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ROLE OF ARTIFICIAL INTELLIGENCE IN SMART AGRICULTURE: OPPORTUNITIES AND CHALLENGES

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ABSTRACT

Artificial Intelligence (AI) is rapidly transforming smart agriculture by enabling precise, predictive, and data-driven farm management practices. AI has emerged as a promising tool for addressing major agricultural challenges, including increasing food demand, climate variability, water scarcity, declining soil fertility, pest and disease outbreaks, and labor shortages, through the deployment of advanced analytical and automation technologies that enhance agricultural productivity, sustainability, and resilience. Several AI-based approaches, such as machine learning, deep learning, computer vision, predictive analytics, expert systems, robotics, and decision-support systems, are being increasingly utilized across diverse agricultural applications, including crop monitoring, disease and pest detection, irrigation scheduling, soil health assessment, crop yield forecasting, weed management, autonomous farming operations, and post-harvest supply chain management. The integration of AI with Internet of Things (IoT) sensors, drones, remote sensing technologies, cloud computing, digital twins, and digital farm advisory systems has further strengthened real-time monitoring, data acquisition, and site-specific decision-making in modern agriculture. AI-driven technologies also contribute significantly toward optimizing water, fertilizer, pesticide, and energy use, improving labor management, and promoting climate-smart and market-oriented agricultural systems. However, despite its enormous potential, the widespread adoption of AI in agriculture remains constrained by several challenges, including high implementation costs, inadequate rural connectivity, poor data quality and management, limited digital literacy, lack of transparency and explainability of AI models, concerns related

to data privacy and security, weak governance frameworks, and unequal access to AI technologies among farmers. This review emphasizes the need for explainable AI, ethical and secure data management practices, utilization of locally relevant datasets, development of low-cost technologies, and farmer-centric innovations to ensure inclusive, sustainable, and efficient AI-driven agricultural development.

KEYWORDS: Artificial Intelligence; Decision-Support Systems; Resilience; Modern Agriculture; Cloud Computing; Sustainable Agriculture.

1. Introduction

The conventional, experience-driven, and manual agriculture is being transformed into data-driven, technology-enriched and intelligent agriculture. Smart agriculture is a paradigm that embodies the transition, with digital technologies, automation, and data analysis enhancing productivity, sustainability, and decision-making processes. Manual observation, seasonality, and generalizing the use of inputs have been the main methods of traditional farming; however, these methods have become increasingly insufficient in the context of increasing food demand, climate uncertainty, resource degradation, and the demand for efficient production (Wolfert et al., 2017). Smart agriculture provides a concept how information from fields, crops, soil, weather, machinery, markets and field operations can be turned into knowledge. Systematic data collection, processing and interpretation of data are revealed by big data to determine the farm management.

The relevance of artificial intelligence is connected with the digital transformation of agrifood systems. Agro-informatics is a base for the collection, organisation and use of agricultural information in agriculture production, monitoring, distribution and decision-support processes. Farm management systems, crop records, climate data, remote sensing instruments, and sensors generate data that is pertinent to agriculture. AI enhances this ecosystem by identifying patterns, categorizing risks, making predictions, and providing recommendations on action (Chen, 2024). As a result, the way farmers manage their agriculture is moving from reacting to predicting and adapting to decisions. The availability of data and intelligent models capable of converting data into timely decisions are critical to future agrifood systems.

In today's farming contexts, there are interrelated environmental, economic, and social pressures that have made the need for AI in agriculture a pressing issue. The food production and conservation of water, the preservation of soil, the decrease in chemical dependency, and ecological sustainability are critical elements for global agriculture. Uncertainty has been increased by climate change and the irregularities in rainfall, drought, heat stress, flooding, pests, and shifts in growing seasons. Farms are also impacted by declining soil fertility, water scarcity, overuse of inputs and a lack of labour. Such challenges demand a tool that can handle complex agricultural information and enable location-specific interventions (Arshad et al., 2024). AI is relevant for agricultural transformation because the climate-smart agriculture promotes food security, sustainable land and water management, and resilient production systems.

These challenges are met by artificial intelligence because it gives the technology the ability to learn from agricultural information and make better decisions. In the field of agriculture, machine learning, deep learning, computer vision, expert system, predictive analysis and artificial cognition are extensively used in research and practices (Pathan et al., 2020). Crop management, soil assessment, disease diagnosis, weed detection, irrigation scheduling, yield forecasting and monitoring of livestock are some of the applications for which machine learning can be used. AI systems can discover latent connections among data sets and help make decisions that would be challenging otherwise by using traditional observation (Liakos et al., 2018). Hence, machine learning is an integral technology of smart agriculture as it converts raw data into predictive insights.

Deep learning has become significant due to its ability to handle more complex data like the images of crops, satellite imagery, drone images and sensor output. It can be helpful in plant disease detection, pest identification, crop classification, fruit counting, weed recognition and plant stress analysis. Problems in the crops can be avoided or losses minimized, while better decisions can be made on the field by identifying problems at an early stage (Kamilaris & Prenafeta-Boldú, 2018). Deep learning improves the monitoring of crops and helps to make recommendations automatically based on visual and environmental information.

In recent times, AI has emerged as a decision support tool in the agricultural systems, as seen in various developments. Weather data, soil properties, crop growth data, irrigation data, and historical yield data can all be used to inform farm planning with AI-based tools. These tools can be used for crop selection, yield prediction, fertilizer recommendation, optimization of irrigation, disease prediction and precision spraying (Benos et al., 2021). AI applications have been seen to be widespread, including crop monitoring, automation, resource management, and production forecasting, which makes AI a key element of smart farming and Agriculture 5.0 driven crop data management (Saiz-Rubio & Rovira-Más, 2020; Thomasson et al., 2025).

The power of AI is that it can enhance prediction, automation, monitoring, optimization and decision-making. AI can generate yield estimates, estimate N status, estimate water requirements, predict disease symptoms, assess potential pest problems, and suggest interventions (Chlingaryan et al., 2018). The importance of these functions is that they are essential to the precision agriculture and inputs like water, fertilizer, pestides and labour can be applied based on the requirements of the field. The focus on yield prediction and nitrogen assessment using machine learning illustrates the potential of AI in enhancing productivity and resource usage efficiency.

Accordingly, this study focuses on the Artificial intelligence in Smart Agriculture and provides its concept, applications, opportunities, challenges and future trends. It reviews how AI is used in crop monitoring, disease detection, irrigation system, soil detection, yield estimation, automation and also in the supply chain efficiency, climate-smart agriculture etc (Javaid et al., 2023). Meanwhile, it considers farmer acceptance, privacy, ethical governance, model generalizability, data quality and infrastructure and affordability as well.

2. Conceptual and Technological Foundations of AI in Smart Agriculture

Smart farming is one of the newest approaches in agriculture using technologies of the internet, computer applications and intelligence systems to make accurate decisions regarding agriculture. The Smart agriculture concept is one step forward compared to traditional farming in which the whole processes rely mostly on observation and personal experiences rather than on information based on computations and collected data in real-time and with real time observation, for accurate management of the farm. Smart farming enables the precise management of all farm activities including plant growth, watering, soil moisture, pest occurrence, weather conditions. This type of farming is characterized by connected and data driven agricultural processes by the integration of digital technologies, sensors, analytical models, and autonomous systems. The key role of analysis of big data for the transformation of the traditional farms is because of the nature of the data which nowadays comes from modern farm systems and it is enormous in volume and variety, requiring analysis in order to derive effective agricultural practices. (Kamilaris et al., 2017)

AI is the basis of smart agriculture as it turns agricultural data into knowledge. These are all considered core AI technologies: machine learning, deep learning, computer vision, natural language processing, expert systems, reinforcement learning and predictive analytics. Machine learning can be used for prediction and classification, like yield prediction, soil analysis, disease identification, irrigation scheduling, etc. Crop image analysis, remote sensing data analysis, pest symptom analysis and plant disease pattern analysis are all beneficial with deep learning and computer vision. Natural language processing can be used to help farmer advisory systems, to power chatbots, and to enable multilingual extension services; expert systems offer rule-based recommendations. Adaptive decision-making in the control of irrigation, greenhouse management and autonomous machinery can be aided by reinforcement learning.

The Internet of Things is among the most crucial enabling technologies for the smart agriculture, which is based on artificial intelligence. The sensors, machines, field devices and digital platforms are linked to each other via IoT, enabling the continuous monitoring of the agricultural environment. The data that can be gathered in real time using IoT systems includes soil moisture, soil temperature, soil humidity, crop well-being, water consumption and field conditions. This will increase farm responsiveness due to the timely information of farm decision support systems and farmers regarding change of field condition. With the advent of IoT in agriculture, the physical farm environment can communicate with a digital platform and provide real-time information on which decisions can be made (Ayaz et al., 2019).

There are also other technologies that enable smart farming with AI. Sensors provide data at the level of the field, drones and satellite imagery provide visual and spatial data, robotics allows for automated operations and cloud computing facilitates data storage and processing. Edge computing reduces the lag time required for data processing by processing data near the field, and geographic information systems (GIS) enable the analysis of spatial patterns of soil, crop, water, and climate properties. These data streams are combined to form a big data analytics that can provide insights to be applied in agricultural management. But, it requires interoperability, infrastructure, connectivity, scalability, and good data management to be successful. In contrast, IoT presents opportunities through the use of sensor networks and automation, but it still has many challenges related to cost, standardization, rural connectivity and implementation (Tzounis et al., 2017).

Crop images, soil parameters, weather data, irrigation records, remote sensing images, pest data, market information, and farm machinery data are examples of agricultural data sources for AI systems. These data can be used for disease surveillance, fertiliser advise, drought watching, crop planning and price forecasting. The process of architecture in AI powered smart farming is basically data collection, data transmission, data storage, data pre-processing, AI data analysis, data recommendation and field application by farmers, smart platforms, irrigation controllers, drones, robots or smart machinery. AI supported smart agriculture is therefore a technical system as well as a socio-digital transformation, which needs to be addressed with regard to farmers, institutions, skills, governance and social acceptance (Klerkx et al., 2019).

3. Taxonomy of AI Applications in Smart Agriculture

The role of AI in smart agriculture is growing in importance as it assists in monitoring, predicting, automating, optimizing, and making decisions in various agriculture fields. The applications fall under five broad categories: Crop Monitoring and phenotyping, Disease and Pest detection, Precision resource management, Agricultural Robotics and Post harvest supply-chain intelligence. Machine learning and deep learning support soil analysis, weather forecasting, crop growth management, and yield prediction in smart agriculture, as shown in Figure 1

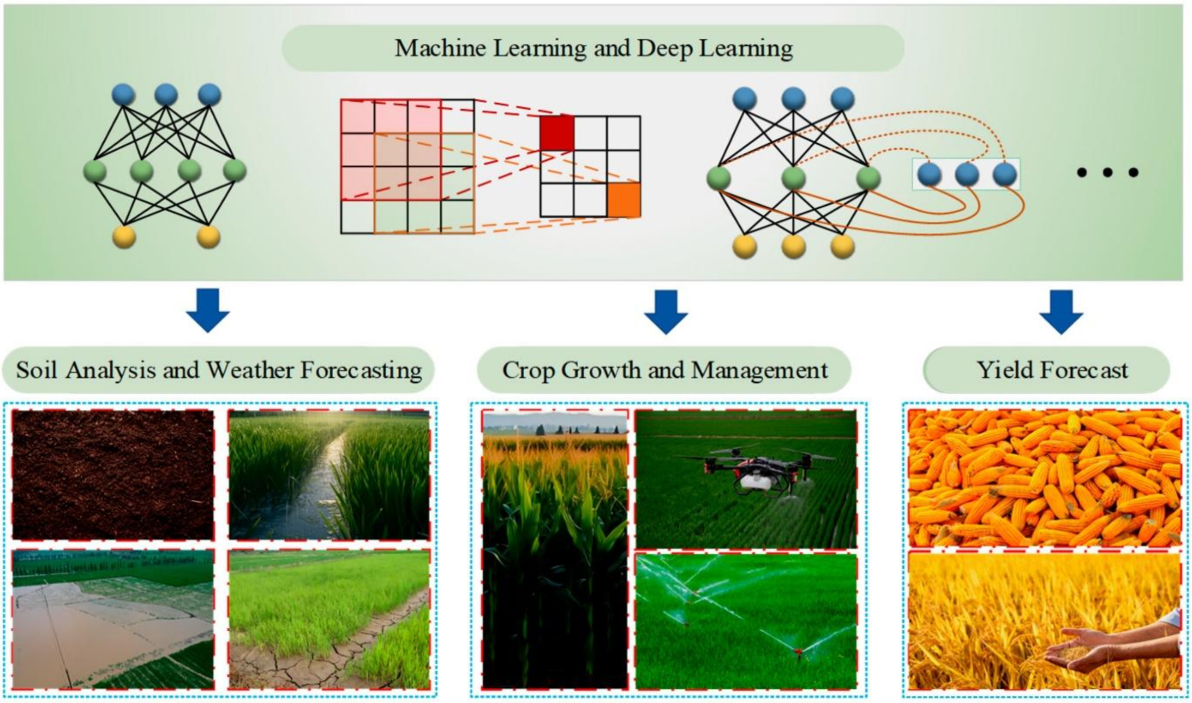

Figure 1. AI-Based Applications in Smart Agriculture
Source: Adapted from Ge et al. (2025)

3.1 AI for Crop Monitoring, Phenotyping, and Plant Health Assessment

Crop monitoring, phenotyping, canopy analysis, vegetation assessment and plant stress identification are among the many applications of AI in agriculture. Images captured by field cameras, aerial video, satellite and remote sensing platforms can be used to assess crop growth, leaf area, canopy structure and health and processed using deep learning and computer vision techniques. These systems assist in identifying early symptoms of water stress, nutrient deficiency, pest damage and environmental stress. The use of AI in crop phenotyping is further advantageous as it allows for the continuous monitoring and accurate assessment of plant traits through visual and spectral data. Agricultural image analysis is a field with significant potential of deep learning applications, particularly where it comes to complex crop and field data (Kamilaris & Prenafeta-Boldú, 2018). Drone remote sensing can also aid precision agriculture by offering high-spatial resolution data for crop monitoring and stress assessment (Maes & Steppe, 2019).

3.2 AI for Disease, Pest, Weed Detection, and Precision Spraying

AI applications for smart agriculture are well-established, such as plant disease, pest and weed detection. Leaf, stem, fruit and canopy images can be used to classify disease symptoms using computer vision and deep learning models, which can aid in early detection and warning. Image-based deep learning has been successfully adopted for the plant disease detection and demonstrates the potential for automated plant disease diagnosis in agriculture (Mohanty et al. 2016). Deep learning models have also been able to detect and classify plant diseases under various crop conditions (Ferentinos, 2018). CNNs have also demonstrated their usefulness in diagnosing rice ailments, illustrating the importance of specialized crop-specific AI diagnostics in rice cultivation (Lu et al., 2017). Another use of AI is in weed identification and precision spraying—where AI technology can differentiate crops from weeds and target herbicides to the specific areas where weeds are located. This minimises the use of chemicals, production costs and contamination of the environment, and promotes sustainable crop protection.

3.3 AI for Precision Resource Management, Soil Health, and Yield Prediction

AI plays a key role in precision irrigation, water management, soil health analysis, nutrient recommendation and yield prediction. By leveraging soil moisture, weather patterns, evapotranspiration, crop development, and data from remote sensing, AI models can suggest irrigation plans and optimize water usage. AI can analyze soil pH, organic matter, nitrogen, phosphorus, potassium, soil texture, and moisture, aiding in fertilizer optimization and fertility predictions in soil and nutrient management. AI-based systems also help with yield predictions, using historical yield records, weather data, soil conditions, crop growth metrics and remote sensing data. Such forecasts contribute to the planning of harvesting, storage, marketing, and use of resources by farmers and policy makers. The field variability analysis, crop-soil interactions and decision making for grain crops are of great significance in precision agriculture and are highly relevant to computer vision and AI-based tools (Patrício & Rieder, 2018).

3.4 AI for Agricultural Robotics, Automation, and Autonomous Operations

One of the key fields where AI is being applied in digital farming is agricultural robotics. Autonomous tractors, robot planters, harvesting robots, spraying drones, robotic weeders, greenhouse automation, and livestock monitoring systems are all examples of applications AI can achieve. They involve technologies that enable conducting agricultural operations with a minimum amount of human intervention through sensor systems, computer vision, navigation algorithm and control. By addressing labour shortages, operational precision, reduction in human drudgery and timely farm activities, robotics can contribute to addressing the above-mentioned issues. Digital farming is becoming more reliant on autonomous systems that operate at the field level and have the ability to perceive, decide and act (Shamshiri et al., 2018). Drones can also assist in automating crop surveillance, field mapping, spraying, and stress detection.

3.5 AI for Post-Harvest Management, Supply Chain, and Market Intelligence

AI can be used in the field, but its benefits also manifest in post-harvest management, food quality inspection, monitoring food storage, optimizing logistics, traceability, predicting demand and market intelligence. Image analysis using Artificial Intelligence can be used for the quality assessment, defect detection, classification and grading of products. The predictive model can be used to estimate demand, predict prices, optimise storage conditions and minimise post-harvest losses. AI can be used in agricultural supply chains to enhance transparency, traceability, and trust between producers, processors, retailers, and consumers, when combined with blockchain technology. The Blockchain technology has been discussed in the field of agriculture and food supply chains due to the tracking, transparency and accountability of products (Kamilaris et al., 2019). Thus, the introduction of AI in smart agriculture does not stop at the farming level, but is applicable to the entire agrifood value chain.

4. Opportunities of AI in Smart Agriculture

AI can hold great potential to help revolutionize the food system, making it more productive, sustainable, resourceful and climate resilient. AI, combined with the other technologies of precision agriculture, IoT, sensors, remote sensing, robotics, and digital advisory, allows farmers to shift from general to evidence-based and site-specific decision-making. The opportunities are significant as agriculture has to be both more productive and less pressuring of the environment and more profitable for the farmer.

4.1 Productivity Enhancement and Food Security

AI can enhance agricultural efficiency in several ways, including crop monitoring, forecasting yield, diagnosing diseases, and optimizing irrigation, as well as providing recommendations for fertilizer use and making decisions at the farm level. AI can analyze soil, weather, crop and yield data to detect crop stress, nutrient deficiencies, pest threats and water shortages in early stages. This will enable farmers to take suitable corrective actions at the right time and minimise losses in production. Precision agriculture is one of the key strategies for contributing to food security as it allows farmers to control variability within the field and boost the efficiency of production (Gebbers & Adamchuk, 2010). This opportunity is further enhanced by AI, which can make better, predictive, and responsive farm decisions.

4.2 Sustainable Agriculture and Environmental Protection

AI can assist farmers in creating sustainable agricultural practices, enabling them to optimize crop yields while also conserving the environment. Digital agriculture can inform agriculture based on data, models and decision-support tools (Basso & Antle, 2020). These systems can help minimize excess use of fertilizers, pesticides, water and energy by suggesting inputs based on real-time field requirements using AI. Using smart farming in agriculture is also crucial for sustainable agriculture as it facilitates the precise monitoring and management of production systems (Walter et al., 2017). Thus, AI can help mitigate environmental damage, better manage soils and water resources, and provide means to advance responsible agricultural intensification.

4.3 Resource Optimization and Climate Resilience

The most promising opportunity offered by AI is resource optimization and handling weather-risk. AI can direct the proper application of water, fertilizer, pesticide and energy at the right time and place. This input management at the farm level decreases farm wastes and cut down on production expenses and increase farm profitability. Implementing PRECISION AGRICULTURE technologies has a positive impact on GHG mitigation, on the productivity of the farms, and on the farm economy (Balafoutis et al., 2017). AI can also help enhance the resilience of climate-smart agriculture by predicting drought, weather variability, heat stress, pest infestation, and yield variability. Precision farming is highly relevant for climate-resilient agriculture (Finger et al., 2019) because it lies at the crossroads of climate-resilient agricultural production and environmental management. Smart monitoring technologies, including drone surveillance, smart irrigation, soil moisture sensing, temperature sensing, pest monitoring, and plant disease monitoring, support AI-based resource optimization and climate-resilient farming, as shown in Figure 2.

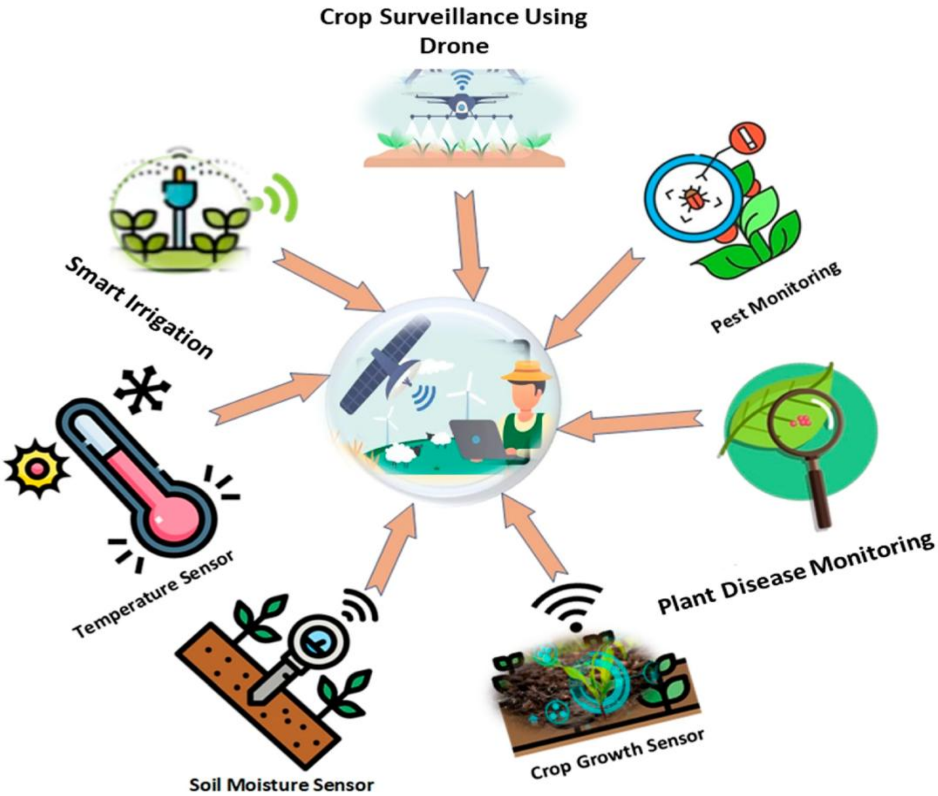

Figure 2. Smart Monitoring Technologies for AI-Enabled Agriculture. Source: Adapted from Kumari et al. (2025).

4.4 Decision Support, Extension Services, and Farmer Income Stability

AI can support farmers' decision making by providing mobile applications, digital advisory platforms, chatbots, dashboards and automated alerts. These can help you make recommendations about crop selection, irrigation, fertilizers, pest management, harvesting, and market planning. In extension, ICTs have already been found useful in agriculture particularly in developing nations where farmers require timely information and knowledge, price information, weather updates, and extension advisory services (Aker, 2011). AI can help improve such services with personalisation, prediction and targeting. This can lead to increased productivity, decreased input expenses, steady farm income and decision-making by smallholder farmers.

4.5 Remote Sensing and Market-Oriented Planning

Another significant chance of smart agriculture through AI is provided by the use of remote sensing. Monitoring of crop growth, stress detection, biomass estimation, soil variability analysis, and yield forecasting can be achieved through the analysis of the satellite imagery, drone data and spatial datasets. In precision agriculture, remote sensing has been a great tool for crop monitoring at the field scale and area scale (Mulla, 2013). Combined with AI, it can assist in production scheduling, inventory management, market predictions, and supply chain coordination. As such, AI can augment the utility of smart agriculture beyond farming to food-system planning.

5. Challenges and Barriers in AI Adoption

AI holds significant promise for revolutionizing smart agriculture, but faces technical, social, ethical, economic, and governance challenges that influence the technology's uptake. AI farming systems rely on digital infrastructure, trust by farmers, technological support, and proper data management. Thus it is not enough to see the barriers to the adoption of AI simply as technical ones; they can also be considered socio-economic and policy issues.

5.1 Unequal Access and Digital Divide

One of the great challenges of a smart agriculture based on AI is the unequal access to digital technologies. Farmers' adoption of digital farming tools varies significantly due to the availability of the tools on the farm, factors related to farm size, income, education, infrastructure and technical support. Investing in AI solutions, sensors, drones, and automated machinery can be challenging for small and marginal farmers, whereas large commercial farms might be more capable of meeting the cost and technology requirements to implement these solutions. This poses the danger that inequalities could be further exacerbated by digital agriculture. The authors Bronson (2019) used the responsible innovation lens for digital farming, given the uneven uptake of these technologies among different communities of farmers. Likewise, automation and digital farming have the potential to transform rural employment and communities, with questions about who is included in this transformation and who might be left behind (Rotz et al., 2019). The major barriers to AI adoption in smart agriculture include unequal access, data ownership concerns, trust deficits, socio-ethical governance issues, commercialization-related power imbalances, and rural labour transformation, as summarized in Table 1.

Table 1. Key Challenges in AI Adoption in Smart Agriculture

Challenge	Key Concern	Impact
Unequal Access and Digital Divide	High cost, poor infrastructure, and limited technical support	Small farmers may be excluded from AI benefits
Data Ownership and Privacy	Unclear data control, third-party use, and weak legal protection	Farmers may hesitate to share data
Trust and Transparency	Black-box AI models and unclear recommendations	Low farmer confidence and poor adoption
Socio-Ethical Governance	Accountability, fairness, regulation, and farmer autonomy issues	Risk of irresponsible or unequal AI use
Commercialization and Power Imbalance	Dependence on proprietary platforms and technology firms	Farmers may lose control over decision-making
Rural Labour Transformation	Automation may reduce or change farm labour demand	Rural livelihoods and work patterns may be affected

5.2 Data Ownership, Privacy, and Farmer Control

AI requires vast amounts of agricultural data including farm records, soil information, crop yields, machinery, weather and market information. However there are issues concerning the ownership of agricultural data and privacy and control over how data is collected and used. Farmers may not know who owns the data and how the data collected is used, or if data is being shared with other parties, if so for what purposes and whether or not farmers are gaining appropriate benefits from the use of data-driven systems. The reluctance of farmers to share data was linked directly to legal ambiguity and uncertain knowledge of who controlled agricultural data (Wiseman et al, 2019). The importance of this can be seen when it is understood that AI in agriculture relies upon continuous sharing of data at all stages of agricultural processes.

5.3 Trust, Transparency, and Benefit Sharing

The trust around AI and smart farming technologies is crucial. If farmers are not familiar with the AI-based systems, how these systems generate recommendations, how farmer data are processed, or if the benefits are equitably distributed, they may be hesitant to adopt these systems. When technologies are with private companies or external service providers, lack of transparency can lead to loss of confidence in digital platforms. Trust, transparency, and benefit sharing were highlighted as essential components of smart farming by the group of Jakku et al. (2019) as farmers are interested in understanding how their data are being used and what benefits they are receiving in exchange. This challenge is particularly important for black-box AI systems, where the reasoning behind the decisions is hard to understand or validate.

5.4 Socio-Ethical and Governance Challenges

There are also broader socio-ethical implications to consider for the use of AI in agriculture. These encompass responsibility for decisions made using AI technologies, justice in access to technologies, reliance on digital platforms, lack of farmer autonomy and a corporate role in agricultural decision making. While smart farming is viewed as a responsible innovation process, Eastwood et al. (2019) contended that there is a need to implement a comprehensive approach to responsible innovation since the socio-ethical challenges are often scattered and neglected. The governance actors also fear about the regulation, accountability, protection of data, and control of technology, which shows a need for better institutional structures and participatory decision-making processes (Regan, 2019).

5.5 Commercialization, Power Imbalance, and Rural Transformation

AI-enabled agriculture is intricately tied to commercial platforms, large data centers, and precision agriculture services. They can boost productivity and efficiency, but can also lead to power imbalances among farmers, technology providers, agribusinesses and data service providers. According to Carolan (2017), big data and precision agriculture are changing food systems, with the increasing reliance on agricultural knowledge on digital platforms and data infrastructures. This is a matter of concern for farmers because they might be locked into a proprietary technology, subscribed service, or an external decision-support system. Furthermore, automation could affect who does what and how much labour is required for various agricultural tasks, and the transformation of rural livelihoods. So, the implementation of AI has to be inclusive, transparent, farmer-centric and socially responsible.

6. Future Directions for Responsible and Sustainable AI-Enabled Agriculture

AI's role in smart agriculture should be directed towards creating explainable, ethical, sustainable, scalable, and farmer-centric systems. Future research should go beyond the accuracy of the models to focus on transparency, ease of use, governance, and implementation in the field as AI increasingly enters irrigation, crop monitoring, pest control, farm automation, and supply-chain management.

6.1 Explainable AI for Transparent and Trustworthy Farm Decisions

Deep learning models are often accurate systems, but it would be hard for them to tell what they are doing in their internal decision-making. This can be challenging in agriculture where some AI suggestions can affect irrigation, pesticide application, fertilizer application, disease management, and harvest timings. Explainable AI can provide insights for farmers and agronomists on why a certain recommendation for an action was given. Interpretability and visualization of deep learning models are crucial to enhance transparency of AI-based decision-making (Samek et al., 2019). Explainable AI is also crucial for the responsible and trustworthy use of AI, as it enhances accountability, user trust and transparency in decision-making (Arrieta et al., 2020).

6.2 Digital Twin-Enabled Simulation for Predictive Farm Management

Digital twins are a promising way forward in smart agriculture. A virtual model of a real system that enables monitoring, simulation, prediction and planning is a digital twin. In agriculture, the digital twin can be applied at the level of a field, a greenhouse, an irrigation system, an animal, a machine or a supply chain. These systems can assist farmers to test various farming scenarios before applying them to the field. They can model irrigation practices, fertiliser application, disease spread, climate stress and predicted yield results, for instance. Digital twins are the merging of physical and digital systems (El Saddik, 2018). They can assist with predictive farm management and better farm planning in conditions of variable environmental parameters in smart farming (Verdouw et al., 2021). The future development of AI in smart agriculture should emphasize explainable systems, digital twins, resource optimization, ethical governance, and farmer-centered solutions, as shown in Figure 3.

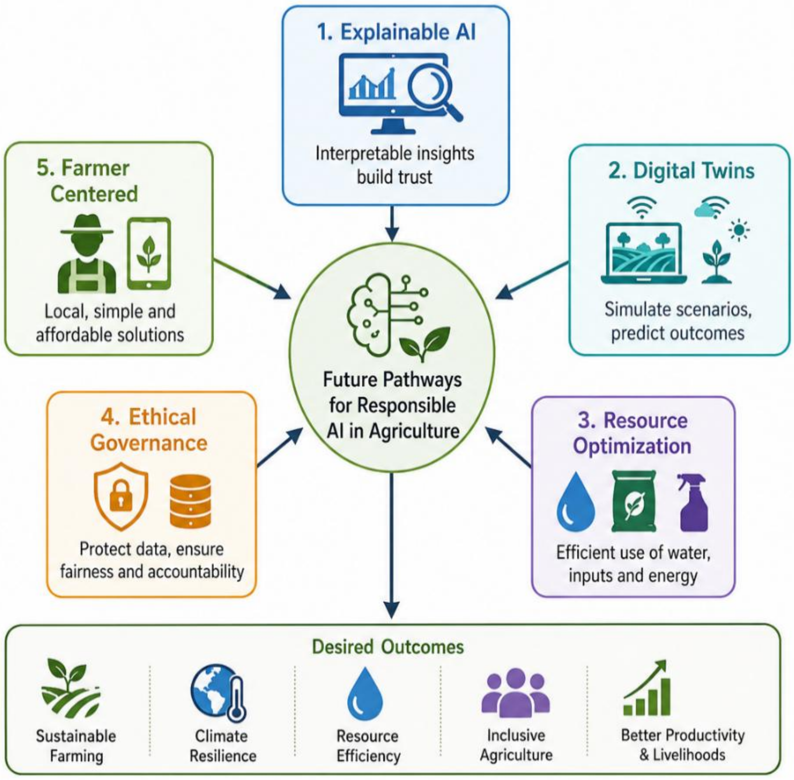

Figure 3. Integrated Framework for Ethical and Sustainable AI Adoption in Agriculture

6.3 AI-Driven Resource Optimization for Sustainable Precision Agriculture

Sustainable precision agriculture relies on future AI systems to optimize agricultural production without compromising environmental well-being. AI should not just boost production, but also help conserve water, chemicals, energy, and waste of resources. Data-driven AI can be used to help plan irrigation schedules, optimize pesticides and herbicides, manage fertilizer usage, predict diseases, plan for climate change, and use farm resources more efficiently. To achieve sustainable precision agriculture, agricultural data must be converted into valuable decisions for both productivity and environmental protection (Linaza et al., 2021). AI can also enhance irrigation efficiency and pesticide/herbicide usage, demonstrating its potential to cut down on wastage of inputs and boost resource-use efficiency (Talaviya et al., 2020).

6.4 Ethical Data Governance and Responsible AI Deployment

Ethical and governance principles are crucial for the future of AI in agriculture. The farm data, crop data, soil data, machinery data, weather data, and market data are all essential for AI systems to function. This raises privacy and ownership, fairness, accountability, transparency and farmer protection issues. If not governed properly, AI can further drive reliance on private platforms and generate inequities in the access to digital benefits. Ethics, ownership of data, transparency and participative decision-making are factors that need to be paid attention to in the context of responsible AI in digital agriculture. Ethical guidelines for AI in agriculture highlight the critical importance of fairness, accountability, transparency, and responsible data utilization for fostering trust in AI adoption (Dara et al., 2022).

6.5 Context-Specific and Farmer-Centered AI Innovation

Future AI applications need to be developed for the actual farms, not from controlled environment systems. The decision of the agriculture would be based upon crop type, soil status, climate, farm size, local language, farmers' knowledge, infrastructure and economic feasibility. AI applications must be localized, nearby to crop, cheap and user-friendly, so as to construct a holistic mechanism for providing the actual field decision support system, covering sensor applications, advisory systems, digital twin, robotics and farm management systems. A farmer-centric approach to the smart agriculture development is an important catalyst in stimulating the user trust, adoption, and sustainability. Hence, future use of AI in smart agriculture will feature a combination of technical development, explanation, sustainability and ethics, with reference to farm level practices.

7. Conclusion

AI has emerged as a pivotal component of smart agriculture and is increasingly shaping the future of farming by enabling more precise, predictive, and data-driven agricultural practices. The present review highlights several important applications of AI in agriculture, including machine learning (ML), deep learning (DL), computer vision (CV), predictive analytics, expert systems, robotics, and digital decision-support systems. These technologies have demonstrated significant potential in improving diverse agricultural operations such as crop monitoring, disease and pest detection, irrigation management, soil health assessment, crop yield prediction, weed management, autonomous farming, and post-harvest supply chain management. Furthermore, the integration of AI with remote sensing (RS), drones, cloud computing, digital twins, and digital farm advisory platforms can substantially transform conventional agriculture into an intelligent, site-specific, and resource-efficient production system, thereby reducing reliance on input-intensive farming practices.

AI offers immense opportunities for enhancing agricultural productivity, strengthening food security, optimizing the use of water and fertilizers, reducing dependence on chemical inputs, promoting climate-resilient and sustainable agriculture, and improving market-oriented farming systems. Despite these promising prospects, the widespread adoption of AI in agriculture remains constrained by several challenges, including high implementation costs, inadequate digital infrastructure and network connectivity in rural regions, digital illiteracy among farmers, concerns related to data quality, transparency, privacy, and security, lack of effective governance frameworks, and unequal access to advanced technologies, particularly among marginal and smallholder farmers. Therefore, addressing these socio-economic, technological, and policy-related barriers will be essential for realizing the full potential of AI-driven smart agriculture in the coming decades.

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