging with all stakeholders, including the public, farmers, policymakers, and environmental organizations, is critical for addressing both privacy and environmental concerns. It is the responsibility of policymakers and environmental organizations, along with local governments, to provide educational resources to other stakeholders explaining the benefits, risks, and safeguards of AI in agriculture. Involving all stakeholders in the decision-making process and considering their perspectives in the development of regulations and guidelines enhances the overall acceptance of AI-driven nanobot applications To organize workshops and collaborative platforms that facilitate discussions and idea exchange among people from different disciplines, promoting a deeper understanding of each field's contributions to nanobotany To develop interdisciplinary educational programs that provide training in both nanotechnology and AI applications in botany, fostering a new generation of botanists with a holistic skill set
Adherence to ethical standards	Establishing and adhering to ethical standards in the research, development, and deployment of AI-driven nanobots is fundamental. Ethical considerations should extend beyond data privacy to encompass broader issues such as biodiversity preservation, ecosystem health, and equitable access to benefits. Regular ethical reviews involving interdisciplinary experts and external ethics committees can guide researchers and developers in navigating complex ethical dilemmas (Habbal *et al*., 2024)
Joint research facilities for easy access	Shared research facilities where botanists and nanotechnologists can work side by side should be established, enabling the seamless integration of nanobots into plant studies.

Conclusion and Future prospects

AI is inevitable in our lives now. It has a transformative role for the future of nanobotany. AI is going to revolutionize agricultural techniques and practices, and the concept of a global village in terms of botanical data will be accomplished. The collaborative approaches and interdisciplinary research outlined provide a roadmap for navigating complex challenges, ensuring the sustainable and responsible integration of nanobots and AI into our botanical pursuits. In this interdisciplinary work, the convergence of nanotechnology, AI, and plant sciences heralds a new era of scientific exploration and innovation with far-reaching implications for the future of our planet. Ethical issues and other concerns related to the use of AI in nanobotany can be addressed for future use by policymakers, scientists, and farmers. Conclusively, the ethical considerations in advancing nanobotany underscore the need for a conscientious balance between innovation and responsible governance, emphasizing transparency, stakeholder engagement, and adherence to ethical standards to ensure the ethical and sustainable evolution of this transformative field. In conclusion, AI will be a future catalyst for nano-botany, collectively ensuring food safety, environmental stability, crop tolerance to environmental stresses, and enhanced production of commercial plant metabolites in a controlled way. Key trends of this synergistic field will be precision in plant monitoring and growth, Smart nano elicitation for enhanced crop yields, AI-enhanced gene editing and plant breeding, Environmental monitoring and sustainability, nano pesticide and smart delivery systems, climate resilience, nanobiosnesors for plant research, automation in agriculture, and AI-guided nanotoxicology in plants, microbes and soil systems.

References

Adefemi, A., E.A. Ukpoju, O. Adekoya, A. Abatan and A.O. Adegbite. 2023. Artificial intelligence (Placeholder2) in environmental health and public safety. *World J. Adv. Res. Rev.*, 20(3): 1420-1434.

Aggarwal, S. and A. Verma. 2022. Transformations in the ways of improving from agriculture 1.0 to 4.0. In *2022 5th International Conference on Contemporary Computing and Informatics (IC3I)* (pp. 170-174).

Agunuru, A.K.R. 2025. AI tools for data performance enhancement: A comprehensive review. *J. Computer Science & Techn. Studies*, 7(6): 639-648.

Ahmad, A., M.Z. Ghouri, N. Munawar, M. Ismail, S. Ashraf and S.O. Aftab. 2021. Regulatory, ethical, and social aspects of CRISPR crops. *CRISPR Crops: The Future Food Sec.*, 261-287.

Alfred, R., J.H. Obit, C.P.Y. Chin, H. Haviluddin and Y. Lim. 2021. Towards paddy rice smart farming: a review on big data, machine learning, and rice production tasks. *IEEE Access*, 9: 50358-50380.

Araújo, S.O., R.S. Peres, J. Barata, F. Lidon and J.C. Ramalho. 2021. Characterising the agriculture 4.0 landscape-emerging trends, challenges and opportunities. *Agronomy*, 11(4): 667.

Arsianti, M., M. Lim, C.P. Marquis and R. Amal. 2010. Assembly of polyethylenimine based magnetic iron oxide vectors: insights into gene delivery. *Langmuir*, 26: 7314-7326.

Ayaz, M., M. Ammad-Uddin, Z. Sharif, A. Mansour and E.H.M. Aggoune. 2019. Internet-of-Things (IoT)-based smart agriculture: Toward making the fields talk. *IEEE Access*, 7: 129551-129583.

Berger, G.S., M. Teixeira, A. Cantieri, J. Lima, A.I. Pereira, A. Valente, G.G. de Castro and M.F. Pinto. 2023. Cooperative heterogeneous robots for autonomous insects trap monitoring system in a precision agriculture scenario. *Agriculture*, 13(2): 239.

Bhagat, R., A.P. Ingle and H. Chen. 2023. Nanosensors and nanobiosensors for sustainable agriculture. In*:* Elsevier, *Nanotechnology in Agriculture and Agroecosystems.* 93-112.

Bhat, S.A. and N.F. Huang. 2021. Big data and ai revolution in precision agriculture: Survey and challenges. *IEEE Access*, 9: 110209-110222.

Boursianis, A.D., M.S. Papadopoulou, P.D. Diamantoulakis, A. Liopa-Tsakalidi, V. Vitsas, P. Samaras and L. Georgiadis. 2022. Internet of Things (IoT) and agricultural unmanned aerial vehicles (UAVs) in smart farming: A comprehensive review. *Internet of Things*, 18: 100187.

Brendel, A.B., M. Mirbabaie, T.B. Lembcke and L. Hofeditz. 2021. Ethical management of artificial intelligence. *Sustainability,* 13(4): 1974-1983.

Casino, F., T.K. Dasaklis and C. Patsakis. 2019. A systematic literature review of blockchain-based applications: Current status, classification and open issues. *Telem. Inform.,* 36: 55-81.

Cheng, J.Y., J.T. Abel, U.G.J. Balis, D.S. McClintock and L. Pantanowitz. 2021. Challenges in the development, deployment, and regulation of artificial intelligence in anatomic pathology. *Amer. J. Pathol.*, 191(10): 1684-1692.

Colipano, J.A. and U. Cagasan. 2022. A review on the impact of organic, conventional and nano fertilizer application in crop production. *Eurasian J. Agricultural Res.*, 6(2): 101-109.

Dawod, R.G. and C. Dobre. 2022. Upper and lower leaf side detection with machine learning methods. *Sensors*, 22(7): 2696.

Demirer, G.S., R. Chang, H. Zhang, L. Chio and M.P. Landry. 2017. Nanoparticle-guided biomolecule delivery for transgene expression and gene silencing in mature plants. *Biophys. J.*, 114: 217.

Deng, P., Y. Gao, L. Mu, X. Hu, F. Yu, Y. Jia, Z. Wang and B. Xing. 2023. Development potential of nanoenabled agriculture projected using machine learning. *Proceedings National Academy of Sciences*, 120(25): e2301885120.

Desai, A.S., A. Ashok, Z. Edis, S.H. Bloukh, M. Gaikwad, R. Patil, B. Pandey and N. Bhagat. 2023. Meta-analysis of cytotoxicity studies using machine learning models on physical properties of plant extract-derived silver nanoparticles. *Int. J. Mol. Sci.*, 24(4): 4220.

Di Filippo, J.I. and C.N. Cavasotto. 2022. Guided structure-based ligand identification and design via artificial intelligence modeling. *Exp. Opin. Drug Discov.*, 17(1): 71-78.

Dixit, S., A. Kumar, K. Srinivasan, P.M.D.R. Vincent and N.R. Krishnan. 2024. Advancing genome editing with artificial intelligence: opportunities, challenges, and future directions. *Front. Bioengin. Biotech.*, 11: 1335901.

Dong, H., J. Lin, Y. Tao, Y. Jia, L. Sun, W. J. Li and H. Sun. 2024. AI-enhanced biomedical micro/nanorobots in microfluidics. *Lab on a Chip*, 24(5): 1419-1440.

Du, Y., S.S. Saha, S.S. Sandha, A. Lovekin, J. Wu, S. Siddharth, M. Chowdhary, M.K. Jawed and M. Srivastava. 2023. Neural-kalman GNSS/INS navigation for precision agriculture. *In*: IEEE, *International Conference on Robotics and Automation (ICRA), London, United Kingdom,* pp. 9622-9629.

Duan, Y., G. Cao, Y. Yu and H. Wang. 2021. Barriers to adopting blockchain in food supply chains: A socio-technical perspective. *Sustainability,* 13(6).

Feynman, R.P. 1959. There's plenty of room at the bottom. Lecture delivered 29 Dec 1959. In *at annual meeting of Am. Phys. Soc. Available at http://www. zyvex. com/nanotech/feynman. html. Accessed February* (Vol. 26, p. 2009).

Flores, J.E., D.M. Claborne, Z.D. Weller, B.J.M. Webb-Robertson, K.M. Waters and L.M. Bramer. 2023. Missing data in multi-omics integration: Recent advances through artificial intelligence. Front. *Art. Intell.*, 6: 1098308.

Fragassa, C., G. Vitali, L. Emmi and M. Arru. 2023. A new procedure for combining UAV-based imagery and machine learning in precision agriculture. *Sustainability*, 15(2): 998.

Gaumet, M., A. Vargas, R. Gurny and F. Delie. 2008. Nanoparticles for drug delivery: the need for precision in reporting particle size parameters. *Eur. J. Pharm. Biopharm.*, 69(1): 1-9.

Ghaffar, N., S. Javad, A.A. Shah, S. Ilyas, A. Hashem, G.D. Avila-Quezada, E.F. Abd_Allah and A. Tariq. 2024. Restoration of antibacterial activity of inactive antibiotics via combined treatment with AgNps. *ACS Omega*, 9(12): 13621-13635.

Grillo, R., B.D. Mattos, D.R. Antunes, M.M.L. Forini, F.A. Monikh and O.J. Rojas. 2021. Foliage adhesion and interactions with particulate delivery systems for plant nanobionics and intelligent agriculture. *Nano Today*, 37: 101078.

Habbal, A., M.K. Ali and M.A. Abuzaraida. 2024. Artificial Intelligence Trust, risk and security management (AI trism): Frameworks, applications, challenges and future research directions. *Exp. Sys. Appl.,* 240: 122442.

Hofmann, T., G.V. Lowry, S. Ghoshal, N. Tufenkji, D. Brambilla, J.R. Dutcher, L.M. Gilbertson, J.P. Giraldo, J.M. Kinsella, M.P. Landry, W. Lovell, R. Naccache, M. Paret, J.A. Pedersen, J.M. Urine, J.C. White and K.J. Wilkinson. 2020. Technology readiness and overcoming barriers to sustainably implement nanotechnology-enabled plant agriculture. *Nature Food*, 1(7): 416-425.

Hu, S.W., T. Ding, H. Tang, H. Guo, W. Cui and Y. Shu. 2023. Nanobiomaterial vectors for improving gene editing and gene therapy. *Mat. Today*, 66: 114-136.

Hundal, G.S., C.M. Laux, D. Buckmaster, M.J. Sutton and M. Langemeier. 2023. Exploring barriers to the adoption of internet of things-based precision agriculture practices. *Agriculture*, 13(1): 163.

Ivezic, A., G. Mimić, B. Trudić, D. Blagojević, B. Kuzmanović, Ž. Kaitović and K. Petrović. 2023. Development of a predictive model of the flight dynamics of the european corn borer, ostrinia nubilalis hubner, 1796 (Lepidoptera: Pyralidae), in the Vojvodina Region, Serbia-implications for integrated pest management. *Agronomy,* 13(6): 1494.

Jang, G., D.W. Kim, H.J. Kim and Y.S. Chung. 2023. Spatial dependence analysis as a tool to detect the hidden heterogeneity in a Kenaf field. *Agronomy*, 13(2): 428.

Jankovic, S.D. and D.M. Curovic. 2023. Strategic integration of artificial intelligence for sustainable businesses: implications for data management and human user engagement in the digital era. *Sustainability,* 15(21): 15208.

Jat, R.A., J.P. Tetarwal and M.L. Jat. 2016. Conservation agriculture-based sustainable intensification of cereal systems in South Asia: A review. *J. Integ. Agri.*, 15(8): 1785-1799.

Javad, S. and A. Butt. eds. 2018. *Nanobotany*. Springer International Publishing.

Javaid, M., A. Haleem, R.P. Singh and R. Suman. 2022. Enhancing smart farming through the applications of Agriculture 4.0 technologies. *Int. J. Intell. Networks*, 3: 150-164.

Jha, K., A. Doshi, P. Patel and M. Shah. 2019. A comprehensive review on automation in agriculture using artificial intelligence. *Art. Intell. Agri.*, 2: 1-12.

Ji, Y., S. Ma, S. Lv, Y. Wang, S. Lu and M. Liu. 2021. Nanomaterials for targeted delivery of agrochemicals by an all-in-one combination strategy and deep learning. *ACS Appl. Mat. Interf.*, 13(36): 43374-43386.

Johnson, M.S., S. Sajeev and R.S. Nair. 2021. Role of nanosensors in agriculture. *In*: IEEE, *International Conference on Computational Intelligence and Knowledge Economy (ICCIKE)*, pp. 58-63.

Jonathan, M., N. Eric and G. Terry. 2023. Precision agriculture in the digital era: Recent adoption on US farms. *AgEcon, Research in Agricultural and Applied Economics.* EIB: 248.

Kamilaris, A., A. Kartakoullis and F.X. Prenafeta-Boldú. 2017. A review on the practice of big data analysis in agriculture. *Comp. Elect. Agri.*, 143: 23-37.

Kamilaris, A. and F.X. Prenafeta-Boldú. 2018. Deep learning in agriculture: A survey. *Computers and Electronics in Agriculture*, 147: 70-90.

Kamilaris, A., R. Cole and F.X. Prenafeta-Boldu. 2021. Blockchain in agriculture. In: Academic Press, *Food Technology Disruptions*, 274-284.

Karunathilake, E.M.B.M., A.T. Le, S. Heo, Y.S. Chung and S. Mansoor. 2023. The path to smart farming: Innovations and opportunities in precision agriculture. *Agriculture*, 13(8): 1593.

Khaled, A.Y., N. Ekramirad, K.D. Donohue, R.T. Villanueva and A.A. Adedeji. 2023. Non-destructive hyperspectral imaging and machine learning-based predictive models for physicochemical quality attributes of apples during storage as affected by codling moth infestation. *Agriculture*, 13(5): 1086.

Khalil, A.M. 2020. The genome editing revolution. *J. Gen. Engin. Biotech.*, 18(1): 68.

Khan, F., O. Khan, M. Parvez, S. Ahmad, Z. Yahya, A. Alhodaib, A.K. Yadav and U. Ağbulut. 2024. K-means clustering optimization of various quantum dots and nanoparticles-added biofuels for engine performance, emission, vibration, and noise characteristics. *Therm. Sci. Engin. Prog.*, 54: 102815.

Khan, M.R., V. Adam, T.F. Rizvi, B. Zhang, F. Ahamad, I. Jośko, Y. Zhu, M. Yang and C. Mao. 2019. Nanoparticle–plant interactions: two-way traffic. *Small*, 15(37): 1901794.

Kiobia, D.O., C.J. Mwitta, K.G. Fue, J.M. Schmidt, D.G. Riley and G.C. Rains. 2023. A review of successes and impeding challenges of IoT-based insect pest detection systems for estimating agroecosystem health and productivity of cotton. *Sensors*, 23(8): 4127.

Kottegoda, N., C. Sandaruwan, G. Priyadarshana, A. Siriwardhana, U.A. Rathnayake, D.M.B. Arachchige, A.R. Kumarasinghe, D. Dahanayake, V. Karunaratne and G.A.J. Amaratunga. 2017. Urea-hydroxyapatite nanohybrids for slow release of nitrogen. *ACS Nano*, 11(2): 1214-1221.

Kusters, R., D. Misevic, H. Berry, A. Cully, Y. L. Cunff, L. Dandoy, N. Díaz-Rodríguez, M. Ficher, J. Grizou, A. Othmani, T. Palpanas, M. Komorowski, P. Loiseau, C.M. Frier, S. Nanini, D. Quercia, M. Sebag, F.S. Fogelman, S. Taleb, L. Tupikina, V. Sahu, J.J. Vie and F. Wehbi. 2020. Interdisciplinary Research in Artificial Intelligence: Challenges and Opportunities. *Frontier*, 3: 577974.

Li, J., L. Yue, F. Chen, X. Cao, B. Cheng, C. Wang, Z. Wang and B. Xing. 2024. Artificial neural networks to investigate the bioavailability of selenium nanoparticles in soil-crop system. *Environ. Sci. Nano*, 11(1): 418-430.

Liu, B., H. Jiang and L. Li. 2024. The innovative applications and prospects of artificial intelligence in agricultural research: Gene editing, crop improvement, and intelligent data analysis. *Adv. Resour. Res.*, 4(4): 624-653.

Liu, R. and R. Lal. 2005. Nanofertilizer. In *Encyclopedia of Soil Science-Two-Volume Set* (pp. 1-5). CRC Press.

Liu, Y., X. Ma, L. Shu, G.P. Hancke and A.M. Abu-Mahfouz. 2020. From Industry 4.0 to Agriculture 4.0: Current status, enabling technologies, and research challenges. *IEEE Transactions on Industrial Informatics*, 17(6): 4322-4334.

Loukil, R., W. Gazehi and M. Besbes. 2024. Improving the classification of a nanocomposite using nanoparticles based on a meta-analysis study, recurrent neural network and recurrent neural network Monte-Carlo algorithms. *Nanocomposites*, 10(1): 309-337.

Lozano, T.A., G. Siesto, M. Fernández-Sellers and A. Caballero-Mancera. 2023. Evaluation of the use of the 12 bands vs. NDVI from Sentinel-2 images for crop identification. *Sensors*, 23(16): 7132.

Ma, M., J. Liu, M. Liu, J. Zeng and Y. Li. 2021. Tree species classification based on sentinel-2 imagery and random forest classifier in the eastern regions of the Qilian mountains. *Forests*, 12(12): 1736.

Mani, J., S. Nagachandrabose, P. Somasundaram and S. Deenan. 2025. Artificial Intelligence integrated Nano biosensor Technology: A breakthrough in early detection and sustainable management of phytonematodes. *Physiol. Mol. Plant Pathol.*, 102756.

Mikolajczyk, A. and D. Falkowski. 2022. One step before synthesis: Structure–property–condition relationship models to sustainable design of efficient TiO_2-based multicomponent nanomaterials. *Int. J. Mol. Sci.*, 23(21): 13196.

Monterio, A. and S. Santos. 2022. Sustainable approach to weed management: The role of precision weed management. *Agronomy,* 12(1): 118.

Mulla, D.J. 2013. Twenty five years of remote sensing in precision agriculture: Key advances and remaining knowledge gaps. *Biosys. Engin.*, 114(4): 358-371.

Munoko, I., H.L. Brown-Liburd and M. Vasarhelyi. 2020. The ethical implications of using artificial intelligence in auditing. *J. Business Ethics,* 167: 209-234.

Nandy, D., A. Maity and A.K. Mitra. 2020. Target-specific gene delivery in plant systems and their expression: insights into recent developments. *J. Biosci.*, 45(30): 1-12.

Nazir, A.S. 2018. Analytical Techniques in Nano Botany. *Nanobotany*, 195-233.

Pandey, N. 2018. Role of plant nutrients in plant growth and physiology. In *Plant nutrients and abiotic stress tolerance* (pp. 51-93). Singapore: Springer Singapore.

Periakaruppan, R., V. Romanovski, S.K. Thirumalaisamy, V. Palanimuthu, M.P. Sampath, A. Anilkumar, D.K. Sivaraj, N.A.N. Ahamed, S. Murugesan, D. Chandrasekar and K.S.V. Selvaraj. 2023. Innovations in modern nanotechnology for the sustainable production of agriculture. *Chem. Engin.*, 7(4): 61.

Prasad, R., A. Bhattacharyya and Q.D. Nguyen. 2017. Nanotechnology in sustainable agriculture: recent developments, challenges, and perspectives. *Front. Microbiol.*, 8: 1014.

Presti, D.L., J.D. Tocco, C. Massaroni, S. Cimini, L.D. Gara, S. Singh, A. Raucci, G. Manganiello, S.L. Woo, E. Schena and S. Cinti. 2023. Current understanding, challenges and perspective on portable systems applied to plant monitoring and precision agriculture. *Biosensors & Bioelectronics*, 222: 115005.

Pronin, C.B. and A.V. Volosova. 2023. A method for solving a system of equations based on the prsciiple of training generative-adversarial neural networks (GAN) using a modified Grover algorithm. *Comp. Nanotech.*, 10(4): 11-15.

Punithavathi, R., A.D.C. Rani, K.R. Sughashini, C. Kurangi, M. Nirmala, H.F.T. Ahmed and S.P. Balamurugan. 2023. Computer vision and deep learning-enabled weed detection model for precision agriculture. *Comp. Syst. Sci. Engin.*, 44(3): 2759-2774.

Radoglou, G.P., P. Sarigiannidis, T. Lagkas and I. Moscholios. 2020. A compilation of UAV applications for precision agriculture. *Computer Networks*, 172: 107148.

Rahmann, G., M. Reza Ardakani, P. Bàrberi, H. Boehm, S. Canali, M. Chander, W. David, L. Dengel, J.W. Erisman, A.C. Galvis-Martinez and U. Hamm. 2017. Organic Agriculture 3.0 is innovation with research. *Organic Agri.*, 7(3): 169-197.

Ramos, O.M., L. Gomez, C. Trujillo and A. Marulanda-Tobon. 2023. Deep Transfer Learning for image classification of phosphorus nutrition states in individual maize leaves. *Electronics*, 13(1): 16.

Reineck, P., L.F. Trindade, J. Havlik, J. Stursa, A. Heffernan, A. Elbourne, A. Orth, M. Capelli, P. Cigler, D.A. Simpson and B.C. Gibson. 2019. Not all fluorescent nanodiamonds are created equal: a comparative study. *Particle & Particle Systems Characterization*, 36(3): 1900009.

Romanovski, V., I. Matsukevich, E. Romanovskaia and R. Periakaruppan. 2023. Nano metal oxide as nanosensors in agriculture and environment. *In*: Academic Press, *Nanometal Oxides in Horticulture and Agronomy,* 321-352.

Saranya, T., C. Deisy, S. Sridevi and K.S.M. Anbananthen. 2023. A comparative study of deep learning and Internet of Things for precision agriculture. *In*: Elsevier, *Engin. Appl. Art. Intell.*, 122: 106034.

Schicktanz, S., J. Welsch, M. Schweda, A. Hein, J.W. Rieger and T. Kirste. 2023. AI-assisted ethics? considerations of AI simulation for the ethical assessment and design of assistive technologies. *Front. Gen.,* 14: 14-22.

Schulte, P.A. and F. Salamanca-Buentello. 2022. Ethical and scientific issues of nanotechnology in the workplace. *Environ. Health Perspec.,* 115(1): 5-12.

Shahhosseini, M., R.A. Martinez-Feria, S.V. Archontoulis and A.W. Lenssen. 2020. Challenges of using machine vision technology in crop production systems. *Comp. Elect. Agri.*, 178: 105752.

Shaikh, T. A., T. Rasool and F.R. Lone. 2022. Towards leveraging the role of machine learning and artificial intelligence in precision agriculture and smart farming. *Comp. Elect. Agri.*, 198: 107119.

Sheng, X., Z. Ai, Y. Tan, Y. Hu, X. Guo, X. Liu, Z. Sun, D. Yu, J. Chen, N. Tang and M. Duan. 2023. Novel salinity-tolerant third-generation hybrid rice developed via CRISPR/Cas9-mediated gene editing. *Int. J. Mol. Sci.*, 24(9): 8025.

Shin, J., M.S. Mahmud, T.U. Rehman, P. Ravichandran, B. Heung and Y.K. Chang. 2022. Trends and prospect of machine vision technology for stresses and diseases detection in precision agriculture. *Agri-Engin.*, 5(1): 20-39.

Silva, A.O.D., B.A.D. Silva, C.F. Souza, B.M.D. Azevedo, L.H. Bassoi, D.V. Vasconcelos, G.V.D. Bonfim, J.M. Juarez, A.F.D. Santos and Carneiro, F.M. 2020. Irrigation in the age of agriculture 4.0: management, monitoring and precision. *Revista Ciência Agronômica*, 51(spe): e20207695.

Soto, I., H. Ceballos and J. Florez. 2019. Challenges and opportunities for using Big Data in agriculture in developing countries. *J. Agri. Inform.*, 10(2): 1-11.

Talati, D., B. Joe and G. Smart. 2024. AI (artificial intelligence) in daily life. *Authorea Preprints*, 1-5.

Tian, H., M. Kah and K. Kariman. 2019. Are nanoparticles a threat to mycorrhizal and rhizobial symbioses? A critical review. *Front. Microbiol.*, 10: 1660.

Tomaszewski, L. and R. Kołakowski. 2023. Mobile services for smart agriculture and forestry, biodiversity monitoring, and water management: Challenges for 5G/6G networks. *Telecom*, 4(1): 67-99.

Torney, F., B.G. Trewyn, V. S.Y. Lin and K. Wang. 2007. Mesoporous silica nanoparticles deliver DNA and chemicals into plants. *Nature Nanotech.*, 2(5): 295-300.

Tripoli, M. and J. Schmidhuber. 2018. *Emerging opportunities for the application of blockchain in the agri-food industry*. Food and Agriculture Organization of the United Nations (FAO) and International Trade Centre (ITC).

Ulhassan, Z., J.A. Bhat, W. Zhou, A.M. Senan, P. Alam and P. Ahmad. 2022. Attenuation mechanisms of arsenic induced toxicity and its accumulation in plants by engineered nanoparticles: a review. *Environ. Pollut.,* 302: 119038.

Varsou, D.D., A. Afantitis, A. Tsoumanis, G. Melagraki, H. Sarimveis, E. Valsami-Jones and I. Lynch. 2019. A safe-by-design tool for functionalised nanomaterials through the Enalos Nanoinformatics Cloud platform. *Nanoscale Adv.*, 1(2): 706-718.

Walter, A., R. Finger, R. Huber and N. Buchmann. 2017. Smart farming is key to developing sustainable agriculture. *Proceed. Nat. Acad. Sci.*, 114(24): 6148-6150.

Wang, X., C. Yan, J.C. Ondry, V. Bodiwala, P. Ercius and A.P. Alivisatos. 2024. An artificial intelligence's interpretation of complex high-resolution in situ transmission electron microscopy data. *Matter*, 7(1): 175-190.

Wen, H., J.M. Luna-Romera, J.C. Riquelme, C. Dwyer and S.L.Y. Chang. 2021. Statistically representative metrology of nanoparticles via unsupervised machine learning of TEM Images. *Nanomaterials*, 11(10): 2706.

Wolfert, S., L. Ge, C. Verdouw and M.J. Bogaardt. 2017. Big Data in smart farming-A review. *Agri. Sys.*, 153: 69-80.

Xue, J. and B. Su. 2017. Significant remote sensing vegetation indices: A review of developments and applications. *J. Sensors*, 2017(1): 1353691.

Yan, J., K. Huang, Y. Wang and S. Liu. 2006. Application of anti-pollution nano-pesticide preparation for chlorfenapyr. *J. Chem. Indu. and Engin., China*, 57(1): 91.

Yan, R., T. Wang, X. Jiang, Q. Zhong, X. Huang, L. Wang and X. Yue. 2020. Design of high-performance plasmonic nanosensors by particle swarm optimization algorithm combined with machine learning. *Nanotechnology*, 31(37): 375202.

Yan, Y., X. Zhu, Y. Yu, C. Li, Z. Zhang and F. Wang. 2022. Nanotechnology strategies for plant genetic engineering. *Adv. Materials*, 34(7): 2106945.

Yulita, I.N., M.F.R. Rambe, A. Sholahuddin and A.S. Prabuwono. 2023. A convolutional neural network algorithm for pest detection using GoogleNet. *Agri. Engin.*, 5(4): 2366-2380.

Zain, M., H. Ma, S. Chaudhary, M. Nuruzaman, I. Azeem, F. Mehmood and C. Sun. 2023. Nanotechnology in precision agriculture: Advancing towards sustainable crop production. *Plant Physiol. Biochem.*, 108244.

Zhang, C. and J.M. Kovacs. 2018. The application of small unmanned aerial systems for precision agriculture: a review. *Precision Agri.*, 19(2): 378-402.

Zhang, P., I. Lynch, R.D. Handy and J.C. White. 2023. A brief history of nanotechnology in agriculture and current status. *In*: Academic Press, *Nano-Enabled Sustainable and Precision Agriculture*, 3-14.

Zhang, P., Z. Guo, S. Ullah, G. Melagraki, A. Afantitis and I. Lynch. 2021. Nanotechnology and artificial intelligence to enable sustainable and precision agriculture. *Nature Plants*, 7(7): 864-876.

Zheng, N., Z. Yao, S. Tao, A. Almadhor, M.S. Alqahtani, R.M. Ghoniem, H. Zhao and S. Li. 2023. Application of nanotechnology in breast cancer screening under obstetrics and gynecology through the use of CNN and ANFIS. *Environ. Res.*, 234: 116414.

Zhi, H., S. Zhou, W. Pan, Y. Shang, Z. Zeng and H. Zhang. 2022. The promising nanovectors for gene delivery in plant genome engineering. *Int. J. Mol. Sci.*, 23(15): 8501.