

Review

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Review

Review of the Current State of Deep Learning Applications in Agriculture

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Abstract: The integration of Deep Learning (DL) into agriculture marks a transformative shift towards Agriculture 4.0, addressing critical global challenges such as food security, climate change, and resource scarcity. This comprehensive review synthesizes the current state of DL applications in agriculture, focusing on key domains: precision crop management, livestock monitoring, soil analysis, and water management. DL, primarily leveraging Convolutional Neural Networks (CNNs), excels in tasks like plant disease detection, weed identification, yield prediction, and animal health monitoring by extracting intricate patterns from complex, heterogeneous data sources such as sensors, drones, and satellites. Emerging architectures like Transformers and methodologies such as transfer learning and data fusion further enhance DL's capability to handle multimodal agricultural data, driving precision and automation. The benefits are substantial—improved accuracy, operational efficiency, resource optimization, and sustainability—yet significant challenges persist. Data scarcity, quality, and bias limit model robustness and generalization, while high computational costs, interpretability issues, and implementation barriers (e.g., cost, infrastructure, expertise) hinder widespread adoption. Looking forward, trends point to deeper integration with IoT and robotics, a data-centric focus, and advancements in Explainable AI (XAI) and edge computing to enable real-time, trustworthy systems. This review underscores DL's potential to revolutionize farming practices while emphasizing the need for collaborative efforts to overcome data and deployment hurdles. By bridging AI research and practical agriculture, it offers a roadmap for researchers and stakeholders to harness DL for sustainable, efficient food production in an increasingly demanding world.

Keywords: deep learning; convolutional neural networks; precision agriculture; smart agriculture; data fusion

I. Introduction

Agriculture stands as a cornerstone of the global economy and human sustenance, yet it faces unprecedented challenges in the 21st century. A rapidly growing global population, projected to reach approximately 9 billion by 2050 (Mukherjee, 2025), exerts immense pressure on food production systems. Compounding this demand are the escalating impacts of climate change, leading to unpredictable weather patterns, increased pest and disease pressure, and resource scarcity, particularly concerning land and water (Agrawal and Kumar, 2025). Traditional agricultural practices, while foundational, often encounter limitations in efficiency, resource management, and the ability to make timely, data-informed decisions in the face of such complex and dynamic conditions (Farjon et al., 2023; Katharria et al., 2025). These limitations necessitate a paradigm shift towards more intelligent, precise, and sustainable farming methods (Keskes and Nita, 2024).

In response to these pressures, the concept of Smart Agriculture, often termed Agriculture 4.0, has emerged (Xuan et al., 2025). This represents a significant transformation, merging conventional farming techniques with an array of modern digital technologies, including the Internet of Things (IoT), Artificial Intelligence (AI) – encompassing Machine Learning (ML) and Deep Learning (DL) – automation, robotics, and sophisticated data fusion techniques (Bouacida et al., 2025). Agriculture 4.0 leverages data streams from diverse sources like ground-based sensors, Unmanned Aerial Vehicles (UAVs or drones), satellites, and AI-driven machinery to fundamentally enhance operational

efficiency, promote environmental sustainability, increase crop yields, and minimize waste (Aijaz et al., 2025; Katharria et al., 2025). A core component of this transformation is Precision Agriculture (PA), which focuses on managing spatial and temporal variability within fields to optimize inputs and improve outcomes (Wang et al., 2022). The earliest introductions of AI in agriculture involved expert systems designed as decision aids for integrated crop management, covering aspects like irrigation and pest control (Mukherjee, 2025).

Within this technological revolution, DL has surfaced as a particularly potent and transformative tool (Ojo and Zahid, 2022). As a subset of ML, DL utilizes artificial neural networks with multiple layers (deep architectures) inspired by the human brain's structure (Saiwa, 2016). Its primary strength lies in its remarkable ability to automatically learn intricate patterns and hierarchical features directly from vast amounts of raw data, particularly unstructured data like images (Mukherjee, 2025). This capability allows DL models to often surpass the performance of traditional ML algorithms and conventional image processing techniques, which typically rely on manually engineered features (Lacroix, 2024; Kamilaris and Prenafeta-Boldú, 2018). The capacity of DL to interpret enormous volumes of complex data has unlocked fresh prospects for data analytics in agriculture (Mukherjee, 2025).

While DL is frequently viewed as a tool for optimizing existing agricultural processes, such as resource allocation or disease identification, its impact extends further (Diaz-Delgado et al., 2025). The ability of DL to analyze complex, heterogeneous data from multiple sources – sensors, drones, satellites, climate models – and facilitate sophisticated automation is fundamentally *enabling* entirely new agricultural paradigms (García-Navarrete et al., 2025). Traditional methods inherently struggle to process and integrate such vast and varied data streams effectively. DL excels at this complex data processing and feature extraction (Mukherjee, 2025), making it possible to derive real-time, highly granular insights and trigger precise interventions (Charisis and Argyropoulos, 2024). Examples include identifying and targeting individual weeds for robotic or laser removal (Aixa Lacroix, 2024) or evaluating precision spraying deposition without traditional tracers (Chintakunta et al., 2023; Rogers et al., 2024). This capability underpins the shift towards hyper-precise management and data-driven decision-making at scales previously unimaginable, forming the technological bedrock of Agriculture 4.0 (Agrawal and Kumar, 2025).

This review aims to provide a comprehensive synthesis of the current state of DL applications within the agricultural sector. It delves into the primary domains of application, specific tasks addressed by DL techniques, the architectures and methodologies employed, and evaluations of their performance and effectiveness. Furthermore, it examines the reported benefits and advantages of DL adoption, alongside the significant challenges and limitations that impede wider implementation. Building upon existing surveys, this work incorporates recent advancements, such as the application of Transformer architectures and Explainable AI (XAI) and places a strong emphasis on the critical interplay between DL, multi-source data fusion, and the advancement of precision agriculture. The overarching goal is to bridge the gap between cutting-edge AI research and practical agricultural applications, offering a valuable roadmap for researchers, industry professionals, and policymakers seeking to harness these powerful technologies.

II. Mapping the Landscape: Domains and Applications of DL in Agriculture

DL techniques are permeating various facets of the agricultural sector, creating opportunities for enhanced efficiency and sustainability across the entire value chain (Agrawal and Kumar, 2025). These applications can be broadly categorized based on the stage of production – pre-harvesting, harvesting, and post-harvesting (Katharria et al., 2025) – or, perhaps more functionally, by the specific agricultural domain they address. Common domain categorizations include crop management, livestock monitoring, soil analysis, and water management (Mahmud et al., 2021). Among these, crop management has emerged as the most extensively researched area for DL applications, likely due to the prevalence of image-based data and the direct link to yield optimization (Xuan et al., 2025).

A. Precision Crop Management

Precision crop management represents a major focal point for DL research and application, aiming to optimize inputs and practices at a granular level (Chintakunta et al., 2023). Key applications include:

- Plant Disease and Pest Detection:** Crop diseases and pests pose a significant threat to global food security, causing substantial yield losses annually (Benos et al., 2021; Kamilaris and Prenafeta-Boldú, 2018). Early and accurate detection is paramount for effective management (Benos et al., 2021). DL models, particularly Convolutional Neural Networks (CNNs), have demonstrated remarkable success in analyzing visual data (images of leaves, stems, fruits) captured from various platforms (handheld devices, drones, fixed sensors) to identify and classify a wide range of diseases and pests (Mukherjee, 2025). Specific examples include identifying diseases in cucumbers (Berdugo et al., 2014), tomatoes (Fuentes et al., 2017), apples (Ren et al., 2020), bananas (Selvaraj et al., 2019), soybeans and recognizing pests in cotton (Wang et al., 2022). Beyond simple classification, some DL models can quantify the severity of infection or be integrated with IoT systems to provide timely alerts to farmers (Albahar, 2023).
- Weed Detection and Management:** Weeds compete with crops for resources, significantly impacting yield and quality (Murad et al., 2023). DL techniques, primarily CNNs, are employed to distinguish weeds from crops based on image analysis (Mukherjee, 2025). This capability enables precision agriculture approaches like site-specific herbicide application through intelligent sprayers or targeted mechanical/laser weeding by agricultural robots (Aixa Lacroix, 2024). Such targeted interventions drastically reduce overall chemical usage, benefiting both the environment and farm economics (Murad et al., 2023). Semantic segmentation models can precisely map weed locations within a field, and ongoing research compares different object detection models like YOLO variants for optimal real-time performance in field conditions (Allmendinger et al., 2025).
- Yield Prediction:** Forecasting crop yield is a critical yet inherently complex task in agriculture, influenced by numerous interacting factors (Bali and Singla, 2022). Accurate predictions aid farmers in making informed decisions regarding harvest logistics, storage, marketing, and resource management (Benos et al., 2021). DL models, including CNNs, Recurrent Neural Networks (RNNs, particularly LSTMs for temporal data), and hybrid architectures, are increasingly used to analyze diverse data streams – such as satellite or drone-based remote sensing imagery, historical weather patterns, soil property data, and past yield records – to generate yield forecasts (Mukherjee, 2025). These techniques have been applied to major crops like wheat, maize (Oikonomidis et al., 2023), soybeans (Sun et al., 2019), rice (Jeong et al., 2022), corn (Abbas et al., 2021), as well as various fruits (Benos et al., 2021).
- Fruit Counting and Detection:** Automated counting and detection of fruits on trees or plants are essential for accurate pre-harvest yield estimation and optimizing harvest management strategies (Mukherjee, 2025). DL-based object detection models (e.g., Faster R-CNN, YOLO, Inception-ResNet) and custom CNNs are trained to identify and count fruits like apples (Fu et al., 2020), citrus (Khattak et al., 2021), mangoes (Pathak et al., 2024) or video footage captured in orchards and fields (Farjon et al., 2023). Density estimation techniques, which predict a map of object density rather than individual instances, also serve as an alternative approach for counting (Agrawal and Kumar, 2025).
- Crop Monitoring and Phenotyping:** DL facilitates continuous monitoring of crop status

throughout the growing season. This includes assessing overall crop health, identifying different growth stages, monitoring nutrient levels (e.g., nitrogen status), and detecting abiotic stresses such as water deficit, salinity, or heat stress (Benos et al., 2021). DL algorithms process data acquired from various sensors mounted on drones, satellites, or ground platforms (Mukherjee, 2025). High-throughput plant phenotyping, leveraging DL for analyzing observable traits, accelerates crop breeding programs by automating the assessment of characteristics like disease resistance or yield potential (Wang et al., 2022).

- **Seed Classification and Quality Assessment:** DL, particularly CNNs, can enhance the efficiency and accuracy of classifying different seed types or assessing seed quality (Mukherjee, 2025). Related applications include estimating the number of seeds per pod in crops like soybeans, which is relevant for yield component analysis (Katharria et al., 2024).

B. Precision Livestock Farming (PLF)

PLF involves applying monitoring, modeling, and management technologies to individual animals, moving beyond herd-level averages (Aijaz et al., 2025). DL contributes significantly to this domain:

- **Animal Health and Welfare Monitoring:** DL models analyze data from wearable sensors (e.g., accelerometers tracking movement) or video cameras to monitor animal health and behavior patterns (Chintakunta et al., 2023). Detecting deviations from normal behavior can serve as an early indicator of health issues, such as lameness in dairy cows or subacute ruminal acidosis (SARA), enabling timely intervention and improving animal welfare (Espinell et al., 2024).
- **Behavior Analysis:** ML and DL models (including RF, SVM, LDA, KNN, DT, MLP, LSTM) are used to automatically classify specific animal behaviors like grazing, resting, ruminating, or feeding from sensor data (Murad et al., 2023). Understanding behavior patterns is crucial for assessing welfare and optimizing management (Keskes and Nita, 2024).
- **Optimizing Production:** By monitoring individual animal data such as feed intake, growth rates, and environmental conditions, DL models can help optimize feeding strategies, predict growth trajectories, and inform breeding decisions (Xuan et al., 2025). Remote counting technologies can also aid in livestock inventory management (Farjon et al., 2023). Applications extend to aquaculture, such as fish detection and monitoring in recirculating systems (Lakhia et al., 2024).

C. Intelligent Soil and Water Management

Optimizing the use of soil and water resources is critical for sustainable and efficient agriculture. DL plays a growing role in:

- **Soil Analysis and Management:** DL models (regression techniques, CNNs, XGBoost, RF, ANNs) are used to predict key soil properties, including soil moisture content, organic matter levels, nutrient availability (N, P, K), pH, salinity, and bulk density (Mukherjee, 2025). These predictions often leverage data fusion, combining inputs from soil sensors, remote sensing platforms (satellite/drone imagery), weather data, and techniques like Time Domain Reflectometry (Awais et al., 2023). DL can also contribute to assessing overall soil health and identifying microbial indicators associated with soil-borne diseases (Chintakunta et al., 2023). Transformer-based models have shown particular strength in fusing multi-source remote sensing data for accurate soil analysis (Saki et al., 2024).
- **Water Management and Precision Irrigation:** Efficient water use is crucial. DL algorithms help

optimize irrigation scheduling by predicting crop water requirements based on factors like soil moisture measurements (from sensors or predicted by models), weather forecasts, evapotranspiration estimates, and crop growth stage (Mujahid Tabassum, 2024). Models employed include CNNs, decision trees, and integrated IoT-DL systems (Lakhiar et al., 2024). DL can also be used to detect leaks in irrigation infrastructure by analyzing flow and pressure data (Alina P., 2024), assess water stress levels in crops using remote sensing data, and even contribute to broader water resource management through forecasting lake water levels or flood risks (Chintakunta et al., 2023).

D. Emerging Application Frontiers

Beyond the established domains, DL is enabling novel applications:

- **Precision Spraying:** Moving beyond simple detection, DL combined with computer vision and XAI is being developed to evaluate the effectiveness of precision spraying systems *after* application, quantifying spray deposition on targets (crops vs. weeds) without relying solely on traditional, labor-intensive methods like water-sensitive papers or fluorescent tracers. This allows for better calibration and verification of systems designed to minimize chemical use (Rogers et al., 2024).
- **Automated Harvesting:** DL-powered object detection (e.g., using YOLO models) is a key component in robotic harvesting systems, enabling robots to accurately identify and locate ripe fruits or vegetables for picking (Mukherjee, 2025).
- **Agricultural Robotics:** AI, particularly DL, is the "brain" behind increasingly sophisticated agricultural robots designed for autonomous tasks such as planting, targeted weeding (including non-chemical methods like laser weeding (Lacroix, 2024), precision spraying, field monitoring, and harvesting (Rane et al., 2024). Vision Transformers are being explored for tasks like multi-object tracking to enhance robotic perception in complex field environments (Sapkota and Karkee, 2024).
- **Supply Chain and Traceability:** DL has potential applications in improving the efficiency, transparency, and safety of agricultural supply chains, for instance, by tracking products from farm to consumer (Saiwa, 2016).

DL applications in agriculture show varied maturity across domains, with crop-related tasks like disease detection and yield prediction being the most advanced, leveraging established CNNs and datasets like PlantVillage, despite some limitations (Tabassum, 2024; Nanobaly, 2024; Alican, 2022). Livestock monitoring, soil analysis, and water management lag in high-performance DL solutions due to complex, diverse data types (Victor et al., 2025; Chintakunta et al., 2023). Emerging areas like precision spraying and autonomous robotics are advancing but face engineering challenges beyond algorithms (Rogers et al., 2024; Aixa Lacroix, 2024). DL is evolving from basic classification, such as identifying diseases or weeds, to advanced predictive tasks like estimating disease severity, yield volume, plant counts, soil properties, and forecasting pest outbreaks, market prices, and harvest timing (Espinell et al., 2024; Benos et al., 2021; Awais et al., 2023; Chintakunta et al., 2023; Alina, 2024). This shift, driven by advancements in regression, time-series analysis (RNNs), and Transformers, supports actionable insights for precision agriculture's demand for quantitative accuracy (Morchid et al., 2024).

III. The Technological Toolkit: DL Architectures and Methodologies

The successful application of DL in agriculture relies on a diverse set of neural network architectures and sophisticated methodologies designed to handle the unique characteristics and challenges of agricultural data (Victor et al., 2025).

A. Foundational Architectures

Several core DL architectures form the backbone of most agricultural applications:

- **Convolutional Neural Networks (CNNs):** CNNs are unequivocally the dominant architecture in agricultural DL, particularly for tasks involving image data (Mukherjee, 2025). Their inherent ability to automatically learn spatial hierarchies of features (from simple edges and textures to complex object parts) makes them exceptionally well-suited for analyzing visual information from crops, soil, and livestock (Hashemi-Beni and Gebrehiwot, 2020). Consequently, CNNs are widely applied in plant disease and pest detection, weed identification, fruit counting and localization, crop type classification from remote sensing imagery, and even soil property estimation when derived from visual or spectral image data (Farjon et al., 2023).
 - *Specific CNN Variants:* A vast array of specific CNN architectures, often originating from broader computer vision research, have been adapted for agriculture (Awais et al., 2023). These include foundational models like AlexNet, VGGNet (e.g., VGG-16), and GoogLeNet (Thakur et al., 2024); deeper architectures like ResNet (e.g., ResNet-50, ResNet-101, ResNet-152V2) (Seyrek and Yiğit, 2024) and Inception networks (e.g., Inception-ResNet, InceptionV3) (Szegedy et al., 2017); efficient models designed for mobile or edge deployment like MobileNet (e.g., MobileNetV2) and EfficientNet (e.g., EfficientNet-B0) (Kulkarni et al., 2021); object detection frameworks like Faster R-CNN, R-FCN (Jiang and Learned-Miller, 2017), SSD (Single Shot MultiBox Detector), and the popular YOLO (You Only Look Once) family (v3 through v11); segmentation networks like U-Net, SegNet, and Fully Convolutional Networks (FCNs); and specialized networks like CountNet for counting or DeepCorn for kernel analysis (Farjon et al., 2023). Hybrid approaches combining CNNs with other architectures, like PlantViT (CNN-Transformer), also exist (Sapkota and Karkee, 2024).
 - *Object Detection Comparison (YOLO vs. Faster R-CNN):* Object detection is fundamental to many agricultural tasks (e.g., identifying fruits, weeds, pests). YOLO and Faster R-CNN represent two dominant, but distinct approaches frequently compared in the literature (Mohyuddin et al., 2024). YOLO models are "one-stage" detectors, performing localization and classification in a single pass (Ren et al., 2017). This generally results in significantly faster inference speeds, making them suitable for real-time applications like robotic weeding or analysis on drones (Sharma et al., 2024). However, earlier YOLO versions sometimes struggled with detecting small or heavily overlapping objects compared to "two-stage" detectors like Faster R-CNN (Kanna S et al., 2024). Faster R-CNN first uses a Region Proposal Network (RPN) to identify potential object regions and then classifies these regions, often leading to higher accuracy, particularly for challenging objects, but at the cost of slower processing speeds (Sharma et al., 2024). Faster R-CNN's RPN and feature pyramid networks may also handle objects of varying sizes more effectively. Recent advancements in the YOLO family (e.g., YOLOv9 (Gui et al., 2025; Santos Júnior et al., 2025), YOLOv11 (Liao et al., 2025) have significantly improved accuracy while maintaining high

speed, showing competitive or even superior performance against Faster R-CNN in specific agricultural benchmarks like weed detection (Sharma et al., 2024) and object detection in Synthetic Aperture Radar (SAR) imagery (Badgujar et al., 2024; Kanna S et al., 2024). The choice between them depends heavily on the specific application's requirements regarding speed versus accuracy trade-offs (Jiang and Learned-Miller, 2017).

- **Recurrent Neural Networks (RNNs):** RNNs are designed to process sequential data, making them suitable for agricultural applications involving time-series information, such as weather patterns, crop growth stages over time, or animal movement data (Victor et al., 2025).
- *Specific RNN Variants:* Long Short-Term Memory (LSTM) networks, a type of RNN designed to handle long-range dependencies, are commonly employed (Egan et al., 2017). Applications include crop yield prediction based on temporal environmental data (Albahar, 2023), modeling and predicting plant or animal growth trajectories (Mukherjee, 2025), assessing crop nutrient status using time-series spectral data (often in hybrid CNN-LSTM models), detecting abnormal animal behaviors indicative of illness (Egan et al., 2017), and classifying crops based on multi-temporal remote sensing data (Chenguan Ren et al., 2020).
- **Transformers:** Originally developed for Natural Language Processing (NLP), Transformer architectures, particularly Vision Transformers (ViTs) adapted for image analysis, are gaining traction in agriculture (Alicia Allmendinger et al., 2025; Khan et al., 2022). Their core mechanism is self-attention, allowing the model to weigh the importance of different parts of the input sequence (or image patches) when making predictions (Alicia Allmendinger et al., 2025).
 - *Applications:* Transformers are being explored for plant disease classification (achieving high accuracy in paddy and other leaf diseases) (Sapkota and Karkee, 2024), crop yield prediction (e.g., the MMST-ViT model fuses visual remote sensing data with meteorological time-series), multi-object tracking in complex agricultural scenes for robotic applications (Sapkota and Karkee, 2024), and notably, for sophisticated data fusion in agricultural remote sensing, particularly for soil analysis where they have shown significant performance gains over conventional methods (Saki et al., 2024). Detection Transformers (DETR) and variants like RT-DETR are also being tested for real-time weed classification (Khan et al., 2022).
 - *Performance & Challenges:* Early results are promising, with ViTs demonstrating high accuracy in disease detection (Sapkota and Karkee, 2024) and Transformer-based fusion significantly outperforming older methods in soil analysis (92-97% performance reported). RT-DETR shows high precision in weed detection tasks (Alicia Allmendinger et al., 2025; Khan et al., 2022). However, Transformers can be computationally intensive to train, and their application in agriculture is less mature compared to the long-standing use of CNNs (Alicia Allmendinger et al., 2025).
- **Other Architectures:** Beyond the main three, other network types appear in specific contexts. Basic Artificial Neural Networks (ANNs) or Multi-Layer Perceptrons (MLPs) were used in early AI agriculture work and sometimes feature in hybrid models or simpler regression/classification tasks (Mukherjee, 2025). Generative Adversarial Networks (GANs) are primarily used for data augmentation, generating synthetic data to expand limited datasets (Mukherjee, 2025). Graph Convolutional Networks (GCNs) have been applied to crop and weed recognition, leveraging relationships between image features. Less commonly mentioned architectures include Deep

Belief Networks (DBNs) (Espinel et al., 2024) and Autoencoders (Chengjuan Ren et al., 2020).

B. Key Methodologies

Alongside architectures, specific training and deployment methodologies are crucial for applying DL effectively in agriculture:

- **Transfer Learning (TL):** This is arguably one of the most critical methodologies in agricultural DL due to pervasive data limitation (Morchid et al., 2024). TL involves taking a model pre-trained on a large, general dataset (like ImageNet) and fine-tuning it on a smaller, specific agricultural dataset (Hossen et al., 2025). This leverages the general feature extraction capabilities learned by the pre-trained model, significantly reducing the amount of agriculture-specific labeled data and training time required to achieve good performance (Albahar, 2023). It is widely used for tasks like plant disease detection, weed identification (Hossen et al., 2025), and crop classification (Bouacida et al., 2025).
- **Data Fusion:** Precision agriculture often requires integrating information from diverse sources to obtain a comprehensive understanding of the farm environment (Mancipe-Castro and Gutiérrez-Carvajal, 2022). Data fusion techniques aim to combine data from multiple sensors (e.g., RGB, multispectral, hyperspectral, thermal cameras), platforms (drones, satellites, ground sensors), and data types (imagery, climate data, soil readings, IoT device data) (Katharria et al., 2025). Effective fusion can lead to more robust and accurate predictions than using any single data source alone (Mancipe-Castro and Gutiérrez-Carvajal, 2022). Examples include fusing SAR and optical satellite data for improved crop mapping or combining ground sensor readings with remote sensing data. Transformers are emerging as a powerful tool for handling the complexity of multi-source data fusion (Saki et al., 2024).
- **Data Augmentation:** Given the scarcity of labeled agricultural data, data augmentation techniques are frequently employed to artificially enlarge and diversify training dataset (Shorten and Khoshgoftaar, 2019). This involves applying transformations to existing images, such as rotations, flips, scaling, brightness/contrast adjustments, or adding noise (Gracia Moisés et al., 2023). More advanced techniques involve using GANs (e.g., Deep Convolutional GANs - DCGANs) to generate realistic synthetic images of crops, diseases, or weeds, further improving model robustness and generalization (Su et al., 2021).
- **Few-Shot Learning (FSL):** FSL methods are explicitly designed to enable models to learn and generalize effectively from a very small number of labelled examples per class (Song et al., 2023). This is highly relevant for agriculture, where obtaining large, labeled datasets for every possible crop variety, disease, or condition is often impractical (Ragu and Teo, 2023). Techniques like Siamese networks (comparing pairs of images) and prototypical networks (learning class prototypes) have shown promise in agricultural FSL applications, such as plant disease classification with limited samples (Mohyuddin et al., 2024).
- **Explainable AI (XAI):** DL models are often criticized for being "black boxes," making it difficult to understand their internal reasoning (Mallinger and Baeza-Yates, 2024). XAI techniques aim to provide insights into how DL models arrive at their predictions (Hassija et al., 2024). This is crucial for building user trust, debugging models, ensuring fairness, identifying potential dataset biases, and facilitating informed decision-making by farmers or agronomists (Espinel et al., 2024). Methods like Class Activation Maps (CAMs) visualize which parts of an input image were most influential for a classification decision, while techniques like LIME (Local

Interpretable Model-agnostic Explanations) provide local explanations for individual predictions (Mallinger and Baeza-Yates, 2024). XAI can be used, for example, to verify that a disease detection model is focusing on actual symptoms rather than background artifacts or to help evaluate the performance of precision spraying systems (Hassija et al., 2024).

- **Other Methodologies:** Other relevant techniques include *Ensemble Learning*, which combines predictions from multiple models to improve overall accuracy and robustness (Benos et al., 2021); *Semi-Supervised Learning*, which leverages large amounts of unlabeled data alongside a smaller labeled set (van Engelen and Hoos, 2020); *Weakly Supervised Learning*, which trains models using less precise labels (e.g., image-level labels for object counting) (Ren et al., 2023); and *Self-Supervised Learning*, where models learn representations from unlabeled data by solving pretext tasks, potentially useful for pre-training on large agricultural datasets (Chiu et al., 2020).

IV. Evaluating Impact: Performance, Effectiveness, and Benchmarks

Assessing the true impact of DL in agriculture requires moving beyond theoretical potential to evaluate quantitative performance, compare effectiveness against existing methods, and understand real-world efficiency gains.

A. Quantitative Performance Analysis

The performance of DL models in agricultural applications is typically measured using a range of quantitative metrics appropriate to the specific task:

- **Classification Tasks:** For tasks like disease identification, weed/crop classification, or seed sorting, *Accuracy* (overall percentage of correct predictions) is widely reported (Maganathan et al., 2020). However, accuracy can be misleading, especially with imbalanced datasets (where one class vastly outnumbers others). Therefore, metrics like *Precision* (proportion of positive identifications that were correct), *Recall* (proportion of actual positives that were correctly identified, also known as sensitivity), and the *F1-score* (harmonic mean of precision and recall) are often used to provide a more nuanced evaluation (Mahmud et al., 2021).
- **Object Detection Tasks:** For locating and classifying objects within images (e.g., fruits, weeds, pests), the standard metric is *Mean Average Precision (mAP)*. This metric considers both the classification accuracy and the localization accuracy (how well the predicted bounding box overlaps with the ground truth box, typically measured by Intersection over Union - IoU) across different confidence thresholds and object classes (Bal and Kayaalp, 2021).
- **Regression Tasks:** For predicting continuous values, such as crop yield, fruit counts, or soil moisture levels, common metrics include *Root Mean Squared Error (RMSE)*, *Mean Absolute Error (MAE)* (which measure the average magnitude of the prediction errors), and the *Coefficient of Determination (R^2)* (which indicates the proportion of the variance in the dependent variable that is predictable from the independent variables) (Hassija et al., 2024).
- **Density Estimation Tasks:** For counting methods based on density maps, metrics like the *Structural Similarity Measurement Index (SSIM)* (comparing map similarity) and *Percentage of Correct Keypoints (PCK)* (evaluating localization accuracy) may be used (Farjon et al., 2023).

Numerous studies report high performance figures for DL models on specific agricultural datasets. Examples include classification accuracies exceeding 99% for plant disease detection using the PlantVillage dataset (Benos et al., 2021), although these results warrant caution (discussed below). Other reported successes include 95.73% accuracy for soybean disease identification using 3D CNNs with hyperspectral data, 91% accuracy for fruit counting using synthetic training data (Bouacida et al., 2025), over 90% accuracy for weed classification in some studies (Chengjuan Ren et al., 2020),

93.7% accuracy for a hybrid DL system predicting crop yield, impressive 92-97% performance benchmarks for Transformer-based data fusion in soil analysis (Saki et al., 2024), and high mAP scores (e.g., 0.935 for YOLOv9 (Sharma et al., 2024), 0.987 for YOLOv9s (Li et al., 2020)) combined with fast inference speeds (e.g., 13.5ms for YOLOv11 (Sharma et al., 2024)) for YOLO models in weed and object detection tasks (Victor et al., 2025).

B. Comparative Assessment Against Traditional Techniques

A consistent finding across the literature is that DL approaches generally outperform traditional ML algorithms (such as Support Vector Machines (SVM), Random Forests (RF), K-Nearest Neighbors (KNN), Decision Trees (DT)) and conventional computer vision or image processing methods in a variety of agricultural tasks (Mukherjee, 2025). For instance, CNNs were found to be superior to traditional methods for estimating the number of seeds in soybean pods (Tamayo-Vera et al., 2024). DL techniques consistently provide higher accuracy in plant disease detection compared to previous approaches (Kamilaris and Prenafeta-Boldú, 2018). Similarly, DL models often achieve more accurate crop yield predictions than traditional ML models (Mahmud et al., 2021). In the domain of data fusion for soil analysis, Transformer-based models have demonstrated significant advantages over both conventional ML and earlier DL methods (Saki et al., 2024). The ability of DL to automatically learn relevant features from complex, high-dimensional data without extensive manual feature engineering is a key factor contributing to this superior performance (Hassija et al., 2024).

C. Real-World Impact and Efficiency Gains

While achieving high accuracy on benchmark datasets is important, the true value of DL in agriculture lies in its real-world impact. DL has the potential to optimize resource use (Saiwa, 2016), lower input costs (Aijaz et al., 2025), reduce labor dependency (Charisis and Argyropoulos, 2024), and promote sustainable practices (Bal and Kayaalp, 2021). However, there is limited quantified evidence showing concrete benefits, such as yield improvements or cost reductions. Some studies show promise—for example, a 60% reduction in crop type prediction error using multimodal DL (Thangamani et al., 2024), and evaluations of reduced chemical use via precision spraying (Rogers et al., 2024). Still, a gap remains between technical feasibility and measurable real-world value (Mahmud et al., 2021).

There is a significant gap between the high performance of DL models on benchmark datasets and their effectiveness in real-world agricultural settings. Studies often report accuracies over 99% on datasets like PlantVillage (Tamayo-Vera et al., 2024), but practical applications reveal issues with robustness and generalization (Charisis and Argyropoulos, 2024). This discrepancy is largely due to dataset limitations—such as controlled image conditions—that allow models to learn irrelevant features rather than actual disease symptoms (Alican, 2022; Morchid et al., 2024). Consequently, these models struggle with real-world variability like lighting, occlusions, and crop differences. To ensure practical readiness, models must be tested under diverse field conditions using datasets that reflect real agricultural environments (García-Navarrete et al., 2025; Victor et al., 2025).

Although DL's potential for cost savings, yield gains, and resource efficiency is widely acknowledged (Mahmud et al., 2021), there is a lack of large-scale, quantified case studies demonstrating these benefits. Most research continues to prioritize algorithmic performance metrics like accuracy, mAP, or RMSE, highlighting a disconnect between technical achievements and real-world impact (Espinel et al., 2024). To encourage broader adoption and justify investment, future work must focus on quantifying return on investment (ROI) and assessing sustainability improvements from DL system implementation (Mukherjee, 2025).

V. Harvesting the Benefits: Advantages of DL Adoption

The integration of DL into agriculture offers a multitude of compelling advantages, driving the transformation towards smarter, more efficient, and sustainable farming practices. These benefits stem primarily from DL's advanced analytical capabilities and its potential to enable automation and precision management.

- **Improved Accuracy and Performance:** A cornerstone benefit is the ability of DL models to achieve significantly higher accuracy compared to traditional machine learning algorithms and conventional methods in various agricultural tasks. This includes more accurate classification of diseases, pests, and weeds; more precise detection and localization of objects like fruits; and more reliable prediction of outcomes such as crop yield (Mukherjee, 2025). This enhanced accuracy translates into more dependable insights for decision-making.
- **Automation and Efficiency:** DL enables the automation of tasks that are traditionally labor-intensive, time-consuming, and sometimes prone to human error (Keskes and Nita, 2024). Examples include automated field scouting for diseases and pests, robotic weed removal, automated fruit counting for yield estimation, and potentially even robotic harvesting (Katharria et al., 2025). This automation leads to significant savings in time and labor costs, freeing up human resources for higher-level management tasks and increasing overall operational efficiency (Li et al., 2024).
- **Enhanced Decision-Making:** By processing vast amounts of complex data from sensors, drones, satellites, and other sources, DL provides farmers and agronomists with timely, data-driven insights that were previously unavailable or difficult to obtain (BAL and Kayaalp, 2021). These insights support better-informed decisions regarding critical aspects of farm management, including optimal planting strategies, precise irrigation scheduling, targeted fertilizer application, effective pest and disease control measures, and determining the ideal timing for harvest (Benos et al., 2021).
- **Resource Optimization and Cost Savings:** DL is a key enabler of precision agriculture techniques, allowing for the variable-rate application of inputs based on specific needs within a field (Li et al., 2024; Mahmud et al., 2021). By accurately identifying areas requiring water, fertilizer, or pesticides, DL systems facilitate targeted interventions, thereby minimizing the overall use of these resources (Chintakunta et al., 2023). This optimization reduces waste, lowers input costs for the farmer, and lessens the potential negative environmental impact associated with excessive resource use (Keskes and Nita, 2024).
- **Early Detection and Proactive Management:** DL models, particularly those analyzing image or sensor data, can often detect subtle signs of problems like plant diseases, pest infestations, nutrient deficiencies, or water stress at very early stages, sometimes even before they are visible to the human eye (Saki et al., 2024). This early detection capability allows for prompt and proactive interventions, which are typically more effective and less costly than reactive measures taken after a problem has become widespread, thereby minimizing potential crop losses and maintaining farm health (Bouacida et al., 2025).
- **Scalability and Monitoring:** DL facilitates the monitoring and analysis of large agricultural areas efficiently (Ojo and Zahid, 2022). When combined with remote sensing technologies like drones and satellites, DL algorithms can process vast amounts of imagery to assess crop health, identify anomalies, map variability, or predict yields across entire fields or even regions, providing a macroscopic view that is difficult to achieve through ground-based methods alone.

(Mukherjee, 2025).

- **Sustainability:** By enabling more precise and efficient use of resources (water, nutrients, energy, chemicals) and potentially reducing reliance on broad-spectrum treatments, DL contributes significantly to the goals of sustainable agriculture (Katharria et al., 2025). Optimized practices can lead to reduced environmental footprints, improved soil health, and greater long-term viability of farming systems (Ojo and Zahid, 2022).

VI. Navigating the Hurdles: Challenges and Limitations in Agricultural DL

Despite the immense potential and reported successes, the widespread adoption and effective implementation of DL in agriculture face numerous significant challenges and limitations. These hurdles span data acquisition, model development, and practical deployment.

A. Data-Related Challenges

Issues related to data represent arguably the most critical bottleneck hindering progress in agricultural DL (Mohyuddin et al., 2024).

- **Availability and Scarcity:** A fundamental problem is the lack of large-scale, diverse, and high-quality datasets specifically curated for many agricultural tasks, crop types, and geographical regions (Li et al., 2024). Collecting agricultural data is often resource-intensive, requiring specialized equipment (sensors, drones), significant time investment (spanning growing seasons), and considerable cost (Xuan et al., 2025).
- **Quality and Labeling:** Raw agricultural data can be noisy, incomplete, or corrupted due to sensor malfunctions, transmission errors, or environmental interference (Ojo and Zahid, 2022). Furthermore, training supervised DL models necessitates accurate annotations (e.g., disease labels, weed bounding boxes, fruit segmentation masks), which is a meticulous and labor-intensive process often requiring domain expertise (Xuan et al., 2025).
- **Diversity and Representativeness:** Existing datasets frequently lack sufficient diversity. They may cover only specific crop varieties, limited growth stages, narrow geographical areas, or data captured under controlled, non-representative environmental conditions (e.g., specific lighting, uniform backgrounds) (Mohyuddin et al., 2024). This lack of diversity severely limits the ability of models trained on such data to generalize to the wide range of conditions encountered in real-world farming.
- **Dataset Bias:** Publicly available datasets, even widely used ones like PlantVillage, can contain inherent biases (van Engelen and Hoos, 2020). These might stem from systematic differences in image capture conditions (lighting, camera angles, background settings) between different classes (Alican, 2022). Models trained on such biased data may inadvertently learn these irrelevant correlations instead of the actual features of interest (e.g., disease symptoms), leading to inflated performance on the biased test set but poor performance in practice. Explainable AI techniques can play a role in detecting such biases (Mohyuddin et al., 2024).
- **Data Imbalance:** Agricultural datasets often exhibit significant class imbalance, where instances of certain categories (e.g., rare diseases, specific weed types) are far less frequent than others (e.g., healthy plants). This imbalance can bias model training, leading to poor performance on minority classes (Wang et al., 2022).
- **Data Integration:** Effectively fusing and analysing data from multiple, heterogeneous sources (e.g., combining temporal weather data with spatial satellite imagery and point sensor readings) remains a complex technical challenge (Li et al., 2024).

B. Model-Related Challenges

Beyond data, challenges exist in the development and behaviour of the DL models themselves:

- **Robustness and Generalizability:** A major recurring issue is the lack of robustness of DL models when deployed in real-world agricultural settings (Gracia Moisés et al., 2023). Models trained under specific conditions often exhibit significant performance degradation when faced with variations in lighting, weather, background complexity (e.g., soil, shadows, overlapping leaves), occlusions, different crop varieties, or diverse field topographies (Farjon et al., 2023). This poor generalization across different datasets, locations, or time periods remains a critical barrier to reliable deployment (Espinell et al., 2024).
- **Interpretability and Explainability:** The inherent complexity of deep neural networks often makes them function as "black boxes," making it difficult to understand the reasoning behind their predictions (Albahar, 2023). This lack of transparency can hinder user trust (especially among farmers and agronomists), complicate debugging efforts, and make it challenging to verify that the model is making decisions based on relevant biological or environmental factors rather than spurious correlations (Victor et al., 2025). The development and application of XAI techniques are crucial to address this (Li et al., 2024).
- **Computational Cost:** Training state-of-the-art DL models typically requires substantial computational resources, including powerful GPUs and significant processing time (Saki et al., 2024). This can be a barrier for researchers or organizations with limited computational budgets (Xuan et al., 2025). Furthermore, deploying complex models for real-time inference on resource-constrained edge devices, such as drones, tractors, or handheld sensors, presents additional challenges related to model size, power consumption, and processing speed (Gracia Moisés et al., 2023).

VII. The Future Farm: Emerging Trends and Research Directions

The application of DL in agriculture is a rapidly evolving field, with current research and development efforts pointing towards several key trends and future directions that promise to further revolutionize farming practices (Osco et al., 2021).

- **Integration and Automation (Agriculture 4.0):** The overarching trend is towards deeper integration of DL with other technologies within the agriculture 4.0 framework (Maganathan et al., 2020). This involves combining DL-powered analytics with IoT sensor networks, advanced robotics, drone platforms, and sophisticated multi-source data fusion techniques to create highly automated, interconnected, and optimized farming systems (Ren et al., 2017). The future envisions increasingly autonomous systems capable of performing tasks like planting, real-time monitoring, targeted treatment application (fertilizers, pesticides, water), and harvesting with minimal human intervention (Feng et al., 2025; Rane et al., 2024).
- **Advanced DL Architectures:** While CNNs remain foundational, there is growing exploration and application of more advanced architectures (Sun et al., 2019). Transformers (including Vision Transformers and Detection Transformers) are showing significant promise for handling complex spatio-temporal dependencies, multimodal data fusion, and potentially offering improved robustness in certain tasks like soil analysis, yield prediction, and real-time object detection (Saki et al., 2024). Research into hybrid models that combine the strengths of different architectures (e.g., CNN-RNN for spatio-temporal analysis, CNN-ViT for enhanced feature extraction) is also likely to continue (Sapkota and Karkee, 2024).

- **Data-Centric AI:** Recognizing data as a primary bottleneck, a significant future direction involves a stronger focus on data itself – a "data-centric" approach (Ficili et al., 2025). This includes concerted efforts to create larger, more diverse, higher-quality, and standardized agricultural datasets, potentially through collaborative initiatives and open data platforms. Techniques to mitigate data scarcity will remain crucial, including further development and refinement of synthetic data generation methods (using GANs or other simulation techniques) (Tamayo-Vera et al., 2024) and leveraging unlabeled data through self-supervised learning approaches for pre-training models on vast agricultural datasets. Addressing and mitigating bias in existing and future datasets will also be critical (Mehmet Alican, 2022).
- **Explainable AI (XAI) and Trust:** As DL models take on more critical roles in decision-making and autonomous systems, the need for transparency and interpretability will intensify (Hossain et al., 2025). Research and development in XAI tailored for agricultural applications will be crucial for building user trust among farmers and agronomists, facilitating model debugging and validation, ensuring fairness and accountability, and potentially meeting future regulatory requirements (Ragu and Teo, 2023). Using XAI not just for explaining predictions but also for diagnosing model failures and uncovering hidden dataset issues will become increasingly important (Hossain et al., 2025). Techniques like inference-only feature fusion are also being explored for enhanced interpretability (Mohyuddin et al., 2024).
- **Edge AI:** To enable real-time analysis and decision-making directly on farm equipment (tractors, robots), drones, or local sensors without relying on constant, high-bandwidth cloud connectivity, deploying DL models at the "edge" is a key trend (Hu et al., 2023). This necessitates research into developing computationally efficient model architectures (e.g., lightweight versions of YOLO, MobileNet, model compression techniques, and hardware acceleration for resource-constrained devices. (Bouacida et al., 2025).
- **Generative AI (GenAI):** The capabilities of large language models (LLMs) and other generative AI techniques are beginning to be explored in agriculture (Mahmud et al., 2021). Potential applications include creating conversational AI agents to provide decision support for farmers (e.g., answering queries based on farm data and external knowledge), accessing and synthesizing information from unstructured sources (reports, manuals), generating synthetic training data, or even optimizing complex farm management plans (Rane et al., 2024). Effective deployment will require modernizing tech infrastructure and establishing robust data foundations within agricultural organizations (Thangamani et al., 2024).
- **Sustainability Focus:** There is a growing emphasis on explicitly designing, evaluating, and optimizing DL applications based on their contribution to specific sustainability goals (Olawumi and Oladapo, 2025). This involves moving beyond purely technical performance metrics to quantify impacts on resource use efficiency (water, energy, nutrients), reduction in chemical inputs, minimization of environmental footprint (e.g., greenhouse gas emissions, water pollution), and promotion of biodiversity and long-term soil health (Tamayo-Vera et al., 2024).
- **Multimodal Learning:** Future agricultural systems will increasingly rely on integrating information from diverse data modalities (Olawumi and Oladapo, 2025). Developing DL models capable of effectively learning from and fusing multimodal data – such as combining visual imagery, spectral data, thermal readings, LiDAR point clouds, time-series sensor data, weather patterns, soil maps, and even genomic information – will be crucial for achieving a holistic understanding and enabling highly precise management (Aarif et al., 2025; Olawumi and

Oladapo, 2025).

- **Addressing Specific Challenges:** Ongoing research will continue to focus on overcoming persistent technical challenges, including enhancing model robustness against real-world environmental variability (García-Navarrete et al., 2025), improving performance in scenarios with heavy object occlusion (e.g., fruits hidden by leaves), further reducing the computational cost of training and inference, and developing lower-cost, accessible sensing and hardware solutions to broaden adoption (Bal and Kayaalp, 2021).

The trajectory of these future trends points towards a significant shift beyond optimizing isolated agricultural tasks (Xuan et al., 2025). The emphasis is increasingly on integrating DL as a core component within complex, interconnected, and autonomous systems that encompass the entire farm operation – the vision of Agriculture 4.0 (Padhiary, 2024). This necessitates not only advancements in DL algorithms themselves but also progress in synergistic technologies like robotics (Aixa Lacroix, 2024), IoT sensing and communication, edge computing for real-time responsiveness (Bouacida et al., 2025), and sophisticated data management and fusion strategies (Tamayo-Vera et al., 2024). Achieving this vision will demand strong interdisciplinary collaboration between computer scientists, agricultural engineers, agronomists, animal scientists, and another domain (Espinel et al., 2024).

Unlocking the full potential of future DL applications in agriculture depends on resolving current foundational issues. While emerging technologies like Transformers (García-Navarrete et al., 2025) and Generative AI (Thangamani et al., 2024) hold promise, their success relies on overcoming challenges such as data scarcity, quality, and bias (Morchid et al., 2024), and ensuring models are both accurate and explainable (Mohyuddin et al., 2024). Without robust, representative data, even advanced models may fail in real-world scenarios. Building trustworthy systems for critical agricultural decisions also requires transparency (Xuan et al., 2025). Key to progress are investments in data resources, including open and synthetic datasets, and the advancement of Explainable AI (Rogers et al., 2024). These foundational efforts are vital for the reliable and widespread deployment of DL in agriculture (Victor et al., 2025).

IX. Conclusion: Synthesizing the Present and Future of DL in Agriculture

DL is revolutionizing agriculture by enhancing crop management, livestock monitoring, soil analysis, and water management through applications like disease detection and yield prediction. CNNs, transfer learning, and emerging Transformers tackle complex data, improving accuracy, automation, and resource efficiency. However, challenges persist: scarce, high-quality datasets limit model reliability, while the opaque nature of DL, high computational costs, and adoption barriers hinder progress. Future trends point to integration with IoT, robotics, and edge computing, emphasizing data quality, explainable AI, and sustainability. Collaborative efforts are essential to overcome data bottlenecks and ensure scalable, trustworthy solutions for smart agriculture.

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