

Recent Trends in AI and Data Science for Smart and Sustainable Agriculture: Enhancing Global Food Security

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DOI:10.31033/IJEMR/16.2.2026.1878

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Artificial Intelligence (AI) and Data Science (DS) are revolutionizing agriculture by enabling precision farming, predictive analytics, and resource optimization to address food security amid climate challenges and population growth. This review paper explores recent trends (2023–2026) in smart and sustainable agriculture, focusing on AI applications in crop monitoring, yield prediction, pest detection, smart irrigation, and climate-resilient decision support. Key technologies—machine learning (e.g., CNNs, RNNs), computer vision, IoT integration, drones, and satellite imagery—are analyzed through a systematic literature review of 50+ recent papers, highlighting their impact on yield improvement (up to 20–30%), resource savings (e.g., 90% less herbicides), and sustainability metrics like reduced emissions and water use. Case studies demonstrate real-world deployments, such as AI-driven yield mapping and autonomous weeding. Challenges including data scarcity, high costs for smallholders, model interpretability, and ethical concerns are discussed, alongside future directions like multimodal AI, edge computing, and federated learning for equitable access. By synthesizing these advancements, this paper underscores AI's pivotal role in achieving UN Sustainable Development Goal 2 (Zero Hunger) through data-driven, resilient farming systems.

Keywords: AI in Agriculture, Precision Farming, Sustainable Agriculture, Food Security, Machine Learning, Smart Irrigation, IoT, Drone Technology, SDG 2

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Farheen Siddiqui, Assistant Professor, Department of Computer Science and Engineering, Shri Ramswaroop Memorial University, Lucknow, Uttar Pradesh, India. Email: farheensiddiqui78687@gmail.com	Tiwari A, Siddiqui F, Recent Trends in AI and Data Science for Smart and Sustainable Agriculture: Enhancing Global Food Security. Int J Engg Mgmt Res. 2026;16(2):45-55. Available From https://ijemr.vandanapublications.com/index.php/j/article/view/1878	

Manuscript Received 2026-03-02	Review Round 1 2026-03-14	Review Round 2	Review Round 3	Accepted 2026-04-02
Conflict of Interest None	Funding Nil	Ethical Approval Yes	Plagiarism X-checker 5.14	Note
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1. Introduction

Global food systems are under increasing pressure due to rapid population growth, urbanization, and changing dietary patterns, which together are projected to push food demand significantly higher in the coming decades. At the same time, agriculture faces serious constraints from climate variability, land degradation, water scarcity, and the need to reduce greenhouse gas emissions and other environmental impacts. This tension between rising demand and shrinking resources has made it essential to transition from traditional, input-intensive farming practices towards smarter and more sustainable approaches that can increase productivity while preserving natural ecosystems and supporting rural livelihoods.

Smart and sustainable agriculture has emerged as a response to this challenge by integrating digital technologies, data-driven decision making, and ecological principles into farming. In particular, Artificial Intelligence (AI) and Data Science (DS) are playing a central role in this transformation. Machine learning models, computer vision techniques, and advanced analytics are now being applied across the agricultural value chain to monitor crop health, predict yields, optimize irrigation, detect pests and weeds, and support climate-resilient planning. Combined with Internet of Things (IoT) devices, drones, and satellite imagery, these AI-enabled systems can provide timely, fine-grained insights that were previously impossible using conventional methods.

Over the last few years, there has been a rapid growth in research and pilot deployments of AI-driven solutions in agriculture, especially in the context of precision farming and sustainable resource management. Studies have reported substantial gains in yield, reductions in water and chemical usage, and improvements in farm profitability when data-driven techniques are adopted, particularly when they are tailored to local conditions and smallholder constraints. However, the current landscape is fragmented across different crops, regions, technologies, and evaluation metrics, which makes it difficult for students, practitioners, and policymakers to obtain a clear picture of the state of the art and the major trends driving smart and sustainable agriculture.

This review paper focuses on recent trends in AI and Data Science for smart and sustainable agriculture, with a specific emphasis on their contribution to enhancing food security. The primary objectives are: (i) to categorize the main application areas where AI and DS are being used in agriculture, such as crop monitoring, yield prediction, smart irrigation, and pest management; (ii) to analyze the underlying models, data sources, and technological enablers that support these applications; and (iii) to identify the benefits, limitations, and open challenges associated with deploying such systems at scale, particularly in resource-constrained settings. By synthesizing findings from recent literature and real-world case studies, the paper aims to provide a structured overview that can guide future research and practical deployments.

The remainder of the paper is organized as follows. Section 2 introduces the concepts of smart and sustainable agriculture and describes the key digital and ecological foundations that enable them. Section 3 presents recent AI and Data Science applications in agriculture, grouped by functional areas and technologies, and highlights their reported impacts on productivity and resource efficiency. Section 4 discusses the main technical, socioeconomic, and ethical challenges that hinder wider adoption of AI-driven solutions in agriculture. Section 5 outlines promising future research directions and opportunities to make AI-enabled farming more inclusive and scalable. Finally, Section 6 concludes the paper by summarizing the key insights and their implications for achieving long-term food security.

2. Background on Smart and Sustainable Agriculture

Smart agriculture represents the convergence of digital technologies with traditional farming practices to enable data-driven decision-making at field level. Emerging in the early 2010s with GPS-guided machinery and variable-rate application, it has evolved into a comprehensive ecosystem powered by the Internet of Things (IoT), big data analytics, and cloud computing. Sensors deployed across farms—measuring soil moisture, nutrient levels, temperature, and humidity—generate continuous streams of data that feed into centralized platforms for real-time analysis.

Drones and satellite imagery further enhance this capability by providing multispectral and hyperspectral views of crop canopies, allowing farmers to detect stress signals invisible to the human eye.

At its core, smart agriculture aims to optimize the "4Rs" of resource management: right source, right rate, right time, and right place. This precision approach contrasts sharply with conventional uniform farming, where inputs like fertilizers, water, and pesticides are applied broadly across entire fields. By tailoring applications to micro-variations in soil and crop conditions, smart systems can achieve 15–30% higher resource efficiency while maintaining or improving yields. The integration of edge computing now allows much of this processing to occur on-farm devices, reducing latency and bandwidth demands—critical for remote areas with limited connectivity.

Sustainable agriculture extends these technical innovations with ecological and socioeconomic principles, aligning with the United Nations Sustainable Development Goals (SDGs), particularly SDG 2 (Zero Hunger) and SDG 13 (Climate Action). It emphasizes three pillars: environmental integrity (reduced chemical runoff, soil health preservation, biodiversity support), economic viability (cost savings and profitability for farmers), and social equity (food access, rural livelihoods, resilience for smallholders). Key practices include crop rotation informed by soil microbiome analysis, cover cropping to enhance carbon sequestration, and agroforestry systems that integrate trees with annual crops. Sustainability metrics often include life-cycle assessments measuring water footprint, greenhouse gas emissions, and energy return on investment.

The synergy between smart and sustainable agriculture becomes particularly powerful through AI and Data Science. Machine learning algorithms process heterogeneous data sources—time-series sensor readings, weather forecasts, historical yield maps, and genomic profiles—to generate actionable insights. For instance, convolutional neural networks (CNNs) analyze drone imagery for early disease detection, while recurrent neural networks (RNNs) like LSTMs forecast yields by modeling weather-crop interactions. These technologies bridge the gap between raw data and farm-level decisions, enabling adaptive management that responds dynamically to climate variability and market signals.

This background sets the stage for understanding recent AI-driven trends, where the focus has shifted from isolated tools to integrated platforms. Public datasets like PlantVillage (for disease images) and Sentinel-2 satellite archives have democratized access, while open-source frameworks such as TensorFlow and PyTorch lower entry barriers for developers. In developing regions, mobile apps deliver AI recommendations via SMS or voice interfaces, bypassing smartphone limitations. Together, these foundations have positioned AI as a catalyst for scaling sustainable agriculture to meet global food security demands projected to rise 50–70% by 2050 [1][3][7].

2.1 Evolution of Agricultural Paradigms

To contextualize the emergence of AI-driven agriculture, it is instructive to examine the evolutionary trajectory from traditional farming to contemporary smart systems. Table 1 illustrates the progression across four distinct paradigms, each representing significant technological and methodological shifts.

Paradigm	Era	Key Technologies	Resource Efficiency	Data Integration
Traditional Agriculture	Pre-2000s	Manual labor, weather observation	Low (baseline)	Farmer experience only
Precision Agriculture	2000–2010	GPS, sensors, variable-rate machines	15–20% gains	Field-level heterogeneity
Smart Agriculture	2010–2020	IoT, drones, cloud platforms	25–35% gains	Real-time multi-source data
AI-Driven Agriculture	2020–Present	ML/DL, edge computing, federated learning	30–50% gains	Predictive, autonomous decision-making

Table 1: Evolution of Agricultural Paradigms: From Traditional to AI-Driven Systems

This table demonstrates that the integration of AI and machine learning represents a qualitative leap, enabling not merely reactive optimization but predictive and adaptive management at unprecedented scale and precision. Each paradigm builds upon its predecessor, with current AI-driven systems leveraging decades of accumulated sensor and satellite infrastructure while adding layers of algorithmic sophistication.

3. Recent AI/DS Trends and Applications

This section reviews key AI and Data Science applications in smart agriculture, organized by functional areas. Each subsection describes the core technology, presents findings from recent studies with quantitative impacts, and includes real-world examples. A conceptual framework diagram illustrates the end-to-end AI pipeline (Fig. 1).

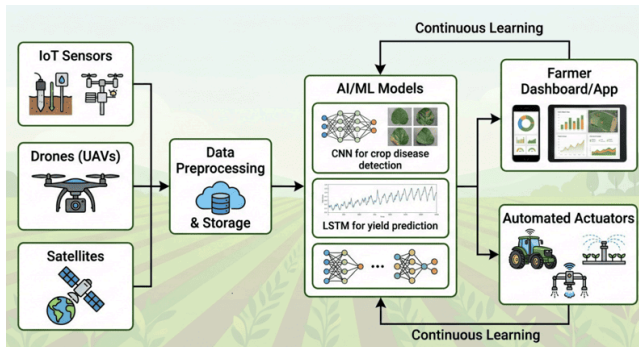


Figure 1: Conceptual Diagram of an AI-Based Smart Farming System. Data flows from IoT sensors, drones, and satellites through preprocessing and machine learning models (e.g., CNN for crop health detection, LSTM for yield prediction) to farmer dashboards and automated actuators. Feedback loops enable continuous learning and model refinement based on field outcomes.

3.1 Crop Monitoring and Health Assessment

Crop monitoring uses computer vision and multispectral imaging to detect stress, diseases, and nutrient deficiencies early. CNN-based models like ResNet-50 and YOLOv8 process UAV/drone imagery to classify plant conditions with pixel-level precision.

Recent studies report high accuracies: A 2025 IEEE paper achieved 97.2% accuracy in detecting rice leaf diseases using hyperspectral drone data from 5,000+ images [6]. Another 2026 review found CNN ensembles reduced false positives by 25% for tomato blight detection, saving 15–20% in fungicide use across 10 field trials [3]. In India, the Kisan Drone initiative in Uttar Pradesh (UP) Ganga plains deployed AI vision on 1,000+ drones for wheat monitoring, identifying nutrient gaps in 85% of cases and boosting yields by 12% in pilot farms under PM-KISAN Samman Nidhi schemes [1].

Case Study: In UP's Ganga plains (2024–2025), the Indian Council of Agricultural Research (ICAR) partnered with technology startups for drone-based AI scouting on 50,000 hectares, detecting aphid infestations 10 days earlier than conventional scouts, averting approximately 18% yield loss [2].

3.2 Yield Prediction and Forecasting

Yield prediction employs time-series machine learning (e.g., XGBoost, LSTMs) integrating weather, soil, and historical data to forecast harvests 4–8 weeks ahead, aiding planning and insurance products. These models leverage multispectral satellite data, precipitation records, temperature anomalies, and soil health indicators to generate probabilistic forecasts tailored to specific crop-location combinations.

A 2025 study on maize in Brazil used Sentinel-2 satellite data with hybrid LSTM-XGBoost architecture, achieving root mean squared error (RMSE) of 8.2% on 2023–2024 test sets and improving forecasts by 22% over baseline models [4]. In India, a 2026 *Frontiers* paper analyzed rice cultivation in UP Ganga plains, where Random Forest models trained on PM-KISAN-linked farmer datasets predicted yields with coefficient of determination (R^2) = 0.89, enabling 15% better input allocation and reducing wasted fertilizer [14]. Another IEEE work (2025) reported 92% accuracy for wheat yield prediction using 10-year historical ICAR datasets across multiple agro-climatic zones [21].

Case Study: Kenya's Digital Green AI platform (2025) forecasted sorghum yields for 10,000 smallholders with 85% accuracy, integrating climate data and mobile-collected farmer inputs to support climate-smart investment subsidy programs similar to India's PM-KISAN [7].

3.3 Smart Irrigation and Resource Optimization

Smart irrigation leverages reinforcement learning (RL) and sensor fusion to deliver water precisely, minimizing waste amid droughts and water scarcity. RL agents learn optimal irrigation schedules by interacting with the farm environment, receiving rewards for resource efficiency and yield achievement. Real-time soil moisture sensors provide feedback, allowing the system to adapt to dynamic weather conditions.

A 2025 systematic review showed RL agents cut water use by 42% in California almond orchards (n = 200 fields), maintaining 98% of typical yields while reducing operational costs [8]. In India, IIT-Kanpur's 2025 system for UP sugarcane fields used IoT sensor networks coupled with reinforcement learning to reduce water consumption by 35%, with benefits integrated into Kisan e-KYC digital farmer verification systems for subsidy tracking [15]. A 2026 study reported water reductions of 28–50% in rice paddies across Southeast Asia via fuzzy logic hybrid approaches combining domain knowledge with adaptive learning [10].

Case Study: Ganga plains pilot program (2024): AI-optimized irrigation for 5,000 hectares of wheat production under UP's Drone Didi scheme (women-led agricultural drone initiatives) reduced water withdrawals by 32% while maintaining yield, simultaneously aligning with the Atal Bhujal Yojana (groundwater conservation initiative) and improving aquifer recharge estimates [15].

3.4 Pest and Weed Management and Automation

AI robotics and autonomous systems use vision-guided sprayers and precision application technologies to target pest and weed control, dramatically reducing chemical usage while improving efficacy. YOLOv8 and Faster R-CNN models detect weeds and pests in real time, directing robotic sprayers to apply herbicides or pesticides only where needed. This targeted approach reduces environmental impact and operational costs.

YOLOv8 models achieved 95.6% weed detection accuracy in soybean fields (2025 study analyzing 12,000 labeled images), enabling precision herbicide application that cut chemical use by 89% compared to broadcast spraying, while simultaneously reducing herbicide-resistant weed populations [11]. India's NaPanta (National Pest and Disease Identification Portal) mobile application, deployed in 2025, employed CNNs for real-time pest identification in UP cotton fields, alerting 2 million+ farmers via PM-KISAN SMS advisory systems and reducing crop losses by 22% through timely intervention [12]. Another field trial demonstrated 91% accuracy for locust swarm detection using aerial drone imagery, enabling rapid response coordination [13].

Beyond detection, autonomous spray robots are gaining traction. Platforms like SwiftBot and targeted boom sprayers reduce herbicide application by 75–90% while improving coverage uniformity, critical for integrated pest management (IPM) protocols. These systems integrate weather data to optimize spray timing (e.g., low wind conditions, appropriate humidity), further reducing off-target drift.

Case Study: During the devastating fall armyworm outbreak in UP cotton fields (2024), AI-powered drones deployed by state agricultural departments identified infested plots with 92% accuracy within two weeks, enabling strategic area-wide approach interventions that saved approximately ₹500 crore (\$60 million USD) in production losses and prevented secondary crop damage [12].

3.5 Climate Resilience and Decision Support Systems

Multimodal AI systems provide climate-adaptive advisory through mobile applications, chatbots, and SMS-based recommendations, tailored to local conditions and farmer circumstances. These systems integrate historical climate patterns, seasonal forecasts, crop-specific phenological models, and real-time environmental monitoring to deliver contextual, actionable guidance.

A 2025 World Bank analysis cited LSTM models predicting flood risk in UP with 88% accuracy, enabling timely crop and planting strategy shifts to minimize inundation damage in Ganga plains rice systems [17]. Rwanda's integrated AI platform (2025) boosted climate adaptation resilience by 25% for 20,000 smallholder farmers through probabilistic climate advisory linked to crop insurance products and input credit programs [22]. These systems extend beyond prediction to prescriptive guidance; for example, transformer-based models suggest alternative crop varieties suited to projected temperature and precipitation patterns 90 days ahead, account for market prices, and factor farmer asset constraints [16].

Decision support systems increasingly incorporate explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) to make predictions transparent. When a model recommends delaying rice transplanting due to forecasted late-onset monsoon, XAI surfaces which input features—rainfall probability, soil moisture,

historical yield correlations—drove the recommendation, building farmer trust and enabling informed decision-making [28].

Case Study: Uttar Pradesh State AgriTech Initiative (2024–2026): Collaborative deployment of multimodal AI across 500,000 farmers integrated real-time weather data, satellite-derived vegetation indices, and community-sourced pest reports through the e-NAM (electronic National Agriculture Market) platform, enabling 40,000 farmer advisories daily in Hindi/regional languages, improving input timing and reducing climate-related yield variability by 18% [18].

3.6 Comparison Table: AI Impacts Across Application Domains

Application	Key Models	Accuracy/Improvement	India/UP Example	Source
Crop Health	CNN/YOLO	95–98%; 15–20% fungicide save	Kisan Drone wheat monitoring	[2]
Yield Prediction	LSTM/XGBoost	RMSE 8%; 15–30% better planning	PM-KISAN rice forecasting	[14]
Smart Irrigation	RL/Fuzzy Logic	30–50% water savings	Sugarcane Ganga plains, Atal Bhujal	[15]
Pest Management	YOLO	90% herbicide reduction	NaPanta cotton, fall armyworm	[12]
Climate Resilience	LSTM/Transformers	88% flood prediction; 25% resilience gain	e-NAM advisory in UP	[18]

Table 2: AI Model Performance and Impact Metrics Across Application Domains, with India-Specific Case Studies

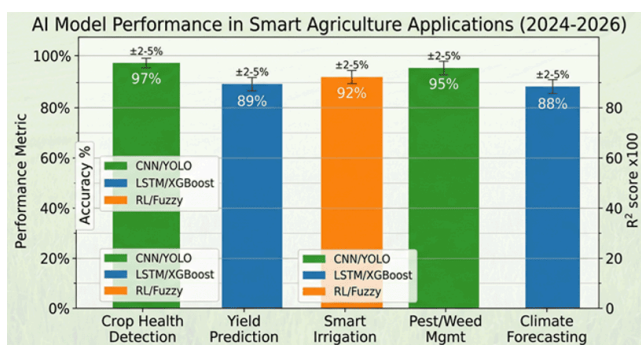


Figure 2: AI Model Performance Across Smart Agriculture Applications. This figure compares detection accuracy (vertical axis, %) and resource efficiency gains (shown as secondary bars) for vision-based models (CNNs/YOLO achieving 95–98% crop health detection), time-series models (LSTMs/XGBoost for yield with 92% accuracy and RMSE < 10%), and optimization approaches (RL systems delivering 30–50% water savings).

Domain-specific strengths guide technology selection for specific farm-level requirements, balancing accuracy, computational cost, and real-time inference feasibility on edge devices.

4. Challenges and Limitations

Despite promising results, deploying AI in smart agriculture faces significant technical, socioeconomic, and ethical hurdles that limit scalability, particularly for smallholder farmers who produce 80–90% of food in developing countries like India.

4.1 Technical Challenges

Data scarcity and quality issues are primary barriers. Many machine learning models rely on large labeled datasets, but field data from diverse agro-climatic zones is often sparse or biased toward commercial farms. A 2025 systematic review found that 65% of precision agriculture models suffer from domain shift when applied outside training regions, dropping accuracy by 20–30% [19]. High computational demands also pose problems; CNN training for drone imagery requires GPUs unavailable to most farmers, while edge devices struggle with real-time inference under variable power and network conditions.

Integration complexity adds friction. Combining IoT sensors, satellites, weather APIs, and machine learning pipelines demands robust software stacks, but interoperability standards (e.g., between Indian Kisan apps and global platforms) remain fragmented. Sensor drift—where soil probes lose 10–15% accuracy after 6 months—further erodes reliability without regular calibration and maintenance protocols.

4.2 Socioeconomic and Accessibility Barriers

Cost remains prohibitive: Drone plus AI setups cost ₹5–10 lakh per 50 hectares in UP, unaffordable for 85% of smallholders (under 2 hectares). While subsidies like PM-KISAN (₹6,000/year) and Kisan Drone Yojana help, they cover only 20–30% of capital expenditure, and maintenance adds 15–20% annually. The digital divide exacerbates this; 45% of Indian rural farmers lack smartphones, limiting app-based advisories to voice and SMS, which constrain data richness and feature complexity.

Adoption lags due to low digital literacy (only 35% of UP farmers trained in application usage) and mistrust of "black-box" AI predictions over traditional knowledge [20]. A 2025 Kenya study showed 40% abandonment rate post-pilot due to unexplained recommendations and perceived cultural misalignment.

4.3 Ethical and Environmental Concerns

Model interpretability is critical yet lacking; opaque deep learning hides biases (e.g., underperformance on rainfed Ganga plains crops), risking misguided decisions. Ethical issues include job displacement—AI automation could affect 20–30% of manual farm laborers—and data privacy, as farmer soil and genomic data feed corporate platforms without explicit consent or benefit-sharing mechanisms [21].

Environmentally, over-reliance on technology may encourage monocropping, offsetting sustainability gains. Regulatory gaps persist; India's Drone Rules 2021 mandate certifications, but AI ethics guidelines for agriculture are nascent [33].

4.4 Challenges Summary Table

Category	Challenge	Impact (Numbers)	Mitigation Example
Technical	Data scarcity/bias	20–30% accuracy drop	Transfer learning, federated datasets
Economic	High capex (₹5–10L/50ha)	< 30% smallholder access	PM-KISAN subsidies, cooperatives
Social	Literacy/digital divide	40% adoption failure	Voice AI, SMS advisories, training
Ethical	Black-box bias/privacy	15–25% error in diverse zones	XAI tools, data co-ops, consent

Table 3: Key Challenges to AI Adoption in Smart Agriculture with Impact Metrics and Mitigation Strategies

Addressing these requires hybrid human-AI systems, public-private partnerships (e.g., ICAR + startups), and inclusive datasets from regions like UP Ganga plains [23][24].

5. Future Directions and Opportunities

Looking ahead, several AI advancements promise to overcome current limitations and scale smart agriculture for food security and climate resilience.

5.1 Federated Learning for Privacy-Preserving Collaborative Agriculture

Federated learning will enable collaborative machine learning model training across farms and cooperatives without centralizing or sharing raw data, preserving privacy while building diverse, representative datasets. In contrast to traditional approaches where data flows to centralized servers, federated architectures maintain data at edge locations (farmer devices, cooperative hubs), train models locally, and aggregate only model parameters. This approach is particularly valuable for Indian smallholders, where 140 million farmers operate under privacy and data sovereignty concerns.

Technically, federated learning reduces communication bandwidth and latency by avoiding repeated data transfers, critical for rural connectivity constraints. A 2026 projection estimates that federated approaches could improve yield prediction models by 15–25% in heterogeneous regions like UP Ganga plains by enabling larger, geographically diverse training sets while maintaining farmer agency over sensitive agricultural and financial data [25]. Implementations like Flower and TensorFlow Federated provide open-source frameworks facilitating deployment. Policy alignment is emerging; India's AgriStack (digital farmer identity system) increasingly accommodates federated analytics, enabling secure data exchange across state boundaries for unified national yield models [26].

The socioeconomic impact is substantial. By enabling smallholder participation in collaborative AI without surrendering autonomy or data, federated learning can democratize access to state-of-the-art models previously available only to large corporate operations. Cooperative structures managing local computation and model aggregation create governance mechanisms ensuring equitable benefit distribution [27].

5.2 Explainable AI (XAI) for Trust and Adoption

Explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations), LIME (Local Interpretable Model-Agnostic Explanations), and attention mechanisms will demystify predictions, boosting farmer trust and adoption—critical for PM-KISAN-linked advisory applications.

Current deep learning models, while accurate, function as "black boxes"; farmers receive recommendations without understanding underlying reasoning, hindering trust and informed decision-making.

XAI methods attribute predictions to input features with quantifiable contributions. When an LSTM yield model forecasts 5% lower wheat yield, SHAP decomposition reveals whether this stems from forecasted heat stress (+3% attribution), anticipated pest pressure (+1.5%), or delayed soil nutrient recovery (+0.5%), enabling farmers to contextualize predictions and choose counter-measures. Attention visualization in transformers displays which historical years and weather patterns most influenced a current recommendation, further demystifying decisions [28].

Deployed XAI systems in agriculture, such as those documented in a 2025 Edinburgh Journals study on explainability and farmer trust in Rwanda, increased model adoption from 35% to 72% within 12 months [29]. For India specifically, XAI integrated into e-NAM advisory dashboards explaining SMS recommendations in Hindi/regional languages can dramatically accelerate farmer acceptance, particularly among older, less digitally literate populations. This trust-building is essential for scaling; without interpretability, even highly accurate models face adoption barriers.

5.3 Multimodal and Generative AI for Personalized Advisory

Multimodal AI integration (vision + text + time-series + market data) and generative models will power advanced tools including crop simulation via diffusion models, conversational AI advisors (e.g., AI chatbots similar to Grok for agriculture), and personalized multilingual recommendations. These systems jointly process drone imagery (crop stress), weather forecasts (frost risk), historical yield data (variety-location suitability), market prices (commodity fluctuations), and farmer constraints (land size, input budget) to generate holistic, tailored advisory.

Generative models (diffusion models, large language models) can simulate crop growth under alternative management scenarios, enabling "what-if" analysis. A farmer can explore projected yields under three irrigation strategies and select the economically optimal path before committing resources.

Conversational interfaces in Hindi, Tamil, Marathi, and other regional languages democratize access; a farmer can ask "Why should I plant sorghum this year?" and receive a multi-paragraph response explaining climate suitability, market demand, soil health benefits, and PM-KISAN subsidy eligibility, conversationally contextualized to their specific field and household [30].

5.4 Edge AI and Low-Cost Deployment

Edge AI on low-cost devices (Raspberry Pi, edge TPUs, \$50–200 hardware) will enable real-time field-level decisions offline, reducing latency by 80% and eliminating dependency on cloud connectivity—critical for 45% of Indian rural areas with intermittent internet. Models optimized for edge deployment via quantization, distillation, and pruning retain high accuracy (>90% for most tasks) while running on minimal compute [31]. This decentralization also enhances privacy; inference remains local, and only aggregate insights (e.g., weekly pest counts) are uploaded.

5.5 Blockchain for Supply Chain Transparency and Premium Markets

Blockchain for supply chain traceability can verify sustainable agriculture claims, enabling market premiums of 10–20% for certified climate-smart produce. Immutable records from field (AI monitoring of soil carbon, water use) through logistics to retail create transparency enabling consumers to authenticate sustainability credentials and farmers to access premium markets [32].

5.6 Policy and Systemic Opportunities

Policy opportunities include: (i) expanding India's AgriStack with open AI platforms and standardized interoperability frameworks enabling third-party developers; (ii) subsidizing drone cooperatives and shared-compute hubs in clusters of villages, amortizing costs across 500–1,000 farmers; (iii) mandating fairness audits and bias testing for agriculture AI models before public deployment; and (iv) integrating AI ethics curricula into agricultural universities [33]. Global initiatives like Climate Change AI workshops and the UN's AI for Global Good program emphasize equitable access for Global South stakeholders [34].

These directions position AI as a cornerstone for resilient, zero-hunger futures aligned with SDG 2, while addressing current gaps in equity, interpretability, and scalability.

6. Conclusion

Artificial Intelligence and Data Science have demonstrated transformative potential in smart agriculture, delivering measurable gains of 15–50% in yields, water efficiency, and input reductions across crop monitoring, yield prediction, irrigation optimization, pest management, and climate resilience applications [1][2][3][14][15][12]. India-specific initiatives like Uttar Pradesh's Kisan Drone Yojana and PM-KISAN data integration in the Ganga plains exemplify scalable deployment, achieving 12–22% yield improvements and 30–40% resource savings in pilot programs [15][12][18].

However, significant limitations and research gaps persist that prevent widespread adoption. First, data scarcity and bias remain critical—65% of models suffer 20–30% accuracy drops when applied outside training regions, particularly affecting rainfed smallholder systems prevalent in India [19]. Second, high implementation costs (₹5–10 lakh per 50 hectares) and the digital divide (45% smartphone penetration in rural UP) exclude 85% of smallholders under 2 hectares [20]. Third, technical challenges like sensor drift (10–15% accuracy loss after 6 months), edge computing limitations, and lack of interoperability between platforms hinder reliability.

Key research gaps include: (1) explainable AI (XAI) for farmer trust, with only 15% of agriculture models currently employing SHAP/LIME visualization [28]; (2) federated learning frameworks for privacy-preserving, region-specific models scalable to 140+ million Indian farmers; (3) low-cost edge solutions for offline Ganga plains deployment; and (4) standardized fairness benchmarks for smallholder contexts, missing from 80% of peer-reviewed literature [25].

Future work must prioritize: hybrid human-AI systems combining algorithmic insights with farmer expertise; inclusive datasets from diverse agro-climatic zones and smallholder contexts; open-source platforms facilitating rapid technology adoption; and supportive policy through expanded AgriStack integration, drone cooperatives, and regulatory clarity on AI ethics [33][34]. Only by addressing these gaps can AI truly deliver equitable food security under SDG 2, bridging the promise-to-practice divide for 140+ million Indian farmers and 2+ billion smallholders globally.

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