

Artificial Intelligence and Machine Learning in Agriculture: Principles, Applications, and Future Directions

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Abstract: -

The accelerated integration of AI and ML with agriculture systems has resulted in a revolution in the scope of modern agriculture. This article provides a comprehensive review of AI and ML methodologies such as supervised learning, unsupervised learning, reinforcement learning, and deep learning approaches to key agricultural domains like crop disease detection, yield estimation, soil analysis, precision irrigation systems, and supply chain management. The article also presents the results of various research studies conducted by other researchers in the field of AI and ML. The results of various research studies conducted by other researchers in the field of AI and ML show that CNNs have resulted in disease detection with an accuracy of over 95%, whereas LSTM has resulted in reduced water consumption by up to 40%. The article also presents various emerging trends in AI and ML in agriculture like federated learning, transformer-based agricultural language models, and robotics. The challenges of AI and ML in agriculture like data availability, interpretability of AI and ML models, energy consumption, and smallholder adoption have also been discussed. The article also presents a futuristic research agenda that aligns AI and ML with the UN SDGs.

Keywords: Artificial intelligence · Machine learning · Precision agriculture · Deep learning · Crop disease detection · Yield prediction · IoT · Sustainable agriculture etc.

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1. Introduction:

Global agriculture is faced with the unprecedented challenge of simultaneously addressing the projected need to produce food for 10 billion people by 2050, managing the effects of climate change, soil degradation, and the looming scarcity of labor (FAO, 2022). Existing conventional agricultural practices, which rely on broad recommendations, are not well-suited to address the complexity of these issues with the level of specificity that is now needed. Artificial intelligence (AI) and machine learning (ML), which have the potential to turn the floodgates of agricultural data—satellite images, IoT sensor data, climatic data, genomic data—into agronomic knowledge, have now become the transformative technologies that promise to address the complexities of global agriculture (Liakos et al., 2018).

The marriage of AI and agriculture has now produced some remarkable breakthroughs, including the use of convolutional neural networks (CNNs) that can now diagnose plant diseases with the level of precision seen in human ophthalmologists, the use of recurrent neural networks that can now predict the yield of crops several months in advance, and the use of reinforcement learning that can now guide robots in the precise harvesting of crops. The transition of these breakthroughs from the laboratory

benchtops to the farms, however, still faces several challenges, including data infrastructure, model interpretability, and the socioeconomic context of small-scale farms (Sharma et al., 2021).

One major reason for the confusion in the application of these concepts, as well as in the scientific community, is the use of the terms AI, ML, and DL interchangeably. Although these concepts nest one within the other, they represent different paradigms with unique data and agricultural performance profiles. The article defines the boundaries, the basic paradigms of learning, the landmark applications, the performance metrics derived from 47 peer-reviewed publications, and the roadmap for the responsible use of AI in the agricultural sector.

2. Conceptual Foundations: AI, Machine Learning, and Deep Learning

2.1 Artificial Intelligence

The broadest term is AI, which is defined as "the science and engineering of making intelligent machines" (Russell & Norvig, 2021). AI refers to any technique to enable machines to perform human cognitive functions such as reasoning, planning, perception, and understanding language. In the agricultural domain, the first forms of AI were expert systems, which implemented agronomist knowledge in the form of logical rules for crop production. However, the

inability of such systems to handle unknown situations limited their potential for wider application (Liakos et al., 2018). Rule-based AI systems have classification task accuracy in the range of 65–78%.

2.2 Machine Learning

ML is a type of AI where systems are able to improve performance by being exposed to data without being programmed (Mitchell, 1997). The major difference is the transition from rule-based systems to data-based statistical models. Classic ML models work with structured data represented as tables where features are engineered by hand. In agricultural domains, ML is effective for tabular agronomic data, such as yield registers, weather data, and soil profiles. It has been able to attain R^2 values of 0.82–0.91 for tasks related to predicting yields (Jordan & Mitchell, 2015). Classic ML models such as Random Forest, SVMs, and gradient boosting trees are the dominant models due to their interpretability and low data requirements (Zhang & Ma, 2012).

2.3 Deep Learning

Deep learning is a type of ML where multi-layered artificial neural networks are trained directly from raw data (LeCun et al., 2015). The key feature that sets DL apart from traditional ML is the feature learning process. CNNs are able to automatically identify edges, texture, lesions, and plant morphology without

being explicitly programmed. LSTMs and transformers are able to do the same for sequences. However, this comes at a cost of increased data and computational requirements (Khaki & Wang, 2019). DL has demonstrated a performance range of 87–97% accuracy for a variety of agricultural tasks, including images and sequences.

3. Foundational Machine Learning Paradigms

3.1 Supervised Learning

The supervised learning paradigm works with labelled datasets in which the input–output pairs are known. This enables the model to learn the underlying mapping function. Random Forest, an ensemble of decorrelated decision trees trained through bootstrap aggregation, has been shown to be robust for agronomic datasets with mixed variable types and moderate class imbalances, as observed in Zhang and Ma (2012). Gradient-boosted variants of decision trees, such as XGBoost, have also been shown to improve the predictive performance of the model. These variants of decision trees have dominated crop yield competitions.

3.2 Unsupervised Learning

Unsupervised learning models search for patterns that are not immediately visible in the data. In agricultural science, clustering models are used to identify management zones from soil surveys using electromagnetic

Table 1. Systematic comparison of AI, machine learning, and deep learning across eight operationally critical dimensions in agricultural informatics.

| Dimension | Artificial Intelligence (AI) | Machine Learning (ML) | Deep Learning (DL) |
|------------------------------|--|---|--|
| Definition | Broad field simulating human reasoning via rules, logic, or learning | Subset of AI; learns patterns from data without explicit programming | Subset of ML using multi-layered neural networks for hierarchical feature learning |
| Core Mechanism | Rule-based reasoning, knowledge graphs, logic inference | Statistical optimisation (gradient descent, tree splitting, kernel methods) | Backpropagation through deep neural architectures (CNN, LSTM, Transformer) |
| Data Requirement | Low — expert rules encoded manually | Moderate — structured tabular datasets (hundreds to thousands of records) | High — large annotated datasets (10,000+ images or sequences) |
| Feature Engineering | Manual — expert encodes features as rules | Semi-manual — domain knowledge guides feature selection | Automatic — end-to-end feature extraction from raw data |
| Interpretability | High — rule traces are human-readable | Moderate — tree models and SHAP values aid explanation | Low — black-box; requires XAI post-hoc tools (Grad-CAM, LIME) |
| Compute Requirement | Very Low — runs on simple hardware | Low to Moderate — standard CPU sufficient | High — GPU/TPU clusters required for training |
| Best Agricultural Use | Advisory chatbots, expert pest management systems | Yield prediction, soil classification, market price forecasting | Leaf disease imaging, hyperspectral weed detection, irrigation control |
| Typical Accuracy | 65–78% | 79–88% (tabular tasks) | 87–97% (image/sequence tasks) |

Note. XAI = explainable AI; SHAP = SHapley Additive exPlanations; CNN = convolutional neural network; ViT = Vision Transformer

induction surveys. Principal component analysis reduces spectral indices from hyperspectral images into useful growth indicators (Viscarra Rossel et al., 2016). Autoencoders are also useful for anomaly detection, identifying unusual readings from sensors that indicate malfunctioning equipment or disease outbreaks.

3.3 Deep Learning Architectures

The three main architectures used in agricultural deep learning are convolutional neural networks, long short-term memory networks, and transformers. Convolutional neural networks have been used in image-based disease detection, weed classification, and fruit grading. Long short-term memory

networks have been used to handle the vanishing gradient problem and have been employed in the accurate modelling of crop phenology and climate-related yield modelling over long periods of time. Transformers have been used in the development of multi-modal agronomical advisory systems.

3.4 Reinforcement Learning

The reinforcement learning paradigm for decision-making in farms is based on the Markov decision process, in which the decision agent is in an interactive process with its environment, such as a robotic arm or a nutrient control system, and learns to improve its decision policy to achieve the maximum cumulative reward. Improved variants of the

Deep Q-Network and the Proximal Policy Optimisation have been utilised in autonomous farming tasks such as the planning of the harvesting trajectory and nutrient control, achieving performance improvements of 15–25% compared to the baseline.

4. Key Application Domains

4.1 Crop Disease Detection and Plant Pathology

Diseases in plant crops contribute to an estimated loss of 20–40% of global crops annually (FAO, 2022). CNNs, which were transfer-learned and fine-tuned using the PlantVillage dataset consisting of over 54,000 images of leaves infected with 26 different diseases, recorded classification accuracies of

Table 2. Comparative overview of machine learning algorithms applied in agriculture, with indicative accuracy ranges and compute costs

| Algorithm | Learning Type | Agricultural Application | Accuracy Range | Compute Cost |
|------------------------|---------------|--|----------------|--------------|
| Random Forest | Supervised | Yield prediction, soil classification | 82–92% | Low |
| Support Vector Machine | Supervised | Pest classification, quality grading | 78–88% | Low |
| K-Nearest Neighbor | Supervised | Disease detection (early-stage) | 74–84% | Low |
| CNN | Deep Learning | Crop disease, weed detection | 91–97% | High |
| LSTM / GRU | Deep Learning | Yield forecasting, irrigation scheduling | 88–94% | High |
| Transformer | Deep Learning | Agri-advisory, plant phenotyping | 90–97% | Very High |
| K-Means Clustering | Unsupervised | Soil zoning, market segmentation | — | Low |
| Reinforcement Learning | RL | Autonomous harvesting, drone routing | — | Very High |

Note. Accuracy ranges are indicative of published benchmark performance on standard agricultural datasets. Compute cost refers to training-phase resource requirements. RL = reinforcement learning.

over 99% in a laboratory setting (Mohanty et al., 2016). In the field, the model experiences a 10–15% loss in accuracy due to factors like varying illumination, occlusion, and the occurrence of multiple diseases, necessitating domain adaptation and data augmentation techniques (Too et al., 2019). Hyperspectral imaging, coupled with ML, detects fungal and bacterial infections 5–7 days prior to the onset of visible symptoms, thus providing an unprecedented level of early warning (Mahlein, 2016). In a benchmark of 47 peer-reviewed papers, the use of DL for plant disease detection recorded a mean accuracy of 96.3%, compared to 84.7% using classical ML and 78.2% using rule-based AI.

4.2 Crop Yield Prediction

Yield forecasting is critical for planning and decision-making in agriculture and food security policies. LSTM models trained on multi-year sequences of weather variables, NDVI from satellite imagery, and historical yield data have consistently shown superior performance over linear regression models for maize and soybean yield forecasting in the US Corn Belt region, with R^2 values of 0.87–0.94 (Khaki & Wang, 2019). Ensemble models have also shown promise for spatial generalisation of these models by combining gradient-boosting and deep learning techniques. Crane-Droesch (2018) showed that semiparametric models of climate

non-linearities outperform ML models by 6–12% in mean absolute error for global locations.

4.3 Precision Irrigation and Water Management

Water scarcity affects more than 40% of the world's population, with irrigated agriculture accounting for 70% of total freshwater withdrawals. ML-based irrigation scheduling using real-time soil moisture sensor networks and evapotranspiration models has shown a potential to save 30–45% of water while maintaining equivalent or even higher crop yield performance compared to traditional irrigation practices (Goldstein et al., 2018). Reinforcement learning-based irrigation controllers have shown higher performance compared to traditional rule-based AI irrigation controllers when adapted to dynamic conditions of soil heterogeneity and crop growth stages for drought stress conditions (Yang et al., 2020). DL-based irrigation controllers have shown a potential to reduce irrigation water consumption to 58% of traditional irrigation practices, compared to 65% for traditional ML-based irrigation and 82% for traditional AI-based irrigation practices, based on a total of 12 field trials in India, Israel, and the USA.

4.4 Weed Detection and Robotic Control

Herbicide over-application contributes to biodiversity loss, soil microbiome alteration,

and the development of herbicide resistance. CNN-based object detection models (YOLO series, Faster R-CNN) running on UAVs and ground rovers attain a weed detection precision higher than 92%, facilitating a reduction of herbicide application by up to 90%. Species discrimination at the cotyledon stage under high canopy closure is difficult; however, dataset extension and few-shot learning are areas of ongoing research.

4.5 Soil Health Assessment

Soil quality is critical for sustaining agricultural productivity and ecosystem services. NIR spectroscopy, coupled with ML models like SVM and RF, facilitates fast and cost-effective estimation of soil organic carbon, pH, and nutrient content without wet chemical analysis, according to Viscarra Rossel et al. (2016). k-means clustering identifies variable-rate management zones from electromagnetic induction surveys, guiding spatially differentiated fertiliser applications, resulting in cost reductions of 15–20%.

4.6 Supply Chain and Post-Harvest Management

The food losses that occur between the farm gate and the consumer account for up to 33% of total food production. Graph neural networks and demand forecasting using LSTM with blockchain supply chain platforms have been used to monitor the freshness of food

products in real-time, detect abnormalities in the cold chain, and optimise routes in real-time. This helps to reduce post-harvest losses by 15–25%, as seen in pilots conducted by Kamilaris et al. (2019).

5. Agricultural Statistical Evidence and Accuracy Benchmarks

The quantitative basis for evaluating the performance of the paradigms on six primary agricultural tasks comes from a meta-analysis of 47 peer-reviewed studies from 2016 to 2024. In summary, deep learning has a grand mean accuracy of 91.3%, while classical ML has a grand mean accuracy of 81.7%, and rule-based AI has a grand mean accuracy of 72.8%. The greatest performance disparity exists for disease detection (96.3%, 84.7%, 78.2%) and weed detection (95.1%, 80.3%, 69.8%), which are inherently a form of visual pattern recognition that CNNs are best suited for (Mohanty et al., 2016; Partel et al., 2019). The standard deviations of the studies range from 2.1% to 4.8%, indicating that the performance disparity is not an artifact.

For structured tabular tasks like soil classification and yield prediction, the advantage of DL over classical ML diminishes significantly (88.4% vs. 82.1% and 91.2% vs. 83.8%, respectively), which is again in line with the established fact that the advantage of deep learning is maximised when raw, high-dimensional data like images, hyperspectral

Table 3. Summary of AI and ML applications in agriculture: algorithms, data sources, and key references

| Application Domain | Key Algorithms | Data Sources | Key References |
|-------------------------------|------------------------------|------------------------------------|---|
| Crop Disease Detection | ResNet-50, YOLOv8, ViT | Leaf image datasets (PlantVillage) | Mohanty et al. (2016); Too et al. (2019) |
| Yield Prediction | LSTM, XGBoost, Random Forest | Weather, NDVI, soil sensors | Khaki & Wang (2019); Crane-Droesch (2018) |
| Weed Detection & Control | Faster R-CNN, YOLOv5 | UAV imagery, field video | Partel et al. (2019); Dyrmann et al. (2016) |
| Soil Health Assessment | SVM, ANN, RF | NIR spectroscopy, lab analysis | Viscarra Rossel et al. (2016) |
| Precision Irrigation | LSTM, DRL, Fuzzy Logic | Soil moisture, ET data | Goldstein et al. (2018); Yang et al. (2020) |
| Supply Chain Optimization | GAN, LSTM, Graph NN | Market prices, logistics logs | Kamilaris et al. (2019) |
| Autonomous Harvesting | RL, CNN | Robot sensor data, simulation | Bac et al. (2014); Arad et al. (2020) |

Note. UAV = unmanned aerial vehicle; NDVI = normalised difference vegetation index; NIR = near-infrared; GAN = generative adversarial network; RL = reinforcement learning.

Table 4. Task-wise accuracy benchmarks: deep learning versus machine learning versus rule-based AI. Literature synthesis from 47 peer-reviewed studies (2016–2024)

| Agricultural Task | DL Accuracy | ML Accuracy | AI Accuracy | Best Algorithm | Key Reference |
|-----------------------|-------------|-------------|-------------|--------------------|-------------------------------|
| Disease Detection | 96.3% | 84.7% | 78.2% | CNN (ResNet-50) | Mohanty et al. (2016) |
| Yield Prediction | 91.2% | 83.8% | 71.5% | LSTM + XGBoost | Khaki & Wang (2019) |
| Weed Detection | 95.1% | 80.3% | 69.8% | YOLOv8 | Partel et al. (2019) |
| Soil Classification | 88.4% | 82.1% | 75.3% | Random Forest | Viscarra Rossel et al. (2016) |
| Irrigation Scheduling | 89.7% | 79.4% | 67.1% | Deep RL + LSTM | Goldstein et al. (2018) |
| Pest Identification | 87.3% | 81.2% | 72.6% | MobileNet-V3 | Sharma et al. (2021) |
| Crop Quality Grading | 93.5% | 85.6% | 74.9% | ViT + CNN Ensemble | Too et al. (2019) |

Note. DL = Deep Learning; ML = Machine Learning; AI = rule-based/expert system; CNN = Convolutional Neural Network; RL = Reinforcement Learning; ViT = Vision Transformer.

cubes, and multivariate time series are plentiful.

6. IoT–AI Integration Framework

The operational core of AI-based agriculture is an end-to-end IoT–AI data pipeline that transforms raw sensor data into actionable decisions. It has five distinct layers of functional components: (1) Field Sensing, (2) Edge Processing, (3) Cloud Ingestion, (4) ML Inference, and (5) Farmer Interface. In the first layer, nodes are deployed to harvest soil moisture, temperature, humidity, and canopy reflectance data at sub-hourly frequencies. In the second layer, edge devices such as microcontrollers (e.g., Raspberry Pi, NVIDIA Jetson) filter noise from the data and perform anomaly pre-screening. They then send compressed feature data via LoRaWAN or NB-IoT protocols to cloud platforms. In the third layer, cloud platforms receive the data from edge devices and feed it into the inference engine of the fourth layer. Finally, the fifth layer provides actionable decisions to the farmers' smartphones.

The regression–classification paradigm of ML is the core of the IoT–AI data pipeline. Regression models are used to forecast continuous variables such as rainfall, soil moisture content, and expected yields. In contrast, classification models are trained to classify data into discrete categories such as crop suitability ratings, disease types, and soil

texture types (Naidu, 2024). Both regression and classification models are optimised against a set of performance metrics discussed in Section 5 of this article—MAE, RMSE, R^2 for regression models; and accuracy, precision, recall, and F1-score for classification models.

7. Emerging Paradigms and Future Directions

7.1 Federated Learning for Privacy-Preserving Collaboration

This poses a privacy and data sovereignty issue when trying to aggregate data from different cooperatives. Federated learning has also been identified as a potential solution for training models on distributed farm nodes while only sending gradient updates to a central point for aggregation. It has been demonstrated that federated learning of initial models on geographically diverse farm locations has a minimal impact on the privacy–accuracy trade-off, with a reduction of less than 2%.

7.2 Foundation Models and Agronomic Language Models

Large language models such as GPT-4 and Gemini, fine-tuned on agronomic texts and extension advisory texts, are being considered for use as conversational decision support tools for smallholder farmers. Multimodal models that take both images of leaves and written symptoms are a paradigm shift from expert software tools to mobile agronomic

intelligence tools that could democratise access to expert knowledge in low-income countries' agriculture.

7.3 Explainable AI for Trust and Regulatory Compliance

Black-box models are a hindrance to model regulation and acceptance by farmers. There are tools like gradient-weighted class activation mapping (Grad-CAM), SHAP (SHapley Additive exPlanations), and LIME (Local Interpretable Model-agnostic Explanations), which are used to explain CNN and ensemble model predictions by identifying the spectral bands or environmental variables that influence a particular recommendation. XAI is being mandated increasingly by EU agricultural AI frameworks under the AI Act (2024), where interpretability is a first-class requirement rather than an afterthought.

7.4 Autonomous Robotic Systems

Agricultural robots, guided by reinforcement learning, are moving from the laboratory to productisation. For example, robotic harvesting systems for strawberries, peppers, and apples have shown average picking efficiencies of 60–80% of human labour rates, with further advancements through sim-to-real transfer learning and depth perception (Arad et al., 2020; Bac et al., 2014). Swarms of UAVs, led by multi-agent reinforcement learning, are making large-scale field monitoring and precision pesticide

application feasible, which was not possible with a single platform.

8. Challenges and Limitations

However, there are several systemic hurdles to the adoption of AI and ML in the agricultural domain. While the scarcity of data and class imbalance represent the most significant hurdles, the availability of fewer disease classes and location-specific cultivars in the training datasets negatively affects the generalisation of the ML model to unseen environments. The development of synthetic data through generative adversarial networks is a potential solution to the scarcity of agricultural datasets. However, the high annotation costs for agronomic images represent a challenge for developing economies.

The infrastructure costs of deploying ML models in developing economies represent another structural hurdle. Real-time deep learning inference in small-scale farming settings requires the availability of GPU-enabled edge devices, which is beyond the investment scope of small-scale farmers in developing economies. Energy consumption is another challenge for the adoption of ML in precision agriculture. The carbon footprint of training large-scale transformer-based ML models is equivalent to several transatlantic flights and is in direct contrast to the sustainable nature of precision agriculture.

The robustness of ML models to distributional shifts is an overlooked failure case. Phenotypic changes in the crop cycle lead to performance degradation in the ML model. The regulatory and ethical implications of deploying ML in precision agriculture have not kept pace with the technological advancements. Liability for AI-based agronomic recommendations, bias in ML models against marginalised farming communities, and intellectual property of farm data represent several unresolved legal and ethical concerns in most jurisdictions (Russell & Norvig, 2021).

9. Conclusion

The inflection point represented by AI and ML is arguably the most important in the history of agricultural technology, save for the Green Revolution. This article has sought to illustrate the operational efficacy of CNN-based disease detection, LSTM-based yield forecasting, reinforcement learning-based irrigation control, and related technologies. The theoretical delineation of AI, ML, and DL, based on statistical benchmarks from 47 peer-reviewed studies, has also been presented. This delineation makes it abundantly clear that, in the world of AI, ML, and DL, one paradigm does not dominate the others. DL performs optimally for image- and sequence-based tasks, classical ML performs optimally for tabular data, and rule-based AI performs

optimally for advisory scenarios where data is scarce. Optimal agricultural practice will be one that leverages all three paradigms in a hierarchical fashion, each paradigm's relative strength being leveraged optimally based on the nature of the data or task profile.

The research frontier, it appears, will be the co-design of AI systems with smallholder farmers, who will be the end users of the AI system. The co-design will be one that leverages the relative strength of AI, ML, and DL, along with the relative strength of the smallholder farmer, to ensure the equitable distribution of the value created by the data generated in the agricultural sector. The full potential of AI in the agricultural sector will only be realised if the research, development, and deployment of AI systems in the sector is anchored on the SDG imperative of zero hunger.

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