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Artificial Intelligence and Machine Learning for precision in agriculture: A comprehensive systematic review

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Abstract

The transformation of the agricultural sector is increasingly driven by the integration of cutting-edge technologies such as Artificial Intelligence (AI), Machine Learning (ML), the Internet of Things (IoT), robotics, and cloud computing. These innovations mark the transition to Agriculture 4.0—a data-driven, sustainable, and highly automated era of farming. This systematic review, following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) methodology, delves into the significant contributions of AI and ML in optimizing agricultural operations, with a specific focus on irrigation management and the precision application of pesticides and herbicides.

The study systematically evaluates scholarly literature and technical reports to map the current state of AI-driven solutions in agriculture, including soil moisture sensing, autonomous weeding, drone-assisted spraying, and decision-support systems for efficient resource allocation. These intelligent systems enable farmers to minimize input costs, reduce environmental footprints, and enhance productivity by applying the right amount of water and chemicals at the right time and place.

Moreover, the review discusses the potential of AI in overcoming challenges such as labor shortages, climate variability, and the demand-supply gap in global food production. It also identifies prevailing limitations in data quality, infrastructure, and farmer adoption, suggesting the need for policy support, training initiatives, and collaborative research. The insights derived from this review serve as a foundation for guiding future innovations and policy development aimed at achieving sustainable and smart agriculture.

Keywords: IoT in Agriculture, Artificial intelligence in agriculture, machine learning, smart irrigation systems, precision pesticide application, agriculture 4.0, agricultural automation, robotics and drones in farming, PRISMA methodology, sustainable farming practices

Introduction

Agriculture has long been a cornerstone of the global economy and remains fundamental to human survival by fulfilling one of the most essential needs food. In many nations, including India, agriculture continues to serve as a primary source of employment. However, traditional farming practices still dominate, and the adoption of advanced technologies is often hindered by several factors, including limited awareness, high implementation costs, and lack of access to information about technological benefits.

A significant knowledge gap exists among farmers in areas such as soil classification, crop suitability, yield prediction, climate variability, pest management, irrigation techniques, and market trends. These deficiencies contribute to inefficient practices, increased costs, and reduced profitability. Moreover, the escalating pressure of feeding a growing global population further intensifies the demand on agricultural systems. From crop selection to post-harvest marketing, inefficiencies at every stage result in substantial economic losses.

As the saying goes, “Information is power.” Access to timely and accurate data regarding crops, environmental conditions, and markets empowers farmers to make informed decisions and mitigate challenges. Emerging technologies such as blockchain, the Internet of Things (IoT), Machine Learning (ML), Deep Learning (DL), cloud computing, and edge computing have the potential to revolutionize agriculture by streamlining information collection and processing.

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These technologies, when integrated into agricultural workflows, can enhance productivity, improve crop quality, and ultimately increase profitability.

Current State-of-the-Art Developments in Agricultural AI

Precision agriculture, driven by data-centric technologies (Figure 1), is becoming a critical approach for improving yield efficiency. Technologies like ML and IoT have already demonstrated transformative impacts in various domains,

including healthcare (Siqueira *et al.*, 2021) ^[11], cyber security (Karie *et al.*, 2019; Doowon, 2020) ^[12, 13], and assistive devices (Meshram *et al.*, 2019; Patil *et al.*, 2018) ^[14, 15]. The rise of DL techniques has further enhanced the capabilities of ML, offering improved accuracy in complex problem-solving scenarios. Additionally, the advent of automated machine learning (AutoML) helps streamline model development, reducing dependency on expert data scientists while enhancing the robustness of predictive models.

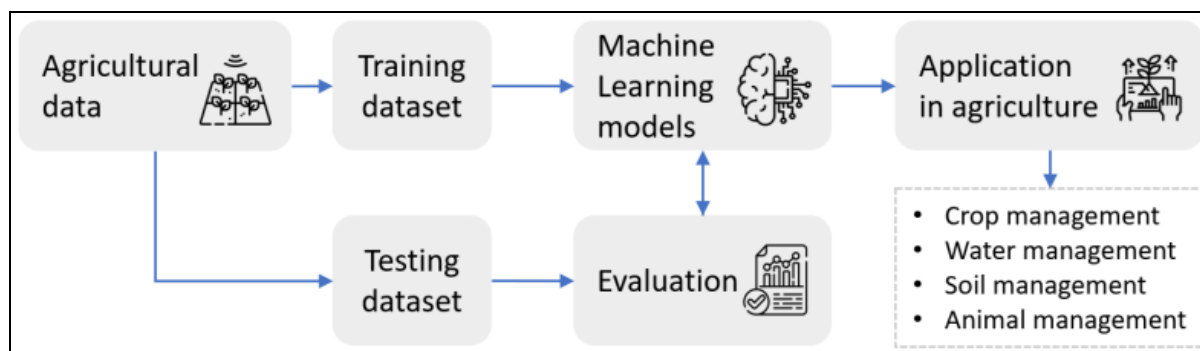


Fig 1: General flow for the creation of Machine Learning models and their application in agriculture.

The general steps followed in conventional farming include:

1. Crop Selection
2. Land Preparation
3. Seed Sowing
4. Irrigation and Fertilization
5. Crop Maintenance (e.g., pesticide application, pruning)
6. Harvesting
7. Post-Harvest Processing

Integrating digital solutions at each of these stages represents a paradigm shift in modern agriculture

Agriculture 4.0: A Digital Transformation

Agriculture 4.0, often referred to as the “Digital Agricultural Revolution,” signifies a transformative phase in agricultural

evolution that integrates advanced digital technologies to optimize and automate farming practices (Araújo *et al.*, 2021; De Clercq *et al.*, 2018; Zambon *et al.*, 2019) ^[1, 3, 4]. These include IoT, artificial intelligence (AI), big data analytics, cloud computing, decision support systems (DSS), advanced sensors, and autonomous robotics (Liu *et al.*, 2020; Trendov *et al.*, 2019; Rose & Chilvers, 2018) ^[34, 7, 8].

At the core of Agriculture 4.0 are sensors and robotic systems that collect field data in real time. This information is transmitted via IoT networks (Figure 2) to local or cloud-based servers for analysis and storage. AI-driven analytical tools then convert raw data into actionable insights. DSS platforms further assist stakeholders by offering data-informed recommendations, enabling strategic and tactical decision-making.

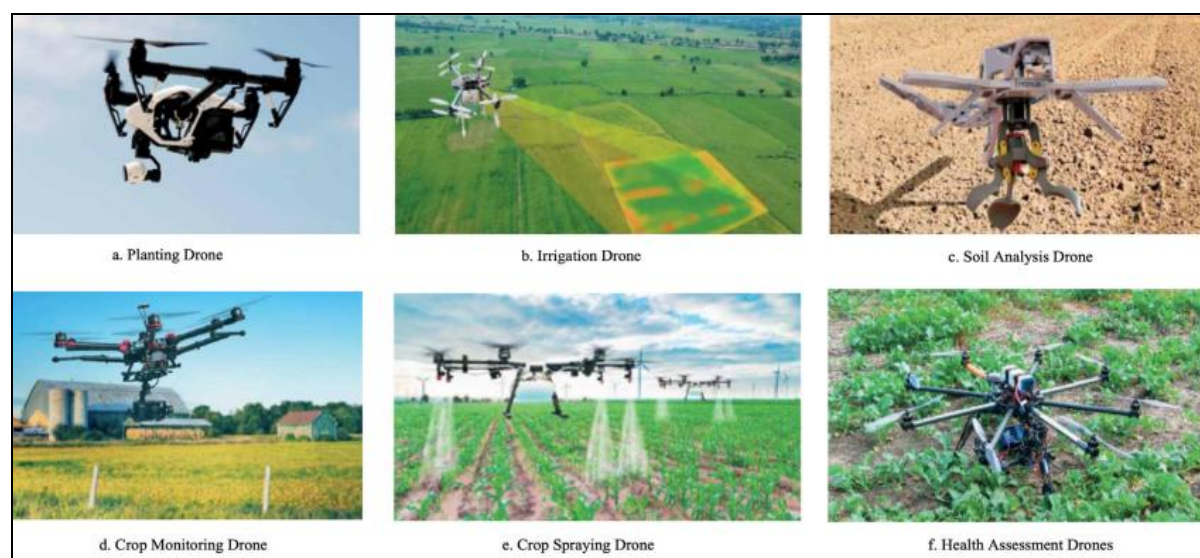


Fig 2: Types of agricultural drones. Source: modern agriculture drones (Unpaprom *et al.*, 2018) ^[43]

Machine Learning a critical component of AI has proven effective in numerous agricultural applications. Defined as a computational technique that enables systems to learn from data without explicit programming (Ahmed & Pathan, 2018) ^[9], ML leverages data to recognize patterns and support decision-

making. Supervised learning techniques utilize labeled datasets to train models, whereas unsupervised learning uncovers hidden structures from unlabeled data (Liakos *et al.*, 2018) ^[10]. A critical challenge in agricultural ML lies in acquiring high-quality, representative datasets. While ML models thrive on large,

diverse datasets, the data collection process can be time-consuming and resource-intensive.

IoT sensors play an instrumental role in addressing this challenge by enabling continuous monitoring of variables such

as soil moisture, climate conditions, crop health, and livestock well-being (Araújo *et al.*, 2021) ^[1]. Over time, this leads to the generation of extensive and rich datasets, vital for training robust and accurate ML models.

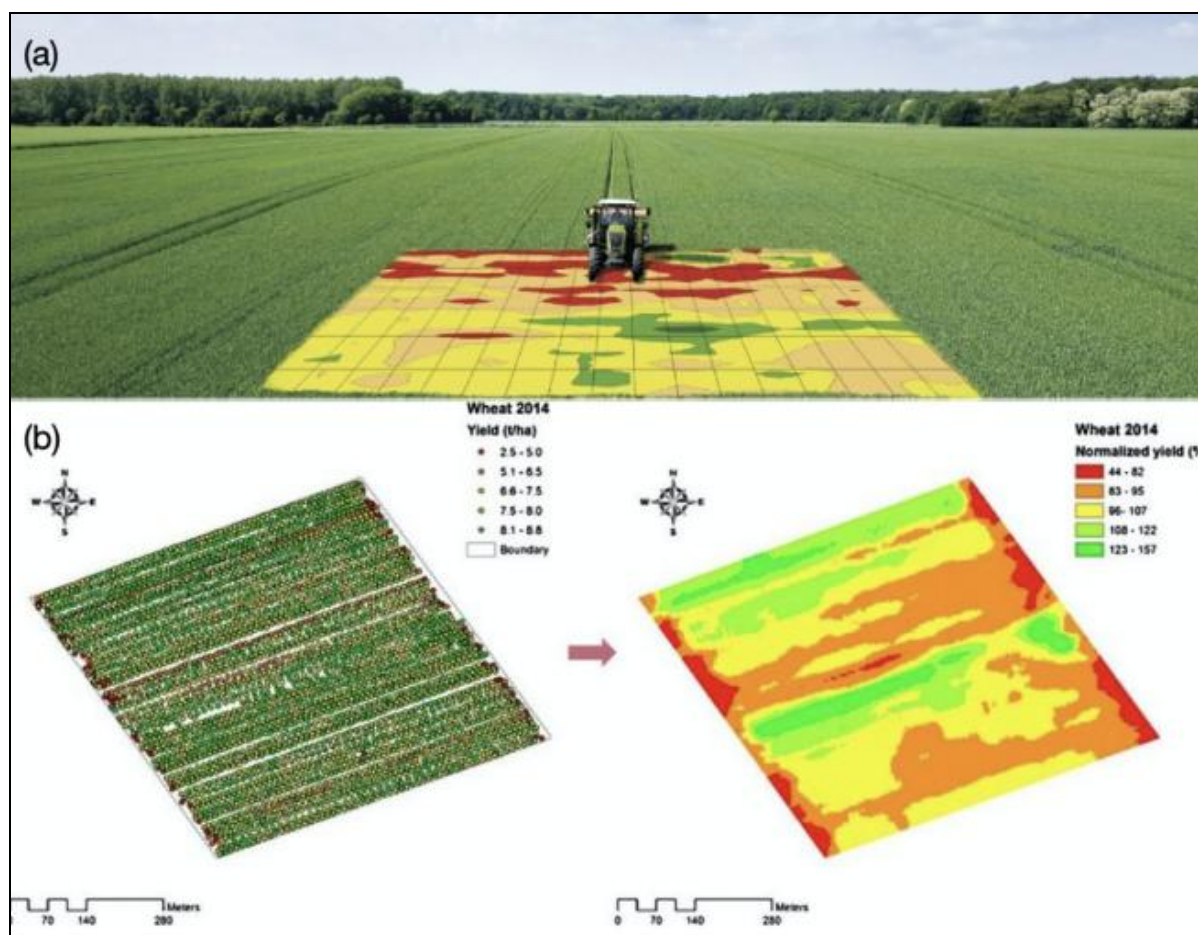


Fig 3: Yield Mapping (a) Sensing for yield (Source: Utah State University) and (b) example of raw yield map versus interpolated yield map using GIS (Source: Cillis *et al.*, 2018) ^[2]

However, data quality must be maintained to ensure the reliability of insights (Fig. 3). For instance, when modelling crop performance, data should reflect all growth stages and associated agronomic parameters. Collaborations between researchers, farmers, and agricultural organizations can accelerate the data collection process and enrich dataset diversity (Ankush Ramrao Gaikhe *et al.*, 2024) ^[40].

A typical workflow for ML model development in agriculture begins with data acquisition from multiple sources. This data is then divided into training and testing sets. The training set is used to teach the model, while the testing set evaluates the model's performance. Once validated, these models can be deployed across several agricultural domains, including crop yield optimization, efficient irrigation management, soil fertility monitoring, and livestock health tracking.

Current State-of-the-Art Developments in Agricultural AI

Artificial Intelligence (AI) encompasses a set of methodologies and technologies designed to replicate or surpass human cognitive functions such as perception, reasoning, planning, and communication (Cook & O'Neill, 2020) ^[25]. Within agriculture, AI is emerging as a transformative force, offering solutions to complex challenges that traditional digital technologies cannot adequately address (Davenport, Guha, Grewal, & Bressgott, 2020) ^[26]. AI is implemented through a combination of

algorithms and software, often embedded in physical platforms including drones, agricultural machinery, and autonomous robots collectively referred to as AI-driven robotics.

The potential of AI lies in its ability to process and synthesize vast and diverse data inputs ranging from high-resolution imagery to environmental sensor data to facilitate precise and timely agricultural decision-making (Ryan, 2019) ^[37]. Applications of AI in agriculture include crop scouting, pest and weed detection, autonomous spraying and harvesting, and post-harvest processing such as sorting and grading (Duckett *et al.*, 2018; Eli-Chukwu, 2019) ^[29, 30]. These technologies offer scalable and sustainable alternatives to traditional farming practices.

A clear distinction must be made between non-smart digital tools (e.g., websites, social media) and smart technologies, which include AI, IoT, and block chain. Similarly, AI robots differ fundamentally from non-AI agricultural machinery (e.g., traditional milking robots) in that they incorporate context awareness, learning, and logical reasoning features typically associated with human intelligence (Sparrow, Howard, & Tallacchini, 2021) ^[39].

AI systems are typically classified into three categories: Artificial Narrow Intelligence (ANI), Artificial General Intelligence (AGI), and Artificial Super Intelligence (ASI). ANI, which refers to AI systems that perform specific tasks at or

above human-level proficiency (e.g., disease detection or autonomous navigation), is currently the only category with widespread application in agriculture (Bostrom, 2014)^[22]. AGI and ASI remain largely theoretical and are outside the scope of this discussion. This paper focuses on applications of ANI in crop-related domains, including soil management, pest and disease control, irrigation optimization, and yield forecasting.

Livestock applications, while relevant, are less frequently addressed in the literature and are thus discussed peripherally (Aggarwal & Singh, 2021; Awasthi, 2020; Bacco, Barsocchi, Ferro, Gotta, & Ruggeri, 2019)^[16, 18, 19]. Table 1 outlines the key areas of agricultural AI deployment, and illustrates the intersection of AI methodologies with agricultural practices.

Table 1: Focused on main applications of agricultural AI.

Application Area	Description of the Application
Soil Management	AI for soil management uses modeling, decision support systems, fuzzy logic, and artificial neural networks (ANNs) for predicting soil structure, temperature, texture, nutrients, and moisture. However, it requires big data and is sensitive to unpredictable meteorological conditions (Eli-Chukwu, 2019) ^[30] .
Pest and Weed Management	AI for pest and weed management helps farmers monitor and identify infected plants quickly. It allows for real-time responses to avoid losses. Methods include artificial neural networks with genetic algorithms, sensor machine learning, digital image analysis, and learning vector quantization (Liakos <i>et al.</i> , 2018) ^[10] .
Disease Management	AI improves the management of pests and diseases by providing early detection. Using captured images, AI systems can detect plant disease areas earlier than visible symptoms to the human eye. AI techniques include computer vision, genetic algorithms, fuzzy logic, and expert systems (Cook & O'Neill, 2020; Liu, 2020; Kakani <i>et al.</i> , 2020) ^[25, 34, 32] .
Crop Management	AI provides tailored recommendations for crop and seed choices, pest management, and optimal irrigation, fertilization, and pesticide application. AI is used for crop growth management, with tools like Calex, Prolog, FARMSYS, Robotics Demeter, and ANNs (Dharmaraj & Vijayanand, 2018) ^[27] .
Water-use Optimisation	AI optimizes water use by analyzing real-time data from soil and plant humidity sensors. By combining soil characteristics and meteorological data, AI can lead to water-use reduction and increased yield (Kakani <i>et al.</i> , 2020) ^[32] .

AI not only enhances productivity but also contributes to market forecasting, value chain optimization, and adaptive crop cycle planning. While precision agriculture has been practiced for several decades (Agarwal D *et al.*, 2024)^[41], AI introduces a paradigm shift by offering intelligent automation and predictive capabilities (Basnet & Bang, 2018; Kakani, Nguyen, Kumar, Kim, & Pasupuleti, 2020)^[20, 32].

Social Aspects of AI in Agriculture

The integration of AI in agriculture is expected to substantially transform labor markets. By 2030, it is projected that up to 97% of manual and pesticide-related tasks could be automated (Rotz, Gravely, Mosby, Duncan, & Finnis, 2019)^[35]. However, AI extends beyond automation to the replication of cognitive roles traditionally filled by farmers, agronomists, and supply chain managers.

While automation predominantly replaces repetitive, low-skill tasks, the implementation of AI introduces new roles that require human oversight, particularly in areas where complex judgment or ethical decision-making is involved (Clifton, Krutzinna, Ryan, & Floridi, 2020)^[24]. In practice, AI systems still rely on human input for monitoring anomalies, verifying system recommendations, and ensuring compliance with food safety standards (Smith, 2020)^[38].

This evolving human-machine interaction in agriculture necessitates a shift in workforce competencies from manual skills to data interpretation and decision support roles highlighting the importance of digital literacy and continuous education.

Environmental Aspects of AI in Agriculture

AI-driven technologies in agriculture are positioned as critical enablers of environmental sustainability. A significant body of literature supports the view that AI contributes to resource-use efficiency, minimization of environmental degradation, and improved food security (Albiero, 2019; Dharmaraj & Vijayanand, 2018; Krishnan & Swarna, 2020; Ruiz-Real, Uribe-Toril, De Pablo Valenciano, & Fernández, 2020)^[17, 27, 33, 36].

AI systems optimize input use by enabling precise application of

water, fertilizers, and pesticides, thereby reducing leaching, runoff, and associated ecological harm (Bogomolov, Lezoche, Panetto, & Alemany Díaz, 2021; Ciruela-Lorenzo, Álvarez-García, & del Río-Rama, 2020)^[21, 23]. For instance, AI-enabled monitoring can detect early signs of crop stress or disease, allowing for targeted interventions and reducing the overuse of agrochemicals (Liu, 2020; Vasconez, Kantor, & Treat, 2019)^[34, 42].

Furthermore, AI enhances biodiversity preservation by facilitating alternative cropping strategies, intercropping, and rotation plans that maintain soil health. These environmentally responsive practices align with the broader goals of sustainable intensification and climate-smart agriculture (Dolfsma, Isakhanyan, & Wolfert, 2021; Isakhanyan & Dolfsma, 2020)^[28, 31].

Conclusion

This study emphasizes the significance of Machine Learning (ML) applications in agriculture, particularly in the domain of crop yield prediction. Machine learning has emerged as a powerful tool for computational analysis, enabling the processing and interpretation of large volumes of historical agricultural data to forecast future outcomes. Among various research areas in agricultural science, crop yield prediction remains a critical focus due to its potential to pre-empt adverse consequences and enhance food security.

The paper presents an overview of the evaluation, practical applications, and key challenges associated with deploying machine learning for crop yield prediction. While many of the themes addressed such as competitive advantages for early adopters, inequitable access due to high implementation costs, and concerns surrounding data privacy are common across multiple industries, agriculture can draw valuable lessons from more mature sectors like healthcare, communication, manufacturing, and infrastructure, where AI adoption is more advanced.

However, agriculture presents unique considerations that necessitate a deliberate, interdisciplinary approach to the integration of AI technologies. Unlike many other sectors,

agriculture directly supports human survival by providing food. Hence, advancements in agricultural AI must be approached with a heightened sense of responsibility. The stakes are significantly higher, and the consequences of success or failure in applying AI to agriculture may have profound implications for food systems and global sustainability.

It is anticipated that through collaborative, cross-disciplinary efforts, agricultural AI will evolve into a robust, trustworthy, and widely accepted technology among farmers. This research was based on a comprehensive literature review and focus group discussions. A notable limitation of the study is its primary focus on crop farming, as most current literature on AI in agriculture centers on crop production, with limited empirical studies in other agricultural domains.

We advocate for more empirical research across diverse areas of agriculture, incorporating interdisciplinary methodologies that consider not only business and productivity outcomes but also the ethical, environmental, and social implications of AI implementation. While this study concentrates on the immediate effects of AI on farmers and farm laborers, future research should examine its broader impact across the entire agricultural value chain from farm to fork including processors, retailers, and cooperatives. Understanding these dynamics is crucial for developing equitable and sustainable AI-driven solutions in agriculture.

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