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AI in Agriculture: A Review of Deep Learning-Based Crop Disease Detection

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Abstract: International food security is largely dependent on farming, but crop diseases continue to threaten crop quality and yield. To minimize losses and maintain sustainable agriculture, plant diseases must be accurately and promptly diagnosed. Automation is very desirable because the traditional methods of visual inspection and laboratory analysis are frequently laborious, subjective, and unavailable in remote locations. Crop disease detection has been transformed by recent advances in deep learning (DL), which enable models to automatically extract discriminative features from plant photos without the need for human assistance. From manual scouting and preliminary image processing to conventional machine learning and more recent state-of-the-art deep architectures, this review tracks the development of disease detection techniques. Across popular crops like rice, maize, and tomatoes, pivotal techniques like convolutional neural networks, transfer learning, ensemble methods, and vision transformers are critically reviewed and compared. Examined are real-world uses like drone imaging, precision agriculture systems, mobile applications, and IoT-based monitoring. Along with fascinating potential directions like multimodal learning, cloud–edge AI fusion, and farmer-centric design, challenges like sparse datasets, environmental heterogeneity, computational cost, and unexplainability are discussed. This review provides a comprehensive picture of creating reliable, field-deployable crop disease detection systems by synthesizing improvements and shortcomings.

Keywords: Agriculture; Deep Learning; Crop Disease Detection; Precision Farming; Convolutional Neural Networks; Vision Transformers.

I. INTRODUCTION

The foundation of the world's food security and the source of income for billions of people, agriculture is a very old and vital human activity. Nearly half of the workforce in countries like India is employed in agriculture, which makes up a significant portion of the GDP [25]. Crop diseases continue to be a significant obstacle, though, with fungi, bacteria, and viruses responsible for an estimated 10–40% of yield loss annually worldwide [1], [31]. These losses affect food supply chains and productivity, leading to social and economic problems, especially in developing nations where smallholder farmers produce the majority of the food [1], [32].

Traditional plant disease diagnosis relies on laboratory tests such as PCR and ELISA or the expert's eye. Despite being accurate, these are either expensive, time-consuming, or not easily accessible in rural or resource-constrained environments [2], [32]. Visual scouting, on the other hand, is arbitrary and prone to mistakes, especially when symptoms resemble those of environmental stress. Therefore, one of the biggest obstacles to sustainable agriculture is the timely diagnosis of diseases.

Researchers are paying more attention to automated methods of plant disease detection as a result of the rapid advancements in computing power, imaging technologies, and artificial intelligence (AI). Initial computer vision approaches relying on hand-designed features and traditional classifiers like Support Vector Machines or k-Nearest Neighbours had limited success but failed under real-world conditions [24]. The emergence of deep learning (DL) has changed this scenario. Convolutional Neural Networks (CNNs), specifically, have shown excellent performance in image classification by learning hierarchical features from raw pixels automatically. A seminal work by Mohanty et al. (2016) trained a CNN on the Plant Village dataset and achieved 99.35% accuracy for 14 crops and 26 diseases and thus made DL a leading paradigm in plant pathology [1]. Later work has achieved similar or better performance with architectures including Reset [17], Dense Net [16], and Efficient Net [7]. More recently, models based on the transformer have appeared, providing the potential to extract long-range dependencies and extending the limits of performance [4], [15].
Even with these developments, implementing DL-based systems into actual farming is still difficult. Most models are trained on datasets that have been carefully curated under controlled conditions, which restricts their robustness in heterogeneous field environments [9], [10]. Challenges like data sparsity, class imbalance, environmental heterogeneity, computational limitations, and lack of explainability remain [11], [28]. Additionally, although research prototypes exhibit

high accuracy, integration into real-world farming devices like IoT platforms, mobile apps, and drone systems remains limited [26].

Motivation and Scope: Many reviews of AI applications in agriculture have been published, but the majority are either from before recent advances in deep architectures or are sweeping in terms of digital farming [2], [33]. Therefore, the goal of this review is to provide a critical overview of the research conducted between 2015 and 2025 on deep learning for crop disease detection. We compare state-of-the-art efforts across different crops, highlight important architectures and applications, critically evaluate the evolution of approaches, and identify research gaps. Practical deployment issues, such as data challenges, system scalability, explainability, and farmer-centric design, are given particular attention. This review seeks to assist researchers, practitioners, and students in creating robust, field-deployable AI systems for agriculture by integrating existing work and outlining future research directions.

II. LITERATURE REVIEW

The progress of automated crop disease detection can be divided into multiple different stages, each characterized by advancements in computing and technology. The process started with basic, manual detection, moved through classical image processing and machine learning, and has finally arrived at the age of deep learning.

A. Plant Disease Detection in Early Developments

The first attempts at plant disease diagnosis were based on farmer and pathologist visual observation, where infections were detected by signs such as spots, discoloration, or wilting. Although this was easy, it was subjective and variable between individuals. For increased reliability, laboratory-based tests such as ELISA and PCR came into use, which gave greater accuracy but with a time and resource expense [2], [32]. These methods paved the way for later digital approaches but were not viable for large-scale inspection of actual agricultural fields

B. Conventional Machine Learning and Image Processing

As digital imaging increased, computer vision techniques started to augment manual diagnosis. Experts employed handcrafted features like texture descriptors, colour histograms, and shape analysis to distinguish between healthy and diseased plants. These attributes were further categorized by algorithms such as SVMs, k-NN, and Random Forests. For instance, Zhang et al. used SVMs on images of grape leaves and achieved accuracies of nearly 89% [24]. Despite showing promise in their early phases, these approaches faltered with environmental fluctuations, such as changes in lighting, occlusions, and cluttered backgrounds, and hence were not deployable in the field [9].

C. Appearance of Convolutional Neural Networks

Computer vision in agriculture was transformed by deep learning, particularly convolutional neural networks (CNNs). This was demonstrated by Mohanty et al. (2016), who achieved 99.35% classification accuracy using CNNs on the 54,306-image Plant Village dataset of 14 crops [1]. The strength of end-to-end learning, in which models learned discriminative features straight from raw pixel values without the need for handcrafted engineering, was highlighted in this seminal paper. Soon after, Ferentinos (2018) used carefully selected datasets to test different CNN architectures, including VGG and Google Net, and reached a maximum accuracy of 99.53% [3]. Although the experiments showed CNNs' capabilities, they also raised concerns about an excessive reliance on controlled imaging settings.

D. Transfer Learning in Plant Disease Detection

Transfer learning proved to be an effective solution because there were not enough labelled agricultural datasets available. Pre-trained models such as ResNet, Dense Net, and Inception were optimized by Too et al. (2019), with Dense Net achieving the best results at 99.75% [4]. Even with small datasets, transfer learning improved performance and allowed for faster training. While it performed better than scratch-trained models, accuracy was still below lab standards, according to Barbedo's (2019) investigation into its application to field images [5]. These studies positioned transfer learning as a key technique, especially for small or unbalanced data sets.

E. Ensemble and Hybrid Methods

As another move towards enhancing robustness, researchers tried ensemble and hybrid models. Shafik et al. (2024) ensembled nine pre-trained CNNs and used them as an ensemble named PDDNet, gaining 97.79% accuracy [10]. Ensemble methods minimized variance and enhanced prediction dependability but heightened computational expense. Atila et al. (2021) concatenated ResNet50 with SVM to pair CNN feature extraction with conventional classification, achieving good performance on tomato leaf diseases [7]. Such methods proved that fusion of models can be better than individual architectures, albeit deployment is still resource-hungry.

F. Object Detection and Localization

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As research progressed, the emphasis shifted from image-level classification to lesion localization. Faster R-CNN was used by Liu et al. (2020) to detect tomato leaves with a mean average precision (mAP) of 88.6% [19]. This was furthered by object detection architectures that could process in real time, like YOLO. When Khan et al. (2023) integrated YOLOv8n into a smartphone app for offline deployment, they were able to achieve 99.04% accuracy when using the system on maize diseases [5]. By including YOLO-Leaf Net, Kaur et al. (2025) expanded YOLO and obtained a mAP50 of 0.990 on a variety of crops [20]. These outcomes marked a shift to field deployment in the real world

G. Lightweight Architectures for Edge Deployment

In regard to the limitations of IoT and mobile devices, researchers focused on lightweight architectures. Mobile Net, through depth wise separable convolutions, significantly cut down parameter sizes without losing accuracy. Dhaka et al. (2023) documented Mobile Net variants with more than 95% accuracy on field datasets, making them appropriate for smartphones and Raspberry Pi [13]. Likewise, Efficient Net, proposed by Tan and Le, balanced depth, width, and resolution of the network, delivering state-of-the-art performance with reduced resources [14]. Albattah et al. (2022) implemented EfficientNetV2-B4 for UAV-based imagery and yielded near-perfect classification (~99.99%) and supported aerial disease surveillance [7].

H. Generative Models and Data Augmentation

Lack of annotated images has spurred research into data augmentation. Generative Adversarial Networks (GANs) have been especially successful in generating synthetic diseased leaf images for dataset balancing. Gajjar et al. (2021) showed that GAN-augmented datasets enhanced CNN generalization to uncommon diseases [12]. Mwebaze et al. (2019) used GANs for cassava datasets, overcoming class imbalance and increasing classification robustness [35]. These approaches overcome dataset limitations, although achieving biological realism with synthetic data is still a challenge.

I. Vision Transformers and Hybrid Architectures

CNNs prevail in the literature, but Vision Transformers (ViTs) are an emerging trend. Through modelling long-range dependencies through self-attention, ViTs have the ability to understand global context outside local CNN filters. Li et al. (2023) introduced PMVT, a MobileViT variant, and reached 93–94% accuracy on wheat, coffee, and rice [4]. Maji et al. (2022) have used ViTs for rice and maize and seen enhanced generalization under field settings [22]. Hybrid models, which integrate CNNs and transformer modules, are more widely researched today, seeking to leverage CNN efficiency and transformer flexibility [11].

J. Reviews and Future Outlook

A number of surveys have abstracted these developments, highlighting progress and limitations both. Reviews universally point towards reliance on curated data, the necessity of normalized benchmarks, and the significance of explainability for real-world uptake [9], [11], [33]. Upadhyay et al. (2025) had postulated that next-generation systems would make use of foundation models and multimodal learning, integrating visual, environmental, and text data to enhance accuracy and credibility [11]. These views suggest that the discipline is shifting away from singular measures of pure accuracy toward more expansive considerations of usability, scalability, and sustainability.

III. DEEP LEARNING TECHNIQUES FOR CROP DISEASE IDENTIFICATION

A. Convolutional Neural Networks (CNNs)

CNNs, or convolutional neural networks have emerged as the workhorse of plant disease detection based on images. Typically, a CNN consists of fully connected layers for classification and convolutional layers for feature extraction [2]. Unlike previous methods with handcrafted features, CNNs learn filters automatically, which detect texture, shapes, and colour variations associated with disease. Their high accuracy on benchmarking datasets has been demonstrated in a number of studies. For instance, Li et al. (2023) claimed that Dense Net obtained 98.27% accuracy on the Plant Village dataset and ResNet-50 attained an F1-score of 95.7% in apple leaf classification [4]. One of CNNs' most significant advantages is weight sharing, which reduces the parameters and avoids overfitting [16]. Nevertheless, because of their reliance on local receptive fields, these extremely deep CNNs can occasionally overlook global context and become over-parameterized and costly to train computationally [11].

Over the years, crop disease tasks have been addressed using a variety of CNN architectures. One of the first architectures to test tomato leaf classification was AlexNet, which debuted in 2012 and was the first to use deep CNNs [33]. Research on cactus leaf disease and maize has used VGGNet, a 2015 algorithm that combined deeper but simpler stacked convolutional layers [24]. Inception, also known as GoogleNet, has been widely used in hybrid models for the detection of complex diseases and has integrated inception modules for multi-scale feature extraction [18]. ResNet, one of the most widely used models in plant pathology today, quickly rose to prominence in the industry after inventing skip connections

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in 2016 [17]. Dense Net, released in 2017, enabled dense layer connections to facilitate feature reuse and has attained exceptionally high accuracies with a number of crops [16]. Mobile Net, also created in the same year, provided light computation via depth wise separable convolutions and has been applied effectively to apps for detecting maize diseases and other mobile or IoT-related projects [13], [28]. Efficient Net lately introduced compound scaling to equilibrate network depth, width, and resolution and Albertha et al. (2022) used its V2-B4 variant to drone images with almost perfect performance [7]. In most real-world applications, these CNNs are employed pre-trained on ImageNet and fine-tuned for the detection of plant diseases, a transfer learning mechanism that accelerates convergence and enhances accuracy in small datasets [10], [34]. Shafik et al. (2024), for instance, fine-tuned nine pre-trained CNNs on Plant Village and ensembled their predictions to reach accuracies of up to 97–98% [10].

B. Transfer Learning and Fine-Tuning

Transfer learning became a pillar of contemporary plant disease identification due to the difficulty in bringing together large annotated agricultural datasets. Under this method, models that have been pre-trained on large-sized datasets like ImageNet are fine-tuned for agricultural images by freezing early layers that extract general visual features and then re-training subsequent layers to specialize in detecting plant diseases [10], [34]. A number of surveys have validated the explosive increase of transfer learning usage in agriculture [11]. Shafik et al. also fine-tuned pre-trained CNNs using the Plant Village dataset of 54,000 images and ensembled the models to obtain 96–97% accuracy [10]. Also, Wang et al. (2024) demonstrated that transfer learning was essential for obtaining over 90% accuracy on multiple crops under conditions of limited field data [11]. The benefits of transfer learning are quick convergence, smaller data needs, and frequently better accuracy than models trained from zero. However, constraints occur when the source domain (for example, natural images of ImageNet) is not similar to the target domain of agriculture, which might lead to poorer generalization. In addition, although transfer learning is beneficial as it minimizes parameter needs, extremely deep models continue to be computationally intensive on mobile and embedded systems and thus compression and distillation of knowledge are significant areas of research [10].

C. Hybrid and Ensemble Models

Hybrid and ensemble methods have been extensively investigated to enhance robustness and minimize variance in plant disease recognition. Ensemble methods aggregate the predictions from multiple models so that their complementary strengths may be harnessed. Shafik et al. (2024) suggested the Plant Disease Detection Network (PDDNet), which combined nine pre-trained CNNs, such as ResNet-50 and DenseNet-201, in early fusion and late voting approaches. Their system performed accuracies of 97.8%, which are higher than single CNN models [10]. Apart from ensembles, deep hybrid architectures bring together CNNs and RNNs to handle temporal or sequential data, e.g., stages of crop growth, while attention or segmentation modules are sometimes incorporated in CNNs to target the model on disease areas [11]. Autoencoders and GANs have also been incorporated into pipelines to enhance feature learning or to create synthetic samples to balance datasets [12]. These methods show that architectural blending can highly enhance performance, but at the cost of heightened computational expense and sophistication.

D. Vision Transformers and Next-Generation Architectures

The advent of Vision Transformers (ViTs) signals a dramatic change in computer vision. In contrast to CNNs, which achieve local features by means of convolutional kernels, ViTs split an image into patches and subject them to self-attention in order to capture long-range relationships [15]. This architecture enables the ViTs to learn more about the global context but usually need big datasets to perform optimally [4]. In agriculture, models based on ViT are currently used with encouraging performances. Li et al. (2023) proposed PMVT, a variant of Mobi Levit, which had 93–94% accuracy in wheat, coffee, and rice datasets, outperforming lightweight CNN models [4]. The study emphasized that CNNs, while powerful, often suffer from local focus and parameter inefficiency, which transformer-based models can address. Other research has explored hybrid CNN–transformer models, which aim to combine the efficiency of CNNs with the global reasoning capability of transformers [11]. Beyond ViTs, vision–language and foundation models are emerging as promising directions. Zero-shot plant disease detection is made possible by models like CLIP, which pair words with images. To make training easier, these models can even create fictitious images of diseases [44]. Although their use in agriculture is still in its infancy, these architectures represent a new frontier for the discipline.

IV. SUMMARY OF RESEARCH

The literature on crop disease detection has advanced significantly, with the majority of studies reporting extremely high accuracy on common benchmarks. Performance has consistently been pushed into the high 90% range by ensemble learning and sophisticated deep architectures, indicating the potential of deep learning to completely transform agricultural monitoring (see Table 1). With mobile and UAV-based systems now demonstrating their viability for field deployment, real-time deployment is starting to become more of a reality. Researchers have listed a variety of image

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datasets, such as Plant Village, Cassava, and Planetdom, and started new data collection initiatives, such as drone-based images for rice [2], [7], [9], [21], and [24]. Comparative surveys confirm that deep CNNs, such as Reset and dense Net, consistently outperform traditional machine learning techniques. The advantages of deep learning techniques are clear.
Without relying on manually created features, CNNs and their related architectures can automatically learn complex patterns in the colour and texture of leaves [16]. Another advantage of transfer learning is that it makes it possible to adapt networks that have already been trained on sizable general-purpose datasets for plant-specific applications. This is particularly helpful in situations where agricultural data is limited [10], [34]. Ensemble approaches and data augmentation techniques, like GAN-based synthetic image generation, have shown great promise in reducing overfitting [10], [12]. Furthermore, high inference speeds are attained by computationally efficient architectures such as YOLO, allowing for deployment via drones and smartphones [5, 6]. The goals of precision agriculture are closely aligned with end-to-end disease management pipelines, which are being made possible by the integration of cloud infrastructure and IoT-based sensors [8], [11], and [26]. There is a domain gap that impairs performance in actual agricultural settings with varying lighting, background, and crop types because many of the best-performing models are trained and evaluated on carefully selected datasets with controlled environments [9], [10]. In-field robustness is rarely thoroughly tested across geographically or climatologically diverse regions [11]. Data imbalance is another persistent issue: rare diseases lack the necessary training images, which results in biased classifiers, whereas common diseases are well-represented [12].
Since deep learning models are largely black boxes that provide predictions but no justification for how they were made, interpretability is also an issue. This undermines confidence among regulators and farmers [11], [27]. Furthermore, computational cost continues to be a barrier because powerful models often require GPU availability, which is unaffordable in rural areas [28]. Last but not least, the majority of studies disregard the end-user perspective, failing to take into account crucial factors that are essential to smallholder farmer adoption, such as language localization, internet connectivity, and affordability [30].

V. CHALLENGES AND LIMITATIONS

Despite the progress, there are still a number of obstacles to overcome when using DL for crop disease detection:

A. Problems with data (imbalance and scarcity)

It is challenging to find high-quality, labelled images of plant diseases. Limited conditions are covered by many datasets, including Plant Village. Field image collection necessitates manual labelling and specialized knowledge. As a result, models are frequently trained on unbalanced or small datasets, which introduces bias in cases where common diseases are overrepresented [9], [12]. The most frequent problem, according to the AI literature, is "limited data" [9]. Performance on rare diseases is deteriorated by imbalanced classes. Rotations and GAN-based synthetic image generation are examples of data augmentation techniques that offer partial solutions but fall short of capturing real-world variance [12]. In practice, a model might come across environmental conditions outside of its training distribution or diseases it has never encountered [10].

B. Computational and Resource Limitations

The most advanced deep learning models can be quite big. Most farmers cannot afford the costly GPUs or cloud servers needed to train deep CNNs. ResNet-50 or dense Net models might not operate in real time on a phone or Raspberry Pi, demonstrating how computationally demanding even inference can be [28]. Additionally, Shafik et al. pointed out that DL models require a lot of parameters and training time, which makes them "complex and impractical" to deploy on small devices [10]. Another issue with battery-powered gadgets is their energy usage. Lightweight architectures like Mobile Net or Efficient Net-lite, as well as techniques like model compression, pruning, and quantization, provide solutions, but frequently at the expense of accuracy [13]

C. Lack of Explainability

The majority of DL models are opaque. Without an explanation, farmers and agronomists might not trust predictions (such as "infected" vs. "healthy"). Moreover, interpretability is becoming more and more required by regulatory frameworks. Explainable AI (XAI) has not been widely used in agricultural research [11]. Although more work is required, saliency maps, Grad-CAM, or attention visualizations may be able to help identify diseased leaf areas. Adoption and explainability are closely related: systems that are transparent are more likely to be used and trusted [27].

D. Difficulties with Deployment and Adoption

Many rural areas have a gap in the adoption of technology. Farmers might not have access to smartphones, the internet, or digital tools. AI systems need to have user-friendly interfaces, support local languages, and be farmer-friendly [26]. Another challenge is maintenance: Drones and IoT sensors need maintenance, and intermittent power supplies or bad

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connectivity can make it difficult to conduct ongoing surveillance. Adoption is also impacted by cultural and financial barriers, since smallholders might be reluctant to invest in or have faith in new technologies [30].

E. Environmental and Ethical Issues

Although DL systems are not technically complex, improper use could unintentionally harm the environment. For instance, models that advocate for overuse of pesticides may result in an increase in chemical load. Although targeted spraying made possible by precision agriculture can help reduce this, over-application may still result from faulty models [25]. Concerns about privacy and data ownership also surface, especially when farm-level data is kept on cloud servers [11]. Careful consideration of the ethical and environmental effects is necessary for sustainable deployment.

VI. FUTURE DIRECTION

Despite these constraints, research is moving in a number of encouraging directions:

A. Multimodal Education

Disease prediction can be enhanced by combining several data sources, such as leaf photos, weather data, soil parameters, and past yield data, rather than depending only on images. CNNs and time-series models such as LSTMs are being combined to create multimodal deep networks, which are starting to emerge [11]. Multimodal fusion, such as combining RGB and hyperspectral imaging, has been shown to increase accuracy [9]. In the future, systems might combine farmer-reported data, IoT sensors, and satellite data into cohesive frameworks [26].

B. Federated learning and edge/cloud AI

One important avenue is to balance computation between cloud platforms and edge devices. Drones and smartphones can be used for lightweight inference, and the cloud can be used for heavy retraining [26]. Privacy-preserving learning across various farms can be made possible by federated learning, in which models are trained across dispersed devices without centralizing raw data [11]. Scalable infrastructures are offered by cloud-AI platforms like Google AI and AWS, and edge accelerators like TPUs and Jetson devices are getting cheaper for use in agriculture [28].

C. Generative and Foundation Models

AI is trending toward foundation models that have already been extensively trained on large datasets. Zero-shot identification of invisible diseases is made possible by vision-language models such as CLIP, which can associate plant photos with textual labels [44]. Generative models, like GANs or diffusion models, can produce artificially contaminated images for training or replicate the progressive spread of disease [12]. By responding to farmer inquiries or incorporating textual agronomic knowledge, large language models may also be beneficial [11].

D. Explainable and Trustworthy AI

In order to improve usability and trust, explainability is becoming more and more important. Heatmaps and confidence intervals are examples of visual explanations that should be included in future DL systems [27]. Interpretability may be improved by hybrid systems that combine expert rules with AI outputs [11]. To make sure that the results are suitable for the context and farmers, cooperation with social scientists and extension agents is also required [30].

E. Low-Cost and Sustainable Innovations

Research is looking into low-cost hardware like open-source software, 3D-printed drones, and solar-powered Internet of Things sensors to guarantee accessibility [8]. It is anticipated that few-shot and transfer learning approaches will lessen dependency on big datasets, which will cut expenses [34]. Sustainable use will be ensured by incorporating DL into eco-friendly procedures such as Integrated Pest Management (IPM) [25].

F. Human-Centred Design

Farmers must continue to play a key role in these developments. Simple mobile apps, local language interfaces, and participatory methods where farmers provide data to enhance models will be given priority in future systems [30]. Initiatives involving citizen science could encourage farmer participation and speed up the creation of datasets. In order to guarantee that AI tools tackle practical agricultural problems rather than scholarly standards, interdisciplinary cooperation between computer scientists, agronomists, and rural communities will be essential [11]

VII. CONCLUSION

The state of the art in deep learning for crop disease detection was examined in this review.
We have seen that AI, especially CNNs and related architectures, can identify diseases from leaf images with very high accuracy on benchmark datasets. Emerging techniques such as Vision Transformers and generative models are pushing

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the boundaries further. Applications are diverse: from smartphone apps to drone surveillance to integrated IoT platforms, all aiming to bring early disease warning to farmers.

Nevertheless, significant challenges remain. Most research models still assume ideal conditions – abundant data, clear images, and generous compute. Bridging the gap to real-world farming requires tackling data scarcity, environmental variability, model efficiency, and usability issues. We have highlighted these gaps and called for solutions such as multimodal sensing, explainable AI, lightweight architectures, and human-centered design.

The potential impact of DL in agriculture is profound. By enabling precise, timely interventions, these technologies can boost yields, reduce losses, and support global food security. Enhanced precision and scalability from DL integration can transform agricultural practices. To realize this vision, researchers, engineers, policymakers, and farmers must collaborate. Future AI-driven farming should be sustainable, transparent, and accessible – ensuring that advanced technology truly works hand in hand with agricultural communities.

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