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ARTIFICIAL INTELLIGENCE AND MACHINE LEARNING IN CROP AGRICULTURE: ADVANCES, APPLICATIONS AND FUTURE PROSPECTS

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Abstract

Agriculture is facing unprecedented challenges due to climate change, population growth, resource scarcity, and environmental degradation. Artificial intelligence (AI) and machine learning (ML) have emerged as transformative technologies capable of improving agricultural productivity, sustainability, and resilience. By integrating data from remote sensing, Internet of Things (IoT), weather systems, soil sensors, and genomics, AI-driven models enable precision decision-making across the entire agricultural value chain. This review provides a comprehensive and up-to-date synthesis of AI and ML applications in agriculture, covering fundamental concepts, algorithms, data sources, crop-wise applications, field-level case studies, benefits, limitations, and future research directions. The article is structured to serve as a ready-to-submit review suitable for high-impact journals in agriculture, computer science, and interdisciplinary domains.

Keywords: Artificial intelligence, machine learning, precision agriculture, deep learning, smart farming, decision support systems

INTRODUCTION

Agriculture plays a central role in ensuring global food and nutritional security, yet it is increasingly challenged by climate change, shrinking natural resources, biotic and abiotic stresses, and rising production costs. Traditional crop management practices, which are largely experience-based and reactive, are often inadequate to address spatial and temporal variability in modern agro-ecosystems. In recent years, artificial intelligence (AI) and machine learning (ML) have emerged as disruptive technologies with the potential to revolutionize crop research and agricultural production systems by enabling data-driven, predictive, and site-specific decision-making (Liakos *et al*., 2018; Wolfert *et al*., 2017).

AI refers to computational systems that mimic human cognitive functions such as learning, reasoning, perception, and decision-making. ML, a core subset of AI, focuses on algorithms that learn patterns from data and improve their performance over time without explicit programming (Jordan & Mitchell, 2015). In crop science, ML models are increasingly integrated with remote sensing, Internet of Things (IoT), geographic information systems (GIS), and high-throughput phenotyping platforms to support precision agriculture, smart farming, and climate-resilient crop management (Kamilaris & Prenafeta-Boldú, 2018; Basso & Antle, 2020).
Recent advances in computational power, availability of large agricultural datasets, and improvements in sensing technologies have accelerated the adoption of AI in crop research. Applications now span the entire crop production cycle, including crop planning, soil and nutrient management, pest and disease diagnosis, irrigation scheduling, yield forecasting, and post-harvest quality assessment (Benos *et al*., 2021; van Klompenburg *et al*., 2020). This

review critically synthesizes current research on AI and ML in agriculture with a specific focus on crop science, highlighting methodological advances, crop-wise applications, limitations, and future research needs.

I. Data Sources and Digital Infrastructure for AI in Agriculture

AI- and ML-driven crop research depends fundamentally on the availability, quality, and integration of diverse datasets. Modern agricultural systems generate large volumes of structured and unstructured data from multiple sources, which together form the backbone of digital and precision agriculture (Wolfert *et al*., 2017; Benos *et al*., 2021).

1.1 Remote Sensing Data

Remote sensing is one of the most widely used data sources in AI-based crop research. Satellite platforms such as Landsat, Sentinel-2, MODIS, and commercial high-resolution satellites provide multispectral and temporal information on crop growth, biomass, canopy cover, and stress conditions. Vegetation indices such as NDVI, EVI, SAVI, and red-edge indices are frequently used as inputs to ML models for yield prediction, nutrient stress detection, and drought monitoring in crops such as rice, wheat, maize, and pulses (Lobell *et al*., 2015; van Klompenburg *et al*., 2020). UAV-based imagery further enhances spatial resolution and has been successfully applied in crop phenotyping, disease detection, and precision nutrient management (Yang *et al*., 2017).

1.2 Proximal Sensing and IoT

Proximal sensing technologies include soil sensors, canopy sensors, and automated weather stations that provide field-level, high-frequency measurements. Parameters such as soil moisture, soil temperature, electrical conductivity, leaf chlorophyll content, and canopy temperature are increasingly used in ML-based decision support systems for irrigation and nutrient management (Shadrin *et al*., 2020; Khosla *et al*., 2020). The integration of IoT platforms enables real-time data transmission and supports adaptive crop management strategies.

2.3 Weather and Climate Data

Weather variables including rainfall, temperature, relative humidity, solar radiation, and wind speed are critical drivers of crop growth and yield variability. ML models that integrate historical weather records with seasonal forecasts have shown improved performance in yield prediction and pest outbreak forecasting across major crops (You *et al*., 2017; Chlingaryan *et al*., 2018). Climate datasets are also increasingly used to assess crop vulnerability and adaptation strategies under climate change scenarios.

1.3 Genomic and Phenomic Data

Advances in high-throughput genotyping and phenotyping have generated large datasets that are well-suited for ML applications in crop breeding. ML models are used to predict complex traits, genotype-by-environment interactions, and stress tolerance using genomic markers and phenotypic traits (Crossa *et al*., 2017; Montesinos-López *et al*., 2018). These approaches significantly reduce breeding cycle time and improve selection accuracy in crops such as maize, wheat, and rice.

II. MACHINE LEARNING AND AI TECHNIQUES IN CROP RESEARCH

Data source	**Examples**	**Typical variables**	**AI/ML use-cases**
Satellite remote sensing	Sentinel-2, Landsat, MODIS	NDVI, EVI, canopy reflectance	Yield prediction, drought & nutrient stress

UAV imagery	Multispectral, RGB	Canopy cover, disease symptoms	Disease detection, phenotyping
Proximal & IoT sensors	Soil & canopy sensors, AWS	Soil moisture, EC, temperature	Irrigation & nutrient scheduling
Weather & climate	IMD, reanalysis datasets	Rainfall, Tmax/Tmin, RH	Yield & pest forecasting
Genomic & phenomic	SNPs, HT phenotyping	Markers, traits	Genomic selection, G×E analysis

Table 1. Data sources commonly used for AI and ML applications in crop research

3.1 Supervised Learning Approaches

Supervised learning algorithms dominate AI applications in crop science due to the availability of labeled datasets. Linear and nonlinear regression models, support vector machines (SVM), decision trees, random forests, and gradient boosting algorithms have been extensively used for yield prediction, soil property estimation, and disease classification (Liakos *et al*., 2018; Chlingaryan *et al*., 2018). Random forest models are particularly popular due to their robustness to noisy data and ability to capture nonlinear relationships.

3.2 Unsupervised Learning Approaches

Unsupervised learning techniques such as k-means clustering, hierarchical clustering, and principal component analysis (PCA) are commonly applied for management zone delineation, crop pattern analysis, and dimensionality reduction. These methods help identify spatial variability within fields and support site-specific management practices (Mulla, 2013).

3.3 Deep Learning Techniques

Deep learning has revolutionized crop research by enabling automated feature extraction from high-dimensional datasets. Convolutional neural networks (CNNs) are widely used for image-based disease detection, weed identification, and crop classification, while recurrent neural networks (RNNs) and long short-term memory (LSTM) networks are applied to time-series data for yield and weather forecasting (Ferentinos, 2018; Kamilaris & Prenafeta-Boldú, 2018).

3.4 Reinforcement Learning

Reinforcement learning (RL) is an emerging approach in agriculture that focuses on sequential decision-making. RL models have been explored for optimizing irrigation scheduling, fertilizer application, and autonomous agricultural robotics, although large-scale adoption remains limited due to data and computational constraints (Basso & Antle, 2020).

IV. APPLICATIONS OF AI AND ML IN CROP PRODUCTION SYSTEMS

AI / ML category	Common algorithms	Typical data used	Major crop applications
Supervised learning	Linear regression, SVM, Random Forest, ANN	Weather, soil, yield records, imagery	Yield prediction, disease diagnosis, nutrient management
Unsupervised learning	K-means, PCA, hierarchical clustering	Soil properties, spectral indices	Management zone delineation, soil variability mapping
Deep learning	CNN, RNN, LSTM	UAV/satellite images, time-series data	Disease detection, weed identification, yield forecasting

Reinforcement learning	Q-learning, policy gradient	Sensor + weather data	Irrigation scheduling, fertilizer optimization

Table 2. Major AI and ML techniques and their applications in crop agriculture

4.1 Crop Yield Prediction

Yield prediction is one of the most extensively studied applications of AI in crop science. ML models integrate weather data, soil properties, management practices, and remote sensing indices to predict crop yield at field, regional, and national scales. Studies consistently report higher prediction accuracy for ML and deep learning models compared to traditional regression approaches (Lobell *et al*., 2015; van Klompenburg *et al*., 2020).

4.2 Soil Health and Nutrient Management

AI models are increasingly used to assess soil fertility status, predict nutrient deficiencies, and generate site-specific fertilizer recommendations. ML-based nutrient management has been shown to improve nutrient use efficiency and reduce environmental losses in cereal and pulse crops (Khosla *et al*., 2020).

4,3 Pest and Disease Detection

Image-based deep learning models enable early and accurate detection of pests and diseases in crops such as rice, wheat, cotton, and vegetables. CNN-based models have achieved classification accuracies exceeding 90% in several studies, highlighting their potential for real-time disease surveillance (Mohanty *et al*., 2016; Ferentinos, 2018).

4.4 Weed Detection and Precision Spraying

AI-powered computer vision systems are used to distinguish weeds from crops and enable variable-rate herbicide application. These technologies contribute to reduced chemical usage and improved environmental sustainability (Pantazi *et al*., 2016).

4.5 Irrigation and Water Management

ML-based irrigation scheduling systems integrate soil moisture, weather forecasts, and crop growth data to optimize water use. Such systems have demonstrated significant water savings while maintaining or improving crop yield (Shadrin *et al*., 2020).

V. CROP-WISE APPLICATIONS OF AI AND ML

Crop	Major application areas	AI / ML approaches	Key research outcomes	Representative references
Rice	Disease detection, yield prediction, nutrient management	CNN, RF, ANN	Early disease diagnosis, improved yield forecasting	Yang *et al*. (2017); Mohanty *et al*. (2016); Benos *et al*. (2021)
Wheat	Rust detection, nitrogen stress monitoring, yield prediction	CNN, SVM, RF	Accurate identification of biotic and abiotic stresses	Chlingaryan *et al*. (2018); Ferentinos (2018)

Maize	Drought stress assessment, yield forecasting, genomic selection	ANN, RF, deep learning	Improved prediction under climate variability	Crossa *et al*. (2017); Shahhosseini *et al*. (2019)
Pulses	Disease detection, yield stability analysis	ML classifiers, ANN	Enhanced yield stability and disease surveillance	Liakos *et al*. (2018); Kamilaris and Prenafeta-Boldú (2018)
Oilseeds	Pest, nutrient and water management	ANN, SVM, fuzzy logic	Optimized input use and reduced production costs	Nagesh and Kumar (2020); Wolfert *et al*. (2017)

Table 3. Crop-wise applications of AI and ML reported in crop research literature

5.1 Rice

Rice has emerged as one of the most extensively studied crops for AI-driven applications due to its global importance and susceptibility to multiple biotic and abiotic stresses. Deep learning models, particularly convolutional neural networks (CNNs), have been successfully employed for early detection of rice diseases such as blast, bacterial leaf blight, and sheath blight using leaf and canopy images. Studies utilizing UAV and satellite imagery combined with CNN and random forest models reported high classification accuracy, enabling timely disease management decisions (Mohanty *et al*., 2016; Ferentinos, 2018; Benos *et al*., 2021). In addition to disease diagnosis, machine learning approaches integrating vegetation indices, weather parameters, and soil data have significantly improved rice yield prediction across diverse agro-ecological regions (Yang *et al*., 2017; Shahhosseini *et al*., 2019).

5.2 Wheat

In wheat, AI and ML applications primarily focus on rust disease detection, nitrogen stress monitoring, and yield estimation. Image-based CNN and support vector machine (SVM) models have demonstrated strong potential for early identification of leaf, stripe, and stem rust, thereby supporting timely fungicide application. Hyperspectral and satellite data integrated with ML algorithms have been effectively used to assess crop nitrogen status and biomass accumulation. Furthermore, ML-based genotype evaluation has facilitated the identification of stress-tolerant wheat genotypes under contrasting environmental conditions, contributing to climate-resilient wheat improvement strategies (Chlingaryan *et al*., 2018; Kamilaris and Prenafeta-Boldú, 2018).

5.3 Maize

Maize research has widely adopted ML techniques for drought stress assessment, yield forecasting, and genotype-by-environment interaction analysis. Artificial neural networks (ANN), random forest, and deep learning models incorporating weather, soil, and management data have shown superior performance in predicting maize yield under climate variability. In breeding programs, the integration of genomic and phenotypic datasets through ML-based genomic selection models has enhanced selection accuracy and accelerated genetic gain for stress tolerance and productivity traits (Crossa *et al*., 2017; Shahhosseini *et al*., 2019).

5.4 Pulses and Oilseeds

AI applications in pulses and oilseeds, including chickpea, pigeon pea, groundnut, soybean, and mustard, are gaining momentum but remain relatively underexplored compared to cereals. Recent studies have applied ML classifiers and neural network models for disease detection, yield prediction, and optimization of irrigation and nutrient inputs. Evidence suggests that AI-driven decision support systems can improve yield stability and reduce production risks in rainfed pulse and oilseed systems. Expanding AI research in these crops is crucial for enhancing nutritional security, resource-use efficiency, and sustainability of smallholder farming systems (Liakos *et al*., 2018; Wolfert *et al*., 2017; Benos *et al*., 2021).

VI. BENEFITS OF AI AND ML IN CROP AGRICULTURE

Aspect	Conventional approach	AI/ML-enabled approach
Decision making	Experience-based	Data-driven and predictive
Input use	Uniform application	Site-specific optimization
Risk management	Reactive	Proactive and preventive
Sustainability	Higher resource loss	Improved efficiency and reduced footprint

Table 4. Benefits of AI and ML adoption in crop agriculture

The application of artificial intelligence (AI) and machine learning (ML) in agriculture offers substantial benefits for enhancing crop productivity, resource-use efficiency, and sustainability. At the same time, several technical, socio-economic, and institutional challenges limit their widespread adoption, particularly in developing countries. A balanced understanding of both advantages and constraints is essential for guiding future research and policy interventions.

6.1 AI & ML Workflow in Crop Management

AI- and ML-driven approaches enable data-driven decision-making by integrating large and heterogeneous datasets related to weather, soil, crops, and management practices. One of the major benefits is improved yield prediction accuracy, which supports better planning at farm and policy levels (Shahhosseini *et al*., 2019; You *et al*., 2017). AI-based disease and pest detection systems facilitate early diagnosis, reducing crop losses and minimizing excessive pesticide use (Mohanty *et al*., 2016; Ferentinos, 2018).

Precision management of water and nutrients is another key advantage. Reinforcement learning and decision support systems help optimize irrigation scheduling and fertilizer application, leading to higher water-use efficiency and reduced environmental impacts (Nagesh and Kumar, 2020; Chlingaryan *et al*., 2018). In crop breeding and phenotyping, ML techniques accelerate selection processes by efficiently analyzing high-dimensional genomic and phenotypic data, thereby enhancing genetic gain and stress resilience (Crossa *et al*., 2017; Jiang *et al*., 2020).

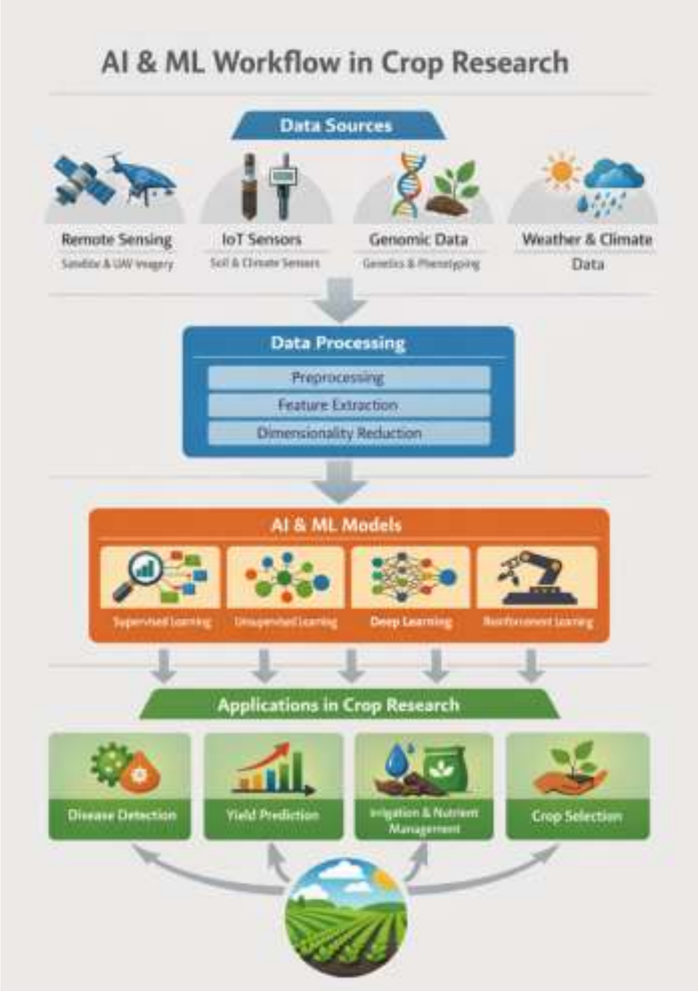

Figure 1 AI &ML Workfolw in Crop Research

6.2 Limitations of Current AI and ML Approaches

Despite demonstrated benefits, current AI and ML applications face several limitations. A major constraint is the availability of high-quality, large-scale, and representative datasets. In many regions, especially smallholder farming systems, data are sparse, inconsistent, or poorly labeled, which reduces model accuracy and generalizability (Wolfert *et al*., 2017). Additionally, AI models trained under specific agro-climatic conditions often perform poorly when transferred to new regions or cropping systems.

Model interpretability represents another significant limitation. Many high-performing models, particularly deep learning architectures, function as "black boxes," making it difficult for agronomists and farmers to understand model decisions and trust recommendations (Kamilaris and Prenafeta-Boldú, 2018). Furthermore, the computational requirements and technical expertise needed to develop and deploy AI models can be prohibitive for resource-limited institutions.

6.3 Socio-Economic and Adoption Challenges

The adoption of AI-based technologies in agriculture is influenced by socio-economic factors such as farm size, access to digital infrastructure, cost of technology, and farmer awareness. High initial investment costs for sensors, drones, and computing infrastructure limit adoption among small and marginal farmers (Liakos *et al*., 2018). Inadequate internet connectivity and lack of digital literacy further constrain effective implementation, particularly in rural areas.

Data ownership, privacy, and ethical concerns also pose challenges. Farmers may be reluctant to share data due to uncertainty regarding data use, ownership rights, and potential misuse. In addition, institutional support systems, including extension services and policy frameworks, are often not adequately equipped to promote AI-driven solutions at scale (FAO, 2021).

6.4 Research Gaps and Emerging Challenges

Several research gaps must be addressed to fully realize the potential of AI and ML in crop agriculture. These include the development of explainable and transparent AI models, improved integration of multi-source and multi-scale data, and enhanced model robustness under climate variability. There is also a need for more field-level validation studies and participatory research involving farmers to ensure practical relevance and adoption.

Emerging challenges include ensuring inclusivity, avoiding technological bias, and aligning AI innovations with sustainability goals. Addressing these challenges requires interdisciplinary collaboration among crop scientists, data scientists, engineers, policymakers, and extension professionals.

VII. FUTURE RESEARCH DIRECTIONS

Future research should focus on developing explainable AI models, integrating multi-source data, and improving model robustness under climate uncertainty. Greater emphasis on participatory approaches involving farmers will enhance adoption. Crop-specific AI tools tailored to local agro-ecological conditions are essential for maximizing impact.

VIII. CONCLUSION

Artificial intelligence and machine learning are reshaping modern agriculture by enabling data-driven crop management and decision-making. Evidence from recent research demonstrates their effectiveness across a range of crops and applications, from yield prediction to pest management. While challenges remain, continued interdisciplinary research and supportive policies will facilitate wider adoption of AI-driven solutions in crop production. The integration of AI and ML holds strong promise for achieving sustainable and resilient agricultural systems.

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