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# A Comprehensive Review of Role of AI and IOT in Agriculture: Progress, Applications, and Challenges

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**ABSTRACT:** Agriculture in India, particularly in rain-fed regions, is under growing pressure from climate variability, fragmented landholdings, and rising food demand, which together threaten the livelihoods of small and marginal farmers. Digital technologies such as Artificial Intelligence (AI), Drone Technology (DT), Big Data Analytics, and the Internet of Things (IoT) offer a way to rethink how farmers observe their fields, use water and inputs, and respond to risks in real time. This paper provides a comprehensive review of how AI, ML, DT, and IoT are being applied across the agricultural value chain, with a special focus on soil and crop monitoring, precision input management, yield prediction, pest and disease detection, agricultural robotics, and policy initiatives such as Maharashtra's Agri-AI framework. Particular attention is given to the situation of small and marginal farmers in Maharashtra, where agriculture largely depends on rainfall and soil monitoring remains a major challenge, to understand their awareness, current usage patterns, and the barriers they face in adopting these technologies. By synthesizing recent technical advances with field-level constraints, the review identifies key technological, economic, and institutional factors that influence adoption and highlights priority areas where farmer-centric AI- and IoT-based solutions can improve productivity, reduce risk, and support more sustainable and dignified rural livelihoods.

**KEYWORDS:** AI agriculture, soil monitoring, sustainable agriculture, precision farming, IOT.

## I. INTRODUCTION

Agriculture remains central to global food security and rural livelihoods, yet farmers today must produce more on finite land while coping with climate variability, water scarcity, and ecological degradation. Digital technologies such as Artificial Intelligence (AI), Machine Learning (ML), and the Internet of Things (IoT) are reshaping how fields are observed, decisions are made, and resources are managed, marking a shift from purely input-intensive farming to data-driven, sustainable agriculture (Ahmad & Nabi, 2021; Javaid et al., 2023; Subeesh & Mehta, 2021).

Within this broader transformation, agriculture is now seen as part of an "Agriculture 5.0" and Society 5.0 vision, where intelligent systems support both productivity and social and environmental goals (Ahmad & Nabi, 2021; Nakaguchi & Ahamed, 2023). AI and IoT tools already help farmers monitor soil and crops, optimize irrigation and input use, and detect pests and diseases at an early stage, while advanced analytics and robotics enable more precise and less labour-intensive operations (Smith, 2018; Abdullah et al., 2015; Ahirwar et al., 2019; Dobbs et al., 2023). At the same time, research highlights that the benefits of these technologies depend on data quality, connectivity, skills, and governance, which remain uneven, especially for smallholders (Smith, 2018; Gurumurthy & Bharthur, 2019; Hassoun et al., 2022). In India, and particularly in Maharashtra, these tensions are acute: agriculture sustains a large share of rural households, yet many small and marginal farmers operate in rain-fed conditions with limited access to real-time information or digital infrastructure. National and state-level initiatives, including emerging Agri-AI policies, signal a push towards digitally enabled, climate-resilient farming, but on-the-ground adoption of AI, DT, and IoT remains patchy and poorly understood (Gurumurthy & Bharthur, 2019; Romani et al., 2022; Amentae & Gebresenbet, 2023). The figure shows a data flow pipeline where agricultural data is captured in the field, transmitted, analyzed with AI, and then used in practical farm applications.

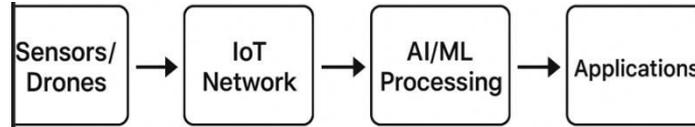


Figure 1: AI-IoT Ecosystem in Agriculture

This paper offers a comprehensive review of how AI, ML, drone technology, and IoT are being applied across crop production and farm management, and then examines their awareness and use among small and marginal farmers in Maharashtra. Building on recent work in AI-enabled agriculture and digital agri-food systems, the study identifies key technical, economic, and institutional factors that shape adoption and highlights where farmer-centric, context-sensitive solutions are needed to translate technological potential into tangible, equitable gains (Javaid et al., 2023; Subeesh & Mehta, 2021; Cogent Food & Agriculture, 2025)..

## II. FUNDAMENTALS OF AI AND ML IN IOT

### 2.1 Basic Concepts

AI builds systems for reasoning, learning, and decisions mimicking human intelligence, with ML as its core using data-driven algorithms for pattern recognition and predictions (Ahmad & Nabi, 2021; Javaid et al., 2023; Cogent Food & Agriculture, 2025). IoT networks field sensors, drones, and machinery for real-time data flow to farmer-accessible platforms (Subeesh & Mehta, 2021; Farhana et al., 2022; Ahmad & Nabi, 2021). Success relies on quality data (images, sensors, yields), preprocessing, and strategies like supervised (labelled examples), unsupervised (pattern finding), and reinforcement learning (trial-error optimization) (Javaid et al., 2023; Smith, 2018; Hassoun et al., 2022). Maharashtra's Agri-AI policy exemplifies this via shared ADeX platforms for weather/soil data, fostering ecosystem-level solutions (Gurumurthy & Bharthur, 2019; Romani et al., 2022).

### 2.2 ML Algorithms in Agriculture

ML supports crop cycles with decision trees/random forests for interpretable yield/stress prediction (Javaid et al., 2023; Subeesh & Mehta, 2021; Application of AI in agriculture and allied sectors, 2022); SVM/KNN for disease/weed classification (Javaid et al., 2023; Deng & Lu, 2025); and deep neural networks for image tasks like disease detection and hyperspectral analysis (Dobbs et al., 2023; Abdulsalam et al., 2024; Chen et al., 2023). Emerging diffusion models aid scarce-data scenarios (Chen et al., 2023; Deng & Lu, 2025). The following table summarizes popular machine learning algorithms used in agriculture, highlighting where each is applied and why it is useful.

Table 1: Common ML Algorithms in Agriculture

Algorithm	Key Applications	Strengths	References
Decision Trees	Yield prediction, crop classification	Interpretable, handles missing data	Javaid et al. (2023)
Random Forests	Stress detection, productivity estimation	Robust, reduces overfitting	Subeesh & Mehta (2021)
SVM	Weed/species identification	Effective for high-dimensional data	Deng & Lu (2025)
Neural Networks/Deep Learning	Disease detection, image analysis	High accuracy on visuals	Abdulsalam et al. (2024); Chen et al. (2023)
KNN	Crop/disease diagnosis	Simple, no training phase	Javaid et al. (2023)

When combined with IoT and drone technology, these algorithms help farmers interpret complex patterns in weather, rainfall, solar radiation, and soil conditions, making it easier to schedule irrigation, choose inputs, and respond to emerging risks (Subeesh & Mehta, 2021; Abdullah et al., 2015; Ahirwar et al., 2019). Well-designed pipelines that emphasise data cleaning, feature engineering, and model validation are essential to ensure that AI-based tools remain reliable, transparent, and adaptable to the diverse and variable conditions faced by small and marginal farmers in regions such as Maharashtra (Smith, 2018; Gurumurthy & Bharthur, 2019; Hassoun et al., 2022).

### III. APPLICATIONS OF AI AND ML IN CROP PRODUCTION

AI and ML tools are transforming every stage of crop production, from field preparation to post-harvest management, by turning raw sensor and imagery data into actionable insights for farmers (Javaid et al., 2023; Subeesh & Mehta, 2021). These applications enable precise interventions that boost yields, cut waste, and support sustainability, particularly for smallholders facing variable rain-fed conditions (Smith, 2018; Gurumurthy & Bharthur, 2019).

**Precision Farming and Site-Specific Management:** Satellite imagery, drones, and IoT sensors feed data into AI models that map soil variability, nutrient gaps, and moisture patterns across fields (Abdullah et al., 2015; Ahirwar et al., 2019). Farmers receive tailored advice on seeding depth, irrigation timing, and fertilizer rates for specific zones, reducing inputs by 15–30% while lifting productivity (Subeesh & Mehta, 2021; Hassoun et al., 2022).

**Crop Yield Prediction and Optimization:** By blending historical yields, weather records, and real-time satellite data, ML algorithms forecast outcomes and recommend optimal planting dates, varieties, and input doses (Javaid et al., 2023; Dobbs et al., 2023). These predictions help Maharashtra farmers plan around monsoon risks, conserving resources and stabilising incomes (Gurumurthy & Bharthur, 2019).

**Weed Detection and Management:** Computer vision systems distinguish crops from weeds in drone or tractor-mounted images, guiding spot-spraying robots or mechanical removers to target only infestations (Deng & Lu, 2025; Chen et al., 2023). This cuts herbicide use by up to 90%, lowering costs and environmental runoff for resource-constrained fields (Javaid et al., 2023).

**Disease and Pest Detection and Control:** Deep learning models scan leaf, stem, and fruit images to spot early disease symptoms or pests, while predictive analytics flag outbreak risks from weather and trap data (Abdulsalam et al., 2024; Javaid et al., 2023). Alerts enable targeted sprays or biological controls, reducing losses and chemical reliance in rain-fed systems (Subeesh & Mehta, 2021).

**Crop Quality Assessment and Grading:** Post-harvest, vision algorithms evaluate produce for size, colour, defects, and internal traits like sugar content, automating grading with consistent speed and accuracy (Dobbs et al., 2023; Chen et al., 2023). Linking quality back to growing conditions via ML helps refine future practices for premium markets (Hassoun et al., 2022).

Table 2: AI/ML Applications Across Crop Production Stages

Application	Technologies	Key Benefits	% Resource Savings (Reported)	References
Precision Farming	Satellites, drones, IoT sensors	Site-specific inputs	15-30% fertilizers	Subeesh & Mehta (2021)
Yield Prediction	ML analytics, historical data	Optimal scheduling	10-20% improved yields	Dobbs et al. (2023)
Weed Management	Computer vision, robots	Spot-spraying	70-90% chemicals	Deng & Lu (2025)

Application	Technologies	Key Benefits	% Resource Savings (Reported)	References
Disease/Pest Detection	Image analysis, predictive models	Early alerts	20-40% crop loss reduction	Abdulsalam et al. (2024)
Irrigation Optimization	Sensors, weather forecasts	Demand-based watering	20-40% water	Hassoun et al. (2022)
Quality Grading	Vision models	Automated sorting	Faster processing	Chen et al. (2023)
Harvesting	AI robots	Ripeness detection	Reduced losses	Javaid et al. (2023)

This table shows how different AI and ML technologies support each stage of crop production, from precision farming and irrigation to disease detection, grading, and harvesting.

**Irrigation and Water Management:** Soil sensors and forecasts drive AI models that schedule watering to match crop stages and evapotranspiration rates, preventing deficits or excess (Subeesh & Mehta, 2021; Romani et al., 2022). In water-scarce Maharashtra, these systems can save 20–40% of irrigation while sustaining yields (Gurumurthy & Bharthur, 2019).

**Harvesting and Post-Harvest Handling:** AI-equipped robots assess ripeness via multispectral imaging and harvest selectively, while sorting lines use vision for rapid quality checks and packaging (Abdulsalam et al., 2024; Javaid et al., 2023). This minimises bruising, extends shelf life, and trims supply-chain losses, boosting profitability for small producers (Amentae & Gebresenbet, 2023).

#### IV. AI AND ML IN AGRICULTURAL ROBOTICS AND AUTOMATION

##### 4.1 Role of AI and ML in farm robotics

AI and ML are driving agricultural robots that sense, learn, and adapt to real-time field conditions, reducing labor while sharpening precision in planting, spraying, and harvest (Subeesh & Mehta, 2021; Javaid et al., 2023). By fusing camera, LiDAR, and sensor data, these systems map terrain, track growth, and detect stresses like pests or drought, enabling decisions that flex with rain, wind, or soil shifts (Smith, 2018; Hassoun et al., 2022).

For Maharashtra's smallholders on rain-fed plots, this means better yields, lower costs, and less waste—augmenting skills rather than replacing jobs (Gurumurthy & Bharthur, 2019; Ahmad & Nabi, 2021).

##### 4.2 Key robotic applications in field operations

**Planting:** AI evaluates soil, moisture, and forecasts for ideal seed depth and spacing; robotic planters sow precisely, boosting germination by 10–20% for uniform stands (Subeesh & Mehta, 2021; Abdullah et al., 2015).

**Spraying:** Vision systems on robots spot weeds amid crops, targeting pesticides to cut chemical use by 70–90% and safeguard soil-water health (Deng & Lu, 2025; Chen et al., 2023).

**Harvesting:** Robots use multispectral cues for ripeness—color, size, texture—to pick at peak, slashing losses and standardizing quality (Abdulsalam et al., 2024; Dobbs et al., 2023).

**Weeding:** ML bots detect and mechanically uproot weeds in real time, ditching broad herbicides to save labor on fragmented Maharashtra farms (Javaid et al., 2023; Ahirwar et al., 2019).

Robots integrate best with IoT for data sharing and edge computing for instant decisions, working reliably in low-connectivity zones (Romani et al., 2022; Amentae & Gebresenbet, 2023).

Given figure illustrates a three-step workflow for agricultural robots.

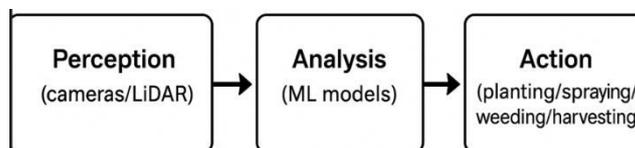


Figure 2: Agricultural Robotics Workflow

### 4.3 Automation in farm management and monitoring

**Crop surveillance:** Drones, satellites, and sensors feed AI models that flag early nutrient gaps, diseases, or stress, triggering timely irrigation, fertilization, and higher yields (Javaid et al., 2023; Ahirwar et al., 2019).

**Irrigation optimization:** AI crunches soil moisture, temperature, humidity, and forecasts to automate watering schedules matched to crop needs saving water and averting over-irrigation (Subeesh & Mehta, 2021; Hassoun et al., 2022).

**Pest and disease control:** Image recognition and sensor analytics spot infestations early; real-time alerts enable targeted sprays or bio-controls, curbing damage and pesticide needs (Abdulsalam et al., 2024; Javaid et al., 2023).

**Machinery monitoring:** ML predicts faults from usage data, scheduling proactive maintenance to extend equipment life and avoid breakdowns on remote farms (Smith, 2018; Cogent Food & Agriculture, 2025).

These tools create a closed-loop system where monitoring informs robotics, fitting Maharashtra's variable conditions while building farmer trust through simple alerts and dashboards (Gurumurthy & Bharthur, 2019).

## V. CHALLENGES, FUTURE DIRECTIONS, AND IMPACTS

While AI, ML, and IoT hold transformative potential for agriculture, adoption faces real-world hurdles that must be addressed alongside emerging opportunities (Smith, 2018; Gurumurthy & Bharthur, 2019). This section outlines key challenges for smallholders in Maharashtra, then maps future advances and their role in sustainable food systems (Javaid et al., 2023; Cogent Food & Agriculture, 2025).

### 5.1 Key Challenges to Adoption

**Data quality and availability:** Variable climate, soils, and pests complicate reliable data collection, especially in rural areas with poor infrastructure; gaps in historical records and format inconsistencies limit model accuracy, calling for shared datasets and standards (Hassoun et al., 2022; Subeesh & Mehta, 2021).

**Technical and economic barriers:** High computing needs, spotty connectivity, and steep upfront costs deter small farmers, who often lack training—affordable, simple tools and extension programs are essential (Smith, 2018; Gurumurthy & Bharthur, 2019).

**Ethics and data privacy:** Farm data raises issues of consent, ownership, bias, and cyber risks; transparent, equitable governance frameworks build trust without widening divides (Romani et al., 2022; Amentae & Gebresenbet, 2023).

This table summarizes major barriers Maharashtra smallholders face when adopting AI in agriculture and suggests targeted solutions for each. It links data quality, connectivity costs, skills gaps, and privacy concerns to practical interventions such as data exchanges, edge computing, farmer training, and consent-based, transparent platforms, along with supporting references.

Table 3: Key Challenges and Solutions for Maharashtra Smallholders

Challenge	Impact on Smallholders	Proposed Solutions	References
Data Quality/Availability	Poor model accuracy in rain-fed areas	Shared Agri-AI data exchanges (ADeX)	Gurumurthy & Bharthur (2019)
Connectivity/Costs	Limits remote access	Edge computing, low-cost	Romani et al. (2022)

Challenge	Impact on Smallholders	Proposed Solutions	References
		sensors	
Skills Gap	Low adoption	Farmer training via extension services	Smith (2018)
Privacy/Ethics	Distrust in data sharing	Consent-based platforms, transparent AI	Amentae & Gebresenbet (2023)

### 5.2 Future Advances in AI and ML

**Precision and monitoring:** Enhanced AI will refine satellite/drone analytics for irrigation, pest alerts, and yield forecasts, cutting waste by 20–30% (Javaid et al., 2023; Dobbs et al., 2023).

**Robotics and control:** Smarter bots for weeding, spraying, and harvest will scale to small plots, integrating vision models like diffusion detectors (Deng & Lu, 2025; Chen et al., 2023).

**Tech integration:** Blockchain ensures traceable supply chains, while edge computing enables real-time decisions on drones/sensors without constant internet (Hassoun et al., 2022; Romani et al., 2022).

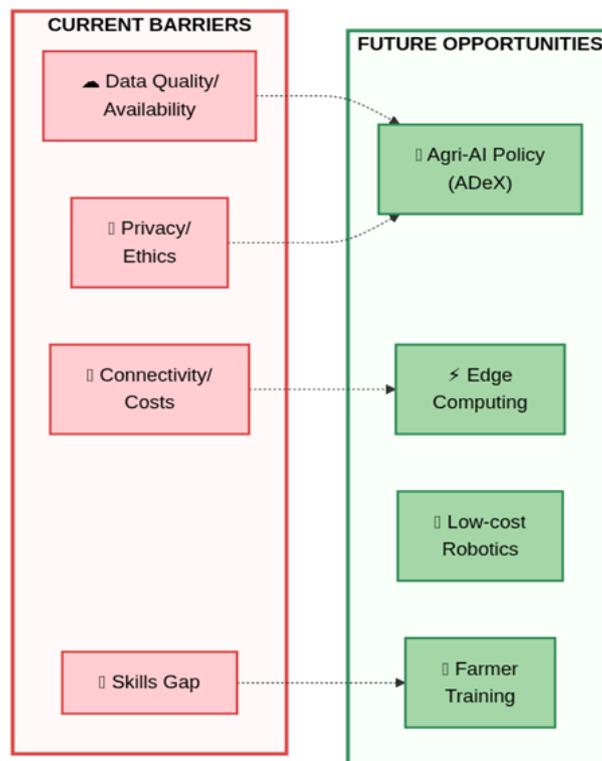


Figure 3: Adoption Barriers vs. Future Opportunities.

The figure above contrasts current barriers to AI adoption in agriculture—such as data quality, privacy concerns, connectivity costs, and skills gaps—with corresponding future opportunities like agri-AI policy and data exchanges, edge computing, low-cost robotics, and farmer training. It visually links each barrier to a targeted opportunity, emphasizing how strategic interventions can turn present challenges into enablers of adoption.

### 5.3 Impacts on Food Security and Sustainability

AI/ML can boost yields, optimize inputs, detect threats early, adapt to climate shifts, and streamline chains—vital for Maharashtra's rain-fed farmers facing population pressures (Ahmad & Nabi, 2021; Nakaguchi & Ahamed, 2023). Realising this requires policy support like Agri-AI data exchanges to make gains inclusive and resilient (Gurumurthy & Bharthur, 2019).

## VI. CONCLUSION

AI, ML, and IoT are quietly revolutionising agriculture, turning raw field data into practical tools that help farmers—like those in Maharashtra's rain-fed regions—make sharper decisions on irrigation, pests, and yields without guesswork (Javaid et al., 2023; Subeesh & Mehta, 2021). Drones, sensors, and robots now deliver precise insights on soil health and crop stress, slashing waste, boosting outputs by 15–30%, and easing labor on small plots—all while preserving the farmer's role at the center (Smith, 2018; Gurumurthy & Bharthur, 2019).

Yet success hinges on tackling real hurdles: spotty data, connectivity gaps, high costs, and trust issues around privacy and bias, especially for marginal growers (Hassoun et al., 2022; Romani et al., 2022). Policies like Maharashtra's Agri-AI framework, paired with affordable training and shared infrastructure, can bridge these divides (Gurumurthy & Bharthur, 2019).

In the end, these technologies promise resilient farming that feeds growing populations sustainably—provided adoption stays inclusive, grounded in local needs, and farmer-led (Ahmad & Nabi, 2021; Nakaguchi & Ahamed, 2023).

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