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Artificial Intelligence in Sustainable Farming Practices

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Abstract

Mounting demographic pressure, with global population forecasted to approach 10 billion by mid-century, has intensified demands on the agricultural sector to produce greater food output from increasingly constrained land and water resources. Agriculture underpins economic stability across many nations and remains central to employment, trade, and food systems worldwide. Compounding these pressures, climate variability and resource depletion are challenging conventional farming paradigms in ways that demand unprecedented technological responses. Artificial Intelligence (AI) has emerged as one of the most promising enablers of agricultural transformation, offering data-driven solutions across planting, irrigation, disease management, and supply chain operations. By incorporating AI into farming systems, resource use can be substantially optimized, and machine learning-assisted genetic improvements can raise yield ceilings while bolstering environmental resilience. This paper examines the spectrum of AI applications in sustainable agriculture, exploring how these technologies support decision-making in crop production and management, enable real-time field monitoring, and generate predictive insights for operational planning. Persistent barriers technological, socio-cultural, and regulatory that continue to impede the full realization of AI's agricultural potential are also critically evaluated.

Keywords: Artificial intelligence, agriculture practices, agricultural management

Introduction

Amid escalating pressures from water scarcity, erratic climatic conditions, and shrinking arable land, agriculture faces a structural challenge that conventional practices alone cannot resolve. The imperative to raise output while simultaneously reducing resource consumption has made technological innovation not merely desirable but essential. Artificial Intelligence (AI) stands at the forefront of this transformation, offering computational tools capable of optimizing nearly every stage of crop production from pre-planting soil analysis to post-harvest logistics (Yu *et al.*, 2021) ^[78]. Its influence extends from environmental impact forecasting to precision resource management and dynamic crop monitoring. AI-assisted analysis of critical environmental variables including soil pH (Neina, 2019; Naz *et al.*, 2022) ^[45, 44], ambient temperature (Ye *et al.*, 2012; Badugu *et al.*, 2024) ^[76, 5], and precipitation (Lebu *et al.*, 2024) ^[35] enables farmers to take timely, evidence-based action against adverse conditions. Continuous sensor-driven monitoring of soil health and microclimate parameters fosters conditions conducive to sustained crop productivity. The deployment of unmanned aerial vehicles (UAVs), autonomous robots, and remote sensing platforms has brought a new level of observational precision to agricultural management. Integrating AI into these systems creates substantial opportunities for waste minimization, efficient input use, and measurable gains in environmental sustainability (Aijaz *et al.*, 2025) ^[3]. Technological advancement in agriculture is important not only for

operational speed but also for improving the overall quality and consistency of farm outcomes (Nautiyal *et al.*, 2025) ^[43]. As Potta (2026) ^[51] noted, when AI is purposefully deployed toward addressing structural inequalities, it transcends its role as a productivity tool and becomes an instrument of systemic equity. The global AI in agriculture market is projected to expand from approximately USD 1.7 billion in 2023 to USD 4.7 billion by 2028 (Mehra, 2023) ^[41] underscoring growing industry confidence in these technologies. While AI complements and enhances existing farm technologies, enabling intelligent automation of complex agricultural tasks, its widespread adoption is still constrained by infrastructure, awareness, and cost barriers. Reflecting this momentum, the Government of India published a policy-oriented roadmap titled 'Future Farming in India: AI Playbook for Agriculture' in October 2025, developed collaboratively by the World Economic Forum, the Office of the Principal Scientific Adviser, IndiaAI (MeitY), and BCG X. This document articulates a framework for the responsible, scalable integration of AI in Indian agriculture, with particular attention to the needs of smallholder and marginal farmers (PIB, 2026) ^[53]. This paper discusses the principal applications of AI in agriculture, examines the challenges confronting its integration into the agricultural domain, and charts probable future directions for AI technology in farming. It also explores the diverse AI-based tools and software solutions that can assist farmers in tailoring their practices to local conditions, while acknowledging the structural impediments

that continue to slow technology adoption.

In the following sections, the latest developments in AI applications in agriculture are discussed in detail.

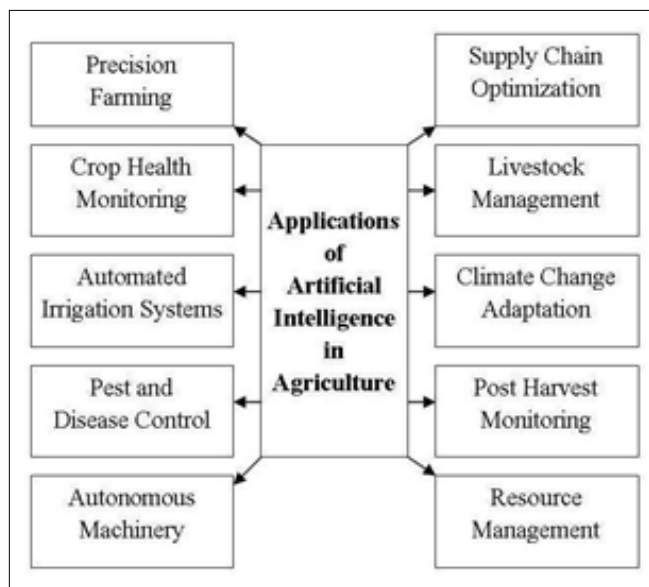


Fig 1: Applications of Artificial Intelligence in Agriculture

Precision Farming

Among the most impactful applications of AI in contemporary agriculture is precision farming, which has redefined the standards of accuracy and operational control in crop management (Karunathilake *et al.*, 2023) ^[28]. At its core, this approach relies on the continuous acquisition of real-time data via GPS-enabled devices and IoT sensor networks, allowing for granular surveillance of soil conditions, microclimatic patterns, and crop health indicators (Castrignan *et al.*, 2020; Ukhurebor *et al.*, 2022) ^[12, 68]. This data feeds into AI-driven decision support systems that determine the optimal timing and quantities for variable-rate application of water, fertilizers, and agrochemicals. Drone-based aerial surveillance further enhances this capability by generating high-resolution imagery used to detect disease outbreaks and assess canopy vigor, thereby guiding responsive field management interventions (Abbas *et al.*, 2023) ^[1].

Beyond crop monitoring, precision agriculture integrates robotic systems that mechanize repetitive field tasks sowing, weeding, and harvesting—thereby reducing the sector's dependence on manual labor (Mahmud *et al.*, 2020) ^[39]. The approach also contributes to the conservation of subsurface water resources by calibrating irrigation inputs to actual evapotranspiration demand, thereby limiting over-extraction from aquifers and reducing ecological disruption (Lakhier *et al.*, 2024) ^[34]. Combining satellite imagery, sensor data, and advanced analytics, precision agriculture enables farmers to manage fields at a level of resolution that maximizes productivity while minimizing environmental footprint.

Agricultural Robotics

The mechanization of labor-intensive farm operations through AI-powered robotics represents a significant shift in how agricultural work is organized and executed (Wang *et al.*, 2021) ^[71]. Modern agricultural robots are equipped with computer vision, deep learning algorithms, and multi-axis

manipulators that enable them to perform complex tasks—such as selective harvesting, precision weeding, and seed placement with consistent accuracy across varied terrain conditions. These autonomous systems can operate continuously, irrespective of diurnal cycles or adverse weather, achieving throughput rates that manual labor cannot match (Bilal *et al.*, 2023) ^[11]. The reduction of human error in these operations also translates into improved product quality and reduced post-harvest waste (Mahmud *et al.*, 2020) ^[39].

A particularly illustrative example is the robotic harvester, which employs image recognition to evaluate fruit maturity in real time, ensuring that only appropriately ripened produce is collected (Mhamed *et al.*, 2024) ^[42]. This selectivity not only preserves market quality standards but also reduces the proportion of immature or overripe produce entering the supply chain. As robotic technologies mature and component costs decline, their integration into mainstream farming operations is expected to catalyze a broader agricultural productivity revolution, particularly in regions confronting chronic labor shortages.

Enhancing Crop Productivity and Crop Management with AI

Accurate yield forecasting is foundational to sustainable production planning, informing decisions on planting schedules, irrigation regimes, harvest logistics, and commodity trading. AI has become a central driver of productivity gains in contemporary agriculture through its contributions to genetic improvement, efficient input allocation, and practical crop management tools that collectively elevate yields and strengthen the genetic resilience of cultivated varieties.

Machine Learning (ML) has established itself as the dominant paradigm for developing crop yield prediction models. These systems are trained on historical field and environmental datasets, validated against withheld observations, and subsequently deployed to generate forward-looking estimates for new growing conditions (Leukel *et al.*, 2023) ^[36]. Prediction operates across spatial scales: at the field level, inputs include soil sensor readings, localized weather records, irrigation schedules, fertilization histories, and pest incidence data; at regional scales, climate model outputs and satellite remote sensing provide complementary contextual information (You *et al.*, 2017) ^[77]. Persistent modelling challenges include data heterogeneity, gaps in observational records, measurement error, and inter-annual climatic variability, all of which compound forecast uncertainty (Singh and Thakur, 2024) ^[61].

Pesticide management is another domain where AI-driven optimization offers considerable value. Conventional spraying whether performed manually or via mechanized ground equipment entails trade-offs between targeting precision and operational efficiency. Manual application offers site-specific control but is time-intensive and physically demanding, while conventional automated systems apply treatments uniformly, often resulting in over-application, chemical runoff, and accelerated resistance development. AI-enabled drone sprayers address these limitations by integrating computer vision with sensor-based crop health assessment, enabling variable-rate, spatially

targeted pesticide delivery that minimizes chemical loading while maintaining pest suppression efficacy. Although still maturing as a technology, AI-guided drone spraying is rapidly gaining traction in precision crop protection programs.

Rapid, accurate diagnosis of plant diseases is equally critical to securing agricultural output and safeguarding food supply chains (Hassan *et al.*, 2023) ^[26]. Disease pressure reduces both crop yield and produce quality, directly affecting producer incomes and contributing to food insecurity (Devarajan *et al.*, 2026) ^[18]. Classical diagnostic approaches involving laboratory analysis and visual field inspection are inherently slow, resource-intensive, and prone to human

error, rendering them inadequate for the scale and speed required in commercial agriculture (Banarase and Shirbahadurkar, 2024) ^[8]. AI-based diagnostic platforms, by contrast, draw on large annotated image datasets to identify disease signatures in photographs captured from ground-level cameras or UAVs, enabling early intervention before losses become severe (Delfani *et al.*, 2024; Olson and Anderson, 2021) ^[17, 47]. These platforms also support predictive analytics by detecting early-stage statistical patterns in historical and real-time data that precede visible symptoms, thus triggering pre-emptive management responses.

Table 1: Overview of AI-based Deep Learning Models for Crop Yield Prediction

Crop	Data Source	Model	Findings	Reference
Soybean	Satellite data	CNN-LSTM (Convolutional Neural Network–Long Short-Term Memory)	High prediction performance, satisfactory results for early prediction (RMSE = 329 and R ² = 0.78)	Sun <i>et al.</i> , 2019 ^[65]
Corn	Hyperspectral imagery	CNN	75.50% classification accuracy	Yang <i>et al.</i> , 2021 ^[75]
Soybean	Satellite data	Combined model (CNN + LSTM) named Deep Yield	Accurate prediction of yield for the past 2 years (RMSE = 4.79)	Gavahi <i>et al.</i> , 202 ^[21]
Wheat, Corn	Spatial-spectral temporal data	SSTNN (Spatial-Spectral-Temporal Neural Network)	Higher yield prediction accuracy (Wheat: RMSE = 0.67 and R ² = 0.83; Corn: RMSE = 0.84 and R ² = 0.68)	Qiao <i>et al.</i> , 2021 ^[55]
Cereal Crop (Wheat, Oats, Barley)	High-resolution UAV image data	CNN-based model	More accurate prediction at the intra-field scale (RMSE = 289.5 and R ² = 0.962)	Nevavuori <i>et al.</i> , 2020

Source: Nautiyal *et al.*, 2025 ^[43]

AI in Post-harvest Management and Cold Chain Logistics

The post-harvest phase encompasses the continuum of operations handling, storage, processing, and distribution that occur between field collection and consumer delivery. Effective management of this phase is central to reducing food losses, which can reach 30–40% of total production for certain perishable commodities, and to preserving nutritional quality through the supply chain. Losses arise from a combination of intrinsic biological processes, including physiological senescence and susceptibility to pathogens, and extrinsic stressors such as chilling injury, heat exposure, and inadequate humidity control. Quantitatively, documented post-harvest wastage in industrialized economies ranges from 2 to 20%, while developing-country losses have been reported between 24 and 40% of production, reflecting disparities in cold chain infrastructure and food handling capabilities (Ferrandez-Pastor *et al.*, 2016) ^[20]. AI-based frameworks deployed across food processing and logistics operations are improving the preservation of seasonal and perishable commodities through enhanced condition monitoring and predictive maintenance. Radio Frequency Identification (RFID) and IoT sensor arrays track the physical and thermal state of consignments throughout the distribution chain, enabling anomaly detection and timely corrective action

(Zhang, 2021) ^[79]. Deep learning architectures have demonstrated particular effectiveness in quality assessment applications. Kollia *et al.* (2021) ^[32] applied CNN and LSTM network combinations to predict cold storage energy requirements and optimize refrigeration cycles. Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks constitute the two most widely employed deep learning frameworks in post-harvest AI applications. CNNs are optimized for extracting spatial feature hierarchies from image data, making them well-suited for visual quality grading, while LSTMs are designed to learn temporal dependencies in sequential data, facilitating time-series forecasting of storage conditions. Their hybrid combination (CNN-LSTM) enables joint modelling of spatial and temporal dynamics. Li *et al.* (2021) ^[37] demonstrated the application of CNNs to apple quality classification, achieving training and validation accuracies of 99% and 98.9%, respectively. Complementing this, Wang and Zhang (2019) ^[73] developed a CNN-based system for sorting harvested apples by size and surface defect status, delivering high accuracy with minimal labor input. In the mango supply chain, Patel *et al.* (2021) ^[49] employed Support Vector Machines (SVMs) to automate the detection and segregation of defective fruit during packing, thereby improving commercial grading standards.

Table 2: Comparison of AI-driven and Traditional Agricultural Techniques

Traditional approaches used	AI-driven approaches	Relative benefits	Constraints	References
Manual labour-based decision making	Precision farming, autonomous machinery, predictive analysis, and drone technology	Improved efficiency, improved yield prediction, and reduced cost of labour; crop monitoring and disease prevention	Higher cost, requirement of technical expertise, and infrastructure	Akintuyi, 2024 ^[4]
Manual crop monitoring and traditional irrigation	All-terrain vehicles (ATVs); automation of planting, weeding, harvesting	15–20% increase in yield, 25–30% reduction in overall investment	Requires training; low accessibility in remote areas	Padhiary <i>et al.</i> , 2024 ^[48]
Old water-based irrigation and weeding practices	Robotic system for weeding and irrigation	Saving water, preserving soil fertility, limiting herbicide/pesticide use; effective labor use	High initial cost and infrastructure requirement	Talaviya <i>et al.</i> , 2020 ^[67]
Manual mapping and survey methods	Use of ML, DL, and Artificial Neural Networks (ANNs) for agricultural mapping	Enhanced land use mapping, crop identification, and disease control	Requirement of technical expertise	Espinel <i>et al.</i> , 2024 ^[19]

Source: Nautiyal *et al.*, 2025 ^[43]

AI-Driven Genetic Modification and Breeding

AI is assuming an increasingly prominent role in crop breeding and genetic modification programs, particularly in the development of cultivars with enhanced tolerance to biotic and abiotic stressors (Rai, 2022; Hafeez *et al.*, 2023) ^[25, 56]. By interrogating large-scale genomic datasets and modelling gene-environment interactions, AI systems can identify the genetic architectures most likely to confer desired agronomic traits, accelerating the development of viable improved varieties (Nolan, 2024) ^[46]. This approach is especially valuable in the identification of alleles associated with drought tolerance, enabling the genetic engineering of crops for deployment in arid or semi-arid regions previously considered marginal for cultivation

(Khan *et al.*, 2022; Nautiyal *et al.*, 2025) ^[29, 43]. Beyond drought adaptation, AI-assisted genomic analysis can simultaneously optimize multiple trait targets—including improved nutritional profiles, accelerated growth kinetics, and reduced dependency on synthetic fertilizers and pesticides. The convergence of AI with precision gene-editing technologies, such as CRISPR-Cas9, opens the prospect of developing high-yielding, climate-resilient varieties tailored to specific agro-ecological zones (Wang and Doudna, 2023) ^[72]. By enabling targeted modifications at the genomic level, these integrated approaches can extend the frontiers of cultivable land and reduce inefficiencies in marginal agricultural systems, thereby strengthening the contribution of crop science to global food security.

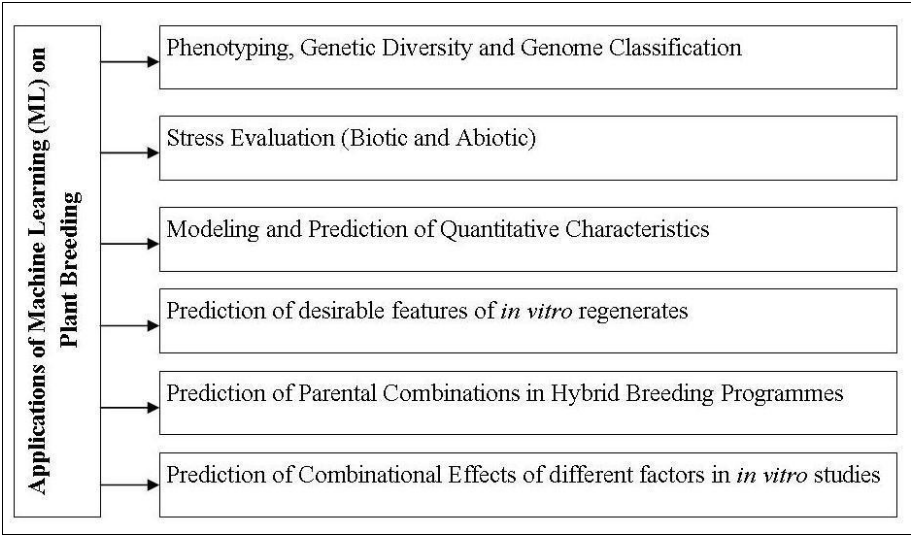


Fig 2: Applications of ML on Plant Breeding

AI-based Smart Irrigation

Autonomous irrigation management, enabled by AI, represents a critical frontier in the effort to reconcile agricultural water demand with the realities of global freshwater scarcity. In controlled environments such as smart greenhouses, AI systems dynamically regulate temperature, humidity, and illumination based on real-time sensor inputs, creating optimal growing conditions while

avoiding wasteful over-application. In open-field settings, AI algorithms synthesize weather forecast data and crop-specific water demand models to flag areas of excess water use and recalibrate irrigation schedules accordingly. These capabilities translate into meaningful improvements in water use efficiency, directly benefiting farmers operating under resource constraints (Sinwar *et al.*, 2020) ^[64]. Smart irrigation represents a shift from schedule-based to

demand-driven water management. Balafoutis *et al.* (2017) [7] described Variable Rate Irrigation (VRI) as a technically advanced system that leverages sensors, GPS positioning, and data analytics to deliver site-specific water volumes, implementable via self-propelled or micro-irrigation configurations. Mid Elevation Spray Application (MESA), a common VRI implementation, has achieved system efficiencies of approximately 85%. Research on the cultivation of *Geranium psilostemon* similarly demonstrated an irrigation efficiency of 87.97% under AI-assisted management relative to conventional techniques (Ercan Oğuztürk *et al.*, 2025). Preite and Vignali (2024) [52] reported that multi-layer perceptron neural networks applied to irrigation scheduling achieved 27% water savings and

57% energy savings, illustrating the dual resource conservation potential of AI-driven systems. Internet of Things (IoT) technologies increasingly complement AI in irrigation management, providing the sensor infrastructure and connectivity required for real-time data acquisition and automated control. Despite their demonstrated value, adoption remains constrained by limited farmer awareness of IoT capabilities and the associated technical knowledge requirements (Khan *et al.*, 2021) [31]. Smart irrigation thus continues to evolve as an interdisciplinary science, integrating agronomy, engineering, and data analytics to deliver productivity gains while measurably reducing the environmental burden of irrigated agriculture.

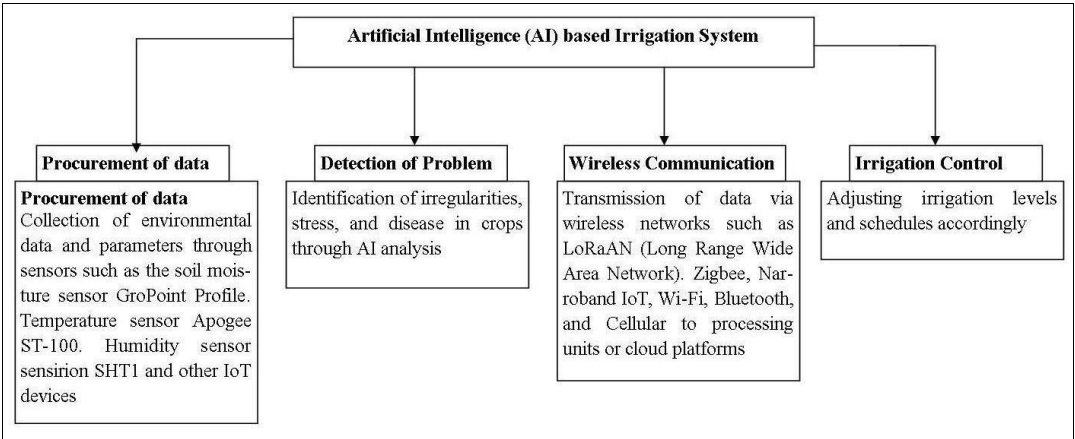


Fig 3: Artificial Intelligence based Irrigation System

Monitoring Livestock Health

Livestock production contributes more than half of total global agricultural output, supplying consumer markets with animal-derived food products, non-food goods, and production inputs. Disease events within livestock populations introduce significant distortions in local and international markets, undermining the commercial viability of herds and threatening the sustainability of smallholder farming systems (Wolfert *et al.*, 2017; Cho, 2024; Maltare *et al.*, 2023) [74, 15, 40]. Unmanaged disease outbreaks can incentivize harmful practices such as indiscriminate antibiotic use, dissemination of misleading health information, and economically irrational market behaviors. The convergence of AI and IoT in livestock health monitoring systems is addressing these vulnerabilities by enabling continuous, remote, and data-driven surveillance of animal health status, behavior, and productivity. One notable advancement in this domain is the CogniHerd system, an AI-IoT integrated platform designed for real-

time health monitoring of livestock (Singh, 2025) [63]. The system deploys an array of hardware components—including ESP8266 Wi-Fi modules, Arduino Uno microcontrollers, audio sensors, temperature probes, and video capture units to collect and transmit physiological and behavioral data from individual animals. Machine learning models trained on annotated health data automate anomaly detection and alert veterinary personnel to early indicators of disease or stress. Similarly, the commercial platform CattleEye deploys UAVs equipped with cameras and computer vision systems to conduct remote behavioral surveillance of cattle herds, identifying deviations from normal patterns such as atypical movement or birthing activity. By correlating behavioral and environmental variables, CattleEye's AI-ML models provide actionable insights on dietary impacts and husbandry conditions that can be leveraged to enhance milk production and overall herd welfare (Cho, 2025; Piddubna, 2026) [16, 50].

Table 3: Components and Technologies in System Setup

Component	Description	Purpose
Drone	Multicolor unmanned Aerial Vehicle (UAVs) with Global Positioning System (GPS) navigation.	Provide mobility and coverage over wide areas.
Thermal cameras	Sensors detect heat signatures from livestock	Identify temperature anomalies indicative of fever or stress
Multispectral cameras	Sensors capturing data in multiple wavelengths (visible, Near-Infrared (NIR) etc.)	Assess skin conditions, hydration levels, and nutrition
GPS Modules	High precision GPS for route planning	Enable accurate, repeatable monitoring paths
AI-Integrated software	Machine learning models trained on livestock health data	Automate data analysis and anomaly detection

Source: Cho (2025) [16]

Table 4: Comprehensive Overview of AI Applications across Agricultural Domains

Application of AI in agriculture	AI-based concept	Benefits	References
Yield Prediction	The multilayer perceptron (MLP) model; Artificial neural networks (ANNs)	Precise estimation of agricultural yield (RMSE = 0.06173, $R^2 = 92.84$); more sustainable and secure food production	Adhaileh <i>et al.</i> , 2022 [2]
Smart Irrigation	IoT; ML	Water-Saving Irrigation (WSA) achieved; 98.3% recognition rate and RMSE = 0.12	Tace <i>et al.</i> , 2022 [66]
Post-harvest management	ANNs; Support Vector Regression (SVR)	Determination of ripeness based on acoustic impulse firmness; quality indices from colour analysis	Kutyaaripo <i>et al.</i> , 2023 [33]
Cold chain logistics	IoT	Real-time tracking of food product status; resolution of load planning and route planning challenges	Liu, 2020
Transportation	Probabilistic localization algorithms, ANN, CNN	Accurate sorting and transportation on farms; firmness detection (RMSE = 0.539, $R^2 = 0.724$); ripeness (RMSE = 1.08)	Zhou <i>et al.</i> , 2023 [80]
Plant breeding	Machine Learning (ML); Robotics	Enhanced breeding information systems; leveraging historical breeding knowledge to enrich ongoing programs	Khan <i>et al.</i> , 2022 [29]
Soil health monitoring	ML; Deep CNN (Convolutional Neural Networks)	Sensor and ML-based analysis of nutrient content, moisture, temperature, and sunlight intensity	Wadoux, 2025 [70]

As the foregoing sections demonstrate, AI has already found substantive application across multiple agricultural domains, enhancing both crop productivity and environmental sustainability. However, the pace of adoption remains uneven, and several systemic challenges continue to restrict the full deployment of these technologies, as discussed in the following section.

Challenges for Integration of AI in Agriculture

A widely held misconception confines AI's relevance to digital and software sectors, obscuring its tangible value in physical farming operations. This perception gap frequently stems from limited exposure to practical AI applications such as precision spraying systems, autonomous harvest robots, and crop disease diagnostics among non-technical stakeholders in the agricultural sector. Bridging this knowledge deficit requires concerted and sustained effort by technology developers, extension services, and educational institutions. Many farmers remain comfortable with established practices, yet as the evidence for AI-driven productivity gains accumulates, interest in adoption is gradually growing. Nevertheless, several interconnected challenges must be addressed to accelerate and broaden this adoption trajectory.

Reluctance to Adopt New Technologies and Processes:

Unfamiliarity with novel systems frequently generates resistance, even when the potential benefits are demonstrable. For farmers, this hesitation is compounded by factors including limited access to technical training, uncertainties about return on investment, and insufficient institutional support structures. This resistance inhibits the diffusion of modern farming practices and constrains the sector's broader competitiveness and sustainability. Framing AI not as a replacement for established methods but as an advanced extension of existing technologies, processing the same field data that farmers already rely upon, may lower psychological barriers to adoption. Effective uptake will require coordinated action: the public sector must create enabling policy environments and invest in extension outreach, while private actors provide accessible, user-adapted tools and training support. Regulatory frameworks that clarify AI's role as a supportive instrument rather than a

threat to farmer livelihoods can further alleviate apprehension.

Lack of Practical Experience with New Technologies and Lengthy Adoption Process:

The depth of technological penetration in agriculture varies markedly across regions, creating significant disparities in AI readiness and adoption capacity. In economically advanced contexts, AI can be integrated into sophisticated farm management ecosystems; in emerging agricultural economies, however, foundational digital infrastructure is often absent, making such integration considerably more challenging. Technology firms seeking to operate in these markets must adopt a proactive strategy, offering not only products but comprehensive training programs and sustained post-deployment support for farmers and agribusiness practitioners willing to transition to AI-enabled operations. One pragmatic pathway involves phased adoption, beginning with simpler digital tools such as agricultural trading platforms or weather advisory applications before progressively introducing more sophisticated AI-driven systems as familiarity and infrastructure develop. This incremental approach allows farmers to build confidence and technical capacity at manageable pace.

Technological Challenges:

AI systems are inherently data-dependent, and their predictive accuracy degrades when training datasets are sparse, heterogeneous, or unrepresentative of local conditions—a common constraint in agricultural contexts where data collection infrastructure is limited. Robotic platforms face additional challenges in adapting to the dynamic and unstructured conditions of farm environments, where terrain variability, weather fluctuations, and crop morphology can exceed the operational parameters of current sensing and control systems. Addressing these limitations demands sustained investment in research, data infrastructure, and sensor development. It is also important that farmers retain meaningful involvement in AI-assisted decision processes, particularly during early adoption phases when system errors may carry significant agronomic or economic consequences.

At a systemic level, full AI deployment requires computing infrastructure, high-bandwidth connectivity, and power reliability that many rural and remote farming communities lack (Sharma *et al.*, 2022; Qazi *et al.*, 2022) ^[54, 60]. The digital divide between urban and rural areas is particularly pronounced in developing countries, where smallholder farmers may be effectively excluded from AI-driven benefits unless governments and private organizations invest explicitly in rural connectivity and digital literacy (Ghosh, 2018) ^[22]. The growing migration of agricultural data to cloud platforms also raises cybersecurity and data privacy concerns, as farm operational data becomes an increasingly attractive target for malicious actors (Charania, 2020) ^[14]. Making AI solutions scalable, affordable, and robust across low-infrastructure settings will be fundamental to ensuring equitable access, and will require collaborative effort among technology providers, governments, and civil society (Redhu *et al.*, 2022) ^[57].

Socio-cultural Barriers:

Social resistance to AI adoption in agriculture is both real and consequential. Farming communities with deep-rooted traditional practices may view AI-driven systems with skepticism, particularly when these technologies are introduced without adequate contextual explanation or community engagement (Ryan, 2023) ^[58]. The transition to AI-integrated farming requires not only technical adjustment but also a cultural shift in how agricultural knowledge is acquired and applied a transformation that typically unfolds slowly and unevenly (Iansiti and Lakhani, 2020) ^[27]. Effective adoption also demands a baseline level of digital literacy and operational competence that many farmers, particularly older practitioners who learned their craft through generational knowledge transfer, may not currently possess (Belcher, 2022) ^[9]. Addressing these socio-cultural barriers will require culturally sensitive educational programs, participatory demonstration projects, and ongoing community outreach that builds trust in AI systems through visible, locally relevant outcomes.

Regulatory and Ethical Concerns:

The application of AI in genetic engineering and crop modification engages a complex regulatory landscape. Regulatory agencies and governments frequently require extensive empirical validation and long-term safety assessments before approving AI-assisted GMO varieties, introducing delays that can defer the delivery of agronomic and nutritional benefits (Thompson and Thompson, 2020) ^[68]. Concurrently, questions surrounding agricultural data ownership and privacy have grown in salience as AI systems increasingly depend on large-scale farm-level data for training and operation (Gupta *et al.*, 2020) ^[24]. Farmers remain appropriately concerned about who controls their operational data, under what conditions it is shared, and how potential misuse is prevented. A transparent regulatory architecture developed through inclusive dialogue involving farmers, policymakers, technologists, and civil society is necessary to balance the imperatives of innovation with responsibilities toward privacy and equity. Cybersecurity threats, including targeted attacks on AI-governed farm management systems designed to disrupt food production, represent an additional dimension of risk that regulatory

frameworks must address proactively.

Economic Implications:

The economic case for AI adoption in agriculture is frequently compromised by high upfront capital requirements and protracted return-on-investment horizons, which may deter producers—especially smallholders in low-income contexts from committing to these technologies. Mechanization and automation also carry the potential to displace agricultural labor in rural communities that depend heavily on farm employment for livelihoods, creating socioeconomic tensions that complicate straightforward cost-benefit calculations (Cervantes-Godoy, 2022) ^[13]. While the medium- to long-term cost trajectory of AI technologies points toward greater affordability as the sector scales, the near-term investment burden can be prohibitive for financially constrained farm enterprises. The challenge of ensuring that AI-driven productivity gains translate into equitable economic benefits for smallholder farmers, rather than concentrating value within large commercial agribusinesses, remains a critical policy concern.

Overcoming the Barriers:

Surmounting the interconnected technological, socio-cultural, and economic challenges to AI adoption in agriculture will necessitate coordinated action across government, industry, and academia. Financial interventions including direct subsidies, affordable credit facilities, and co-investment programmes can lower the capital burden for resource-constrained farmers. Structured, outcome-oriented training programs that provide both initial instruction and sustained follow-up support are essential to building farmer competency and confidence (Lukuyu *et al.*, 2012) ^[38]. Regulatory frameworks must evolve to address data privacy and ethical dimensions without unduly constraining beneficial innovation. Collaborative public-private partnerships can facilitate the development of AI tools that are appropriately adapted to the operational realities of smallholder and rural farming systems, including simplified user interfaces, offline functionality, and local-language support (Sharma *et al.*, 2023; Singh and Jain, 2022) ^[59, 60, 62]. The systematic documentation and international sharing of successful AI implementation case studies can build credibility and inspire cautious adopters, while evidence-based policymaking ensures that technology investments reach underserved farming communities regardless of geographic or economic status (Gumbi *et al.*, 2023) ^[23].

AI in Indian Agriculture: Recent Policy Developments and Implementation Initiatives

India's AI Impact Summit 2026 underscored the country's commitment to deploying AI as an instrument of inclusive national development, articulating a vision anchored in the principles of equitable welfare and human-centric governance. Within this policy framework, AI is positioned as an ethical enabler of improved public service delivery and cross-sectoral sustainable development (PIB, 2026) ^[53]. Indian agriculture, serving a farming population of hundreds of millions and confronting mounting challenges of climate variability, soil degradation, and market volatility, represents one of the most consequential domains for this AI strategy. The following subsections describe key

government-led AI initiatives that are reshaping how farmers access information, manage crops, and navigate climate risks.

AI-Enabled Advisory and Decision Support Services for Farmers:

Kisan e-Mitra, operationalized in 2023, is a multilingual, voice-enabled AI chatbot developed to improve farmer access to information on flagship government welfare schemes, including PM Kisan Samman Nidhi, the Kisan Credit Card, and the Pradhan Mantri Fasal Bima Yojana. Supporting queries across eleven regional languages, the platform handled over 8,000 farmer inquiries daily, and had cumulatively addressed more than 93 lakh queries as of December 2025, substantially expanding the reach of scheme-related advisory services in rural areas (PIB, 2026) ^[53].

The National Pest Surveillance System (NPSS), launched in 2024, applies AI and ML to the early identification of pest outbreaks and crop diseases at scale. Farmers upload photographs of affected crops through a dedicated mobile application or online portal, and the system uses image analytics to provide real-time diagnosis and tailored crop protection advisories. As of December 2025, NPSS supported the identification of over 432 pest species across 66 crops and was actively used by more than 10,000 agricultural extension workers (PIB, 2026) ^[53].

A targeted AI pilot program during Kharif 2025 demonstrated the potential of location-specific monsoon onset forecasting to improve sowing decisions across parts of 13 Indian states. Implemented in collaboration with the India Meteorological Department (IMD) and the Development Innovation Lab-India, the pilot used an open-source ensemble modelling framework integrating NeuralGCM, the ECMWF Artificial Intelligence Forecasting System (AIFS), and 125 years of historical IMD rainfall data. Probabilistic forecasts were disseminated via SMS through the mKisan portal to approximately 3.88 crore farmers across five regional languages. Post-season surveys in Madhya Pradesh and Bihar found that between 31 and 52 percent of recipient farmers adjusted their planting strategies in response to the forecasts, with reported modifications spanning land preparation, sowing windows, and input selection (PIB, 2026) ^[53].

Data-Driven Governance through the Digital Agriculture Mission:

The Digital Agriculture Mission, inaugurated in 2024, constitutes India's most comprehensive effort to build a digitally integrated agricultural ecosystem. The Mission leverages verified farmer, landholding, and crop datasets in combination with AI, remote sensing, and advanced data analytics to deliver timely, farmer-centric digital services and strengthen evidence-based governance (PIB, 2026) ^[53]. Its core infrastructure components include AgriStack, the Krishi Decision Support System (KDSS), and a nationwide soil mapping initiative.

AgriStack provides each enrolled farmer with a unique digital identity (Farmer ID) linked to records of land ownership, livestock, crop history, and government benefits utilization, enabling secure, verifiable access to agricultural services. Against a target of 11 crore Farmer IDs by 2026–

27, over 7.63 crore registrations had been completed as of November 2025, including 1.93 crore IDs for women farmers. The platform incorporates a mobile-enabled Digital Crop Survey that records real-time, plot-level data on crop type and cultivated area, having covered 492 districts and over 23.5 crore plots during the Rabi 2024–25 season (PIB, 2026) ^[53].

The Krishi Decision Support System (KDSS) serves as an integrated analytical hub, synthesizing satellite imagery, meteorological information, soil and water resource data, crop statistics, and government scheme records to generate outputs including digital crop maps, soil health maps, yield assessments, and real-time drought and flood monitoring. These outputs support crop diversification advisories and model-based yield estimations for insurance purposes, while also providing government agencies with reliable operational intelligence for evidence-based policy implementation (PIB, 2026) ^[53].

The Nationwide Soil Resource Mapping project, administered by the Soil and Land Use Survey of India (SLUSI), is generating high-resolution (1:10,000 scale) village-level soil inventories by integrating satellite imagery with ground-truthed field observations. These standardized soil maps establish a scientific basis for land-use planning, crop variety selection, and sustainable agricultural practice promotion. As of September 2024, approximately 29 million hectares had been mapped against a total target of 142 million hectares of agricultural land, with ₹1,076 crore allocated across six states: Andhra Pradesh, Madhya Pradesh, Maharashtra, Rajasthan, Tamil Nadu, and Uttar Pradesh (PIB, 2026) ^[53].

AI-Enabled Crop Insurance for Resilient Agriculture:

The Pradhan Mantri Fasal Bima Yojana (PMFBY) was designed to provide financially accessible crop insurance to Indian farmers against production losses arising from natural hazards, with premium contributions set at 2% for Kharif food and oilseed crops, 1.5% for Rabi equivalents, and 5% for commercial and horticultural crops. In the north-eastern states and hill territories, the government bears the full premium burden to ensure coverage for the most vulnerable farming populations. The scheme has progressively integrated AI-powered technologies to enhance operational transparency, accelerate claim assessment, and strengthen fraud detection mechanisms, making it India's most extensive crop insurance program (PIB, 2026) ^[53].

Future Perspectives

The trajectory of AI in agriculture points toward an increasingly integrated technological ecosystem in which autonomous decision-making permeates every production stage from soil preparation and varietal selection to harvest, processing, and market delivery. Predictive analytics platforms, powered by real-time fusion of satellite imagery, weather data, and IoT sensor feeds, will allow farm managers to anticipate and respond to yield-limiting stressors before they become economically significant. AI-driven price forecasting and demand modeling will further enable farmers to optimize cropping portfolios and marketing decisions in an increasingly volatile commodity environment.

As computational power grows more accessible and AI algorithms become more data-efficient, their deployment on resource-limited devices in remote agrarian settings will become increasingly feasible, broadening the demographic reach of these technologies. This shift is likely to substantially mitigate persistent labor and resource shortages that constrain productivity in smallholder systems. Large agribusiness corporations are already beginning to recognize the long-term value proposition of AI-driven agriculture, and their investment will be critical to sustaining the pace of innovation. The transformative potential of AI extends beyond yield improvement to include environmental dimensions: AI-optimized farming systems are expected to reduce per-unit carbon emissions, improve nutrient use efficiency, and minimize agrochemical

runoff, contributing to the broader goal of climate-smart agriculture.

Realizing this potential will require not only continued technological innovation but also supportive policy environments, inclusive financing mechanisms, and research institutions committed to translating scientific advances into accessible farm-level tools. The future trajectory of worldwide agriculture will be shaped by the extent to which AI technologies are integrated into mainstream farming practice through collaborative, multi-stakeholder effort. Ongoing technological advancement is expected to progressively reduce the cost and complexity of AI implementation, enabling more widespread participation in data-driven agricultural systems and contributing to long-term global food security and economic development.

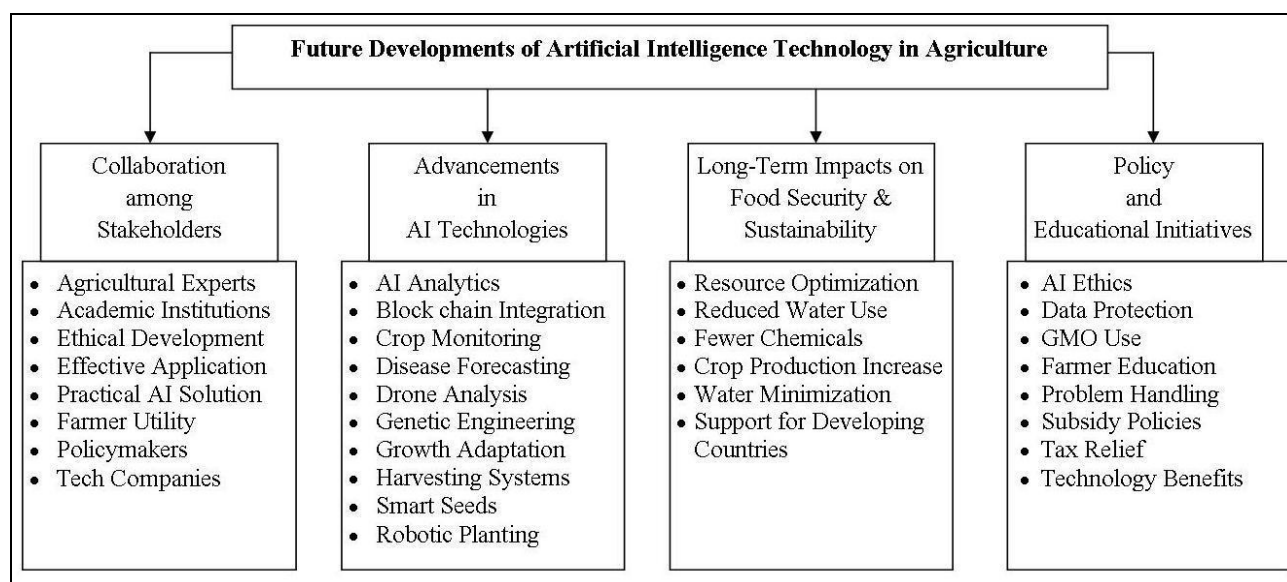


Fig 4: Future Developments of Artificial Intelligence Technology in Agriculture

Conclusion

Artificial Intelligence is catalyzing a profound reorganization of agricultural systems, equipping the sector with capabilities that are fundamentally redefining how crops are cultivated, resources are managed, and food security is sustained in an era of compounding global challenges. Through precision farming applications, AI enables granular, data-driven field management integrating satellite imagery, drone surveillance, and distributed sensor networks to monitor crop health and soil conditions in real time, thereby empowering farmers to act decisively and efficiently. From smart irrigation and automated disease diagnosis to robotics-assisted harvesting and AI-guided genetic improvement, the technological repertoire now available to the sector is transforming what is operationally achievable in food production.

IoT-enabled connectivity is amplifying AI's impact by extending real-time monitoring capabilities across the full agricultural value chain, improving both upstream productivity and downstream logistics efficiency. Remote crop monitoring, automated irrigation management, and precision input delivery collectively reduce production costs and environmental externalities while improving output quality and consistency. These systems are particularly valuable in addressing water scarcity, where AI-guided

irrigation achieves measurably superior efficiency relative to conventional approaches.

This paper has examined AI's transformative role in agriculture through a structured analysis of its principal application domains including robotics, machine learning, precision farming, and post-harvest management—and evaluated the evidence for yield improvement, operational efficiency gains, and environmental benefits. Concurrently, it has addressed the structural barriers that constrain AI adoption, emphasizing the need for coordinated action among policymakers, technology developers, agricultural stakeholders, and educational institutions. Establishing an enabling environment for AI in agriculture requires simultaneous attention to infrastructure investment, regulatory clarity, data governance, and human capacity development.

Looking forward, the full realization of AI's agricultural potential depends on the willingness of stakeholders across the food system to invest in inclusive, ethically grounded, and context-sensitive technological strategies. With continued innovation, policy support, and collaborative research, AI has the capacity to drive agriculture toward greater sustainability, resilience, and equity ensuring that global food systems can meet the nutritional and economic demands of a growing world population while substantially

reducing their environmental footprint.

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