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Review article

Artificial intelligence in agriculture: Techniques and Outcomes

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ABSTRACT

Artificial Intelligence (AI) is emerging as a transformative driver of modern agriculture by enabling intelligent, data-driven solutions across crop production, soil and water management, climate forecasting, pest and disease detection, livestock monitoring, and supply chain optimization. The review article systematically addresses and provides answers to the five-research scope of purpose. This review establishes the relevance of AI to current agricultural needs by synthesizing how these technologies align with the demands of precision, sustainability, and resilience. The article highlights the agricultural parameters such as yield, soil health, water resources, and livestock well-being that are being effectively monitored and managed through AI applications. It examines key techniques including machine learning, deep learning, computer vision, and robotics, which underpin advancements in predictive analytics, automation, and decision support. The review evaluates measurable outcomes, including yield improvements, reduced chemical and water use, enhanced energy efficiency, and optimized post-harvest processes. Finally, the study identifies major challenges such as data heterogeneity, affordability barriers, digital literacy gaps, and ethical concerns, while also discussing future prospects for broader and equitable adoption. This review provides actionable insights for researchers, practitioners, education, extension and policymakers, contributing to the development of sustainable and resilient agricultural practices through AI by aligning its findings with this scope of purposes.

Keywords: Artificial Intelligence, Agriculture, Precision Farming, Machine Learning, Deep Learning, Smart Farming

Agriculture is one of the most important sectors in human civilization being backbone of food supply, rural economy, and socio-economic growth worldwide. The demand of food is consistently increased due to world population is growing at unprecedented rate in history for development of sustainable livelihood. Therefore, the conventional agriculture is unable to meet these growing demands. The promotion of agricultural research and innovation is required under emerging global challenges like climate change, population increase, environmental degradation, and resource limitation. With the growing need for sustainable food systems and precision agriculture practices, the research environment in agriculture has grown significantly, incorporating a wide array of topics varying from plant science, soil science, and agroecology to technological applications such as AI, the Internet of Things (IoT), remote sensing, and machine learning (ML). The incorporation of sophisticated automated technologies is becoming a necessity not just to enhance food production but also to sustain the livelihoods of over a billion people worldwide (Dahiya *et al.,* 2024; Gupta *et al.,* 2018).

During the industrial revolution in the 19th century, the deployment of machines is significantly required to shift from manual labour to mechanized production. The rapid advancement of information technology in the 20th century, particularly following the development of computers and its associated technology like AI

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and IoT was established. Today, AI has evolved into a transformative force, gradually but decisively augmenting and, in many areas, replacing traditional human labour across industries (Bhati *et al.,* 2020; Kumar *et al.,* 2021a; Mathivanan *et al.,* 2024; Punia *et al.,* 2021; Rajasekar *et al.,* 2023). In current scenario, the agriculture sector faces many challenges like labour shortages, increasingly stringent regulations, and a declining number of active farmers, which needs to search a technology-based solutions like the IoT, big data analytics, AI/ML. These technologies are providing more efficient and productive data-driven decision-making, precision agriculture, and sustainable resource utilization for transforming of farming (Kumar *et al.,* 2021b; Mohammed & Munir, 2025).

Farmers can determine the optimal timing for harvesting fruits, grains and vegetables with overall high-quality using AI technologies (Onyeaka *et al.,* 2023). AI technologies also used for continuous monitoring of soil and crop health, facilitating timely interventions and better resource management (Laskar, 2024; Sharma *et al.,* 2024). Real-time data analysis improves crop production by supporting more precise and efficient farming practices (John & Rose, 2024). Furthermore, AI integration with other technologies promotes smarter water usage for optimizing yields and it is beneficial to conserve this critical resource (Siva *et al.,* 2024). The integration of AI with robotics and drones for agricultural operations further expands capabilities of these systems to detect weeds, pests, and diseases, identify nutrient deficiencies, and assess crop yield and quality with high accuracy to get more resilient and productive farming systems (Kumar *et al.,* 2024).

In spite of above a review article on AI in agriculture is essential to synthesize the rapidly expanding knowledge and limitations of research and innovation in this interdisciplinary field. A comprehensive review will help clarify current techniques, assess the effectiveness of AI-driven solutions, and identify emerging trends, gaps, and future research directions. This article will be valuable not only for researchers and practitioners but also for policymakers, education, extension and agribusiness stakeholders seeking to harness AI for enhanced agricultural productivity and sustainability. This review article is directed by the following key research scope of purposes:

- How artificial intelligence is relevant to the needs of modern agricultural systems?
- Which key agricultural parameters are currently being effectively monitored and managed using AI techniques?
- What are the major AI techniques being applied in different domains of agriculture?
- What are the measurable outcomes and impacts of AI implementation on agricultural productivity, sustainability, and decision-making processes?
- What are the current challenges, limitations, and future prospects associated with the integration of AI technologies in agriculture?

CONCEPT OF AI AND ITS RELEVANCE TO MODERN AGRICULTURAL SYSTEMS

AI in agriculture encompasses the use of computers and algorithms to mimic cognitive functions learning from data and making intelligent decisions to improve farming practices. AI can integrate with machines to analyse vast datasets such as weather records, soil sensor readings, crop images, etc. and draw predictions that would be difficult for humans to discern manually. In agriculture, these capabilities translate into systems that can forecast crop yields, diagnose plant diseases from images, optimize irrigation and fertilizer use, and even drive farm machinery autonomously.

Machine learning models can also integrate sensor data (soil moisture, temperature, etc.) to recommend optimal farm management actions like when and how much to irrigate or fertilize. Traditional agricultural practices struggle to keep pace with rising food demand and environmental challenges. AI offers a way to "*farm smarter*" leveraging data and automation to make better decisions in real time. For instance, precision agriculture powered by AI uses GPS-guided equipment, drones, and IoT sensors to gather real-time data on crop and field conditions. AI analytics then interpret these data to guide precise interventions such as seeding at the right density, delivering water or fertilizer exactly where needed, or spotting disease outbreaks early. Such intelligence-driven farming can significantly boost yields and reduce waste, which is essential for sustainable intensification. Moreover, AI aligns with the concept of integrated farm management and precision farming by giving farmers new tools to control and optimize every aspect of production. Drones equipped with AI can survey large fields swiftly to detect crop stress or pest hotspots, enabling timely and targeted responses. Ground robots and autonomous tractors can handle labor intensive tasks like weeding, planting, or harvesting with high efficiency, addressing rural labor shortages. AI-driven platforms also provide decision support: for example, forecasting models predict weather and market trends, helping crops planting plan or marketing strategies with greater confidence. In essence, AI acts as a force multiplier for farmers extending their knowledge and capabilities by analysing complex data and automating decisions that lead to improved outcomes. Table 1 depicts a summary of artificial intelligence/machine learning techniques used in agriculture and Table 2 provides some important data sources used in the application of AI for agriculture. As one recent study notes, "*AI gives new meaning to modern agriculture*" by making farming more intelligent, accurate, and productive. Given the global imperative to produce more food sustainably, AI potential to increase agricultural production, profitability, and adaptability makes it a highly relevant tool in modern agricultural systems.

ARTIFICIAL INTELLIGENCE APPLICATIONS IN AGRICULTURE

Artificial intelligence has many applications in the agriculture and its related areas which are provided in Fig. 1 and elaborated in the following sub sections.

Table 1: Summary of artificial intelligence /machine learning methods used in agriculture

ML techniques	Suitable relationships	Key strengths	Limitations	Evaluation metrics	Typical use cases in agriculture
Linear Regression (LR) (Rai *et al.,* 2022)	Linear	Simple, interpretable	Poor performance with nonlinear data	R^2, RMSE	Yield prediction from few agronomic parameters
Support Vector Machine (SVM) (Das *et al.,* 2020)	Linear & Non-linear (with kernels)	High accuracy on small datasets	Sensitive to parameter tuning	Accuracy, Precision, Recall	Crop classification, pest disease detection
Random Forest (RF) (Ali *et al.*, 2015)	Non-linear	Handles large variables, robust	Less interpretable	R^2, RMSE, MAE	Soil moisture mapping, biomass estimation
Gradient Boosting (GBM/XGBoost/ LightGBM) (Huber *et al.,* 2022)	Non-linear	Best for tabular data, high performance	Risk of overfitting	RMSE, MAE, R^2	Yield forecasting, phenology prediction
Artificial Neural Networks (ANN) (Fenu *et al.,* 2021)	Highly non-linear	Learns complex relationships	Requires large data	Accuracy, Loss	Climate-crop modeling, disease diagnosis
Convolutional Neural Networks (CNN) (Sa *et al.,* 2018)	Spatial features	Works well with imagery	Computationally heavy	IoU, F1-score	Crop type mapping, weed detection
Deep Learning (RNN/LSTM) (Hewage *et al.,* 2020)	Temporal relationships	Captures seasonal trends	Needs long time-series	MAE, RMSE	Weather-based yield forecasting

Table 2: Data sources and application areas for artificial intelligence in agriculture

Data source	Platform/Examples	Derived features	Application areas	Sources
Satellite imagery	Sentinel-2, Landsat-8, MODIS, Resourcesat-2	NDVI, EVI, LAI, canopy structure	Crop monitoring, drought assessment	(Drusch *et al.,* 2012; Huete *et al.,* 2002; Roy *et al.,* 2014; Tucker, 1979)
Weather data	AWS, ERA5, IMD, NASA power datasets	Temp, rainfall, humidity	Yield modeling, disease risk alerts	(Hersbach *et al.,* 2020; Jones & Thornton, 2013)
Soil data	SMAP, ICAR soil grids	Soil moisture, nutrients	Precision irrigation, fertigation scheduling	(Entekhabi *et al.,* 2010)
UAV/Drone data	RGB, multispectral cameras	High-resolution vegetation indices	Weed detection, plant stress analysis	(Raymond Hunt *et al.,* 2011; Zhang & Kovacs, 2012)
Field IoT sensors	Soil probes, weather nodes	Real-time moisture & climate data	Smart irrigation automation	(Li et *al.,* 2014; Ojha *et al.,* 2015)
Farmer/Survey data	Mobile apps, extension surveys	Management practices, crop type	Socio-agronomic decision support	(Frelat *et al.,* 2016; Lobell *et al.,* 2008)

AI applications in crop monitoring and management

A vital agricultural practice, crop monitoring is essential for identifying stressors like illnesses, pest infestations, water scarcity, and nutrient deficiencies. (Lee *et al.,* 2010; Virnodkar *et al.,* 2020). Mostly conventional techniques are often costly, time-consuming, and scale-constrained, while AI techniques provide automatic system for gathering and interpreting data from a variety of sources, such as field sensors, drones, and satellites (Ayoub Shaikh *et al.,* 2022; Virnodkar *et al.,* 2020).

AI image processing tools evaluate aerial or satellite imageries to determine the health of the vegetation using vegetation indices such as the Normalised Difference Vegetation Index (NDVI) (Ali *et al.,* 2024). Deep learning models may have the capability to classify crop diseases, crop stress, leaf chlorophyl content through multispectral and hyperspectral images with remarkable accuracy, even at early stages. For instance, convolutional neural networks (CNNs) have been successfully applied to diagnose diseases in crops such as wheat, rice, and maize (Li *et al.,* 2021). Farmers can

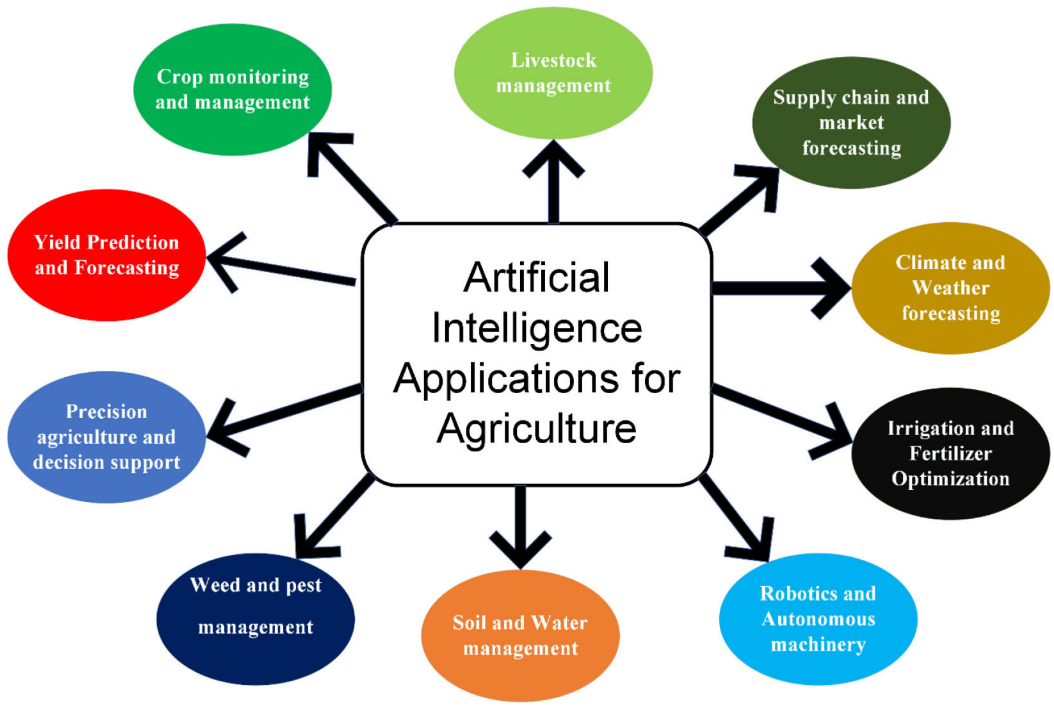

Fig. 1: Some major applications of artificial intelligence in agriculture

sustain use of chemicals and they also reduce the stress in crops by applying quickly and precisely treatments (Li *et al.,* 2021).

AI also assists in predicting crop growth patterns by utilising weather forecasts, soil composition, and historical climate data for effective crop harvest planning and distribute resources through predictive models (Singh *et al.,* 2025).The machine learning algorithms namely Support Vector Machines (SVMs) and Random Forests (RFs) are shown excellent results in estimating crop maturity, predicting yields, and optimising planting schedules (Basu & Narayan, 2025; Singh *et al.,* 2025).

Yield prediction and forecasting

Accurately predicting crop yields before harvest is a critical task for farm management and the broader food supply chain. The AI models ingest historical yield data along with a multitude of features such as weather records, soil properties, crop management practices, remote sensing indices, and more to learn patterns that affect yield outcomes (Sakthipriya & Chandrakumar, 2024; Gupta *et al.,* 2022). Once trained on past data, the model can take current season inputs (e.g., actual weather up to date and forecasted weather, current crop condition indices) and predict final yield with a useful degree of accuracy. An AI model also correlates satellite-derived vegetation index trajectories with final yields based on training data from previous years. This yield prediction in mid-season for field can help in logistical planning. Moreover, yield prediction models are being linked with farm decision support systems. For instance, if an AI yield model forecasts a lower-than-desired output, the system might simulate different interventions (irrigation boost, additional fertilization) to see if they could improve the outcome, essentially providing prescriptive suggestions (Patel & Bunkar, 2025).

Precision agriculture and decision support

Precision agriculture is used to control field parameters for facilitating micro-level decision-making using site-specific data boost crop yields and resource efficiency (DeLay *et al.,* 2022). It helps in the reduction of wastage of resources like water, fertiliser, and pesticides exactly with increasing crop yield. Decision support systems (DSS) combine with AI algorithms and farm management software is capable to take or suggest variety of actions including weather, plant growth stage, and soil nutrient levels (Shams *et al.,* 2024). The best interventions can be found by simulating a variety of scenarios using expert systems and reinforcement learning. AI-powered irrigation systems are capable for automatically schedule watering cycles and track soil moisture in real time. These systems reduce water use by up to 30–50% while ensuring crops receive the optimal amount of hydration. AI models also assist in adjusting fertiliser application rates according to soil analysis and crop demand, enhancing nutrient uptake and reducing input costs.

AI in weed and pest management

Pest and weed control are serious issues in agriculture that have a big impact on crop quality and yield (Buhler *et al.,* 2000). Over use of chemicals leads to resistance build up, environmental damage, and economic losses (Sharma *et al.*, 2021). AI may provide sustainable solution of effective use of chemicals for focused therapy and early detection of disease. Deep learning and computer vision is used for automate the machines to recognise and categorise weeds in real time (Dhanya *et al.,* 2022). These machines are equipped with high-resolution cameras and trained algorithms can distinguish between crops and weeds at the seedling stage and apply herbicides with pinpoint accuracy (Dhanya *et al.,* 2022; Sharma *et al.,* 2021). This targeted application of herbicides protects nearby crops and lowering the need for herbicides. Similarly, to find insect infestations, AI models examine sensor and image data (Singh & Goel, 2020). Moreover, integrated pest management (IPM) programs now employ AI-driven traps and surveillance systems, which automatically count insect populations and notify farmers when thresholds are surpassed (Vaidheki *et al.,* 2023).

Soil and water management

Good soil health and enough water availability is very crucial for sustainable agriculture practice. The integration of information from satellite images, lab tests, and soil sensors, equipped with AI facilitates intelligent soil management system. Machine learning models can forecast salinity problems, soil fertility levels, and erosion risk, directing remedial measures like crop rotation plans or the application of organic amendments (Shahane & Shivay, 2021). AI enables intelligent irrigation systems for water management that customise irrigation schedules by combining soil moisture levels, rainfall forecasts, and evapotranspiration rates (Awasthi *et al.,* 2023; Gupta *et al.*, 2014, 2016, 2017). The farmers can mitigate drought stress and optimize water use, especially in arid and semi-arid regions by leveraging predictive analytics (Maharjan *et al.,* 2025). AI also plays a key role in flood forecasting and watershed management. AI enabled hydrological models can replicate sediment transport and water flow, enhance infrastructure planning and assist communities in getting ready for severe weather events (Kumar *et al.,* 2023).

Robotics and autonomous machinery

Labour intensive agricultural tasks like planting, harvesting, spraying, and sorting are being revolutionised by the combination of artificial intelligence and robotics (Sharma & Shivandu, 2024). AI algorithms are used by autonomous tractors, drones, and harvesters to navigate, avoid obstacles, and carry out tasks. Robotic harvesters with AI and computer vision are able to recognise ripe fruits, gently pick them, and harvest them without causing harm to the plant (Zhou *et al.,* 2022). These robots solve the labour shortage and speed up harvesting in orchards and greenhouses. AI enabled drones are utilised for crop condition monitoring, pesticide application, and field mapping. AI algorithms process drone imagery to create 3D field maps, detect anomalies, and identify yield zones. Additionally, post-harvest processing uses AI-powered sorters to categorise produce according to size, ripeness, and quality, increasing market value and lowering post-harvest losses (Upadhyay & Bhargava, 2025).

Resource Management (Irrigation and Fertilizer Optimization)

The effectively management of resources like water and nutrients is crucial for both farm profitability and environmental sustainability. AI techniques in this domain often involve predictive analytics and control systems that continuously adjust resource application based on sensor data and crop models. AI models analyze inputs such as soil moisture sensor readings, weather forecasts, crop growth stage, and even plant stress indicators to determine optimal irrigation timing and quantity. Coupled with IoT-controlled valves or smart irrigation equipment, the AI system can autonomously execute irrigation decisions, essentially acting as an automated irrigation manager.

For fertilizer and nutrient management, AI techniques use a combination of sensor analytics and decision support algorithms. These AI systems can generate variable-rate fertilizer prescriptions maps that indicate how much fertilizer to apply in each section of a field. Tractors equipped with GPS and variable-rate technology then execute these prescriptions. For example, AI-controlled drip irrigation in India *"Saagu Baagu"* project contributed to a 5% reduction in fertilizer use and 9% reduction in pesticide use, while still increasing yields, indicating more efficient input use.

Climate and weather forecasting

AI plays a pivotal role in climate-smart agriculture by improving the accuracy and granularity of weather forecasts (Gupta *et al.,* 2022). AI algorithms that can learn from past weather data and remote sensing inputs improve traditional meteorological models (Gupta *et al.,* 2022; Upadhyay & Bhargava, 2025). Farmer decision-making regarding crop selection, planting dates, and risk management techniques is aided by both short- and long-term climate forecasts. Additionally, AI models assist with climate impact assessments by identifying crops and regions that are at risk. AI is also utilised in the planning of climate adaptation. Researchers and decision-makers can assess crop varieties resilience, create insurance plans, and create adaptive strategies by modelling various climate scenarios (Prasad *et al.,* 2025).

Supply chain and market forecasting

AI is used throughout the agricultural value chain and is not just on farms. Predicting changes in supply and demand, organising logistics, and cutting down on food waste are all part of supply chain optimisation (Pandey & Mishra, 2024). To predict changes in demand and price, machine learning models examine past sales data, consumer behaviour, and market trends. This information aids in the efficient planning of production and marketing plans by farmers, cooperatives, and agribusinesses. AI is utilised in logistics for cold chain management, real-time tracking, and route optimisation. Product quality is guaranteed and transit losses are decreased with predictive maintenance of storage and transportation infrastructure. Blockchain integrated with AI provides transparency and traceability in food supply chains, enhancing consumer trust and enabling provenance tracking from farm to fork (Rana *et al.,* 2019; Sharma & Balamurugan, 2020).

AI in livestock management

The use of AI in animal agriculture is expanding quickly. Real-time data on the productivity, behaviour, and health of livestock is gathered by sensors, wearable technology, and cameras (Poongodi *et al.,* 2020). AI systems analyse this data to identify stress levels, reproductive cycles, and diseases. AI is used by automated milking systems to monitor milk quality, analyse udders, and identify cows. AI-powered feeding systems also optimise rations according to animal weight, and their activity. Early detection of aberrant behaviour or disease symptoms in poultry farming is made possible by computer vision and sound analysis, which allows for prompt interventions.

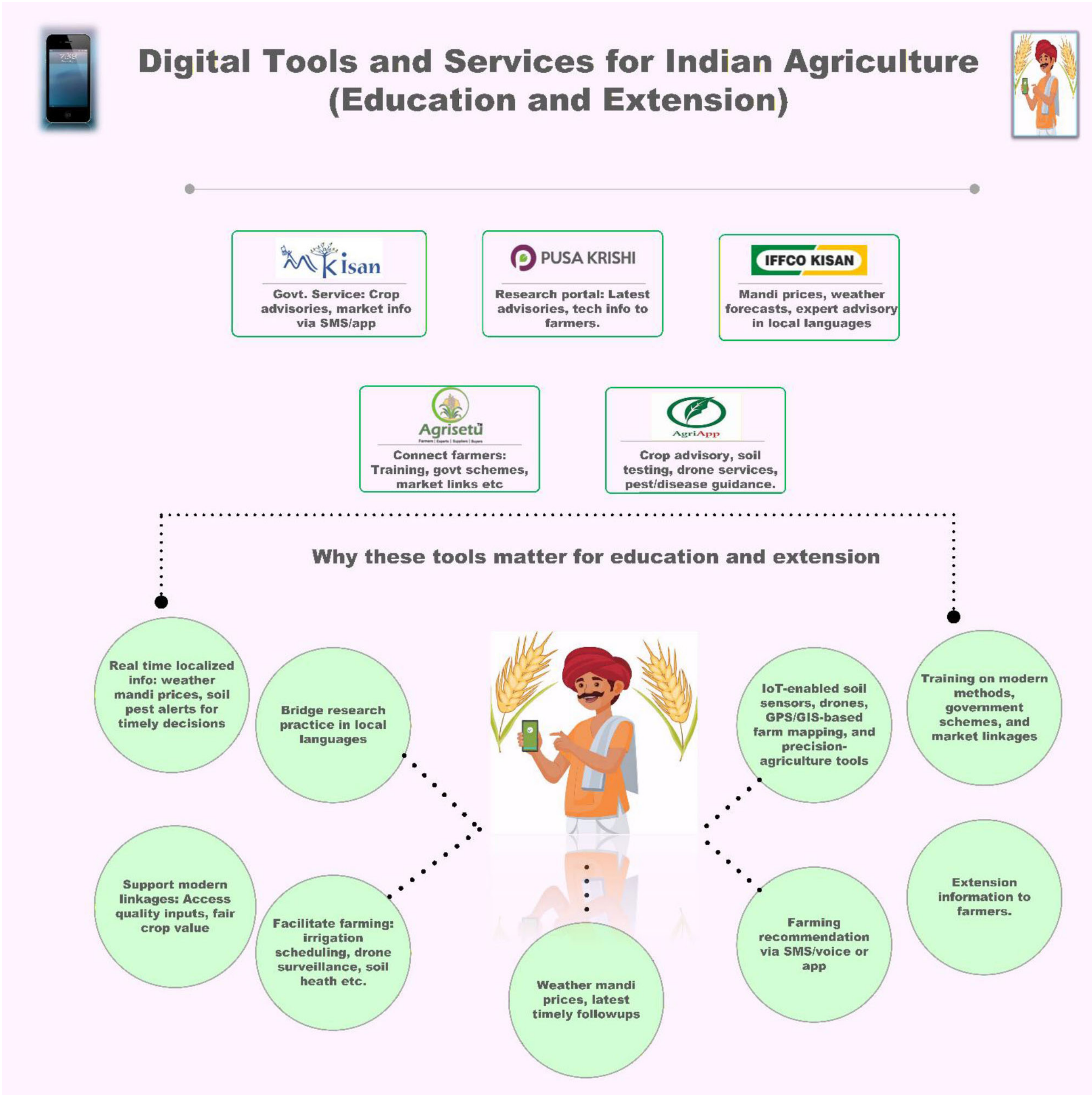

Fig. 2: Graphical representation of the important modern digital tools and platforms for education and extension in Indian agricultural system

KEY TOOLS AND PLATFORMS FOR EDUCATION/ EXTENSION PROGRAM IN INDIA

The education and extension services for the farmers is very useful and benefit from the integration of modern technologies, scientific knowledge, and decision-support tools. This digital technology enhances the farmers understanding and capacity to adopt best practices in their crop management. The graphical representation of valuable modern digital tools and platforms are shown in Fig. 2. The description of mostly valuable tools and platforms for education/extension program in Indian agriculture provided as,

- **mKisan**: A government-backed mobile service delivering crop advisories, weather alerts, market price information, and other farming recommendations via SMS/voice or app.
- **IFFCO Kisan**: It is the popular application among Indian farmers offers mandi (market) prices, weather forecasts, expert advisory, and helpline support in local languages. Its aim to enhance the agri-business ecosystem with a sustainable and climate-resilient agri-commodities value chain.
- **AgriApp**: A comprehensive "smart-farming" platform providing crop advisory, soil testing services, drone services (if available), pest/disease guidance, and inputs marketplace.
- **Agrisetu**: Designed to connect farmers, buyers and

stakeholders, and also offers information/training on modern methods, government schemes, and market linkages.

- **Pusa Krishi**: A portal/app developed for dissemination of latest agricultural research, cropping advisories and extension information to farmers.
- **Mobile Apps / ICT + Tech Tools beyond Apps:** Use of technologies like IoT-enabled soil sensors, drones, GPS/GIS-based farm mapping, and precision-agriculture tools for efficient irrigation, crop monitoring, pest/disease detection etc.

OUTCOMES AND IMPACTS OF AI IMPLEMENTATION ON AGRICULTURE

The deployment of AI technologies in agriculture has initiated to yield tangible outcomes, with measurable impacts on farm productivity, sustainability metrics, and decision-making processes. A case study in India (*"Saagu Baagu"* project), chili farmers using AI-driven advisory and monitoring systems saw an average 21% increase in yields per acre with the reduction of 9% drop in pesticide use and 5% less fertilizer (Saagu Baagu, 2023). In California, integrating AI for vineyard management led to a 25% boost in grape yield in a pilot, attributed to optimized irrigation and disease control (Aijaz *et al.,* 2025). Some concrete outcomes for use of AI in agriculture includes as;

- Early pest and disease detection using AI-based image recognition reduced crop loss by up to 30% (Umamaheswari *et al.,* 2023).
- Improved harvest timing using AI weather forecasting and phenological analysis.
- Soil health monitoring through AI interpretation of sensor and satellite data.
- AI-assisted autonomous tractors and drones have increased operational efficiency and reduced labour costs by 20–40% (Hoque & Padhiary, 2024).
- Up to 40% less water usage with AI-guided irrigation (Hoque & Padhiary, 2024).
- At least 15–30% reductions in fertilizer usage with AI enabled precision farming (Panotra *et al.,* 2025).
- Dramatic pesticide and herbicide reductions as demonstrated by AI guided robotics.
- Reducing chemical load on soils and non-target species.
- AI-optimized pump controls in irrigation saved 17% water uses and 33% in pumping costs (Chou, 1988).
- Supply chain optimization using AI has cut post-harvest losses by 15–25% and improved market price prediction for farmers (Elufioye *et al.,* 2024).
- Customized advisory services (via AI chatbots and mobile apps) improved decision-making among smallholder farmers and significantly increase in net their farm income (Yashabh *et al.,* 2025).
- Smart crop rotation and planting pattern optimization using AI reduced soil fatigue and increased biodiversity and resilience.

FUTURE PROSPECTS AND RESEARCH GAP

The future of AI in agriculture is noticeable by transformative potential that extends well beyond current applications. Key future directions include:

- Edge AI integration in farm equipment (tractors, drones, sensors) will enable real-time decisions without relying on cloud connectivity.
- Explainable AI models will enhance farmer trust by clarifying how decisions and recommendations are made.
- AI-powered autonomous farms will enable hands-free operations in precision, remote, or vertical agriculture systems.
- Climate-smart agriculture will be driven by AI predicting weather extremes, selecting climate-resilient crops, and simulating adaptive practices.
- Blockchain-AI convergence will ensure traceability, food safety, and automated compliance in agricultural supply chains.
- On-field robotics guided by AI will reduce human labour needs in repetitive tasks like planting, weeding, and harvesting.
- AI-optimized nutrient management will tailor fertilization plans to micro-variability in soil, enhancing sustainability.
- Real-time yield forecasting using AI will aid better market planning, pricing decisions, and export strategies.
- Pest and disease prediction models will proactively alert farmers, reducing crop damage and chemical use.
- Remote sensing and AI fusion will allow for large-scale monitoring of crop health, irrigation needs, and yield anomalies.
- AI-driven market intelligence will empower farmers to align production with demand trends and price dynamics.

Research gaps need to be addressed

Despite promising advances, several critical gaps remain in the literature and practice of AI in agriculture:

- AI models must generalize better across crops, regions, and farming systems to support diverse agroecological contexts.
- High-quality, standardized, and openly accessible agricultural datasets are critical to improve AI model scalability and reliability.
- More research is needed on the long-term socio-economic impacts of AI on smallholder and marginalized farming communities.
- Understanding how farmers interact with AI tools is essential

to improve usability, trust, and real-world adoption.

- Robust ethical, legal, and governance frameworks are necessary to guide the safe and fair use of autonomous AI in agriculture.
- Integrating AI with indigenous and local knowledge can improve model accuracy, cultural relevance, and user acceptance.

CONCLUSION

AI has emerged as a transformative tool in agriculture, enabling data-driven, precise, and sustainable farming practices. In fulfilling the first scope of purpose, this review demonstrated the relevance of AI to the urgent needs of modern agriculture, where technologies are revolutionizing every stage of the value chain from crop health monitoring and yield prediction to precision irrigation, livestock management, and market forecasting. The second scope of purpose was addressed by identifying the agricultural parameters most effectively monitored and managed through AI, while the third scope of purpose was met by highlighting the role of machine learning, deep learning, computer vision, robotics, IoT, drones, and remote sensing in advancing real-time and autonomous farm management. The fourth scope of purpose was achieved by synthesizing evidence of measurable impacts, including increased productivity, reduced input usage, improved decision-making, and resilience to climate variability, particularly in resource-constrained and climate-sensitive environments. Finally, in meeting the fifth scope of purpose, the review acknowledged persisting challenges such as limited access to high-quality data, digital infrastructure gaps, low digital literacy, contextual adaptability of models, and ethical concerns.

Looking forward, the future of AI in agriculture lies in scalable, explainable, and decentralized systems that integrate indigenous knowledge and farmer feedback. With strategic investments in AI-driven research, education, and digital infrastructure, agriculture can harness AI not only as a tool for efficiency but as a catalyst for global food security, rural development, and sustainable transformation. AI represents a transformative force for sustainable agriculture, balancing productivity with long-term ecological and social resilience. It is right time to investment in AI related research, education, and infrastructure for digital agriculture mission in India.

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