

A Survey of Deep Learning and IoT Technologies for Sustainable Smart Agriculture: Enhancing Productivity and Environmental Sustainability

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Abstract: The rapid development of Internet of Things (IoT), artificial intelligence (AI), edge computing, remote sensing and cloud platforms is reshaping agriculture from periodic observation toward continuous, data-driven management. This study surveys the convergence of IoT and deep learning (DL) for smart and sustainable agriculture, focusing on crop monitoring, disease and stress detection, irrigation, yield prediction, soil intelligence, resource optimization and environmental sustainability. The review finds that IoT provides fine-grained sensing and connectivity, while DL learns nonlinear spatial and temporal relationships from sensor streams, images, weather observations and historical farm records. CNNs are widely used for visual crop diagnostics, whereas LSTM/GRU, CNN-LSTM and Transformer models address temporal forecasting. Major gaps include fragmented single-task systems, laboratory-style datasets, limited multimodal integration, weak field-scale validation and inconsistent measurement of water, energy, chemical inputs and productivity. The proposed research direction is an integrated multimodal IoT-DL framework with edge-cloud intelligence, uncertainty-aware prediction and adaptive, sustainability-aware actuation.

Keywords: Internet of Things, deep learning, smart agriculture, sustainable agriculture, crop disease detection, smart irrigation, edge AI, multimodal learning.

Introduction

Agriculture is under simultaneous pressure from climate variability, water scarcity, soil degradation, labor constraints, increasing input costs and the need to produce more food with lower environmental impact. Digital agriculture has emerged as a response in which sensing, communication, analytics and automation are integrated into farm operations. Recent surveys describe IoT as a core enabling technology because connected sensors can continuously observe soil, weather, crop and equipment conditions and transmit these observations for analysis and control [1]-[4]. A 2024 review concludes that IoT can support higher agricultural productivity while also identifying implementation challenges that must be addressed for sustainable deployment [1].

Deep learning complements IoT by providing data-driven inference over large and heterogeneous datasets. Instead of relying only on hand-crafted thresholds, DL models can learn representations from images, time series, geospatial information and multimodal observations. CNNs are particularly effective for image-based crop and disease analysis; recurrent models such as LSTM and GRU are suited to temporal dependencies; and attention/Transformer architectures offer mechanisms for long-range dependencies and multimodal fusion. A comparative survey of DL and IoT for precision agriculture shows that the two technologies are increasingly being combined for pest and disease detection, soil analysis, yield prediction and other precision-farming tasks [3].

The central question of this survey is therefore not whether IoT or DL is useful independently, but how their convergence can create reliable and sustainable agricultural decision systems. The objective is to synthesize the literature, compare the dominant technical approaches, identify unresolved limitations, and formulate a research direction in which productivity and environmental sustainability are optimized together.

Related Work

This survey synthesizes representative review and research literature on IoT-enabled agriculture, deep learning for agricultural intelligence, precision irrigation, crop-health monitoring, yield prediction, edge/IoT architectures and digital water management. Priority is given to recent peer-reviewed reviews and broad surveys that discuss system architecture, application domains, challenges and future directions. The literature is organized by the function of the technology in the farming pipeline: sensing, connectivity, analytics, prediction, decision support and actuation.

Recent IoT surveys consistently identify a layered architecture involving sensing devices, communication networks, processing platforms and agricultural applications [1], [2], [4]. The sensing layer commonly contains soil-moisture, temperature, humidity, light, rainfall, electrical-conductivity and water-flow sensors, complemented by cameras, drones and remote-sensing platforms. The communication layer can include Wi-Fi, cellular networks, Zigbee and LPWAN technologies. Long-range, low-power communication is particularly attractive for distributed farms, while edge computing is increasingly used to reduce latency and bandwidth requirements. The analytics layer may be located in gateways, cloud platforms, or a hybrid edge-cloud architecture.

The literature also shows a transition from simple monitoring toward predictive and prescriptive agriculture. Earlier IoT solutions primarily displayed measurements or triggered threshold-based irrigation. More recent systems use ML/DL to predict soil moisture, disease risk, yield or crop stress and then recommend interventions. A 2025 review highlights the broader movement toward automated monitoring and control through IoT-based technologies while emphasizing continuing technical and implementation challenges [2].

Crop disease and pest detection

Crop disease detection is one of the most mature DL applications because plant symptoms can often be represented visually. CNNs and transfer-learning architectures learn hierarchical image features and can classify disease categories from leaf or canopy images. The literature reports strong performance in controlled datasets, but field deployment is more difficult because illumination, background, cultivar, growth stage, camera angle and disease severity vary substantially. The comparative DL-IoT survey notes that agricultural datasets require careful acquisition, augmentation and annotation and identifies data quality as a major factor in practical performance [3].

An important direction is multimodal disease diagnosis. Rather than treating an image as the only evidence, a system can combine visual features with humidity, temperature, leaf-wetness or historical disease observations. This can reduce false positives caused by visual ambiguity and may improve early warning. However, such systems require synchronized datasets and careful validation across locations and seasons.

Irrigation and water management

Water management is one of the strongest use cases for IoT-DL integration. Soil-moisture sensors provide direct measurements, while weather forecasts, evapotranspiration estimates and crop stage provide contextual information. Deep temporal models can learn how recent moisture levels and environmental

conditions affect future irrigation demand. Recent reviews of digital technologies for agricultural water management identify IoT, AI, remote sensing, smart sensors and related technologies as important approaches, with efficient irrigation among the most common applications [5].

The major limitation of threshold-only irrigation is that the same threshold may not be appropriate for different soils, crops or growth stages. Predictive irrigation attempts to estimate near-future soil moisture or water demand and decide whether irrigation should occur. A sustainability-oriented design should additionally include pumping energy, water availability and crop productivity in the decision objective rather than minimizing water consumption alone.

Yield and crop-condition prediction

Yield prediction is inherently temporal and spatial. Weather conditions, soil properties, crop variety, management actions and disease pressure interact over time. LSTM and GRU networks have therefore been explored for sequential agricultural data, while CNN-LSTM architectures can combine spatial representation and temporal dynamics. Critical reviews of ML, remote sensing and IoT approaches indicate that combining heterogeneous data sources can improve agricultural forecasting and decision support [6].

Despite these advances, yield models face transferability problems. A model trained for one region or season may lose accuracy when soil, climate, cultivar or management practices change. This motivates domain adaptation, transfer learning, continual learning and uncertainty estimation. A useful smart-agriculture model should indicate not only a prediction but also its confidence, especially when decisions have economic or environmental consequences.

Soil intelligence and anomaly detection

IoT sensors can monitor soil moisture, temperature, salinity and related properties at high temporal resolution. Deep autoencoders and other representation-learning methods can identify anomalous readings caused by sensor drift, communication errors or unusual farm conditions. Soil data can also be fused with topography, remote sensing and historical samples to estimate spatial variation. Recent practical applications of AI in soil monitoring illustrate how environmental and remote-sensing variables can be combined with machine learning to create digital soil information at field scale [7].

The main challenge is that ground-truth soil measurements are expensive and sparse. Models can therefore appear accurate on limited samples while generalizing poorly to unseen fields. Sensor calibration, uncertainty quantification and spatially representative sampling are essential for trustworthy soil intelligence.

Comparative Review of Major Approaches

Reference	Approach	Typical data	Main strengths	Main limitations	Sustainability relevance
[1]	Rule/threshold systems	Sensor values	Simple, low cost, interpretable	Poor adaptability; limited context	Basic water/resource control
[2]	Conventional ML	Structured sensor/history	Efficient and interpretable	Feature engineering; weaker	Good for targeted optimization

				multimodal learning	
[3]	CNN / Transfer Learning	Crop images	Strong visual representation	Domain shift; dataset dependence	Early disease detection; targeted chemicals
[4]	LSTM / GRU	Time-series sensors/weather	Models temporal dependence	Long-term dependency and training issues	Predictive irrigation and crop stress
[5]	CNN-LSTM	Images + sequences	Spatial-temporal modeling	More computation; data alignment	Integrated crop monitoring
[6]	Transformer / multimodal DL	Long sequences + mixed modalities	Long-range and cross-modal relationships	Compute and data requirements	Joint productivity-resource optimization
[7]	Edge-cloud DL	IoT streams + local inference	Low latency and scalable training	Deployment complexity	Reduced bandwidth and responsive control

Figure 1. shows the pictorial representation of the above discuss survey papers comparison.

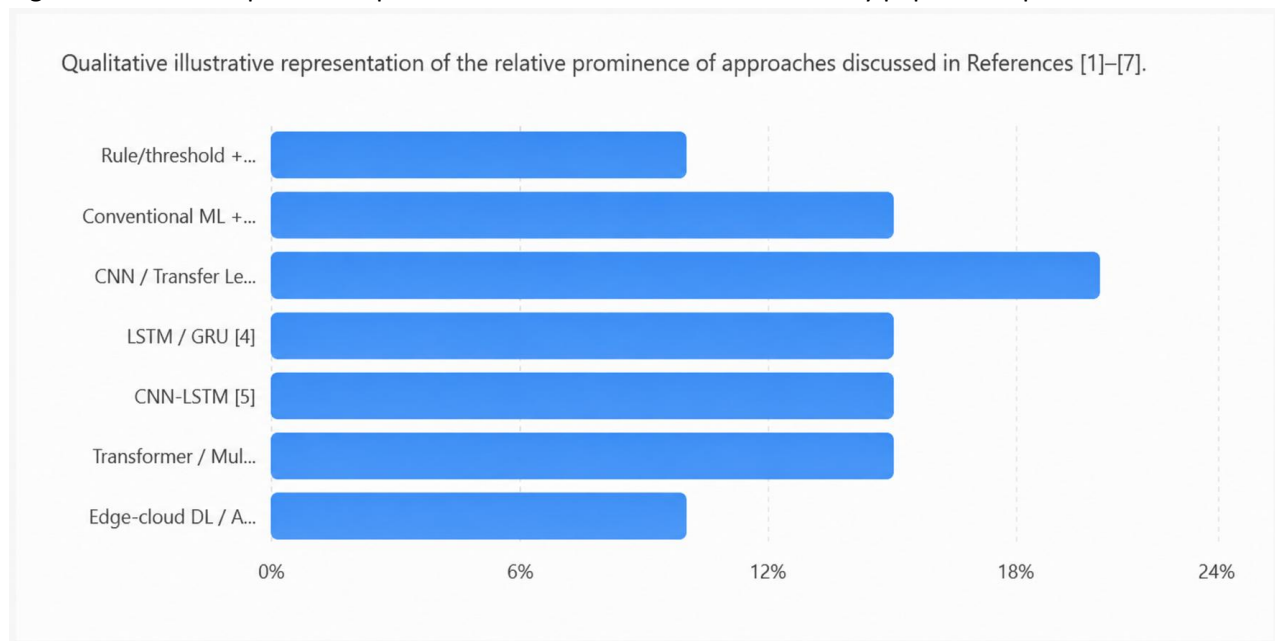


Figure 1. Comparision of literature survey

Key Contributions

1. A structured synthesis of IoT and deep-learning approaches across crop disease and pest detection, irrigation and water management, yield and crop-condition prediction, and soil intelligence.
2. A comparison of rule/threshold systems, conventional machine learning, CNN/transfer learning, LSTM/GRU, CNN-LSTM, Transformer/multimodal DL and edge-cloud DL approaches.
3. Identification of the need to evaluate productivity and environmental sustainability jointly rather than optimizing prediction accuracy or a single agricultural task alone.
4. Identification of research gaps in multimodal data fusion, field-scale and multi-season generalization, edge deployment, explainability, cybersecurity and sustainability metrics.
5. A proposed closed-loop research direction combining IoT sensing, multimodal DL prediction, resource-aware optimization, edge/cloud processing and adaptive actuation.

Objectives

1. Develop an IoT-based sensing architecture for continuous collection of soil, crop, weather and resource data.
2. Develop CNN-based models for image-driven crop disease and stress detection.
3. Develop LSTM or Transformer models for temporal sensor and weather prediction.
4. Design multimodal fusion of image, sensor, weather and historical farm data.
5. Develop a sustainability-aware optimization module for irrigation and agricultural input decisions.
4. Implement edge-cloud intelligence for low-latency inference and scalable model training.
5. Evaluate prediction accuracy together with water savings, energy savings, input reduction, yield and latency.

Proposed Research Framework Methodology

The proposed framework integrates IoT sensing, edge computing, deep learning, multimodal data fusion, uncertainty-aware prediction, and sustainability-constrained resource optimization to support intelligent and adaptive agricultural decision-making. The framework is designed as a closed-loop system in which data collected from the field are processed and analyzed to generate decisions, which are subsequently implemented through actuators and continuously evaluated through feedback.

IoT Sensing Layer:

The sensing layer collects heterogeneous real-time agricultural data using soil, weather, crop, water-flow, and equipment sensors, along with cameras for capturing crop and field images. These data provide information on soil moisture, temperature, humidity, crop condition, irrigation status, environmental parameters, and equipment operation.

Connectivity Layer:

The connectivity layer provides reliable communication between field sensors, edge devices, and cloud infrastructure using appropriate wireless and Low-Power Wide-Area Network (LPWAN) technologies. It enables timely transmission of sensor and image data while considering the communication constraints of agricultural environments.

Edge Computing Layer

At the edge, incoming data are preprocessed to reduce noise, detect anomalies, handle immediate data-quality issues, and perform latency-sensitive inference. Deploying suitable models at the edge reduces communication overhead and enables rapid responses to time-critical agricultural conditions.

Deep Learning Layer

The deep learning layer employs Convolutional Neural Networks (CNNs) for image-based crop and disease analysis and LSTM, GRU, or Transformer-based models for learning temporal patterns from sensor, weather, and historical agricultural data.

Multimodal Fusion Layer

Representations obtained from heterogeneous data sources are integrated through feature-level or representation-level multimodal fusion. This enables the system to jointly exploit visual, environmental, temporal, and historical information for improved agricultural intelligence.

Decision and Optimization Layer

The decision layer generates uncertainty-aware predictions and performs sustainability-constrained resource optimization. Irrigation and other agricultural inputs are optimized by simultaneously considering productivity objectives and constraints related to water, energy, fertilizer, pesticide use, and environmental sustainability.

Actuation Layer

The resulting decisions are transmitted to irrigation systems and other farm equipment for automated or assisted intervention. Feedback from the field is continuously returned to the sensing layer, creating a closed-loop adaptive agricultural management system.

Scope

The scope of this research is to develop an IoT–deep learning-based multimodal framework that integrates sensor, image, weather, and historical farm data for intelligent agricultural decision-making. The framework aims to optimize water, energy, fertilizer, and pesticide usage while improving crop productivity and environmental sustainability. Future work will explore multimodal Transformers, foundation models, federated learning, continual learning, and reinforcement learning for adaptive and efficient smart farming.

Discussion

The results should be interpreted as a template for a future experimental study. Actual values should be replaced with measurements obtained from a validated dataset or field deployment. Recommended additional metrics include precision, recall, F1-score, RMSE/MAE for forecasting, irrigation volume, energy consumption, input reduction, yield, inference latency, memory use and number of actuator decisions.

Conclusion

Problem Statement Addressed : A multimodal framework is needed to balance agricultural productivity with water, energy, fertilizer, pesticide use, and environmental sustainability under varying field conditions. This work addresses the there is a need for an integrated IoT–deep learning framework that combines multimodal data for adaptive resource management while improving productivity and environmental sustainability.

Method Used: The proposed methodological direction integrates heterogeneous IoT sensor streams, crop images, weather observations and historical farm records. CNN-based models are considered for image intelligence, while LSTM/GRU or Transformer models are considered for temporal sensor and weather data. Feature- or representation-level fusion is followed by uncertainty-aware prediction and a resource-optimization module. Edge devices perform rapid local inference, while cloud services support storage, training and periodic model updates

Key findings: A key research need is an integrated multimodal, closed-loop framework that jointly improves productivity, resource efficiency, and environmental sustainability.

Limitations and Future Work: Future work should investigate foundation models and multimodal Transformers adapted to agricultural domains, federated learning for farms that cannot share raw data, continual learning for seasonal drift, and reinforcement learning for sequential resource-management decisions.

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