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Machine Learning in Agriculture: A Comprehensive Survey of Applications, Methods, Challenges, And Future Directions

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***Abstract*—Agriculture is undergoing a data-driven transformation in response to climate variability, resource constraints, increasing food demand, and the need to improve productivity without proportionally increasing environmental pressure. Machine learning (ML) provides a family of statistical and computational methods that can learn relationships from multisource agricultural data and support prediction, classification, monitoring, and decision-making.**

This survey reviews recent literature on ML and deep learning (DL) in crop yield prediction, disease and pest detection, weed recognition, soil and nutrient management, irrigation, remote sensing, phenotyping, and agricultural automation. A structured literature-review protocol is presented covering database search, screening, quality assessment, evidence extraction, and thematic synthesis. The survey highlights a shift from isolated image-classification models toward multimodal systems that combine IoT, satellite/UAV imagery, weather, soil, and management data. Recent reviews report strong use of Random Forest (RF), gradient boosting, support vector methods, convolutional neural networks (CNNs), and long short-term memory (LSTM) models; however, model accuracy alone is insufficient for safe agricultural recommendations. Key unresolved issues include dataset bias, regional generalization, inconsistent evaluation, uncertainty, explainability, privacy, computational constraints, and limited field validation.

The paper concludes with a research agenda emphasizing multimodal learning, explainable and causal ML, edge AI, privacy-preserving learning, standardized benchmarks, and farmer-centered deployment.

***Index Terms*—agriculture, machine learning, precision agriculture, crop yield prediction, deep learning, computer vision, remote sensing, Internet of Things, smart farming, explainable artificial intelligence.**

I. INTRODUCTION

Agriculture is a complex socio-technical system in which crop performance depends on interacting biological, environmental, economic, and management factors. Conventional decision-making has traditionally relied on field observations, agronomic expertise, historical experience, and periodic sampling. Digital agriculture changes this workflow by enabling continuous measurement through sensors, satellite imagery, unmanned aerial vehicles (UAVs), farm machinery, weather stations, and management records [1], [2].

Machine learning is particularly relevant because agricultural observations are heterogeneous and often nonlinear. Yield depends simultaneously on weather, soil, crop genotype, management, disease pressure, and spatial variability. ML can learn such relationships from historical observations and generate predictions or classifications for decision support [1], [3]. Recent systematic reviews show continued growth in ML/DL studies, especially for yield prediction and computer-vision tasks [4]– [8].

The literature is also moving beyond proof-of-concept accuracy. Recent work shows that a model with strong predictive performance may still produce unstable input recommendations, particularly when used to infer site-specific fertilizer rates [9]. Likewise, systematic analysis of maize-yield papers found frequent problems in reporting and interpreting metrics, which can make results appear more favorable than they are [10]. These findings motivate a survey that evaluates not only algorithms, but also data, validation, deployment, interpretability, and research gaps.

The main contributions of this survey are: 1) a structured review methodology for ML in agriculture; 2) a taxonomy of agricultural applications and data sources; 3) a comparative analysis of classical ML, ensemble learning, and DL; 4) a synthesis of deployment and integration issues involving IoT, remote sensing, edge computing, and privacy-preserving learning; and 5) a research-gap matrix and future research agenda.

II. RESEARCH QUESTIONS

RQ	Research question
RQ1	Which agricultural problems are most frequently addressed using ML/DL?
RQ2	Which data sources, features, and algorithms dominate recent studies?
RQ3	How do classical ML, ensemble, and deep-learning approaches differ in suitability?
RQ4	What methodological and deployment limitations prevent reliable field adoption?
RQ5	Which research directions can improve robustness, interpretability, scalability, and sustainability?

III. LITERATURE-REVIEW METHODOLOGY

This survey uses a structured review protocol rather than a narrative-only selection. The protocol was designed around PRISMA-style principles used by recent agricultural reviews [4], [5], [7], while the evidence synthesis was organized around the research questions above. Searches emphasized peer-reviewed literature from IEEE Xplore, ScienceDirect, SpringerLink, MDPI, Frontiers, PubMed-indexed records, and publisher or institutional pages for bibliographic verification.

A. Search Strategy

The principal search concepts were combined using Boolean operators: ("machine learning" OR "deep learning" OR "artificial intelligence") AND (agriculture OR farming OR "precision agriculture") AND ("crop yield" OR disease OR weed OR irrigation OR soil OR fertilizer OR remote sensing OR IoT). Additional targeted searches were used for emerging themes including explainability, federated learning, edge AI, and multimodal agricultural data.

B. Inclusion and Exclusion Criteria

Criterion	Included	Excluded
Publication type	Peer-reviewed journal/conference papers and high-quality systematic reviews	Blogs, commercial pages, non-technical summaries
Time emphasis	Primarily 2020–2026 for recent trends; foundational works retained	Older work without foundational relevance
Domain	Crop/soil/water/plant-health/farm-management applications	Unrelated AI applications
Evidence	Studies describing data, model, task, and evaluation	Papers without sufficient methodological detail
Relevance	Direct contribution to ML/DL-enabled agricultural decision support	Purely conceptual material with no agricultural linkage

C. Screening and Quality Assessment

Records were conceptually screened in three stages: title/abstract relevance, methodological relevance, and evidence quality. Greater weight was assigned to systematic reviews, peer-reviewed empirical studies, and papers with explicit data sources and evaluation protocols. Studies were not treated as directly comparable when datasets, targets, geographic regions, or evaluation protocols differed materially.

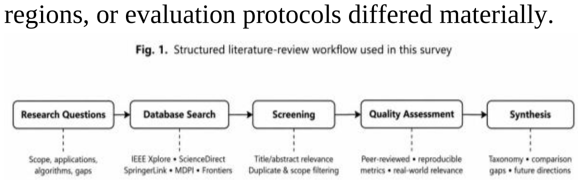

Fig. 1. Structured literature-review workflow used in this survey.

IV. DATA SOURCES AND ML TASKS

Agricultural ML systems can be grouped by the type of input data and the decision task. Tab. I summarize the principal data modalities identified in the literature.

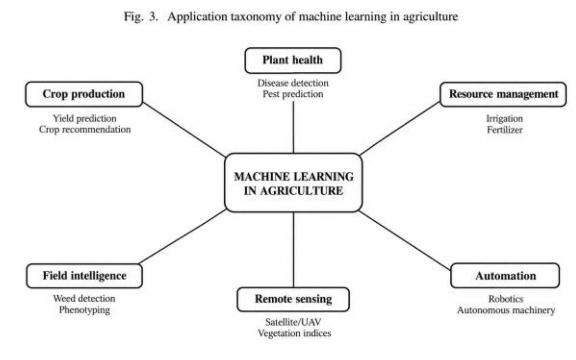

Fig. 3. Application taxonomy of machine learning in agriculture.

Data modality	Representative variables	Typical tasks
Weather	temperature, rainfall, humidity, solar radiation	yield prediction, disease risk, irrigation
Soil	pH, N-P-K, moisture, texture, EC, organic matter	crop/fertilizer recommendation, yield
Remote sensing	NDVI/EVI/LAI, multispectral/hyperspectral bands, SAR	yield, crop mapping, stress detection
RGB/thermal images	leaf, canopy, fruit, weed imagery	disease, weed, maturity, phenotyping
IoT/time series	soil moisture, microclimate, irrigation events	forecasting, control, anomaly detection
Management records	seed variety, planting date, fertilizer, irrigation	yield, optimization, decision support

Recent yield reviews consistently identify temperature, rainfall, soil variables, and vegetation indices among the most frequently used features [4], [5], [7]. For rice, satellite indices and climate variables are prominent inputs, while generalization and ground-truth availability remain important limitations [11]. Tree-crop research similarly emphasizes combining weather, soil, plant, and remote-sensing information rather than relying on a single modality [12].

V. MACHINE-LEARNING METHODS

A. Classical Supervised Learning

Regression and classification methods remain important when datasets are relatively small, tabular, or structured. Linear regression offers interpretability and a useful baseline. Decision trees provide readable rules, while support vector machines can perform well in high-dimensional feature spaces. Random Forest is particularly attractive because it handles nonlinear relationships, mixed feature types, and moderate noise without extensive feature scaling [1], [4].

B. Ensemble and Boosting Methods

Random Forest, Gradient Boosting, XGBoost, and stacking methods are widely used for agricultural prediction.

Recent reviews report increasing use of ensemble methods in crop-yield prediction [4], [5]. Their practical advantage is that they can model nonlinear interactions while retaining manageable training requirements for tabular data.

C. Deep Learning

CNNs are dominant for image-based tasks because convolutional layers learn hierarchical spatial features. LSTM and related recurrent architectures are useful for weather, sensor, and other temporal sequences. Transfer learning can reduce the amount of task-specific training data required, while newer transformer-based vision models can improve representation capacity at the cost of higher computational requirements [13]-[16].

D. Hybrid and Multimodal Learning

The recent trend is toward combining complementary data and models-for example, CNN-derived image features with weather and soil variables, or tree-based models with remote-sensing indices. Such fusion is promising because agricultural outcomes are driven by multiple interacting processes. However, multimodal models also increase data-alignment, missing-data, and deployment complexity.

Model family	Strengths	Limitations	Best-fit agricultural tasks
Linear/Logistic Regression	Simple, interpretable, low compute	Limited nonlinear capacity	Baselines, risk scores
Decision Tree	Readable rules	Can overfit	Classification, recommendation
Random Forest	Robust, nonlinear, mixed features	Larger models; less transparent than a single tree	Yield, soil, fertilizer
SVM/SVR	Strong with high-dimensional data	Sensitive to scaling/tuning; costly at scale	Disease, yield
XGBoost/GBM	Strong tabular performance	Hyperparameter sensitive	Yield, resource optimization
CNN	Excellent spatial feature learning	Needs labeled images and compute	Disease, weed, fruit detection
LSTM/RNN	Temporal dependency modeling	Training complexity; long-term limitations	Weather, sensor, yield series
ViT/Transformers	Strong global representation	High data/compute requirements	Advanced image analysis
Federated learning	Privacy-preserving collaboration	Communication and heterogeneity	Multi-farm collaborative learning

VI. MAJOR APPLICATIONS

A. Crop-Yield Prediction

Crop-yield prediction is one of the most mature agricultural ML applications. Reviews spanning hundreds of studies show continued use of Random Forest, linear regression, gradient boosting, neural networks, CNNs, and LSTM models [4], [5]. Inputs include climate, soil, management, and vegetation indices. A key methodological lesson is that yield prediction should be separated from causal recommendation: accurately predicting yield under observed conditions does not necessarily mean that a model can correctly recommend an intervention such as fertilizer rate [9].

For rice, systematic evidence indicates that neural networks and tree-based models are common, with satellite and climate variables serving as important inputs; overfitting and regional transfer remain open issues [11]. Tree-crop studies report wide variation in reported accuracy and emphasize that small datasets can create deceptively optimistic results [12].

B. Disease and Pest Detection

Image-based plant disease detection is a major computer-vision application. Typical pipelines contain image acquisition, preprocessing, segmentation or localization, feature learning, and classification. CNNs are the dominant approach, while recent work is exploring vision transformers and hybrid models [14]-[16]. Disease-prediction models increasingly combine host, pathogen, and environmental variables, moving beyond image-only diagnosis [17].

C. Weed Detection and Precision Spraying

Weed recognition supports targeted intervention by distinguishing crops from weeds in field imagery. Deep learning reviews show strong interest in object detection and semantic segmentation for large-scale grain systems [18]. Practical deployment requires robustness to illumination changes, occlusion, plant growth stage, camera motion, and diverse field backgrounds.

D. Irrigation and Water Management

ML can estimate soil moisture, irrigation demand, evapotranspiration, or crop stress from sensor and weather data. Human-centered design is particularly important: irrigation recommendations must be understandable and actionable rather than merely accurate. Recent work argues that explainability and iterative stakeholder feedback should be integrated into AI-guided irrigation systems [19].

E. Fertilizer and Nutrient Management

ML can model spatial yield response and support site-specific input recommendations. However, recent experimental evidence shows that economically optimal fertilizer-rate recommendations can be sensitive to algorithm and covariate selection even when yield prediction is accurate [9]. This makes uncertainty quantification and causal validation essential.

F. Soil, Phenotyping, and Fruit Maturity

AI-enabled sensing is increasingly used for non-destructive estimation of crop quality, maturity, and phenotypic traits. Spectrometry and imaging combined with ML can provide high-spatiotemporal-resolution information that is difficult to obtain through destructive sampling alone [20].

VII. INTEGRATION WITH IoT, REMOTE SENSING, AND EDGE COMPUTING

The most useful agricultural ML systems are not isolated predictive models; they are pipelines connecting sensing, analytics, decision support, and field action. IoT devices provide local observations, while satellite and UAV platforms add spatial context. Cloud infrastructure enables large-scale training, whereas edge computing can reduce latency and dependence on connectivity.

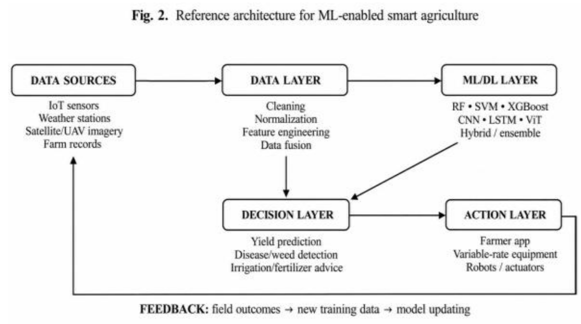

Fig. 2. Reference architecture for ML-enabled smart agriculture.

Recent reviews identify ML-IoT integration as a major direction for real-time monitoring and precision agriculture [21], [22].

Multimodal fusion is especially important because no single sensor observes all relevant causal factors. A practical system may combine soil moisture, weather, crop imagery, and historical management data. The main engineering challenge is temporal and spatial alignment, missing data, sensor calibration, and maintaining a model as field conditions change.

VIII. COMPARATIVE ANALYSIS OF AGRICULTURAL ML APPROACHES

Dimension	Classical ML	Deep Learning	Hybrid / Multimodal
Data volume	Low–medium	Medium–very high	Medium–very high
Feature engineering	Often required	Learned automatically for images/sequences	Mixed
Interpretability	Generally higher	Often lower	Variable
Compute	Low–medium	Medium–very high	High
Image tasks	Good with engineered features	Excellent	Excellent
Tabular tasks	Strong	Not always superior	Often strong
Temporal tasks	Moderate	LSTM/transformers strong	Strong
Field deployment	Easier	Needs optimization	More complex
Main risk	Underfitting / limited representation	Overfitting, domain shift	Data alignment and complexity

The literature does not support a universal 'best' algorithm. Instead, algorithm choice should be conditioned on data modality, sample size, computational budget, target variable, and deployment context.

For small structured datasets, well-tuned tree ensembles can be preferable to deep networks. For images, CNNs and newer vision architectures are generally more appropriate.

For time-series data, recurrent or transformer models may provide advantages when sufficient data are available.

IX. EVALUATION AND REPRODUCIBILITY

Agricultural ML studies commonly report RMSE, MAE, R^2, MAPE, accuracy, precision, recall, and F1-score. Recent yield reviews identify RMSE, R^2, and

MAE as especially common [4]. However, metric choice must match the task and error consequences. For disease screening, false negatives can be more consequential than false positives; for yield prediction, systematic bias and uncertainty may matter more than a single aggregate score.

Evaluation should therefore include: (1) geographically separated test sets when possible; (2) temporal hold-out tests; (3) external validation across seasons; (4) uncertainty intervals; (5) class-imbalance reporting; (6) baseline comparisons; and (7) complete metric definitions and units. The systematic review of maize-yield studies found frequent errors in metric interpretation and reporting, demonstrating the need for stronger reporting standards [10].

X. CHALLENGES

A. Data Quality and Dataset Bias

Agricultural datasets are often fragmented, expensive to label, and geographically biased. Plant-disease datasets may contain clean laboratory images that do not represent field conditions.

Recent disease reviews identify geographic bias, data-quality trade-offs, and limited diversity as persistent concerns [15], [16].

B. Generalization and Domain Shift

A model trained on one crop variety, region, sensor, or season may degrade under different conditions. Yield reviews repeatedly identify regional generalization as an unresolved issue [11], [12].

Domain adaptation, transfer learning, calibration, and multi-region validation are therefore important.

C. Explainability and Trust

Farmers and agronomists often need actionable reasons rather than only a prediction. Explainable AI can expose influential features, image regions, or temporal signals.

Human-centered AI is particularly relevant for irrigation and farm management where the final decision remains with the farmer [19].

D. Privacy and Data Governance

Farm data can be commercially sensitive. Centralizing all observations may be undesirable because of privacy, ownership, and connectivity constraints. Federated learning enables collaborative model training without requiring raw data to leave local sites, but introduces communication overhead and statistical heterogeneity [23], [24].

E. Computational and Economic Constraints

High-capacity models can require GPUs, reliable connectivity, and skilled maintenance. These requirements may conflict with smallholder settings. Lightweight models, model compression, edge inference, and energy-aware learning are promising directions.

XI. RESEARCH-GAP ANALYSIS

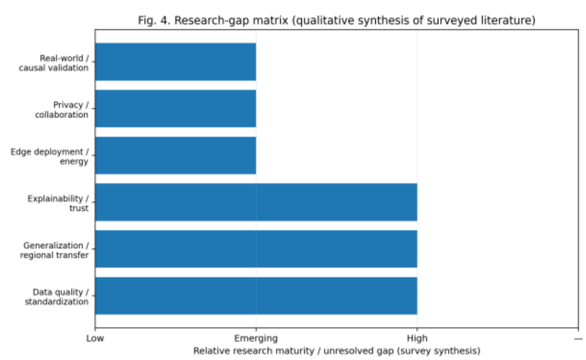

Fig. 4. Research-gap matrix based on qualitative synthesis of the surveyed literature.

Gap	Evidence in literature	Research need
Dataset standardization	Different sensors, regions, crops, labels, and metrics limit direct comparison [4], [11], [15]	Open benchmark datasets with metadata and standardized protocols
Regional transfer	Models may fail across regions/seasons/cultivars [11], [12]	Domain adaptation, calibration, cross-region validation
Evaluation quality	Metric interpretation/reporting problems documented in 207 maize-yield papers [10]	Reporting checklists, uncertainty, external validation
Causal decision support	Yield prediction may not imply correct intervention recommendations [9]	Causal ML and on-farm randomized/precision experiments
Real-world disease detection	Dataset bias and laboratory-to-field gap remain [15], [16]	Field-collected, diverse, longitudinal datasets

Edge/low-resource AI	Advanced models may be computationally expensive [15], [22]	Compression, quantization, efficient architectures
Privacy-preserving collaboration	FL faces heterogeneity and communication costs [23], [24]	Agriculture-specific FL, secure aggregation, adaptive personalization
Farmer-centered AI	Actionability and interpretability remain important [19]	Explainable, multilingual, human-in-the-loop systems

XII. FUTURE RESEARCH DIRECTIONS

A. Multimodal Foundation Models

Future systems can jointly process images, sensor time series, weather, text-based farm records, and geospatial information. The goal should not simply be larger models, but robust representations that transfer across crops and regions.

B. Explainable and Causal ML

Research should distinguish correlation-based prediction from intervention planning. Combining ML with causal inference and on-farm experimentation could improve recommendations for irrigation, fertilizer, and pest management.

C. Edge AI and TinyML

Low-power models deployed on cameras, microcontrollers, and farm gateways can support real-time detection without continuous cloud connectivity. Compression, pruning, quantization, and knowledge distillation should be evaluated under real field constraints.

D. Federated and Privacy-Preserving Learning

Federated learning can enable multi-farm collaboration while reducing raw-data sharing. Future studies should address non-IID agricultural data, intermittent connectivity, personalization, communication efficiency, and secure aggregation [23], [24].

E. Standardized Field Benchmarks

Benchmark suites should include multiple seasons, regions, crop varieties, sensor types, and realistic field conditions. This would reduce the current tendency to compare models using incompatible datasets and metrics.

F. Sustainable and Human-Centered Optimization

Future ML objectives should include water, fertilizer, pesticide, energy, and economic constraints rather than optimizing prediction accuracy alone. Multi-objective decision support can make agricultural AI more aligned with sustainability goals.

XIII. CONCLUSION

Machine learning is becoming a central component of digital and precision agriculture. The literature demonstrates strong potential across yield prediction, disease and pest detection, weed recognition, soil and nutrient management, irrigation, phenotyping, and agricultural automation. Classical ML remains highly competitive for structured agricultural data, while deep learning is particularly effective for images and complex temporal or multimodal signals.

The survey also shows that the next phase of agricultural AI is not simply an algorithmic race for higher accuracy. Reliable deployment requires representative data, transparent evaluation, uncertainty estimates, geographic and temporal validation, explainability, privacy protection, and economic feasibility. Recent evidence on fertilizer recommendations and evaluation reporting illustrates why predictive accuracy alone cannot guarantee sound agricultural decisions [9], [10].

A robust research agenda should therefore prioritize multimodal and transferable models, explainable and causal learning, edge-efficient deployment, privacy-preserving collaboration, standardized benchmarks, and farmer-centered interfaces. Progress along these directions can help move agricultural ML from isolated prototypes toward dependable decision-support systems that improve productivity, resilience, and resource efficiency.

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