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Role of artificial intelligence in agriculture: A comprehensive study for modern agriculture

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Abstract
Artificial Intelligence (AI) is revolutionizing the agricultural sector by enhancing productivity, efficiency, and sustainability. This survey explores the role of AI in agriculture, its applications, current advancements, challenges, and future prospects. It reviews various AI techniques, including Machine Learning (ML), Deep Learning (DL), computer vision, and robotics in crop monitoring, disease detection, yield prediction, precision farming, and more. The integration of AI in agriculture is helping farmers make data-driven decisions, minimize resource wastage, and improve food security globally. This survey further elaborates on key case studies and global initiatives, includes technical insights into AI algorithms, and proposes a comprehensive roadmap for future adoption of AI-driven smart agriculture solutions.

Keywords: Artificial intelligence, agriculture, smart agriculture, internet of things, automation and robotics

1. Introduction

Agriculture is not just a cornerstone of human civilization but a vital industry that underpins global food security, economic development, and rural livelihoods. It feeds billions, fuels economies, and sustains communities across the globe. Despite its importance, agriculture is increasingly confronted by a multitude of formidable challenges. These include the adverse impacts of climate change, scarcity of natural resources like water and arable land, the growing threat of pest and disease outbreaks, soil degradation, diminishing biodiversity, and a shrinking agricultural labor force due to urban migration and aging populations. Compounding these issues is the rising global population, which is projected to reach approximately 9.7 billion by 2050. According to the United Nations Food and Agriculture Organization (FAO), to meet the food demands of this burgeoning population, global food production must increase by at least 70% by the mid-21st century. This dramatic increase in food production must be achieved in a sustainable, resource-efficient, and environmentally responsible manner [1].

Traditional farming practices while historically effective are proving inadequate in meeting these modern-day demands. Conventional methods often rely on manual labor, experience-based decision-making, and generalized practices that do not account for the variability of climate conditions, soil health, or crop behavior at a micro level. These limitations hinder the capacity for precision and efficiency, ultimately affecting productivity, profitability, and ecological sustainability. Furthermore, the unpredictability introduced by climate change such as shifting rainfall patterns, extreme weather events, and new pest dynamics has made agriculture more vulnerable than ever before [2].

In response to these critical challenges, agriculture is undergoing a paradigm shift, driven by the integration of digital technologies. One of the most transformative developments in this space is the application of Artificial Intelligence (AI). When combined with other technologies such as the Internet of Things (IoT), remote sensing, big data analytics, Geographic Information Systems (GIS), cloud computing, and robotics, AI has the potential to revolutionize modern agriculture by enabling data-driven, adaptive, and automated farming practices [3].

AI brings intelligence and adaptability to various stages of the agricultural value chain. At the pre-cultivation stage, AI models can assist in land suitability analysis, crop selection based on climate and soil data, and the prediction of optimal sowing periods using weather forecasts. During the cultivation stage, AI-powered precision agriculture tools help monitor crop health using drone and satellite imagery, detect diseases and nutrient deficiencies in real time, and recommend precise fertilizer and irrigation schedules, thereby conserving resources while maximizing yield. AI-enabled robotics and autonomous machines can automate labor-intensive tasks such as planting, weeding, and harvesting, addressing the ongoing labor shortage crisis. Post-harvest, AI can optimize storage, transportation logistics, market forecasting, and supply chain management to reduce food loss and improve market access [4]. This digital transformation, often referred to as Agriculture 4.0, is not without its challenges. The adoption of AI technologies in agriculture requires significant investment, digital literacy, infrastructure development, and policy support. Issues such as data privacy, interoperability between systems, and the need for region-specific training datasets also pose technical and ethical hurdles. Nonetheless, the long-term benefits of AI-driven agriculture are substantial. These include enhanced productivity, reduced environmental impact, improved decision-making, and the ability to achieve sustainable food systems capable of feeding the world's growing population [5].

This survey provides a comprehensive and multidisciplinary overview of the role of Artificial Intelligence in transforming agricultural practices. It delves into the various AI methodologies applied in agriculture including machine learning, deep learning, computer vision, and natural language processing and explores how these technologies are implemented in real-world agricultural contexts. Furthermore, it examines the limitations, ethical concerns, and policy frameworks associated with AI adoption, and evaluates its overall impact on agricultural productivity, environmental sustainability, and socio-economic outcomes.

By critically analyzing the current state, opportunities, and future directions of AI in agriculture, this survey aims to serve as a valuable resource for researchers, practitioners, policymakers, and stakeholders seeking to understand and contribute to the ongoing digital transformation of global agriculture.

2. AI Technologies in Agriculture

2.1 Machine Learning and Deep Learning

Machine learning (ML) is a subset of AI that uses algorithms to detect patterns in data and make decisions or predictions based on it. In agriculture, ML is used in crop classification, plant disease detection, weather forecasting, and yield prediction. Algorithms like Support Vector Machines (SVM), Random Forests, k-Nearest Neighbors (kNN), and Gradient Boosting are commonly used.

Deep learning (DL), a more advanced form of ML, uses neural networks with many layers (especially convolutional neural networks, or CNNs) for complex pattern recognition tasks. DL excels in analyzing large datasets, such as satellite images, drone footage, and hyperspectral images. Recurrent Neural Networks (RNNs) and Long Short-Term Memory (LSTM) networks are applied in temporal data modeling like crop growth analysis over time [6].

2.2 Computer Vision

Computer vision is a crucial subset of AI that enables machines to interpret and analyze visual data such as images and videos. In agriculture, computer vision technologies are widely applied to automate and enhance traditional farming practices. One of the most significant applications is disease identification, where images of crop leaves are analyzed to detect early signs of disease. This early detection enables timely intervention, preventing crop losses and improving yield quality. Additionally, drones equipped with high-resolution cameras provide overhead surveillance of large fields, enabling farmers to monitor plant growth stages, detect anomalies, and assess canopy coverage. Real-time video data from field robots is also used for identifying and managing weeds and pests, offering a precision approach that reduces the reliance on chemical interventions. Moreover, computer vision supports fruit ripeness and size estimation, guiding farmers on optimal harvest timing. Recent technological advancements have introduced sophisticated object detection and segmentation algorithms, including YOLOv8, SSD (Single Shot Detector), and Faster R-CNN, which facilitate accurate localization and classification of plant features and anomalies in complex environments. These models are pushing the frontier of precision agriculture by offering scalable and cost-effective monitoring solutions [7].

2.3 Robotics and Automation

Robotics and automation are revolutionizing agricultural operations by taking over repetitive, labor-intensive tasks and performing them with high accuracy and efficiency. Autonomous robots equipped with AI capabilities are increasingly being used for seeding and planting through GPS-guided seed drills, ensuring consistent spacing and depth, which are crucial for optimal crop development. In the domain of weeding, AI-powered mechanical weeders can distinguish between crops and weeds, removing only the unwanted plants and minimizing the use of herbicides. Harvesting has also benefited greatly from automation; robotic arms with integrated visual sensors can identify ripe fruits, assess their quality, and delicately pick them without damaging the produce. This technology is particularly useful in fruit orchards and vegetable farms, where manual harvesting is time-consuming and labor-intensive. Furthermore, smart sprayers embedded in autonomous robots can detect crop areas that require treatment and apply agrochemicals precisely, significantly reducing input costs and environmental impact. Companies like Agrobot, Ecorobotix, and Blue River Technology have developed advanced robotic systems that have demonstrated measurable productivity gains and resource savings, making automation an attractive proposition for modern farmers [9].

2.4 Natural Language Processing (NLP)

Natural Language Processing (NLP) serves as a vital interface between AI systems and human users by enabling machines to understand, interpret, and respond to human language. In agriculture, NLP is making technology more accessible to farmers, especially those with limited technical skills or literacy. One of the key applications of NLP is in developing chatbots and virtual assistants that provide real-time advice on weather, pest control, fertilizer use, and best farming practices. These systems can process user queries in multiple regional languages, making them particularly effective in multilingual regions. Voice-based interfaces further simplify interactions, allowing even illiterate farmers to use digital advisory tools via spoken commands. Additionally, NLP is employed in parsing agricultural documents, such as research reports, manuals, and policy briefs, to extract relevant information automatically. This functionality enables quick access to crucial knowledge and decision-support systems. By bridging communication gaps, NLP enhances the usability and outreach of AI tools, thereby empowering a broader farming community to adopt and benefit from digital innovations [8].

2.5 IoT and Sensor Integration
The integration of the Internet of Things (IoT) with AI is transforming farms into smart, connected ecosystems capable of self-monitoring and adaptive response. IoT involves deploying various sensors across the agricultural landscape to continuously gather data on critical environmental parameters, such as soil moisture levels, pH values, ambient temperature, relative humidity, CO_2 concentration, and sunlight intensity. These data streams are vital for understanding the microclimate and soil conditions that influence crop growth. AI models process this real-time sensor data to make informed decisions, such as when to irrigate, fertilize, or apply pesticides. The inclusion of edge computing or Edge AI enables some of these computations to be performed locally on the sensors or edge devices themselves, minimizing latency and dependence on cloud connectivity. This is especially beneficial in remote farming areas with limited internet access. The combination of IoT and AI supports precision agriculture practices by ensuring timely interventions, optimizing resource use, and reducing operational costs while improving productivity and sustainability [10].

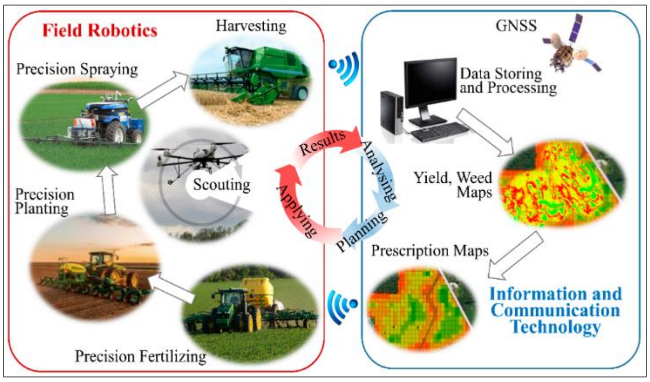

Fig 1: AI technologies applied in agriculture [14]

3. Applications of AI in Agriculture
3.1 Precision Agriculture
Precision agriculture is a modern farming approach that involves managing intra-field variability to optimize crop yield and resource use. AI enhances precision agriculture by enabling farmers to make data-driven decisions based on real-time insights. For example, Variable Rate Application (VRA) technologies allow for precise administration of fertilizers, pesticides, and water based on the specific needs of different field zones. AI also facilitates geo-fencing and field zoning, which improve the efficiency of farming operations. Through multispectral and hyperspectral imaging from satellites and drones, AI systems can detect plant stress, nutrient deficiencies, and water scarcity. Machine learning algorithms analyze these images and compute indices like the Normalized Difference Vegetation Index (NDVI) and Soil Adjusted Vegetation Index (SAVI), providing granular insights that guide targeted interventions [11].

3.2 Crop and Soil Monitoring
Monitoring soil and crop conditions is essential for sustainable agricultural practices. AI tools enable continuous surveillance of soil properties and crop growth, supporting informed decisions on cultivation and resource management. Machine learning models classify soil types using data from satellite imagery and ground-based sensors. Predictive analytics are applied to generate fertility maps, helping determine the best crop types and planting schedules for a given field. Furthermore, AI models assess erosion risks by analyzing terrain features and vegetation cover, which helps in implementing preventive strategies. This form of predictive soil analytics improves overall crop selection, irrigation efficiency, and fertilizer management, ultimately leading to enhanced productivity and environmental conservation [12].

3.3 Pest and Disease Detection
Timely detection and identification of pests and diseases are critical to minimizing crop losses. AI models, particularly convolutional neural networks (CNNs), are trained on extensive image datasets of infected plant leaves to classify and detect specific diseases. Advanced deep learning techniques, including transfer learning using architectures like VGG16, ResNet50, and InceptionV3, have significantly improved detection accuracy. Real-time pest surveillance is made possible using object detection models such as YOLO (You Only Look Once), which can identify and track pests in dynamic environments. Mobile applications like Plantix and AgroAI leverage these technologies to offer instant diagnostic services. Farmers can simply upload photos of affected crops to receive immediate feedback and treatment recommendations, reducing dependency on traditional extension services [13].

3.4 Yield Prediction
Accurate yield prediction is essential for strategic planning, including logistics, market supply, and crop insurance. AI models utilize a wide range of input variables such as historical yield data, soil characteristics, weather patterns, and planting schedules to estimate expected output. Regression analysis is frequently used to model the relationship between these variables and yield outcomes. Time-series forecasting is conducted using neural networks, including LSTM models, which can capture temporal dependencies and patterns. Additionally, clustering and decision tree algorithms are employed to simulate various production scenarios. By offering reliable forecasts, AI supports effective supply chain management and reduces uncertainty in agricultural planning [15].

3.5 Weed Detection and Management
Weeds are a significant threat to crop productivity, often competing for nutrients, water, and light. AI-powered computer vision systems are used to distinguish between crops and weeds based on morphological features. These systems guide robotic weeders that can either mechanically remove weeds or apply herbicides with pinpoint accuracy, thereby reducing chemical usage and environmental impact. Deep learning models, trained on annotated datasets, have achieved weed classification accuracies of over 90% in several studies. The precision and efficiency of AI in weed management offer a sustainable alternative to traditional, labor-intensive methods [16].

3.6 Irrigation Management
Efficient irrigation is vital for crop health and water conservation, particularly in water-scarce regions. AI systems integrate data from weather forecasts, soil moisture sensors,

and evapotranspiration models to determine optimal irrigation schedules. These systems can automatically activate irrigation mechanisms when certain thresholds are met, ensuring that crops receive water precisely when needed. This real-time automation not only conserves water but also prevents over-irrigation, which can lead to root diseases and nutrient leaching. Platforms like CropX and NetBeat exemplify the successful integration of AI with irrigation systems, providing scalable solutions that adapt to both small and large farm operations [17].

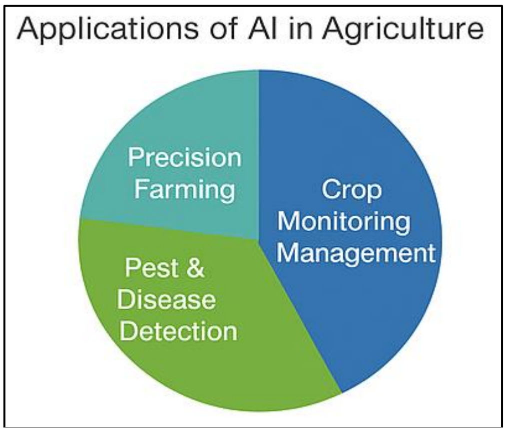

Fig 2: Application areas of AI in agriculture

4. AI-Driven Platforms and Tools [18]

- **IBM Watson Decision Platform:** Provides agronomic insights, weather analytics, and yield models.
- **Microsoft AI for Earth:** Supports data-driven sustainability projects.
- **Google Earth Engine:** Analyzes satellite imagery for land-use and crop cover.
- **Plantix:** Mobile-based disease diagnosis using deep learning.
- **Taranis:** Combines high-resolution aerial imagery and AI for early crop threat detection.
- **AgNext:** AI for quality assessment in agri-supply chains.
- **FarmBeats by Microsoft:** Collects farm data using sensors, drones, and AI analytics.

5. Case Studies

5.1 India, Krishi Mitra and CropIn Technologies

India has embraced AI in agriculture through several initiatives. The Krishi Mitra chatbot, developed by government-backed institutions, provides localized farming advice using NLP in regional languages. Additionally, CropIn Technologies leverages AI and satellite imagery for real-time farm data analytics, offering predictive intelligence on crop health, yield forecasting, and weather patterns. This has empowered over 7 million farmers across 50 countries [19].

5.2 United States, Blue River Technology

Blue River Technology's "See & Spray" system is a notable case of AI implementation. This AI-powered robotic system uses computer vision and ML to identify and treat individual plants. It enables precision weed control by applying herbicides only where needed, reducing chemical use by up to 90% and improving yield quality [20].

5.3 Netherlands, Wageningen University Smart Greenhouses

Wageningen University in the Netherlands has developed AI-based greenhouse systems where environmental parameters like humidity, CO_2, and light are automatically controlled using ML algorithms. These smart greenhouses optimize resource usage while ensuring consistent crop production, particularly in tomato and lettuce farming [21].

5.4 Kenya, Agrix Tech and Digital Green

In Kenya, Agrix Tech has created mobile apps that diagnose plant diseases using deep learning. Similarly, Digital Green uses AI-driven video content to educate smallholder farmers. These solutions address challenges like low literacy and limited access to extension services by simplifying the technology interface [22].

5.5 China, DJI Drones and AI Integration

DJI, a leader in agricultural drones, has deployed UAVs embedded with AI models for aerial surveillance, mapping, and crop health assessment. China's Ministry of Agriculture has integrated AI in national programs for pest surveillance and precision rice farming, significantly increasing productivity [23].

6. Challenges and Limitations

With the above advantages of AI in agricultures, there are some limitations and challenges to implement it [24].

6.1 Data Scarcity and Annotation

High-quality annotated agricultural datasets are limited. Crop diseases may vary by geography, and public datasets often lack diverse representation. Manual annotation is expensive and time-consuming, limiting model accuracy in the field.

6.2 Infrastructure Constraints

AI technologies rely on robust digital infrastructure, which is lacking in many rural areas. Limited internet access, absence of sensor networks, and unreliable power supply can hinder the deployment of smart farming solutions.

6.3 Cost and Affordability

AI tools, especially robotics and drones, can be expensive. Small and marginal farmers, who constitute the majority in developing countries, may not afford these solutions without subsidies or community-based access models.

6.4 Algorithm Bias and Transferability

Models trained on data from one region may perform poorly in another due to differences in crop varieties, soil types, or weather conditions. Algorithm bias can result in inaccurate predictions, leading to suboptimal decisions.

6.5 Policy and Regulatory Issues

There is a lack of regulatory frameworks addressing data privacy, liability in automated decisions, and standards for AI system certification. Policy clarity is essential for large-scale AI adoption.

7. Future Prospects

7.1 AI-Powered Autonomous Farming

Fully autonomous farms using AI-powered robots for sowing, weeding, and harvesting are in development. These systems can work around the clock with minimal human intervention, improving labor efficiency and reducing costs.

7.2 Integration with Blockchain for Traceability

Combining AI with blockchain technology can enhance transparency in supply chains. It ensures end-to-end traceability from farm to fork, improving consumer trust and enabling fair trade practices.

7.3 Edge AI and 5G
Edge computing allows AI processing to occur locally on devices like drones or sensors, reducing dependency on internet connectivity. Combined with 5G, it enables real-time decision-making in remote fields.

7.4 Federated Learning for Collaborative Modeling
Federated learning allows decentralized AI training on multiple devices without sharing raw data, protecting privacy while building generalized models. This is ideal for agricultural data collected from dispersed farms.

7.5 Sustainable AI and Climate-Smart Agriculture
AI will play a central role in climate-smart agriculture by optimizing input use, predicting climate risks, and recommending adaptive strategies. Energy-efficient algorithms and low-carbon AI models are emerging to ensure environmental sustainability.

8. Conclusion
AI holds immense potential to transform agriculture into a smart, resilient, and sustainable sector. With its ability to process complex datasets and generate actionable insights, AI can significantly enhance productivity, reduce waste, and support climate resilience. However, realizing this potential requires investment in digital infrastructure, policy reform, farmer education, and ethical considerations. By fostering collaboration between researchers, governments, and the private sector, AI can be harnessed to secure the future of global agriculture.

9. References

1. Javaid M, *et al*. Understanding the potential applications of Artificial Intelligence in Agriculture Sector. Adv Agrochem. 2023;2(1):15-30.
2. Patel SK, Sharma A, Singh GS. Traditional agricultural practices in India: An approach for environmental sustainability and food security. Energy Ecol Environ. 2020;5(4):253-271.
3. Pantazi XE, *et al*. Wheat yield prediction using machine learning and advanced sensing techniques. Comput Electron Agric. 2016;121:57-65.
4. Singh A, *et al*. AI and IoT-based smart agriculture systems. Procedia Comput Sci. 2020;167:1250-1259.
5. Zhai Z, *et al*. Decision support systems for agriculture 4.0: Survey and challenges. Comput Electron Agric. 2020;170:105256.
6. Kumar L, Singh DK. Hardware response and performance analysis of multicore computing systems for deep learning algorithms. Cybern Syst. 2022;22(3):68-81.
7. Kumar L, Singh DK. A comprehensive survey on generative adversarial networks used for synthesizing multimedia content. Multimedia Tools Appl. 2023;82(26):40585-40624.
8. Hirschberg J, Manning CD. Advances in natural language processing. Science. 2015;349(6245):261-266.
9. Macrorie R, Marvin S, While A. Robotics and automation in the city: A research agenda. Urban Geogr. 2021;42(2):197-217.
10. Kumar L, Badal N. An Effective Method of Hybrid Encryption on IoT.
11. Shafi U, *et al*. Precision agriculture techniques and practices: From considerations to applications. Sensors. 2019;19(17):3796.
12. Pierce FJ, Lal R. Monitoring the impact of soil erosion on crop productivity. In: Lal R, editor. Soil erosion research methods. Routledge; 2017. p. 235-263.
13. Li L, Zhang S, Wang B. Plant disease detection and classification by deep learning: A review. IEEE Access. 2021;9:56683-56698.
14. Gonzalez-de-Santos P, *et al*. Field robots for intelligent farms inheriting features from industry. Agronomy. 2020;10(11):1638.
15. Van Klompenburg T, Kassahun A, Catal C. Crop yield prediction using machine learning: A systematic literature review. Comput Electron Agric. 2020;177:105709.
16. Singh V, *et al*. Unmanned aircraft systems for precision weed detection and management: Prospects and challenges. Adv Agron. 2020;159:93-134.
17. Darshna S, *et al*. Smart irrigation system. IOSR J Electron Commun Eng. 2015;10(3):32-36.
18. Spanaki K, *et al*. Disruptive technologies in agricultural operations: A systematic review of AI-driven AgriTech research. Ann Oper Res. 2022;308(1):491-524.
19. Shah V, *et al*. Krishi Mitra: Growing Smarter with AI-Powered Farming.
20. Panpatte S, Ganeshkumar C. Artificial intelligence in agriculture sector: Case study of blue river technology. In: Proceedings of the second international conference on information management and machine intelligence, 2021.
21. Garcia ME, Marín TJN, Lasso CA. Smart Greenhouse and Agriculture 4.0. Revista Científica. 2023;46:37-50.
22. Kiaka R, Kimana RV. Digital Technology in Kenyan Agriculture: A scoping report. Working Paper 67. Cape Town: Institute for Poverty, Land and Agrarian Studies, University of the Western Cape, South Africa, 2024. Available from: https://plaas.org.za/digital-technology-inkenyan-agriculture-a-scoping-report/
23. He T, Ji Y. China's techno-economic statecraft amid US-China Strategic Rivalry: AI and the "New Whole-State System". Orbis. 2023;67(4):605-625.
24. Mohan SS, *et al*. Role of AI in Agriculture: Applications, Limitations and Challenges: A Review. Agric Rev. 2023;44(2).