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A review on application of artificial intelligence in agriculture

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Abstract

The world's expanding population and dwindling agricultural land resources pose a serious threat to future food security. Conventional farming practices are losing their capacity to maintain productivity in an unpredictable climate. Artificial Intelligence has the capability to transform many of industries, including soil analysis, crop management, irrigation optimization, pest surveillance, weed detection, and post-harvest processing. This review evaluates the effects of recent advancements in AI-driven agricultural solutions on input efficiency, sustainability, and profitability. Because AI enabled systems outperform conventional statistical methods as of speed, accuracy and scalability, they are crucial tools for modern precision farming. The integration of AI with IoT, satellite imaging, cloud computing, and deep learning models holds great promise for developing intelligent, real-time agricultural ecosystem frameworks. This review also highlights various applications of Artificial Intelligence in agriculture field.

Keywords: Artificial intelligence, precision agriculture, food production, weed management

1. Introduction

The agricultural sector remains a fundamental component of numerous economies, particularly in developing nations, where it offers significant employment opportunities and guarantees a reliable food supply. Yet, as the global population expands, the limits of traditional farming have become increasingly clear ^[1]. In addition to protecting the environment and using resources more effectively, modern agriculture has the capability to satisfy the increasing demand for food. Innovative solutions can result from addressing issues like deteriorating soil quality, increasing greenhouse gas emissions, waste management, and inefficient resource use. We can increase productivity and preserving our natural resources for future generations through adopting sustainable practices ^[2]. With food demand climbing worldwide, the need for crops that are both higher in quantity and better in quality has never been more urgent. In response, governments are attempting to ease this transition by offering farmers financial support, low-interest credit, and access to improved seeds, machinery, and digital technologies. At the policy level, efforts are also being made to tighten supply chains, reduce post-harvest losses, curb food waste, and encourage consumers to adopt more sustainable habits and support local producers. Despite these initiatives, crop productivity is still significantly affected by weeds, pests, and a wide range of plant diseases that threaten yields each season ^[3]. Meeting future food requirements will demand even more effort. Estimates suggest that by 2050, global food production will need to grow by approximately 70% to feed a proposed population of 9.1 billion. Without substantial additional investment and advancement in the agricultural sector, nearly 370 million people could remain undernourished by mid-century ^[4]. Artificial Intelligence (AI) has evolved as a powerful tool for addressing many of the challenges linked to sustainable farming and agricultural waste management ^[5]. By integrating AI into routine agricultural activities, several operations such as weather prediction, prompt detection of plant diseases and efficient allocation of resources can be carried out with far significantly increased precision than traditional methods allow ^[6]. For example, AI-enabled irrigation systems are capable to reduce water uses by nearly 30% while still improving crop yields. Similarly, when applied to waste management, AI can streamline sorting processes, increase recycling efficiency by around 25%, and contribute to lower greenhouse gas emissions ^[7].

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The incorporation of AI into agriculture is not new. It began with early expert systems like GOSSYM in 1985, which laid the groundwork for more advanced technologies. Since that period, significant advancement has been made in machine learning (ML), deep learning (DL), computer vision (CV), and robotics that transformed agricultural operations on a global scale ^[8]. Today, tools such as drones, satellite imaging, and AI-assisted remote sensing offer farmers highly detailed perspectives on the temporal and spatial characteristics of their fields. These technologies give immediate information on factors such as crop health, moisture in soil and nutrient conditions allowing farmers to avoid excessive input use and make more informed decisions ^[9]. AI is also making waste management systems more efficient by automating sorting and recycling operations, improving supply chain coordination, and reducing overall waste generation ^[10]. Furthermore, AI-driven automation has been shown to reduce chemical inputs and lower carbon emissions, supporting broader environmental sustainability goals ^[11]. Despite these advances, adopting AI technologies is still a challenge for many small-scale farmers. High investment costs, limited digital skills, poor internet access, and the absence of location-specific datasets continue to restrict their ability to benefit from digital innovations ^[12]. Rural areas, in particular, struggle to obtain drones, IoT devices, and the computing power required to operate sophisticated AI

systems ^[13]. If left unaddressed, this digital divide risks deepening existing social and economic inequalities within the agriculture sector. Closing these gaps will require comprehensive government support, improved technological infrastructure, affordable smart farming tools, and training programs that empower farmers to make effective use of AI. By automating labour-intensive tasks with technologies like robotic harvesters, precision weeding robots, and drone-based crop sprayers, artificial intelligence (AI) increases agricultural productivity by reducing human error and the need for manual labour ^[14]. Research on artificial intelligence is growing in India, but it is mostly concentrated in the field of agriculture and involves only 50 to 75 specialists from prestigious universities. Inadequate resources, administrative roadblocks, inadequate infrastructure, and subpar datasets are among the difficulties that impede advancement. Although the government's 2018 budget increase for Digital India to USD 477 million was encouraging, there are still serious institutional problems. If AI is to revolutionize agriculture with significant precision and speed, reducing human error and reliance on manual labour it must be applied practically to increase supply chain efficiency and transparency for farmers. Coordinated research efforts and practical testing are necessary for the successful adoption of AI-driven solutions ^[15]. Various challenges of Agriculture sectors are mentioned in Fig 1.

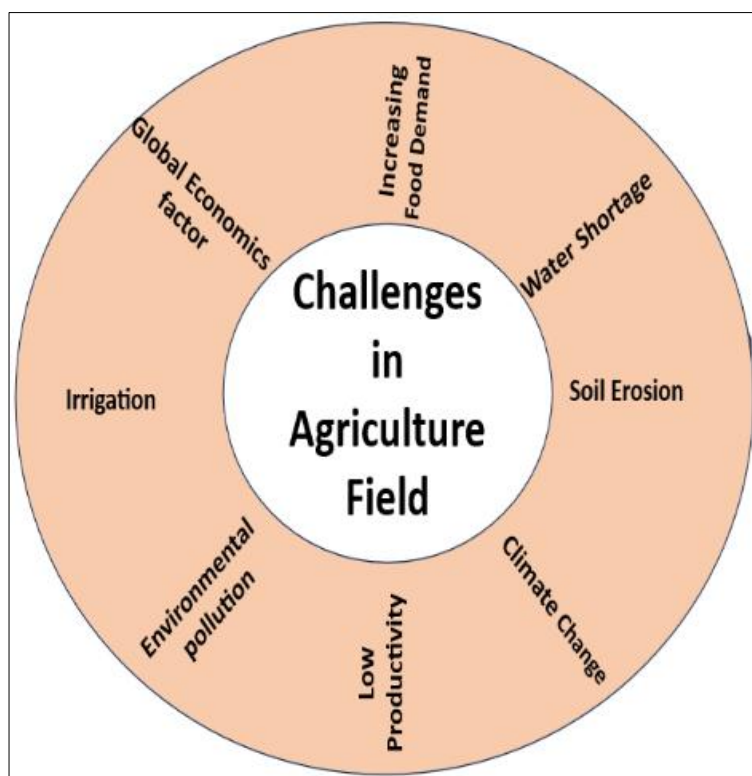


Fig 1: Challenges in Agriculture Sectors

Agriculture in Japan is integrating advanced technologies like sensors and robotics, resulting in an increase in crop yields by 30% and improved water efficiency. However, challenges such as limited internet access in rural areas and high costs of digital tools hinder adoption for small farmers. Germany's emphasis on modern waste management has led to a 40% rise in recycling rates and a 20% decrease in emissions, faced with difficulties like the need for specialized knowledge and public reluctance towards strict

waste-sorting practices. In the Netherlands, innovative practices in agriculture have optimized resource management, enhancing productivity through precision farming. Nonetheless, issues such as data gaps and the necessity for technical training in agricultural communities pose challenges to full digital adoption. Dealing with these issues is vital for the continued progress and sustainability in these sectors ^[2]. This review highlights the use of artificial

intelligence in agriculture field and its application to solve the challenges of agriculture sectors.

2. Applications of AI in agriculture: The following Fig 2 represents Various Application of AI in Agriculture sectors-

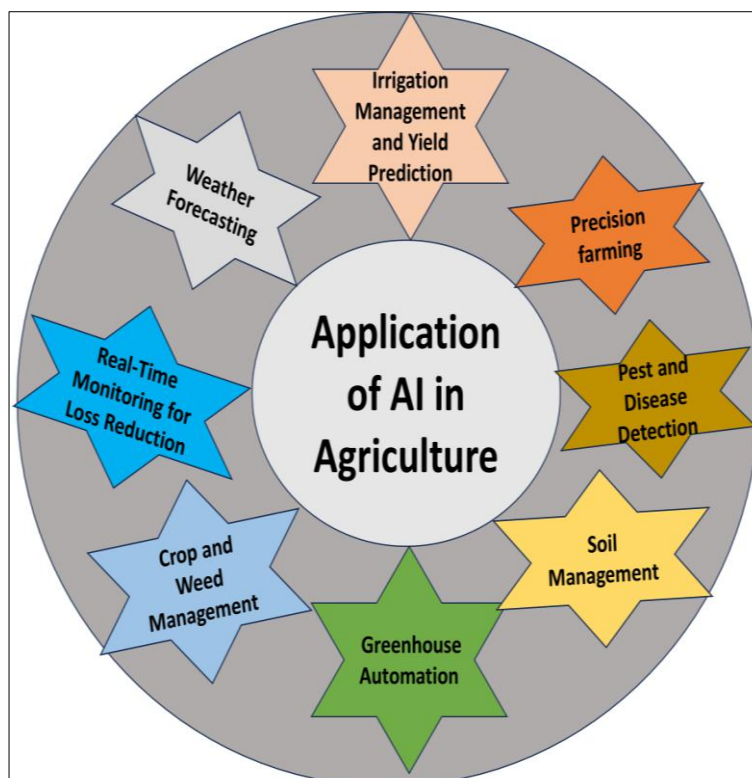


Fig 2: Various Application of AI in Agriculture

2.1 Pest and Disease detection

One of the leading causes of crop losses worldwide remains pest and disease, often reducing yields long before farmers can detect the problem. Deep learning techniques especially Convolutional Neural Networks (CNNs) have become valuable tools for identifying diseases directly from leaf images and field photographs in recent years. These models can recognize subtle symptoms such as changes in color, unusual patterns, and irregular leaf shapes with impressive accuracy, frequently performing better than conventional diagnostic methods ^[16, 17].

Beyond ground-level imaging, drones equipped with advanced remote-sensing systems allow for continuous monitoring of wide agricultural areas ^[41]. They can quickly locate pest-infected zones, highlight stress signals in crops, and detect abnormal growth trends that may otherwise go unnoticed ^[18, 19]. Detecting these issues early helps farmers minimize pesticide use, avoid widespread damage, and ultimately maintain healthier and more productive fields ^[20, 21].

2.2. Weather forecasting

Accurate weather forecasting is essential for planning day-to-day and seasonal agricultural activities. Modern machine learning (ML) models draw on long-term climate records, satellite data, and real-time atmospheric measurements to generate reliable short- and long-range weather predictions ^[16, 22]. Farmers can make better decisions with these insights about when to irrigate, apply fertilizers, adjust cropping patterns, or schedule harvesting, ultimately reducing risks and improving overall farm efficiency.

2.3 Soil Management: Soil includes nitrogen, potassium, phosphate, water that is essential for agriculture as it

provides vital nutrients and proteins, necessary for healthy crop growth and development ^[23]. The practices of Soil management have advanced significantly with the adoption of IoT-based monitoring systems. These systems use sensors to track necessary soil elements such as nutrient levels, pH, moisture status, and electrical conductivity in real time. AI techniques then analyse this continuous flow of data and generate tailored fertilizer recommendations for different sections of the field ^[24, 25]. In addition, machine learning-driven digital soil mapping provides more accurate assessments of soil fertility, allowing farmers to apply nutrients precisely where they are required and improve overall land productivity ^[26, 27].

2.4. Crop and weed management: Farmer's anticipated profits are greatly reduced by weed invasions, which may result in a 48% decrease in wheat yield and a 50% loss in corn and dried beans. Certain weeds are poisonous and pose a threat to public health in addition to competing with crops for essential resources like sunlight, water and nutrients ^[28]. AI-driven weed detection systems have greatly improved the accuracy of distinguishing weeds from crop plants. These models analyze UAV-captured images, spectral patterns, or high-resolution ground photographs to reliably separate unwanted vegetation from healthy crops ^[29]. Using this information, autonomous robots and variable-rate sprayers can precisely target weeds without affecting surrounding plants, which significantly reduces unnecessary herbicide application ^[30]. In crop management, machine learning (ML) tools play an equally important role by tracking plant development through vegetation indices such as Normalized Difference Red Edge (NDRE), Normalized Difference Vegetation Index (NDVI), and Enhanced Vegetation Index (EVI) obtained from drone or satellite

imagery. These indices provide early signals of nutrient imbalances, crop stress, or irregular growth, enabling farmers to respond quickly and maintain higher productivity levels^[18, 31]. Senthilnath *et al.* demonstrated the effective use of multispectral sensors for real-time crop monitoring. By collecting reflectance data across several spectral bands, these sensors allow for accurate evaluation of the physiological state of crops and the surrounding environment. A key focus of their work is establishing linear regression relationships between NDVI and critical agronomic parameters such as plant nitrogen content, biomass accumulation, and overall crop Vigor. By generating accurate NDVI-based indicators, the system provides actionable insights into crop health. This facilitates timely decision-making, particularly in resource allocation related to fertilizer application, irrigation scheduling, and stress detection. Ultimately, the use of multispectral sensing technology helps optimize resource management, enhance yield outcomes, and promote more efficient and sustainable crop management practices^[32].

2.5. Greenhouse Automation

Greenhouse cultivation relies heavily on maintaining consistent environmental conditions to support healthy plant growth. Key variables like light levels, temperature, humidity, and CO₂ concentration are continuously monitored by contemporary IOT sensors. The collected data from these sensors are processed by AI-based control systems, which adjust irrigation schedules, manage ventilation, and regulate nutrient delivery automatically to maintain optimal growing conditions^[33, 34].

2.6. Irrigation management and yield prediction

Smart irrigation systems make use of IoT-based soil moisture-based sensors, on-site data of weather and models of AI that estimate crop water requirements to create highly efficient watering schedules. By adjusting irrigation according to real-time field conditions, these systems help conserve water while avoiding problems like over-irrigation, waterlogging, or drought-related stress^[33]. Accurate yield prediction is another essential component of modern agriculture, especially for supply chain management and market planning. Machine learning (ML) models combine information from soil properties, weather patterns, historical yield databases, and remote sensing imagery to generate reliable yield estimates. These advanced models consistently outperform traditional statistical approaches in forecasting crop productivity under varying conditions^[34, 35].

2.7. Real-time monitoring for loss reduction

AI-enabled remote sensing technologies and IoT platforms have made it possible to track crop conditions, livestock health, and storage environments in real time. Drones carrying multispectral or thermal imaging sensors can recognize prompt signs of crop stress, pest attacks, or inadequate water availability long before these problems are noticeable to farmers on the ground^[19, 25]. With automated alerts generated from these systems, farmers can respond immediately, preventing both pre-harvest and post-harvest losses and improving overall efficiency and productivity across the entire agricultural value chain^[20, 21].

2.8 Precision farming: Precision agriculture combines satellite imagery, GIS technologies, and GPS-enabled

machinery to manage fields with much greater accuracy. AI-driven decision support systems use these data sources to recommend variable-rate applications of seeds, fertilizers, and pesticides, helping farmers minimize resource wastage and adopt more sustainable practices^[26, 36]. In addition, yield maps generated through machine learning provide detailed insights into how productivity varies across different parts of a field, allowing farmers to design more targeted and effective management strategies^[35].

2.9 Waste management: In Singapore, the adoption of AI-based systems in waste management has helped boost recycling rates by nearly 25%^[2]. When AI is combined with IoT sensors, drone surveillance, and satellite imagery, it can automatically pinpoint areas where crop residues, spoiled biomass, or other forms of agricultural waste have accumulated. Computer-vision tools further enhance this process by detecting contamination, decay, or pest-affected waste, allowing for faster intervention and more efficient collection operations^[37]. Machine-learning techniques are also transforming organic waste processing. These models can estimate compost maturity, monitor microbial dynamics, and assess carbon-to-nitrogen ratios and temperature variations. Such predictions enable operators to fine-tune moisture levels, aeration, and feedstock combinations, speeding up the composting cycle while improving the final nutrient quality. Similarly, AI contributes to anaerobic digestion systems by forecasting methane production and optimizing the conditions inside the digester, leading to more stable and efficient bioenergy generation^[37, 38].

2.10 Fertilizer and pesticide spraying in agriculture

Talaviya *et al.* discuss an advanced sensor-based system designed to improve the precision and efficiency of fertilizer and pesticide spraying in agriculture. The system incorporates wireless sensor networks (WSNs), gyroscopes, and accelerometer sensors, which work together to monitor spraying activity in real time. These sensors detect abnormalities such as inconsistent spray flow, device tilting, or machine vibration that may indicate potential operational problems^[39]. Agricultural robotics research begins in the early 1980s, and Japan was the first to release a robot made specially for spraying pesticides^[40].

2.11 Agriculture Robotics

The agricultural industry has experienced significant changes over the past few decades, shifting from human power resources to digitalized technology. Robots and AI have become increasingly prominent, and are now used for tasks such as fruit picking, weeding, and crop sensing. These machines are also useful in plant breeding and precision farming, as well as labour input tasks. Robots for agriculture have been created to carry out accurate and precise farming operations and can take over or enhance certain tasks that are typically done by humans. There are two main types of robots used in agriculture: self-propelled mobile robots and vehicle-borne robots^[42].

3. Conclusion

AI based technologies are playing a vital role in boosting agricultural productivity across the entire farming cycle. By improving the way soil properties are analysed, optimizing water use, and enabling prompt detection of diseases and pests, artificial intelligence helps farmers make faster and

higher accurate decisions. Farm management can be much more precise and have a much smaller environmental impact when IOT sensors, drones and automated systems are integrated with machine learning (ML), deep learning (DL) and computer vision (CV). Although high implementation costs, limited connectivity, and the need for user training still pose challenges particularly for small and rural farmers AI continues to be a key driver of sustainable, data-driven agriculture.

4. Conflict of interest: The author declares no conflicts of interest.

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