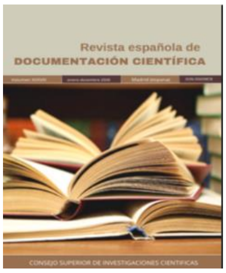

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Harnessing Artificial Intelligence for Sustainable Agricultural Systems

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Abstract: Agriculture, a fundamental element of human civilization, is crucial for ensuring food security and economic stability. The sector currently faces significant challenges due to rising global populations, climate change, and dwindling natural resources. To address these issues, sustainable agricultural practices are needed that increase efficiency while reducing environmental impact. Recent advancements in artificial intelligence (AI) present transformative opportunities to enhance agricultural sustainability. This paper investigates how AI is being integrated into farming to optimize productivity, resource management, and environmental stewardship. The study synthesizes over 300 academic articles, focusing on 180 key publications that detail AI applications in field management, nutrient utilization, water efficiency, and weed control. AI, through machine learning and predictive analytics, enables data-driven decisions that improve crop performance and minimize waste. In field management, AI helps monitor crop health and predict yields; advanced sensors and IoT devices enable precise nutrient application, reducing fertilizer use and environmental damage. For water management, AI optimizes irrigation and detects leaks, ensuring efficient water use. In weed control, AI-based image recognition allows precise identification and treatment, minimizing herbicide use. The integration of AI into agriculture not only boosts economic outcomes but also aligns with sustainability goals. By examining case studies globally, the research demonstrates AI-driven practices' effectiveness in enhancing resource efficiency and sustainability. The findings highlight the necessity for continued AI investment and stakeholder collaboration to overcome implementation barriers like cost and technical expertise. Ultimately, the study advocates for a strategic approach to leveraging AI to build resilient and sustainable agricultural systems capable of nourishing future generations.

Keywords: Agriculture, Sustainability, Artificial Intelligence, Resource Management Efficiency, Environmental Impact

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1. Introduction

The Food and Agriculture Organization of the United Nations (2021) predicts that the global population will approach 10 billion by 2050, thereby necessitating a substantial increase in food production. Achieving this objective requires strategic planning and effective management practices. Despite the advancements brought by the Green Revolution that improved crop yields in many regions, ongoing challenges persist, notably in maintaining produce quality and nutrition amidst climate change (Ahmad et al., 2019). The agricultural sector is burdened by multiple obstacles, including labor shortages, seasonal labor fluctuations, reduced agricultural land, and the demand for sustainable wages (Habib-ur-Rahman et al., 2022). These labor shortages are exacerbated by rural-to-urban migration, which impacts agricultural productivity. Additionally, climate change introduces irregular weather patterns such as prolonged droughts, altered rainfall, increased temperatures, and floods, all of which disrupt farming operations (Benedetti et al., 2019). Expanding cropping areas to meet demand often increases resource use, contributing to climate change and leading to natural resource depletion, including deforestation and soil erosion (Abbas et al., 2021).

Inconsistent rainfall and reduced water availability have led to declining crop yields (Aryal et al., 2019), while rising temperatures and humidity adversely affect crop growth (Asseng et al., 2019). Moreover, soil quality degradation, driven by chemical use and mono-cropping, exacerbates these challenges. This degradation creates a cycle where increased fertilizer use worsens soil fertility, requiring additional chemical inputs (Mosier et al., 2021). Therefore, addressing these environmental and resource-related issues is critical.

Artificial Intelligence (AI) has emerged as a vital tool in overcoming agricultural challenges (Aleminew & Alemayehu, 2020). AI technologies, including machine learning and deep learning algorithms, enhance yield and production management by mimicking human cognitive functions (Xu et al., 2021; Baweja, 2018). Notably, Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs) are prominently used in agricultural data analytics (Debnath, 2022). Digital urban farming, automation, and indoor farming are innovative strategies leveraging AI to boost crop yield, minimize food loss, and improve resilience to climate change (Balogun et al., 2022; Lowenberg-DeBoer, 2020).

Deep Convolutional Neural Networks (DCNNs) are particularly effective in plant health assessment and nutrient value analysis, as well as diagnosing plant diseases and detecting water content (Dyrmann et al., 2016; Taha, 2022). AI also facilitates disaster risk assessment and drought stress identification, providing timely warnings to prevent crop loss (Gupta et al., 2023). For instance, CNN models like ResNet50 have shown high accuracy in detecting drought stress in maize, outperforming traditional methods (An et al., 2019). Although AI models encounter challenges in detecting and differentiating weeds due to variable stages and patterns (Su, 2020), innovations such as smart sprayers with machine vision enhance detection and precision spraying (Vijayakumar, 2023; Olsen et al., 2019).

Successfully applying AI in agriculture requires addressing factors such as chemical use and labor skills (Dhanaraju et al., 2022). It is crucial to evaluate AI's feasibility and efficacy in real-world scenarios beyond controlled environments (González-Calatayud, 2021). This study systematically reviews AI technologies in agriculture, focusing on nutrient, water, and weed management with the following objectives: (1) to assess AI's potential for improving input use efficiency in agriculture and (2) to investigate AI applications in nutrient, water, and weed management to enhance crop yield.

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The structure of this paper includes: research methodology in Section 1, AI for maximizing agricultural input efficiency in Section 2, a revolution in agriculture in Section 3, AI technologies in agriculture in Section 4, results and discussion in Section 5, limitations in Section 6, prospects in Section 7, and conclusions in Section 8.

2. Methodology

2.1 Review Principles

This research follows two primary approaches to explore the role of Artificial Intelligence (AI) in agriculture. The first approach provides a general overview of AI concepts and their potential applications within the farming sector, emphasizing sustainability and operational efficiency through practical case studies and real-world scenarios. The second approach uses a document review research methodology, focusing on an in-depth analysis of existing literature on automation technologies in agriculture, specifically targeting AI applications in nutrient management, irrigation, and weed disposal (Abubakar & Aina, 2019).

The study is designed to evaluate both the advantages and limitations of AI in farm management, utilizing a three-stage research methodology. In the first stage, the current agricultural challenges are identified, particularly those that AI could address, such as increasing crop yield, reducing resource consumption, and minimizing labor requirements. In the second stage, relevant studies and publications are examined to understand the role of AI technologies in agriculture. The third stage involves discussing the findings, including the methodologies used, to provide insights into AI's impact on agricultural practices and its potential future applications.

2.2 Literature Search Strategy

The literature search employed a comprehensive review of both historical and current studies on AI's role in agriculture. Reputable online databases, including Scopus, Google Scholar, Science Direct, Web of Science, and PubMed, were used as sources. Additionally, data from the United Nations Food and Agriculture Organization (UNFAO) was included to provide a broader perspective on AI's global impact on agriculture. The search focused on identifying studies exploring machine learning (ML) concepts, AI in nutrient management, AI-based irrigation systems, and AI applications in weed identification and control.

The search strategy employed a set of targeted keywords to ensure the scope of the review covered AI's most relevant applications in agriculture. Keywords included "machine learning concepts," "artificial intelligence in agriculture," "AI for nutrient stress detection," "AI challenges in farming," "AI-based irrigation management," "AI in weed identification," "deep learning in agriculture," and "AI for weed control." These keywords allowed for an exhaustive exploration of the practical implications of AI in agricultural operations, including automation and efficiency improvements.

The study employed strict criteria for selecting relevant research papers. Articles published in the last 10 years were prioritized, but earlier foundational research was included when necessary to provide historical context. The inclusion of empirical studies focusing on real-world applications of AI in agriculture ensured that the review was grounded in practical outcomes. Studies had to be peer-reviewed and offer direct insights into how AI technologies are implemented in farming operations, such as the use of AI for resource management or crop health monitoring.

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2.3 Inclusion and Exclusion Criteria

The inclusion criteria for this review emphasized studies that explored AI's role in optimizing resource management within agriculture. Studies focusing on AI applications that provide real-time data for managing fertilizers, water, and weed control were prioritized. These studies demonstrated direct benefits to farming operations in terms of increased efficiency, resource optimization, and precision farming techniques.

Additionally, only articles that presented empirical data on AI applications in actual agricultural settings were included. Examples of AI applications included sensor networks, drones, satellite imaging, and automated systems to enhance crop management and pest control. These studies offered evidence of how AI technologies improve operational outcomes in real-world farming environments.

The exclusion criteria eliminated studies focused solely on theoretical or speculative discussions of AI. The review specifically avoided articles that lacked empirical evidence or case studies demonstrating AI's practical benefits in agriculture. Furthermore, studies not published in English or those without full-text access were excluded from the review to maintain the quality and reliability of the research.

2.4 Limitations

This study acknowledges several limitations in the methodology used. First, while over 170 papers were reviewed, the research is limited to studies published between 1999 and 2024. Although this provides a broad range of data, AI technologies are rapidly evolving, and more recent developments may not be fully represented. Thus, future advancements in AI that could significantly impact agriculture may not have been captured in this review.

Another limitation involves the diversity of agricultural practices across different regions. Much of the reviewed literature focuses on developed countries with access to advanced agricultural technologies, including AI. This may limit the generalizability of the findings to regions with less advanced infrastructure or fewer technological resources. Future research should examine AI applications in a wider range of geographic and economic contexts to understand their broader applicability.

Moreover, the literature search relied heavily on online databases, which could introduce some bias in the selection process. While the study aimed to include a diverse range of research, the availability of published work is not uniform across all regions. As a result, the review may not fully represent the global impact of AI in agriculture, particularly in underrepresented regions where fewer studies have been published. The reliance on empirical studies focusing on short-term outcomes, such as crop yield improvements and water-use efficiency, also presents a limitation. Many of the reviewed studies do not address the long-term sustainability of AI technologies in agriculture. There is a need for future research to evaluate AI's long-term impacts, including its effects on soil health, biodiversity, and environmental sustainability.

3. Revolution in Agriculture: Towards Smart Farming

Agriculture has undergone significant transformations throughout human history, evolving from simple manual practices to advanced technological applications. This evolution can be categorized into distinct eras:

1. Agriculture 1.0: The initial phase of agriculture, marked by manual labor and rudimentary tools such as plows and shovels. This era was characterized by minimal yields and subsistence farming (Padhy et al., 2023; Charles et al., 2020).

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2. Agriculture 2.0: Emerging during the industrial age of the 19th century, this era introduced the use of chemicals, advanced tools, and machinery. Although it significantly increased agricultural productivity, it also led to environmental issues such as pollution, deforestation, and ecological damage (Hemathilake & Gunathilake, 2022).

3.Agriculture 3.0: This phase focused on the integration of technological advancements including precision farming, robotic operations, and software solutions to enhance efficiency and yield while reducing labor and resource consumption. It aimed to address longstanding challenges such as weed management, plant nutrition, and irrigation (Yang et al., 2021; Ghorbani et al., 2019).

4. Agriculture 4.0: The current era of agriculture leverages cutting-edge technologies such as Data Analytics, Artificial Intelligence (AI), Cloud Computing, sensors, and the Internet of Things (IoT). These innovations build upon the advancements of Agriculture 3.0 by further streamlining and optimizing farming practices, thus enhancing overall productivity and sustainability (Nungula, 2024; Alam, 2023).

This progression highlights the ongoing technological evolution in agriculture, with each era introducing new tools and methodologies to address the sector's challenges and improve its efficiency.

According to Abbas et al. (2023), case studies on sunflower farms in Pakistan reveal significant economic and environmental inefficiencies. Using epsilon-based measures and Tobit truncated regression models, the studies show that over 50% of the 240 sampled producers were environmentally inefficient, and 70% were economically unproductive (Javaid et al., 2022). In contrast, smart farming practices have emerged as a solution to these inefficiencies. By integrating technologies such as the Internet of Things (IoT), drones, GPS-based precision farming models, and data analytics, smart farming has revolutionized traditional agricultural practices (Akhter, 2022). These technologies address limitations in farming operations that were previously resource-intensive and time-consuming, such as soil quality, moisture management, and climate control (Durai & Shamili, 2022). With these advancements, farmers can achieve higher crop yields and more efficient management of resources like fertilizers and chemicals (Sisinni, 2018). The progression from traditional practices to data-driven smart farming underscores the industry's evolution towards enhanced productivity and sustainability, reflecting the foundational role of agriculture in human civilization and its adaptation to modern technological solutions.

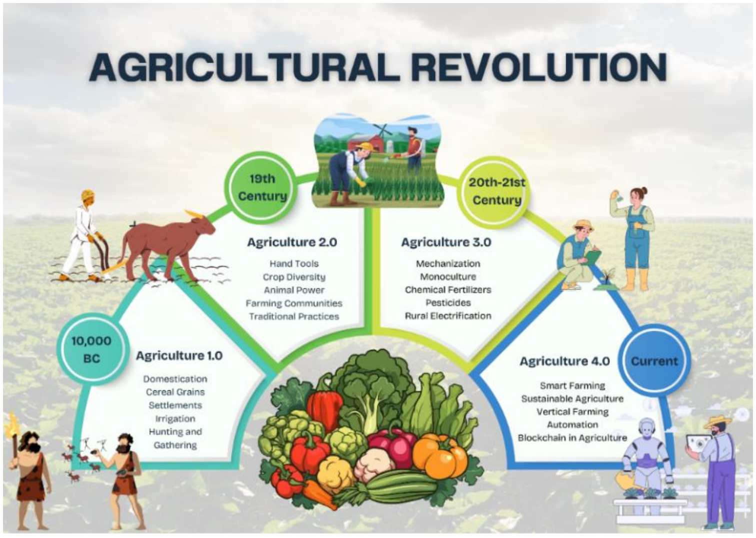

Figure 1. Development during the agricultural revolution

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4. Artificial Intelligence in Agriculture

Artificial Intelligence (AI) is an advanced technology developed to mimic human cognitive processes such as learning, problem-solving, and decision-making (Siemens, 2018; Fan, 2020). AI achieves these capabilities through the training of software algorithms using extensive datasets, enabling it to predict and solve complex agricultural challenges by identifying input-output relationships (Khanna & Kaur, 2019). AI applications like machine learning (ML), deep learning (DL), and data analytics have had a transformative impact across various industries, including agriculture. In particular, AI has revolutionized traditional farming practices through the integration of cutting-edge technologies such as ML algorithms, robotics, wireless sensor networks (WSN), and the Internet of Things (IoT). These innovations have significantly improved the collection, storage, and analysis of agricultural data, ultimately enhancing farm productivity and operational efficiency (Ferentinos, 2018). This article explores AI's applications in agriculture, the associated challenges, and potential solutions.

4.1 Machine Learning

Machine learning, the process through which systems learn from data without explicit programming, has proven to be highly valuable in agriculture. ML algorithms are widely used for data-intensive tasks, such as precision agriculture, where data from sensors, drones, and satellites are analyzed to optimize farming operations. For example, ML techniques can process data on soil properties, climatic conditions, and crop health, helping to improve irrigation strategies, fertilizer use, and pest management (Kamilaris & Prenafeta-Boldú, 2018).

Another crucial application of ML in agriculture is crop disease detection. Traditional methods of disease identification rely on visual inspection, which can be laborious and prone to human error. ML-powered systems, particularly those using image classification techniques, offer more efficient solutions. A study by Sladojevic et al. (2016) demonstrated the use of convolutional neural networks (CNNs) to identify plant diseases based on leaf images, achieving high accuracy rates. Such systems can help farmers detect and manage diseases earlier, reducing crop loss.

4.2 Deep Learning

Deep learning, a subset of ML, involves neural networks with multiple processing layers capable of learning complex patterns. DL has gained traction in agriculture for tasks such as image recognition, object detection, and predictive modeling. One promising application of DL is automated pest and weed detection. Conventional methods of pest and weed control are often labor-intensive and depend on chemical interventions. In contrast, DL-based systems can analyze images of fields to differentiate between crops and weeds, allowing for more precise and eco-friendly interventions (Liakos et al., 2018).

Moreover, DL has been utilized to improve crop yield prediction. Accurate yield forecasts are essential for food security and resource allocation. A study by Jiang et al. (2019) illustrated how DL models could integrate various data sources, including environmental factors, soil conditions, and crop characteristics, to predict yield more accurately than traditional statistical models. Such advancements enable better decision-making for farmers and agricultural policymakers, fostering more efficient resource use.

4.3 Neural Networks Involved in AI

4.3.1 Convolutional Neural Networks (CNNs)

Convolutional Neural Networks (CNNs) are a type of deep learning model specifically designed for processing grid-structured data, such as images (Asad & Bais, 2020). CNNs stand out in image processing and classification tasks compared to other AI models due to their structure, which typically consists of three layers: convolution, pooling, and fully connected layers (Bajwa et al., 2015).

1. Convolution Layer: The core feature of CNNs, this layer applies mathematical operations (kernels) to a 2D pixel grid, enabling the AI to efficiently analyze and extract features from images. This makes CNNs particularly useful in agricultural applications such as detecting plant diseases or identifying weeds in fields (Ashoka et al., 2022).
2. Pooling Layer: This layer performs data extraction by reducing the dimensionality of feature maps, simplifying the representation of the image while retaining key information.
3. Fully Connected Layer: This final layer combines the extracted features and classifies the image based on the learned patterns.

CNNs also handle preprocessing tasks such as resizing, colorizing, and normalizing images for efficient processing (Mugo et al., 2021). The model segments images to distinguish relevant objects (e.g., crops) from their backgrounds, using advanced techniques to extract image features like spectral properties and visual textures (Lezoche, 2020) (Fig.2). In more complex scenarios, CNNs require additional algorithms like Principal Component Analysis (PCA) or Linear Discriminant Analysis (LDA) to improve accuracy and adaptability in different geographical landscapes (Li et al., 2023).

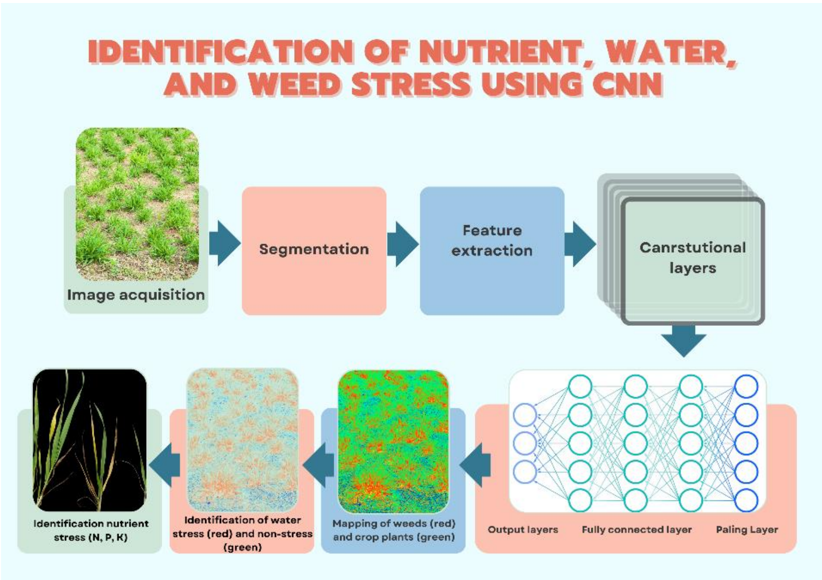

Figure 2. Identification of nutrient, water, and weed stress using CNN

Deep Convolutional Neural Networks (DCNNs) like SegNet have demonstrated superior performance in identifying and segmenting color images compared to other models (Badrinarayanan et al., 2017). Enhancements in DCNN architecture include the integration of ResNets, which optimize error propagation in non-linear learning

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models, and Inceptionv3, which reduces the number of calculation parameters, improving the efficiency and performance of AI models.

In agricultural applications, DCNNs are used for various tasks, including nutrient detection in plants. For instance, Tran et al. (2019) employed Inception-ResNetv2 and autoencoders to classify nutrients in tomatoes. Other studies have shown that DCNNs can identify oilseeds and plants based on their nutrition status (Abdalla et al., 2021).

A notable application of CNNs in agriculture is the use of the VGG-16 model to categorize rice paddy images at different growth stages, under various stress levels. With over 30,000 images from five rice species, this CNN achieved over 90% accuracy in detecting stressed crops (Anami et al., 2020). This demonstrates the potential of deep learning (DL) models in resource management within farming operations. These models can also be adapted for use on mobile devices, enhancing the convenience for field staff. However, CNNs have hardware limitations when processing large datasets. This challenge can be mitigated by using pre-trained models, which allow for quicker deployment in real-world agricultural scenarios (Noon et al., 2020).

4.3.2 Artificial Neural Networks (ANNs)

Artificial Neural Networks (ANNs) are designed to mimic the human brain's neural network, with the ability to self-organize, adapt to new data, and deliver complex results (Shah et al., 2020). ANNs, structured similarly to the human brain's neural pathways, contain three layers: 1) the input layer, 2) the hidden layer, and 3) the output layer. This structure allows ANNs to process non-linear information and perform parallel reasoning, adjusting predictions and outputs based on changes in input data (Abdipour et al., 2019). One significant advantage of ANNs is their adaptability in forecasting and predicting outcomes in dynamic environments. For example, in agriculture, ANNs can forecast crop yields using a system with three key components: 1) the Crop Disease Diagnosis Module (CDDM), 2) the Crop Yield Prediction Module (CYPM), and 3) the Image Pre-processing Module (IPM) (Jeong, 2018). These modules work in tandem to process images of crops, detect disease, and predict yields based on various factors such as climate and crop conditions. The Image Pre-processing Module (IPM) normalizes image data for efficient processing, while the Crop Disease Diagnosis Module (CDDM) analyzes images to identify crop diseases (Alves et al., 2017). Finally, the Crop Yield Prediction Module (CYPM) forecasts yield by considering multiple risks like climate, disease, and crop health, using data from sources such as web APIs (Barbedo, 2019). This case study illustrates how ANNs can enhance decision-making in agricultural practices by improving crop management and yield forecasting.

5. Results and Discussion

The agricultural sector faces mounting pressures due to rising food demand and various challenges. Traditional farming practices are increasingly inadequate, necessitating innovation and optimization to meet consumer needs effectively. Producers are grappling with issues such as climate change, mono-cropping, and excessive chemical use, which exacerbate the challenges faced (Cowls et al., 2023). To address these challenges and increase productivity, the industry must enhance efficiency and adopt advanced practices. One effective approach to boost crop productivity is the use of chemical fertilizers. Chemical fertilizers have been instrumental in improving plant nutrients and yields, particularly in wheat production. Over the past 45 years, they have demonstrated a significant correlation with increased productivity (Hassan et al., 2020).

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This underscores the importance of adopting and optimizing such solutions to meet the forecasted agricultural demands (Fig. 3)

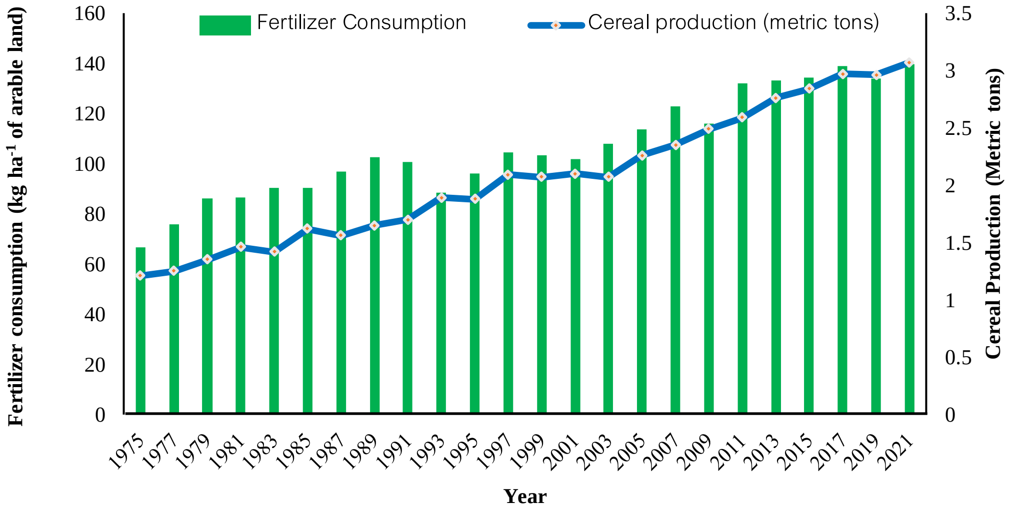

Figure 3. Trends in Fertilizer Consumption for Cereal Production
Data sources: World Bank Group (2024)

The use of chemical fertilizers, while effective in enhancing crop productivity, poses significant long-term environmental risks. Increased application of chemicals can lead to adverse effects such as water eutrophication, air pollution, heavy metal accumulation, and greenhouse gas emissions. For instance, a study on cotton fields found that diesel machinery contributed the most to greenhouse gas emissions, followed by irrigation and chemical fertilizers, with over 1.1 tons of CO2 equivalent per hectare (Abbas, 2022). In the absence of chemical fertilizers, crops are more susceptible to nutrient deficiencies, creating a dependency on chemical inputs. This issue, along with plant diseases caused by fungi, insects, bacteria, and viruses, poses severe threats to crop health and productivity. Early detection of these problems, which can manifest as symptoms like colored spots, blight, rots, and wilts, is crucial for preventing widespread damage (Kaur et al., 2019). However, specialist expertise required for such detections is often inaccessible to many producers. Artificial Intelligence (AI) and automated tools offer a cost-effective alternative for managing these issues. AI can assist in precise nutrient management and early disease detection, alleviating the reliance on human experts. Additionally, AI can optimize water management and irrigation practices, crucial for sustainable agriculture, especially given that nearly 85% of global water resources are used in farming (Chauhan et al., 2022). With increasing population and urban development, efficient water use is critical. Figure 4 illustrates the anticipated impact of population growth on water availability per capita in India over the next 25 years.

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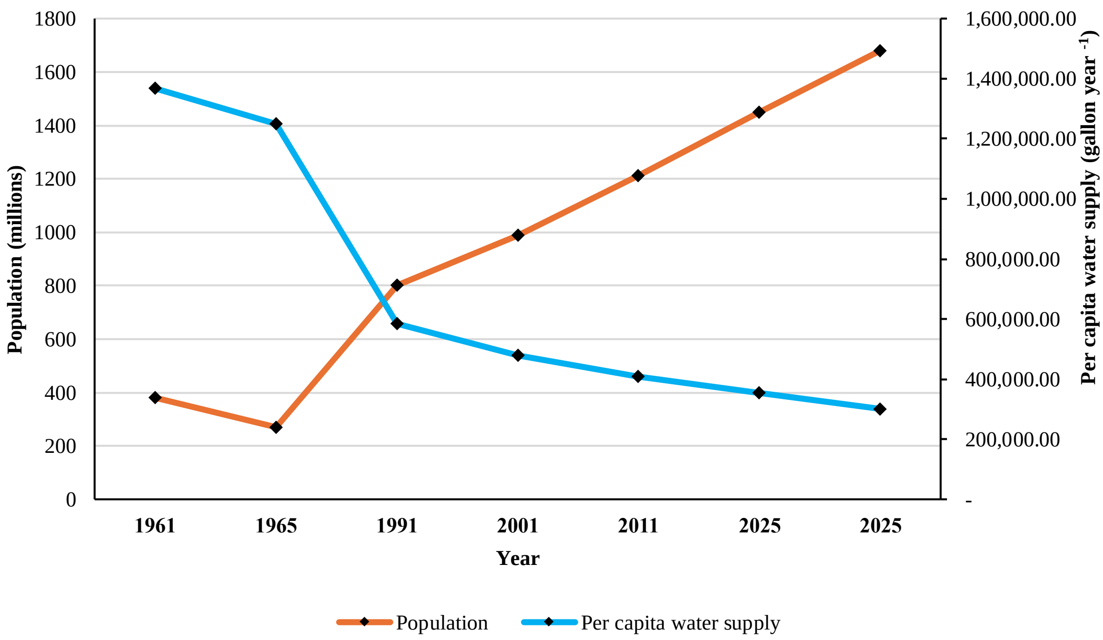

Figure 4. Population and per capita water supply per year in India
Data sources: KPMG International 2010; Office of the Registrar General & Census Commissioner, India

The data indicate a significant decline in water availability per capita in India, from approximately 1.4 million gallons in 1951 to about 0.4 million gallons by 2011 (Chakraborti et al., 2019). This reduction highlights a severe water scarcity issue exacerbated by increasing demands, projecting frequent droughts and water shortages across domestic, agricultural, and industrial sectors if not addressed.

Weed management is a critical and persistent challenge in agriculture. Weeds compete with crops for essential resources such as water, nutrients, and sunlight, leading to significant yield losses if not properly controlled. As illustrated in Figure 5, weeds can cause substantial reductions in crop yield across various types of crops (Gharde et al., 2018). Traditional weed control methods, including manual removal and the use of herbicides, are labor-intensive, time-consuming, and expensive. Additionally, the excessive use of herbicides poses several environmental risks, such as soil degradation, water contamination, air pollution, and the accumulation of harmful chemical residues on crops (Partel et al., 2021). While AI and automated systems offer promising solutions to the challenges of weed management, there are still obstacles to their widespread adoption. The initial investment costs for automated equipment and the necessary infrastructure can be prohibitive for small-scale farmers. Additionally, there is a need for skilled personnel to operate and maintain these systems. Despite these challenges, the long-term benefits, including cost savings, increased productivity, and environmental sustainability, make automated weed management a viable and attractive option for the future of agriculture (Elstone, 2020).

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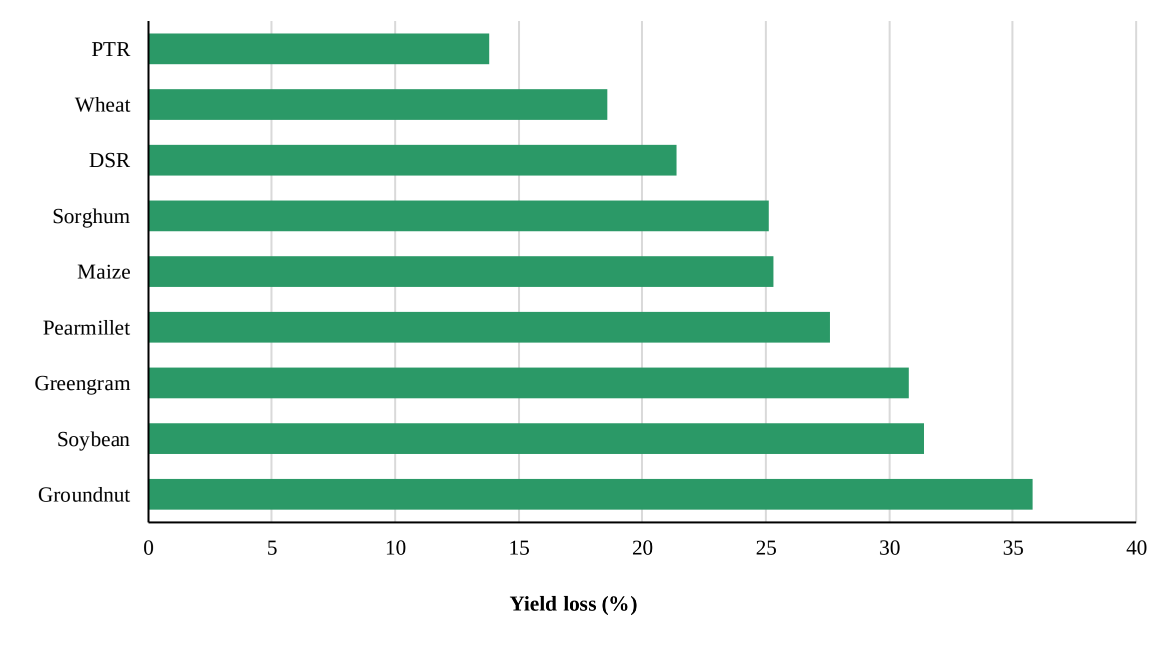

Figure 5. Actual yield losses (%) due to weeds in different crops (Gharde et al., 2018)

The integration of AI and automated technologies in weed management represents a significant advancement in modern agriculture. These systems not only enhance the efficiency and effectiveness of weed control but also contribute to more sustainable farming practices. As technology continues to evolve, it is likely that automated weed management will become an increasingly important tool for farmers worldwide, helping to address the critical challenge of weed control while minimizing environmental impact.

Table 1. Applications of various ML and DL techniques in agriculture

Author	Applications	Model	Performance
Albuquerque et al. (2020)	Irrigation management	Mask RCNN	Models can perform well in different datasets
Azimi et al. (2020)	Sorghum stress detection from nitrogen-deficient state	CNN	Outperform other AI models
Alibabaei et al. (2021)	Irrigation management for tomato	DQN, CNN	Helps save water by 20–30% and tomato yield increase by 11%.
Chen et al. (2021)	Nitrogen level detection in rice	SVM (Support Vector Machine)	88% detection accuracy
Subeesh et al. (2022)	Automated weed recognition	AlexNet, GoogLeNet, Inception V3, Xception	InceptionV3 shows outstanding performance compared to other models
Zhu et al. (2022)	Stress detection for rice	DS-CNN, ND-CNN	Comparative studies indicate that ND-CNN performed better than DS-CNN
Zimit et al. (2023)	predictive based control of precipitation in a water-scarce region	ANFIS, FFNN, and MLR	All three models perform well. Able to manage water resources

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5.1 Drone Technology for Crop Management

Unmanned Aerial Vehicles (UAVs), or drones, have matured from their military and videographic origins into essential agricultural tools. Equipped with AI software and advanced sensors, drones revolutionize precision farming through enhanced field inspection, precise irrigation, and improved fertilization management. This paper explores the capabilities, applications, and benefits of drone technology in precision agriculture.

1. Sensor Capabilities

1.1 Hyperspectral Sensors: Hyperspectral sensors capture images within narrow wavelength ranges (10-20 nm), across approximately a hundred light bands, providing detailed insights into plant health and nutrient composition (Castaldi et al., 2016).

1.2 Multispectral Sensors: Multispectral sensors, capturing fewer light bands (five to ten), are instrumental for broader applications, including crop monitoring and general field assessments.

2. Applications in Precision Farming

2.1 Nutrient Detection: The integration of AI algorithms with hyperspectral and multispectral sensors facilitates the detection of essential nutrients such as phosphorus, potassium, nitrogen, and sulfur. This capability supports targeted nutrient management, enhancing crop health and yield (Sagan et al., 2019).

2.2 Field Inspection: Drones provide high-resolution spatial images, offering an efficient alternative to manual labor for field inspections. This aerial perspective is more cost-effective and time-efficient (Zhang, 2019).

2.3 Health Monitoring: By utilizing various sensors, drones monitor plant health, detect water stress, and identify weed infestations, allowing for timely interventions that enhance crop management (Andriolo et al., 2020).

3. Benefits

3.1 Enhanced Efficiency: The deployment of drones drastically reduces the time and cost associated with traditional field inspections, augmenting operational efficiency (Chougule & Mashalkar, 2022).

3.2 Improved Decision-Making: Data collected by drones enable precise irrigation, targeted application of plant treatments, and effective weed control. This results in improved crop yields and minimized losses (Bian et al., 2019).

3.3 Environmental Impact Monitoring: Drones equipped with AI can identify soil degradation and predict environmental risks such as floods or droughts, providing early warnings for preventive action (Adede et al., 2019; Ennouri et al., 2021).

4. Additional Applications

4.1 Pest Detection: Real-time sensor data from drones facilitate the prompt identification of pest issues, enabling rapid response to mitigate damage (Orchi et al., 2022).

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4.2 Soil Fertility Management: Drones assist in managing soil fertility by analyzing soil conditions and guiding the precise application of fertilizers and chemicals (Helfer et al., 2020; Spanaki, 2021).

The integration of drones with AI technology and advanced sensors significantly enhances precision agriculture by improving monitoring capabilities, increasing efficiency, and supporting informed decision-making. This technological advancement promotes optimized crop management and contributes to sustainable environmental practices.

5.2 Nutrient Stress Management Using AI Technology

Artificial Intelligence (AI) technology has emerged as a powerful tool in managing nutrient stress in plants. Through advanced methodologies and various case studies, AI is helping to enhance nutrient detection and analysis, improving accuracy, efficiency, and disease detection in crops.

1. AI for Nutrient Detection

1.1 Photosynthetic AI: AI systems are employed to detect both macronutrient and micronutrient levels in crops such as hydroponic tomatoes and maize. One approach involves using chlorophyll fluorescence data to identify specific nutrient deficiencies. For example, a notable decrease in sulfur levels can be detected using this method (Kalaji, 2014).

1.2 Fluorescence Parameters: AI leverages fluorescence parameters as reliable indicators of plant nutritional status, effectively detecting deficiencies in essential nutrients and supporting improved nutrient management (Condori et al., 2017).

2. Methods for Nutrient Analysis

2.1 Photosynthetic Activities: AI evaluates nutrient levels by analyzing fluorescence transients in plant leaves, which helps in identifying deficiencies in critical nutrients like phosphorus (P), calcium (Ca), nitrogen (N), iron (Fe), and potassium (K) (Aleksandrov, 2022).

2.2 Chlorophyll Fluorescence: The Join Imaging Platform (JIP) test utilizes chlorophyll fluorescence to assess the overall physiological status of plants, providing insights into the health of photosystem I and II and enabling the detection of nutrient stresses (Hernández & Lopez, 2020).

3. Accuracy and Efficiency

3.1 Artificial Neural Networks (ANNs): ANNs have shown high accuracy in detecting nutrient deficiencies. For instance, an ANN model achieved an accuracy rate of over 97% in identifying nutrient deficiencies in ginger. Models such as VGG-16 and MobileNetV2 also demonstrate high accuracy rates, exceeding 95% for various applications (Butte et al., 2021; Jung et al., 2021).

3.2 Receiver Operating Characteristic (ROC) Curve: The ROC curve is instrumental in evaluating AI model performance, with ANNs exhibiting faster and more accurate performance compared to other models.

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4. Disease Detection

4.1 AI Models for Disease Identification: Advanced AI models, including R-CNN, YOLOv3, Mask R-CNN, and RetinaNet, have been employed to detect diseases in crops such as rice. Among these, YOLOv3 has demonstrated superior performance with a mean average precision (mAP) of 79% (Jung et al., 2021).

4.2 Deep Learning (DL) Models: Deep Learning models, particularly Convolutional Neural Networks (CNNs), are highly effective in classifying plant diseases such as potato blight. By analyzing extensive photographic data, these models differentiate between healthy and diseased plants with high accuracy (Afzaal et al., 2021).

AI technology offers robust solutions for managing nutrient stress in plants, enhancing both nutrient detection and disease management. By leveraging advanced AI methodologies, agricultural practices can achieve greater precision and efficiency, ultimately contributing to improved crop health and yield.

5.3. Irrigation Management Using AI

Artificial Intelligence (AI) technologies play a pivotal role in enhancing irrigation management and addressing challenges posed by drought and hydrologic imbalances in agriculture. This paper discusses AI methodologies that improve drought prediction and irrigation management, offering innovative solutions for modern agricultural practices.

1. Drought Prediction and Management

1.1 AI in Drought Forecasting: AI models are instrumental in predicting drought conditions and assessing hydrologic imbalances that impact agricultural operations. The use of accurate data is imperative for the early detection of droughts, enabling timely and effective interventions (Mallya et al., 2013; Alizadeh & Nikoo, 2018).

1.2 Machine Learning Models: Machine learning (ML) models analyze weather patterns to forecast drought risks. Remarkably, models such as GoogleNet have achieved high prediction accuracy for crops like maize, okra, and soybean (Chandel et al., 2020). Additionally, Deep Convolutional Neural Networks (DCNN) have surpassed traditional ML models in image analysis accuracy, enhancing prediction capabilities (Rasti et al., 2020).

2. Advanced AI Models for Irrigation

2.1 Thermal Imaging: AI models utilizing thermal imaging are effective for monitoring water stress in crops. For instance, the Inception-ResNet-v2 model combines deep learning with transfer learning to accurately detect thermal stress in crops such as sugarcane (Melo et al., 2022). This non-destructive approach provides critical insights into water stress levels.

2.2 Artificial Neural Networks (ANNs): ANNs exhibit strong performance in identifying water stress stages across various crops. ANN models have achieved up to 93% accuracy in detecting water stress in lettuce farms (Osco et al., 2019). These models are also used to forecast soil moisture and evapotranspiration, utilizing minimal data inputs (Arif et al., 2012).

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3. Comparative Analysis and Innovations

3.1 Hyperspectral Imaging: The use of close-range hyperspectral imaging, combined with AI techniques, enhances early detection of stress conditions in crops. AI models leveraging hyperspectral data can detect stress up to 10 days sooner than traditional models like the Normalized Difference Vegetation Index (NDVI) (Behmann et al., 2014).

3.2 Neuro-Drip Irrigation: ANN-based neuro-drip irrigation systems optimize subterranean water management by employing precision farming and wireless sensor networks. This technology enhances water use efficiency and reduces costs, promoting sustainable agricultural practices (Hinnell et al., 2010).

The integration of AI technology in irrigation management provides innovative solutions to mitigate drought impacts and optimize water resources. By leveraging advanced models, agriculture can achieve greater precision and sustainability, ultimately improving crop yields and resilience to environmental challenges.

5.4 AI for Detection and Management of Weed Stress

Weeds are a significant challenge in agriculture due to their competition with crops for essential nutrients and resources, which ultimately impedes crop development and decreases productivity (Soltani et al., 2017). Traditional weed management methods, primarily reliant on chemical herbicides, encounter several issues such as the emergence of herbicide-resistant weed species and profound environmental and health impacts (Amato-Lourenco et al., 2020). This paper reviews the challenges associated with chemical herbicides and explores the advancements in automated weed control technologies, which offer promising solutions to these issues.

1. Challenges with Chemical Herbicides

1.1 Herbicide Use: Although herbicides are considered cost-effective for large-scale weed control, their extensive application often results in environmental pollution and health risks for farmworkers (Balafoutis et al., 2017). The uniform application of herbicides over entire fields not only increases costs but also contributes to significant environmental degradation.

1.2 Consumer Preferences: There is an increasing consumer demand for organic and sustainable agricultural products, which encourages the exploration of alternative weed management strategies (Ampatzidis et al., 2018). This trend reflects a larger societal shift towards environmentally friendly and health-conscious food production practices.

2. Advancements in Automated Weed Control

2.1 Sensor-Based Solutions: Automated weeding technologies are gaining popularity as they utilize sensors for precise weed detection and management. These systems employ advanced classification criteria, such as "green on brown" (GoB) and "green on green" (GoG), to improve the accuracy of weed control (Allmendinger et al., 2022).

- **GoB** employs spectral data in near-infrared and visible wavelengths to distinguish between green vegetation and soil.
- **GoG** uses image detection algorithms to differentiate between crops and weeds, enhancing precision in managing weed populations.

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2.2 Precision Application: AI-driven approaches enable targeted herbicide applications using geo-referenced weed maps, which significantly reduce chemical usage and the resultant environmental impacts (Zhang et al., 2022; Espejo-Garcia et al., 2020). This method allows for the specific targeting of weed-infested areas, minimizing unnecessary application over healthy plants.

3. Benefits of Automated Weeding

3.1 Efficiency and Safety: Automated weeding devices prove especially beneficial for large-scale farming operations where manual weeding is inefficient. These devices reduce chemical usage and limit physical disruption to crops, thus enhancing both operational efficiency and crop safety (Torres-Sánchez et al., 2013; Luvisi et al., 2016).

3.2 Environmental Impact: By precisely targeting weeds, AI-based tools help in reducing chemical contamination of food products and surrounding environments. Such technologies contribute to lowering the ecological footprint of agricultural operations (Jha et al., 2021; Weiss et al., 2020).

Table 2. Overview of commercially available Spot Spraying systems

Company	Product	Technology and Model	Detection Solution	Applications	Chemical Reduction Efficiency Rate
Kilter AX-1	Kilter Systems	RTK-based crop detection and selective spraying in vegetables	Robot	Robot	unknown
AgriCon	H-Sensor	AI-based weed detection in cereals and maize	Bi-spectral camera	Tractor mounted	50% reduced
Agrointelli	Robotti	Combining Deep Learning and BigData	RTK-GPS, autonomous, Lidar, Camera	Robot	40–60% reduced
Weed-It	Weed-It	Detection of green vegetation	Blue LED-lighting and spectrometer	Tractor mounted	95% reduced (only in crop-free areas)
Ecorobotix	ARA	CNN-based weed detection in sugar beet and spot spraying	Multi-camera vision system	Tractor mounted	Up to 95%
BASF, Bosch, Amazone	Smart spraying	Camera-based weed coverage measurement and spot spraying	Bi-spectral camera	Tractor mounted	70% reduced

Data Source: Allmendinger et al. (2022)

Weeds pose significant challenges to agricultural productivity by competing for essential resources and nutrients. Traditional weed management practices, such as chemical herbicides, are increasingly problematic due to herbicide-resistant weed species and adverse environmental impacts (Soltani et al., 2017). Recent advances in AI and automated technologies offer promising improvements in precision and efficiency for weed management.

1. Advancements in Automated Sprayers

1.1 Technological Progress: The development of automated sprayers has progressed significantly, integrating AI to facilitate precise patch and spot spraying techniques. Such advancements help to reduce herbicide dosage and enhance targeting accuracy, ultimately minimizing environmental impacts (Fernandez-Quintanilla et al., 2018).

1.2 Suitability: AI-assisted sprayers are well-suited for both large-scale crops such as maize, wheat, and soybeans, and high-value crops like vegetables and beets. These technologies boost operational efficiency and alleviate the workload of field operators (Villette et al., 2021; Jin et al., 2022).

2. Historical and Recent Innovations

2.1 Early Systems: Initial automated systems, like those by Lee et al. (1999), had limited functionality and required considerable time for weed detection. Recent technological advances have greatly enhanced these systems' capabilities (Balafoutis et al., 2017).

2.2 Modern Solutions: Innovations such as the H-Sensor by Agricon GmbH and the "See and Spray System" by Blue River Technology have reduced herbicide usage and improved application precision, marking significant progress in automated weed control (Balafoutis et al., 2017).

3. AI and Machine Learning Models

3.1 Detection Accuracy: Recent studies have shown that deep learning models, such as Support Vector Machines (SVM), YOLOV3, and Mask R-CNN, exhibit high accuracy in weed detection, with YOLOV3 and Mask R-CNN achieving approximately 94% accuracy (Osorio et al., 2020). These models outperform traditional image processing methods and human analysis (Rosset & Gulden, 2020).

3.2 Integration with IoT: The integration of AI with Internet of Things (IoT) technologies has enhanced data relay networks, allowing comprehensive field data collection (temperature, humidity, moisture) to inform decision-making processes (Shahzadi et al., 2016).

4. Challenges and Limitations

4.1 Data Limitations: AI models, especially in unpredictable environments, are challenged by the availability and quality of data. Extensive datasets are required for training to ensure model accuracy and adaptability (Hill et al., 2016; Chu et al., 2021).

4.2 Complexity of Weed-Crop Interactions: Understanding and modeling the complex interactions between weeds and crops remain challenging for AI developers. Despite technological progress, models struggle with the diverse and dynamic conditions of real-world applications (Price et al., 2018; Kiala et al., 2022).

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5. Future Directions

5.1 Improved Accuracy: Ongoing advancements in AI and machine learning, particularly in deep convolutional neural networks (DCNN) and artificial neural networks (ANN), promise further enhancements in weed detection and management capabilities (Hall et al., 2017; Chu et al., 2021).

5.2 Increased Dataset Quality: Advancing the quality and breadth of datasets is essential for developing more robust AI models capable of efficient performance in varying field conditions (Hill et al., 2016).

6. Limitations

Despite the significant potential of artificial intelligence (AI) to revolutionize agricultural practices, its integration encounters numerous obstacles. These challenges include job displacement, inadequate data resources, infrastructure constraints, high implementation costs, and educational deficits. Addressing these issues is essential for the effective incorporation of AI into global agricultural operations.

1. Job Displacement and Impact on Employment

The automation potential of AI in agriculture raises concerns about job displacement. As AI technologies advance, they can perform labor-intensive tasks such as planting, harvesting, and weed control, which currently employ a substantial portion of the global agricultural workforce. Lowenberg-DeBoer et al. (2020) suggest that AI-driven automation might replace up to 20% of agricultural jobs worldwide, risking significant unemployment in rural regions. This shift has profound socioeconomic implications, particularly in developing countries where agriculture represents a primary source of livelihood.

2. Data Collection and Availability

2.1 Resource Intensive

Robust AI systems in agriculture depend on extensive data sets, critical for training machine learning algorithms. Smaller or under-resourced farms often lack the infrastructure necessary for comprehensive data collection and management. The processes involved are resource-intensive and frequently exceed the technical capabilities of many farming operations, thus hindering AI implementation. Consequently, the advantages of AI tend to favor farms possessing the required technological resources to sustain data-driven activities.

2.2 Geographical Variability

A significant hindrance in applying AI is the geographical variability in agricultural practices. Farming techniques, equipment, and standards vary by region, which can restrict the applicability of AI algorithms trained on localized data sets. Variability in soil types, climate conditions, and crop varieties, even within the same region, complicates the adaptation of AI to specific locales. Lacking region-specific training data, AI models may fail to deliver accurate predictions, thereby limiting their practical application in diverse agricultural environments.

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3. Infrastructure Challenges

3.1 Connectivity Issues

Rural and remote farms often struggle with limited internet connectivity, impeding the deployment of AI technologies that depend on cloud computing, real-time data transmission, and remote monitoring. The absence of stable, high-speed internet access poses a substantial barrier to integrating AI in agriculture, inhibiting the widespread adoption of these technologies (Talaviya, 2020).

4. High Costs and Accessibility

4.1 Implementation Costs

The initial investment required for AI solutions in agriculture is frequently prohibitive for small-scale or low-income farmers. These costs encompass AI-enabled equipment and technologies, as well as ancillary infrastructure like sensors and data storage systems. Consequently, AI remains accessible predominantly to financially capable farmers, restricting its broader dissemination.

4.2 Technological Skills

Beyond financial hurdles, effective AI utilization in agriculture demands a certain degree of technological literacy. Many farmers, particularly those with limited formal education, may lack the necessary skills to operate and maintain AI systems. This skill gap further limits their ability to capitalize on AI advancements.

5. Educational and Training Needs

5.1 Training Programs

To bridge the knowledge gap and facilitate AI adoption in agriculture, comprehensive educational and training programs are indispensable. Such initiatives would equip farmers with essential skills for utilizing AI effectively, covering areas like basic AI concepts, data collection, equipment maintenance, and troubleshooting. Enhancing technical proficiency among farmers could render AI adoption more inclusive and effective over time.

7. AI in Sustainable Development Goals (SDGs)

The integration of Artificial Intelligence (AI) into agricultural systems can significantly contribute to several Sustainable Development Goals (SDGs) outlined by the United Nations. These goals aim to address various global challenges, and AI offers potential solutions for improving productivity, sustainability, and resilience in agriculture. Below is a detailed examination of the SDGs that are particularly relevant to the application of AI in sustainable agricultural practices:

1. SDG 2: Zero Hunger

Objective: End hunger, achieve food security, improve nutrition, and promote sustainable agriculture.

AI's Contribution: AI enhances agricultural productivity through precision farming techniques that optimize crop planning, irrigation, and pest management. By analyzing data on crop health, weather patterns, and soil conditions, AI facilitates improved decision-making that supports food security and agricultural sustainability.

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2. SDG 12: Responsible Consumption and Production

Objective: Ensure sustainable consumption and production patterns.

AI's Contribution: AI aids in optimizing the use of resources such as water, fertilizers, and pesticides, thereby reducing waste and environmental impact. AI-driven systems ensure that these resources are applied efficiently, promoting sustainable agricultural practices and minimizing ecological footprints.

3. SDG 13: Climate Action

Objective: Take urgent action to combat climate change and its impacts.

AI's Contribution: AI technologies contribute to climate action by monitoring environmental conditions and predicting climate-related impacts on agriculture. This includes forecasting extreme weather events and enabling the adoption of climate-resilient farming practices, thereby mitigating the adverse effects of climate change.

4. SDG 6: Clean Water and Sanitation

Objective: Ensure availability and sustainable management of water and sanitation for all.

AI's Contribution: AI enhances water management in agriculture by optimizing irrigation practices based on real-time data on soil moisture and crop needs. This efficient water use helps in conserving water resources and ensuring sustainable agricultural practices.

5. SDG 15: Life on Land

Objective: Protect, restore, and promote sustainable use of terrestrial ecosystems, manage forests sustainably, combat desertification, halt and reverse land degradation, and halt biodiversity loss.

AI's Contribution: AI supports sustainable land management by monitoring soil health, assessing biodiversity, and detecting land degradation. These insights facilitate informed decisions that protect and restore terrestrial ecosystems, contributing to the preservation of biodiversity and sustainable land use.

6. SDG 8: Decent Work and Economic Growth

Objective: Promote sustained, inclusive, and sustainable economic growth, full and productive employment, and decent work for all.

AI's Contribution: AI improves agricultural productivity and economic outcomes by automating tasks and enhancing efficiency. While AI may displace certain agricultural jobs, it also creates opportunities for new skills and roles related to AI technology, contributing to economic growth and the creation of decent work.

7. SDG 9: Industry, Innovation, and Infrastructure

Objective: Build resilient infrastructure, promote inclusive and sustainable industrialization, and foster innovation.

AI's Contribution: AI drives innovation in agricultural practices and infrastructure, such as smart farming technologies and automated systems. This advancement supports the development of resilient infrastructure and promotes sustainable industrial practices in agriculture.

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8. SDG 17: Partnerships for the Goals

Objective: Strengthen the means of implementation and revitalize the global partnership for sustainable development.

AI's Contribution: Effective implementation of AI in agriculture often requires collaboration among governments, private sector entities, research institutions, and international organizations. These partnerships are essential for driving innovation, sharing knowledge, and ensuring equitable access to AI technologies.

Indirect Contributions:

SDG 1: No Poverty: By increasing agricultural productivity and supporting smallholder farmers, AI can enhance incomes and help alleviate poverty in rural areas.

SDG 3: Good Health and Well-being: AI improves food safety and reduces reliance on harmful chemicals, which contributes to healthier food systems and public health.

8. Conclusions

This study investigates the application of AI technology in the agricultural sector through a comprehensive review of academic research and case studies. The findings highlight that AI technology offers substantial benefits to farming operations, particularly in areas such as nutrient detection, weed management, and irrigation control. These advancements contribute to enhanced precision farming practices, optimizing resource management, mitigating environmental risks, and increasing productivity. AI technologies, including machine learning and advanced sensors, play a pivotal role in addressing current agricultural challenges. They facilitate precise monitoring of crop health, efficient weed control, and accurate water stress management. Despite these advantages, it is essential to continue research to fully understand the potential benefits and limitations of AI integration in agriculture. This includes examining the broader social, financial, and environmental implications of AI technology. Future research should focus on exploring the effects of AI across different dimensions to ensure its benefits are maximized while addressing any potential drawbacks. By doing so, AI can further advance the agricultural sector, improve crop yields, and contribute to global goals of reducing hunger and enhancing food security.

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