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REVIEW ARTICLE

ARTIFICIAL INTELLIGENCE IN AGRICULTURE: CURRENT TRENDS AND INNOVATIONS

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ABSTRACT

Artificial intelligence (AI) presents an opportunity to offer innovative solutions to long-standing challenges in agriculture. This review study provides an overview of AI applications in agriculture, focusing on its applications to predict and monitor crop growth rate and yield, climate change and weather patterns, pests and diseases management, weed management, animal production, agricultural machinery, crop irrigation, and soil management, and crop fertilization. AI technologies, including machine learning, computer vision, and precision agriculture, are explored. This review highlights the significant potential of AI to improve agricultural productivity, efficiency, and sustainability. Furthermore, the challenges and limitations of AI adoption in agriculture, including data quality and availability, infrastructure requirements, and ethical considerations, are also discussed. Overall, this study demonstrates the transformative power of AI in agriculture and highlights the need for continued research and investment in this critical field to build more resilient and sustainable agricultural production systems.

KEYWORDS

Artificial intelligence; agriculture; machine learning; deep learning

1. INTRODUCTION

In 2018, the Food and Agriculture Organization (FAO) reported persistent hunger worldwide, raising concerns about the potential failure to achieve the Sustainable Development Goal (SDG) of ending hunger by 2030 (SDG-2) (Saint Ville et al., 2019). Additionally, food insecurity has been increasingly linked to chronic illnesses, such as heart disease, diabetes, and hypertension, particularly in developing countries (Mosadeghrad et al., 2019). Technological advancements that boost agricultural productivity are crucial to address these challenges and meet the growing global population's demand for readily available, fresh, and healthy foods.

Artificial Intelligence (AI) applications have emerged as a promising solution to enhance agricultural productivity (Goralski and Tan, 2022). AI-powered techniques empower farmers to perform more tasks with fewer resources, improving crop quality and ensuring a speedy go-to-market strategy (Manonmani et al., 2024). These AI approaches mimic traits and behaviors comparable to human intelligence, enabling AI systems to reason, learn, and carry out critical agricultural tasks. Various branches of AI, including computer vision, robotics, machine learning, neural networks/deep learning, and natural language processing, are being harnessed to drive greater efficiency and productivity in modern agricultural practices. The deployment of these cutting-edge AI technologies is profoundly impacting areas such as weather and climate change monitoring, crop production optimization, and animal husbandry.

This concise review is an essential contribution to the literature by providing a comprehensive overview of the current applications of AI across the agricultural domain. Specifically, it examines how AI is being leveraged to predict and analyze crop growth rates, estimate yields, forecast climate patterns and weather events, optimize animal production, automate agricultural machinery, and enable more effective weed, disease, and pest control.

By synthesizing the latest developments in this rapidly evolving field, this review is one of the first that offers valuable insights for researchers, policymakers, and industry stakeholders seeking to leverage the transformative potential of AI in addressing global food security challenges and promoting sustainable agricultural practices. Its coverage of AI applications across the agricultural value chain makes it a significant resource for those interested in understanding the profound impact of these technologies on the future of agriculture.

2. AI AND AGRICULTURE

2.1 Crop Growth Rate and Yield

AI models have been increasingly applied for accurate crop yield projections. Researchers evaluated six AI models for predicting agricultural yields in the Midwestern United States, including non-parametric regression, ensemble, and neural network models (Kim et al., 2019). The deep neural network (DNN) model outperformed other methods, achieving a mean absolute error of 21-33% for soybean and 17-22% for corn yield predictions. Their study demonstrated the potential of DNN models to forecast soybean and corn yields before the harvesting months, enabling farmers to develop informed post-harvest strategies, estimate gross margins, and plan farm expenses accordingly. However, the authors recommended further integrating the DNN model with spatial statistical approaches to reduce location-specific clustering errors. In another study, researchers employed a neural network model to forecast tomato yield, growth, and water use in an automated greenhouse environment (Ehret et al., 2011). They found that including radiation as an input variable enhanced the performance of the neural network models in predicting yield. Furthermore, they argued that AI tools provide new insights into crop performance, which can be readily incorporated into crop simulation models. Researchers revealed that artificial neural networks (ANNs) outperformed regression algorithms and gene-expression programming in predicting the growth rate of rice plants (Liu et al., 2021). The ANN model effectively predicted crop yields for different rice varieties using atmospheric inputs and fertilizer consumption data

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(Dahikar and Rode, 2014).

2.2 Climate Change and Weather Prediction for Agriculture

Agriculture is highly susceptible to weather conditions, and accurate climate predictions are crucial for minimizing weather-related losses (Premachandra and Kumara, 2021). AI approaches in weather forecasting have gained prominence, demonstrating improved effectiveness over traditional methods (Lam et al., 2023). For instance, the GraphCast system, employing a graph neural network (GNN) approach, can predict the interaction between hundreds of global weather variables at a 0.25-degree resolution for the next ten days in less than a minute (Lam et al., 2023). GraphCast has been applied to track tropical cyclones and intense heat waves. Several studies have leveraged AI-driven models and machine learning algorithms to simulate the impact of climate on crop yields (Challinor et al., 2018; Liu et al., 2020). Researchers utilized deep learning techniques to analyze satellite data for climate change monitoring (Zhang et al., 2021). Machine learning algorithms have been shown to improve the accuracy of short-term weather predictions for agricultural planning, which is critical for making informed irrigation decisions and integrating weather forecasts into optimized crop management strategies (Javaid et al., 2023; Vandal et al., 2019).

2.3 Pests and Disease Management

Crop protection involves the deliberate use of products, equipment, and strategies to safeguard crops against pests and diseases (Wang et al., 2023). According to the U.S. Department of Agriculture (USDA), insect and disease infestations in agriculture are economically significant, as they can cause substantial losses in crop quality and productivity, with up to 70% of yield being lost due to plant pests (Baquedano et al., 2021; Selvaraj et al., 2019). Therefore, effective disease management requires an in-depth understanding of host-vector dynamics, genetics, climate change, and pathogen epidemiology. Applying contemporary AI management strategies, such as remote sensing for prompt and precise pathogen detection and pest infestation forecasting, can alleviate the burden of plant diseases and pests in agriculture.

Researchers demonstrated the efficacy of an ultra-lightweight efficient network (ULEN) in promptly identifying pests and diseases through plant image analysis (Wang et al., 2023). The ULEN efficiently identified pest infestations and plant diseases with fewer parameters, making it compatible with low-processor platforms, even those without graphics processing units (GPUs). Consequently, the ULEN is more accurate and environmentally friendly for detecting pests and diseases. Sarma et al. (2022) developed a smart agriculture support system that combined AI and Internet of Things (IoT) technology for disease categorization in tomato crops. Convolutional Neural Networks (CNNs) excelled in offering autonomous decision support for disease classifications. Fuzzy clustering and CNNs have proven reliable and efficient in detecting crop diseases in various vegetable species, particularly in hot and humid environments. Selvaraj et al. (2019) developed an AI-based system for detecting banana diseases and pests, utilizing deep convolutional neural networks. Three CNNs were employed to develop the detection model, and the system demonstrated 90% accuracy in identifying pests and plant diseases.

2.4 Weed Management

Weeds pose a significant challenge by competing with crops for essential resources such as water, light, and nutrients, leading to substantial yield reductions (Spitters and Van Den Bergh, 1982). A study showed a staggering 25.35% yield loss in wheat production due to weeds (Dangwal et al., 2010). However, adopting AI approaches for weed management has alleviated farmers' concerns about agricultural output losses. Researchers investigated the performance of two different embedded GPUs as smart sprayer processing units, focusing on target detection and image processing for target and non-target weeds (Patel and Bhatia, 2024). Both GPUs achieved 89-91% target detection and spraying accuracy in the first scenario involving artificial weeds and plants. In the second scenario with actual weeds (portulaca and sedge) and pepper plants, the more powerful GPU (NVIDIA GTX 1070 Ti) outperformed the less powerful GPU (NVIDIA Jetson TX2), with an overall accuracy of 71% and a recall of 78%.

Furthermore, the effectiveness of weed control was enhanced through the development of an AI algorithm integrated with Real-Time Kinematic Global Positioning System (RTK-GPS) technology. The smart sprayer created weed maps and predicted data collection activities after each weeding operation (herbicidal). This integration helps reduce the number of agrochemicals needed compared to traditional methods, where entire fields are sprayed. The AI algorithm targets only the exact locations where weeds are found, reducing costs and excessive use of synthetic chemicals in the environment.

2.5 Animal Production

Animal health and productivity are inextricably linked, with an animal's regular eating habits providing valuable insights into its well-being. The efficacy of a Faster R-CNN (Regions with Convolutional Neural Networks) method in pig farming, which involved developing an algorithm to identify unique pig behavior in the feeding area (Yang et al., 2018). The technique achieved a precision rate of 99.6% and a recall rate of 86.33%. Utilizing video surveillance reduces labor costs associated with production and provides farmers with more options regarding the breeds they wish to raise based on the observed feeding habits. However, farmers often lack access to adequate AI resources or appropriate information.

Researchers developed an automated system for identifying sheep breeds using a convolutional neural network model tailored for smart agriculture applications (Himel et al., 2024). The automated approach identified 1,680 sheep photos based on facial features, with each photograph depicting four different sheep breeds. The ensemble approach combined multiple models, including Xception, VGG16, InceptionV3, InceptionResNetV2, and DenseNet121, utilizing multiple optimizers and loss functions to determine the best potential combinations. This classification system aids sheep producers in differentiating between various sheep breeds. However, researchers highlighted certain significant factors that may reduce the precision of sheep breed identification, such as lighting conditions, specific facial features of each sheep, and image quality (Himel et al., 2024).

Researchers employed a camera-based automated early warning system that uses image software to identify issues in broiler houses early in the production cycle (Kashiha et al., 2013). By positioning cameras above the floor area of 28,000 broilers, an analysis program converted the photos into an animal distribution index. Consequently, a linear real-time model was created to simulate the animal distribution index, and the process produced real-time results for 95.24% of events, demonstrating the method's efficacy in detecting malfunctions throughout the production phase. Nevertheless, detecting animal abnormalities, feeding behaviors, and malfunctioning feeding can be challenging, depending on the population size of the animals (Neethirajan, 2020). Sensors, big data, and machine learning (ML) can also be employed to monitor and predict potential disease outbreaks in broiler houses precisely. Visual analysis (VIA) systems are considered helpful monitoring methods that can be utilized in developing integrated management systems and have been examined in pig production (White et al., 2004).

2.6 Agricultural Machinery

Over the past several years, various environmentally friendly AI techniques have been developed to increase the productivity and efficiency of agricultural machinery. One of the most critical considerations in production is the work area. Factors influencing the calculation of the working area, such as the shape of the field, driver behavior, and the number of fields runs made by the machine (Waleed et al., 2020). Therefore, accurate working area calculation enables farmers to make informed decisions about resource allocation and machinery utilization and calculate and predict yield per unit area. An automated intelligent system using the Internet of Things (IoT), Global Positioning System (GPS), and AI has been developed to monitor the movement of agricultural machinery and precisely calculate the working area.

2.7 Crop Irrigation and Soil Management

Monitoring soil moisture is one of the critical components for optimal resource use and higher crop output. Researchers created a model that used ANN to estimate soil moisture in paddy fields (Arif et al., 2013). The model generated strong linear correlations between the estimated and observed soil moisture values. In the absence of extensive meteorological data, the ANN is successful in predicting soil moisture. Traditional irrigation methods are one of the leading causes of water scarcity (Anitha et al., 2023). Conventional irrigation systems are inefficient and wasteful. Therefore, they implemented an intelligent solar irrigation system utilizing ANN algorithms and IoT (Anitha et al., 2023). Solar panels, sensors, a water pump, IoT devices, a water storage tank, and ANN algorithms are used in the system. The gathered data from the sensors, which included soil moisture, temperature, and humidity, was used to manage the water pump. The method works well to determine the best irrigation schedules and avoid over-irrigation. In another study, Sapaev et al. (2023) developed an intelligent irrigation system using deep learning (DL) to adjust the amount of water supplied to each plant type based on plant recognition. The system consists of hardware and software as technological components. One component is connected to cameras to identify the plants and use the database for the correct amount of water.

2.8 Challenges and Limitations of AI Adoption In Agriculture

While AI holds immense potential to revolutionize agriculture by enhancing crop yields, improving resource allocation, and reducing waste, its widespread adoption in the agricultural sector faces significant challenges and limitations ((Araújo et al., 2023). These include data quality and availability concerns, infrastructure requirements, ethical considerations, and the need for context-specific solutions.

One of the critical challenges is the issue of data privacy, security, and ownership, as highlighted by (Wolfert et al., 2017). AI applications in agriculture raise ethical concerns regarding using and managing sensitive data, such as farmers' personal information, crop yields, and farm operations. Ensuring accountability, transparency, and fairness in AI decision-making processes is crucial to maintaining trust and facilitating widespread adoption. Furthermore, AI-powered decision-making systems heavily rely on the quality and quantity of data they are trained on. If the training data is biased or incomplete, the AI systems can perpetuate and amplify these biases, leading to potentially discriminatory or unfair outcomes (Shaikh et al., 2022). Addressing these biases and ensuring AI systems' responsible development and deployment is a critical challenge.

Another significant limitation is the substantial infrastructure requirements for implementing AI solutions in agriculture. Technologies such as drones, sensors, satellite imaging, and high-performance computing necessitate significant investments (Sapaev et al., 2023). However, as highlighted in 2022 study, approximately 24% of the farming land globally is occupied by smallholders, and the costs associated with these infrastructure requirements can be prohibitively expensive, impeding AI adoption, particularly in developing regions (Shaikh et al., 2022; Lowder et al., 2016; Jha et al., 2019).

Data availability and quality, especially in low-income countries, also pose challenges to the effective implementation of AI in agriculture. While AI algorithms require high-quality and abundant data to make accurate predictions and decisions, agricultural data is often noisy, incomplete, and inconsistent, particularly in developing countries where limited infrastructure hinders data collection processes (Wolfert et al., 2017; Goel et al., 2021).

To address these challenges, further research and investments are needed to develop context-specific AI solutions tailored to different agricultural systems' unique challenges and requirements. This includes efforts to improve data collection and management practices, develop cost-effective and scalable infrastructure solutions, and ensure AI technologies' ethical and responsible development and deployment in agriculture.

Moreover, effective collaboration between researchers, policymakers, and industry stakeholders is crucial to navigating the complex landscape of AI adoption in agriculture. By addressing these challenges and limitations, the full potential of AI can be unlocked to drive sustainable and efficient agricultural practices, contributing to global food security and environmental sustainability.

3. Conclusion

This comprehensive review has explored the diverse applications of AI in agriculture, highlighting its transformative potential to enhance crop yields, mitigate the impacts of climate change, optimize resource utilization, and improve overall agricultural productivity. From computer vision for crop monitoring and disease detection to machine learning for predictive analytics and precision farming, AI has demonstrated promising results across various domains, including crop growth rate enhancement, yield optimization, pest and disease management, weed control, animal production, agricultural machinery automation, crop irrigation, soil management, and fertilization strategies.

However, despite the numerous benefits, the widespread adoption of AI in agriculture faces significant challenges and limitations. Data quality and availability issues, substantial infrastructure requirements, ethical considerations surrounding data privacy and algorithmic bias, and the lack of standardization and regulation pose hurdles to seamless AI integration. Addressing these challenges is crucial to fully unlocking the potential of AI in driving sustainable and efficient agricultural practices.

To this end, there is an urgent need to develop and implement data-driven decision-making frameworks, invest in robust and scalable infrastructure, and foster collaboration among stakeholders, researchers, and industry experts. Such collaborative efforts should focus on developing standardized protocols, regulations, and best practices for responsible AI adoption in agriculture. Furthermore, establishing AI-driven educational and training programs for farmers and agricultural professionals is essential to facilitate effective technology transfer and capacity building.

Policymakers and funding agencies also play a pivotal role in supporting AI research and development initiatives in the agricultural domain. Encouraging policy support and dedicated funding mechanisms can catalyze innovation and drive advancements in AI-powered solutions tailored to the unique challenges of diverse agricultural systems. Moreover, future research should prioritize developing comprehensive frameworks for evaluating the environmental and social impacts of AI in agriculture. These frameworks should encompass a holistic assessment of factors such as carbon footprint, resource consumption, and implications for rural livelihoods and communities. By addressing these critical aspects, the sustainable and equitable integration of AI in agriculture can be ensured.

In conclusion, while AI holds immense promise for revolutionizing agricultural practices, realizing its full potential requires a concerted effort from all stakeholders to address the existing challenges and limitations. By fostering cross-disciplinary collaboration, investing in infrastructure and capacity building, and prioritizing ethical and responsible AI development, the agricultural sector can harness the power of AI to enhance food security, promote environmental sustainability, and drive economic growth in developed and developing regions.

Conflicts of Interest

The authors declare no conflicts of interest.

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