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Review article

Solutions and challenges in AI-based pest and disease recognition

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ABSTRACT

The global food crisis, exacerbated by the intensification of crop diseases and pests, poses a significant threat to food security and nutrition. Currently, approximately 350 million people are experiencing extreme hunger, and this number is projected to rise to 943 million by 2025. Consequently, there is an urgent need for effective pest and disease management strategies in agriculture. Traditional identification methods are limited by accuracy, cost, and dependence on human expertise, which hinders timely and efficient pest and disease control. This study investigates the potential of artificial intelligence, particularly deep learning techniques, to enhance the detection and classification of plant diseases and pests. The research focuses on addressing four main challenges: data scarcity, outdated network architectures, computational constraints of terminal devices, and resource and compatibility issues. This paper reviews recent advancements in AI technologies, including few-shot learning, innovative training methods and network architectures, lightweight models, as well as deployment and hardware technologies. Additionally, it discusses the integration of AI in agriculture, highlighting the importance of few-shot learning and the application of new technologies such as Generative Adversarial Networks and Transformers in enhancing pest and disease identification. By providing a comprehensive review of state-of-the-art methods and identifying the unique value of AI in revolutionizing agricultural practices, increasing efficiency, and promoting sustainability, this study makes a significant contribution to the field.

Contents

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1. Introduction

The global food crisis, the largest in modern history, presents a significant threat to food security and nutrition (Min et al., 2019). According to the World Food Program USA (World Food Programme, 2024), nearly 350 million people worldwide are currently experiencing the most extreme forms of hunger, with nearly 49 million on the brink of famine. The World Bank (Andree et al., 2024) suggests that improvements in food insecurity may stall, posing a risk of reaching a new high of 943 million people facing severe food insecurity by 2025. Behind these staggering figures lie countless individuals—children, women, and men—enduring the devastating consequences of extreme hunger. Malnourished mothers give birth to malnourished babies, perpetuating a cycle of hunger from one generation to the next. Pests and diseases pose a major threat to global food security and nutrition by reducing the quantity and quality of food crops. A study (Savary et al., 2019) indicates that pests and diseases cause an average loss of 21.5% in wheat, 30.3% in rice, 22.6% in maize, 17.2% in potato, and 21.4% in soybean worldwide. These losses are particularly devastating for populations already facing hunger (CABI, 2023).

Plant pest and disease pandemics pose a persistent and increasingly alarming risk due to globalization, climate change, and human activity (Ristaino et al., 2021). These factors can facilitate the rapid spread of pests and diseases across regions and continents, further exacerbating food security challenges. Effective control and management of pests and diseases are essential to mitigate these risks, with accurate pest and disease recognition being a critical component. However, pest and disease identification presents significant challenges for researchers, farmers, extension agents, and policymakers. The diversity and complexity of pests and diseases, which vary in morphology, genetics, life cycle, host range, distribution, and impact, require substantial expert knowledge for accurate recognition. Inadequate diagnostic tools and expertise, especially in resource-poor environments, exacerbate the prevalence and harm caused by pests and diseases. The rapid emergence and spread of new or invasive pests and diseases due to global trade, climate change, and land-use changes further complicate this issue.

Traditional identification methods for plant diseases and pests primarily rely on expert visual inspection or specialized laboratory analysis, but these approaches suffer from limitations such as low accuracy, high costs, and time consumption, as well as heavy dependence on human expertise (Huo and Tan, 2020; Sibanda et al., 2021). Consequently, there is a rising demand for alternative techniques that address these challenges while offering rapid, accurate, and accessible identification solutions. Recently, artificial intelligence (AI) has emerged as a transformative tool in this domain, significantly improving detection and classification capabilities. AI-driven systems, powered by deep learning, can automatically learn and extract critical features from images of plant leaves, stems, fruits, and flowers, facilitating the identification of symptoms and damage caused by pathogens or insects (Liu et al., 2021; Li et al., 2021b; Liu and Wang, 2021). Moreover, AI enables scalable disease and pest diagnosis in remote areas where access to expert knowledge and laboratory resources is limited, thereby overcoming geographic constraints (Selvaraj et al., 2019).

In agriculture, AI applications—often termed "Agri-AI"—are transforming traditional farming practices by integrating precision farming techniques, optimizing crop yields, and enhancing pest and disease management. Through data analytics and machine learning, AI optimizes crop production by predicting the best planting times based on weather patterns and soil conditions, leading to greater efficiency and productivity (Shaikh et al., 2022; Gupta and Tripathi, 2024). In the

Table 1
Traditional methods vs. AI-driven approaches in plant pest and disease recognition.

Method	Precision	Cost	Efficiency	Automation	Data dependency	Resource requirements	Scenario generalization
Traditional Methods							
Artificial Inspection	Low	Low	Low	Low	Low	Low	Low
Image Processing	Moderate	Low	Moderate	Low	Low	Low	Moderate
AI-based Methods							
Machine Learning	Moderate	Moderate	Moderate	Middle	High	Moderate	Moderate
Deep Learning	High	High	High	High	High	High	High

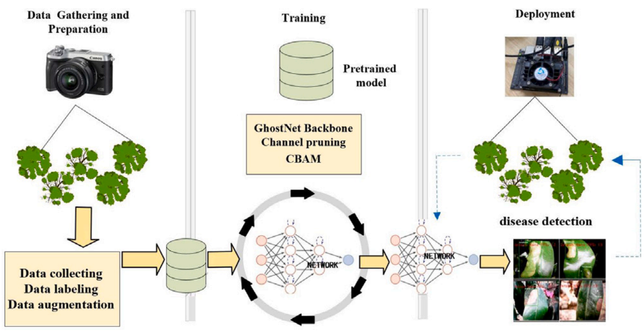


Fig. 1. Schematic diagram of a common process paradigm for the application of artificial intelligence to pest and disease identification (Xiao et al., 2023).

realm of pest and disease management, AI-driven systems can identify and categorize infestations with high accuracy, enabling timely and targeted interventions. These systems analyze crop images to detect early signs of diseases or pest activity, often before they are visible to the human eye (Kose et al., 2022). Beyond crop management, AI also plays a vital role in livestock care by monitoring animal health, predicting breeding periods, and detecting early signs of illness or distress (Tullo et al., 2019). Additionally, AI contributes to climate change mitigation by aiding in weather pattern prediction, water resource management, and promoting sustainable farming practices (Sanders et al., 2021). As these advancements progress, AI is poised to revolutionize agriculture by offering innovative solutions that enhance efficiency, sustainability, and resilience in the face of evolving challenges. In contrast to traditional methods, AI-based systems offer distinct advantages across several dimensions, as highlighted in Table 1. These include higher precision, greater efficiency, improved scalability, and increased automation, all of which are essential for addressing the complex and time-sensitive nature of pest and disease management. However, AI-driven approaches also come with their own set of challenges, such as higher initial costs, increased data dependency, and the need for substantial computational resources. Nonetheless, the potential of AI to overcome the limitations of traditional methods makes it a powerful tool for transforming pest and disease recognition in modern agriculture.

In the nascent phase of integrating AI methodologies into the realm of pest and disease identification, a substantial corpus of research has been predicated upon the paradigm of transfer learning (Sladojevic et al., 2016; Mohanty et al., 2016; Ramcharan et al., 2017; Wang et al., 2017; Cheng et al., 2017; Arivazhagan and Ligi, 2018; Ferentinos, 2018; Ahmed et al., 2019; Rahman et al., 2020). The schematic representation of this process is delineated in Fig. 1. Initially, a compendium of plant disease imagery is amassed via the instrumentality of smartphones, digital cameras, and other imaging devices, subsequently subjected to meticulous annotation by experts within the pertinent domain. Leveraging this curated dataset, a pre-trained AI model undergoes a process of fine-tuning to align with the specific exigencies of the designated pest recognition endeavor. Ultimately, the model, once refined, is deployed on the target device, thereby facilitating the accurate identification of pests in situ.

A substantial body of academic work aims to address one or more challenges within the workflow of plant pest and disease recognition. However, existing review articles primarily classify and summarize the research based on technological methods or application scenarios of models, without fully encompassing the entire workflow involved in this process. Specifically, there is a lack of systematic, process-oriented reviews that comprehensively summarize the research achievements across different stages of plant pest and disease recognition. This paper aims to fill this gap by offering a comprehensive overview of AI-based plant pest and disease recognition through a process-oriented perspective. Specifically, the challenges encountered at various stages of the process, including the data scaling limitations during the dataset annotation phase, the obsolescence issues arising from the frequent changes in model architectures, the deployment difficulties caused by limited computational resources at the terminal, and the hardware resource and compatibility issues during the deployment phase, converge into four major research trajectories: few-shot learning, innovative training methodologies and network architectures, lightweight models, and deployment technologies, as shown in Fig. 2. Furthermore, the review discusses potential applications and future research directions in this multifaceted field.

2. Few-shot learning

Few-shot learning (FSL) is a sophisticated technique (Finn et al., 2017; Snell et al., 2017) designed to train models using only a limited amount of labeled data, making it particularly pertinent for agricultural pest and disease recognition. In the agricultural sector, the acquisition of large-scale labeled datasets is often challenging and resource-intensive, thereby underscoring the critical importance of FSL. This section begins with a comprehensive review of the existing datasets used in agricultural pest and disease recognition, highlighting the most widely utilized datasets in the field, while also examining their inherent limitations and the challenges they encounter. It then moves on to survey the application of FSL in this field from three main perspectives: parameter optimization, data augmentation, and metric learning. While these approaches differ in their technical focus—parameter optimization improves the learning dynamics under sparse supervision, data augmentation expands the effective dataset size through transformations or synthetic samples, and metric learning enhances the model's ability to distinguish between fine-grained categories—their goals are closely aligned. Together, they represent complementary strategies for improving model performance under limited data conditions, and are often used in combination to maximize generalization.

2.1. Dataset overview

In the field of agricultural pest and disease recognition, existing research, in addition to investigating and collecting data on pests specific to certain crops to build proprietary datasets, also makes use of several public datasets for model training and evaluation. These datasets can be broadly classified into two types: one type encompasses large-scale datasets covering a wide range of pest and disease types, while the other consists of proprietary datasets targeting specific pests and diseases. Table 2 presents a comparative overview of these commonly used datasets, summarizing their scale, class composition, and the specific challenges that make few-shot learning necessary.

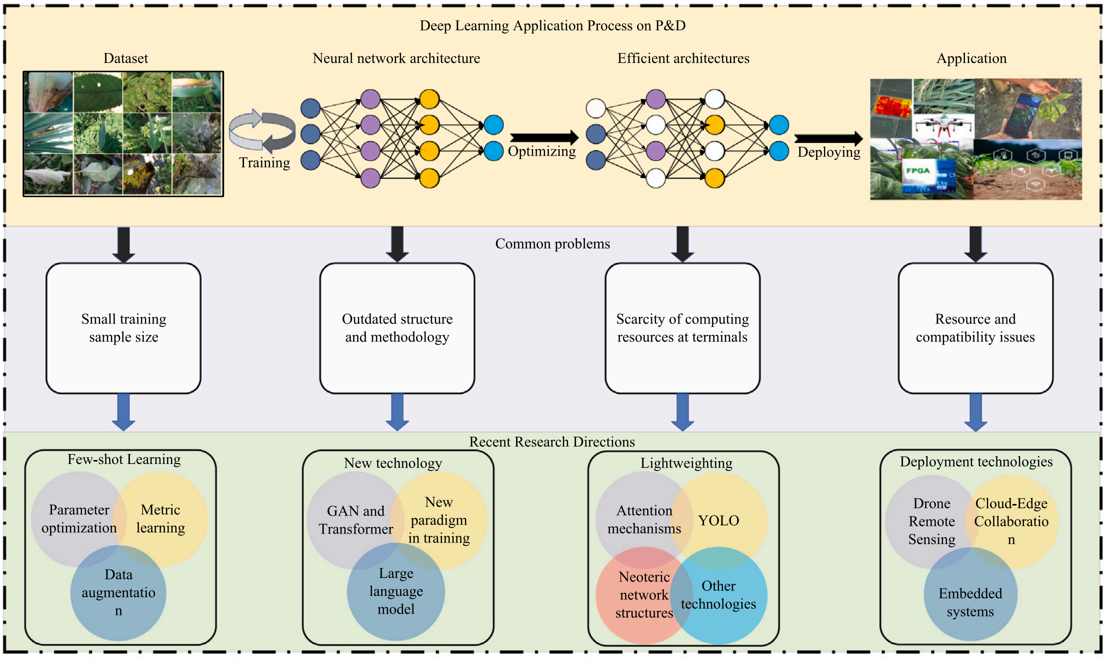


Fig. 2. An overview of the challenges and solutions in deep learning for plant disease and pest detection throughout the process.

Table 2
Summary of widely-used plant–pest and — disease image datasets emphasizing data-collection challenges.

Dataset	Primary task	Crops/pests	Classes	Images	Public	Key challenges
PlantVillage (Hughes et al., 2015)	Classification	17 crops	38	54 305	Yes	limited field variability
IP102 (Wu et al., 2019)	Classif./Detect.	8 crop insects	102	75 222	Yes	Long-tailed class distribution
PlantDoc (Singh et al., 2020)	Detection	13 crops	≈30	2 569	Yes	Small sample size and noisy labels
CropDeep (Zheng et al., 2019)	Classif./Detect.	31 vegetables and fruits	31	31 147	Yes	varied acquisition conditions
Pest24 (Wang et al., 2020b)	Detection	24 field pests	24	25 378	Yes	Tiny objects and dense instances
AgriPest (Wang et al., 2021b)	Detection	4 crops/14 pests	14	49 707	Yes	Small sample size and occlusion
IDADP (Yuan et al., 2022)	Classification	11 crops	52	>50 000	No	class imbalance

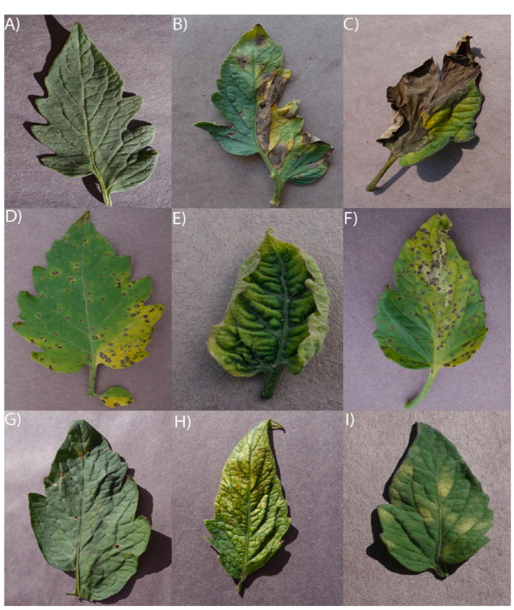
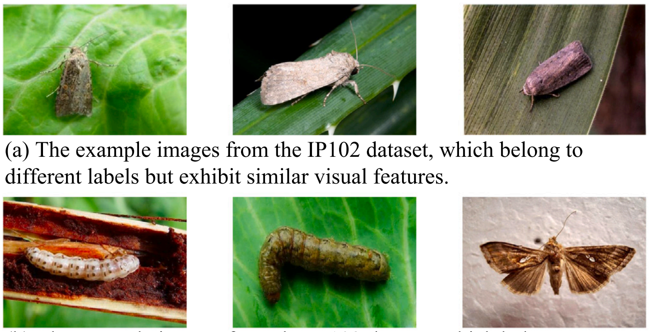


Fig. 3. Example images from the PlantVillage dataset. Different labels with simple and similar background (Hughes et al., 2015).

Large-scale datasets are exemplified by PlantVillage (Hughes et al., 2015) and IP102 (Wu et al., 2019). The PlantVillage dataset includes 54,303 images of healthy and unhealthy leaves, classified into 38 categories based on species and diseases. Although it is large in scale, it still faces several challenges in practical applications. Firstly, as shown in Fig. 3, the images in the PlantVillage dataset feature relatively uniform backgrounds and lack scene diversity, which makes the model susceptible to background bias. This can significantly affect the model's accuracy when applied to different environmental conditions and lighting scenarios (Noyan, 2022). In comparison, the IP102 dataset is larger, containing approximately 75,000 images covering 102 different types of plant pests and diseases. The IP102 dataset faces challenges from its long-tailed distribution, where certain categories contain minimal samples, while others have an abundance of samples, making it difficult for the model to balance the data across different categories and leading to a tendency to ignore the features of minority classes. Furthermore, the IP102 dataset exhibits small inter-class differences, for example, some pest and disease types have visually similar features, as shown in Fig. 4(a), while intra-class variation is large, for example, pests and diseases show significant differences at various lifecycle stages, as shown in Fig. 4(b). This phenomenon hinders the model's generalization ability when dealing with pest and disease recognition at different stages. Compared to some general large models, such as Contrastive Language-Image Pretraining (CLIP) (Radford et al., 2021), which has been trained on 400 million text-image pairs and Segment Anything model(SAM) (Kirillov et al., 2023), trained on 11 million data, the scale of agricultural pest and disease datasets is still insufficient, limiting their ability to achieve the desired level of generalization in real-world applications.



(a) The example images from the IP102 dataset, which belong to different labels but exhibit similar visual features.

(b) The example images from the IP102 dataset, which belong to same label but exhibit different visual features.

Fig. 4. Example images from the IP102 dataset: (a) illustrating the small inter-class differences; (b) demonstrating the large intra-class variation (Noyan, 2022).

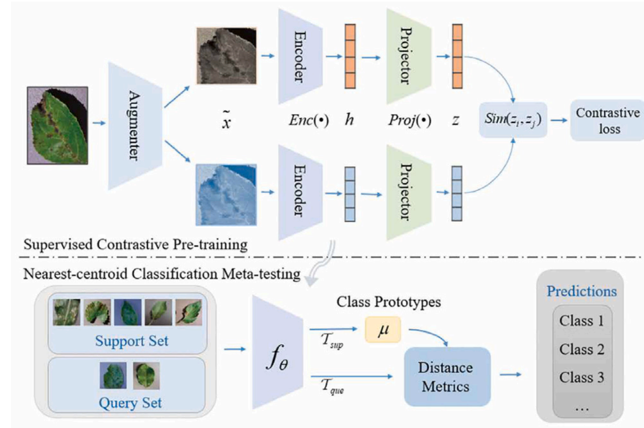


Fig. 5. An overview of supervised contrastive few-shot learning framework where different images are constructed by different ways of data augmentation to form contrasts (Mu et al., 2024).

Proprietary datasets usually offer more detailed annotations and higher-quality images, with PlantDoc (Singh et al., 2020) being a representative example. This dataset involves 13 plant species and 17 disease types, containing 2,598 high-quality images. However, the annotation process for the PlantDoc dataset took approximately 300 h, indicating the high cost of data collection. Given its relatively small scale, this dataset still faces challenges in deep learning model training, particularly regarding FSL. Despite this, FSL techniques can significantly improve the model's recognition accuracy and generalization ability by leveraging prior knowledge or other learning strategies, even with limited labeled data.

Therefore, in light of the limitations of existing datasets, FSL has become an effective solution to the problem of data scarcity, particularly in agricultural pest and disease recognition tasks, and shows great potential for improving model performance under data-limited conditions. By leveraging parameter optimization, data augmentation and metric learning strategies, few-shot learning enables models to generalize better from a limited number of annotated samples. Specifically, it mitigates the influence of background bias by focusing on class-discriminative features rather than background correlations, thereby improving model robustness. Moreover, few-shot learning methods can address long-tail distributions by emphasizing rare class representations and optimizing decision boundaries with minimal supervision. Additionally, techniques such as data augmentation and generative modeling further enhance the diversity of training samples, alleviating the challenge of collecting large-scale datasets.

2.2. Few-shot learning with parameter optimization

In the application of deep learning models for plant disease recognition, a significant challenge lies in the limited availability of training samples. Sparse datasets inherently heighten the risks of overfitting and convergence issues, thereby limiting a model's generalization capability and predictive accuracy on unseen samples (Saleem et al., 2019). To mitigate these challenges, researchers primarily focus on parameter optimization strategies. These involve reducing model redundancy by decreasing the number of parameters or fine-tuning initial settings to optimize the starting point. Such systematic optimizations not only alleviate overfitting but also expedite model convergence, guiding the model towards a more robust and generalizable solution (Sun et al., 2023).

Multi-task learning represents a critical advancement in reducing model parameters, merging similar tasks into a unified model that leverages data across tasks. This approach has proven effective in agricultural AI applications, as exemplified by Wang et al.'s (Wang et al., 2022b) two-stream hierarchical bilinear pooling model, which demonstrated notable gains in plant and disease identification accuracy. Concurrently, transfer learning leverages pre-trained models as a foundation for learning with limited data, further refining initial parameters for plant disease recognition. Studies by Wu (2020) and Mehedi et al. (2022) have demonstrated the efficacy of this method across various plant species. However, challenges persist, such as the dependence on task correlation in multi-task learning and the misalignment of pre-trained models in transfer learning. To overcome these limitations, FSL has emerged as a promising approach, optimizing model parameters with minimal data and integrating multimodal data sources for improved generalization (Sun et al., 2023). Recent studies have demonstrated the potential of FSL in enhancing plant disease recognition, with models like those developed by Hu et al. (2019) and Zhong et al. (2020) showcasing superior performance in small sample settings through innovative parameter fine-tuning and optimization techniques.

Despite advancements in multi-task and transfer learning for plant disease recognition, challenges remain. Multi-task learning, while promising, requires high task correlation to prevent performance degradation and demands complex models and computational resources, which are often limited in agricultural contexts. In order to solve these limitations, some new methods have been developed, such as meta-learning, spatial structure optimizer and joint optimization. Meta-learning optimizes model parameters with minimal data, reducing dependence on task correlation while enabling rapid adaptation to diverse conditions. Its compact architectures and efficient optimization strategies help mitigate computational demands, while its integration of multimodal data and external knowledge sources allows for more effective knowledge transfer beyond pre-trained models (Sun et al., 2023). Hu et al. (2019) introduced a tea leaf disease identification method that integrates Support Vector Machine-based segmentation and a Conditional Deep Convolutional Generative Adversarial Network for data augmentation, significantly enhancing VGG16's generalization capabilities. Wang and Wang (2019) leveraged a contrast loss Siamese network with k-nearest neighbors, optimizing feature representations for small sample classification. Further innovations include Zhong et al.'s (Zhong et al., 2020) Conditional Adversarial Auto-Encoder for citrus disease recognition and Ren et al.'s (Ren et al., 2019) relational network-based classifier, which achieved a 41.9% improvement in accuracy over transfer learning on small datasets. These studies collectively underscore the potential of FSL to enhance the accuracy, robustness, and generalization of plant disease identification in diverse agricultural scenarios.

2.3. Few-shot learning with data augmentation

Data augmentation is a common approach to overcoming limited sample challenges in pest and disease identification by enhancing model generalization and accuracy. Generative Adversarial Networks (GANs) are notably effective in agricultural applications (Mu et al., 2024). For instance, Chen and Wu (2023) employed deep convolutional GANs to synthesize grape leaf lesion images, while Haruna et al. (2023) used style GANs with adaptive discriminator augmentation and Laplace filtering to improve rice leaf disease detection in fast region-based convolutional neural networks. Hu and Fang (2022) addressed small tea leaf sample challenges using SinGAN to generate additional data for disease recognition. Besides GANs, spectral analysis combined with deep learning is widely applied in agriculture, as demonstrated by Huang et al. (2023a) with K-conditional boundary equilibrium GANs for spectral enhancement. Bi and Hu (2020) leveraged a Wasserstein GAN with label smoothing regularization to manage small sample sizes, while Song et al. (2023) applied GANs for maize disease detection.

Beyond GANs, direct image transformation techniques are also prevalent. Li and Lee (2022) used Mixup and Cutmix algorithms to augment data for citrus greening disease research. In a related study, Li et al. (2023a) employed a denoising diffusion probabilistic model for synthetic image generation in citrus disease diagnostics. Abbas et al. (2023a) introduced a hybrid contrast-enhancement approach for cucumber and potato leaf disease identification. Additionally, Wang et al. (2022a) developed an improved Swin Transformer to boost feature extraction in cucumber leaf disease detection. Gao et al. (2022) expanded wheat disease datasets using mirror flips, rotation, and noise, while Zhang et al. (2021), Pratap and Kumar (2023), Mu et al. (2024), and Zhang et al. (2023c) employed various image manipulation techniques like flipping, translation, and noise addition to simulate disease severity variations, as shown in Fig. 5.

2.4. Few-shot learning with metric learning

Metric learning emphasizes quantifying similarity between samples by computing distances, making it especially pertinent in scenarios with limited sample sizes. In plant pest and disease identification, metric learning leverages transfer learning by employing pre-trained models to extract generalizable features for similarity matching. This approach not only adapts models quickly to specific agricultural applications but also mitigates challenges related to data scarcity.

Siamese networks, a cornerstone of metric learning, typically consist of two or more weight-sharing branches that process paired inputs concurrently, using metrics like Euclidean distance or cosine similarity to measure output vector distances. In agricultural contexts, characterized by limited sample sizes, diverse categories, and subtle inter-class differences, Siamese networks have proven effective in addressing these challenges. For instance, Wang and Wang (2019) applied a FSL method with a Siamese network to classify plant leaves, achieving high accuracy with minimal labeled data. Similarly, Goncharov et al. (2020) used Siamese networks to develop a multifunctional platform for plant disease management. Thuseethan et al. (2022) utilized a lightweight Siamese network with contrastive loss to compare tomato leaf images, yielding strong results. Additionally, Zhang et al. (2023d) integrated Siamese networks with an Inception module to recognize apple leaf diseases, emphasizing similarity between leaf image pairs.

To improve model performance in scenarios with limited samples, researchers have introduced the triplet loss function, a critical metric learning technique that trains networks by comparing relationships among three samples. Argüeso et al. (2020) employed the triplet loss function within Siamese networks, optimizing feature representations as shown in Fig. 6. This method is particularly effective in low-data scenarios. Uzhinskiy et al. (2021) demonstrated its utility in plant disease detection and moss classification, highlighting its potential for similarity-based classification tasks. Afifi et al. (2020)

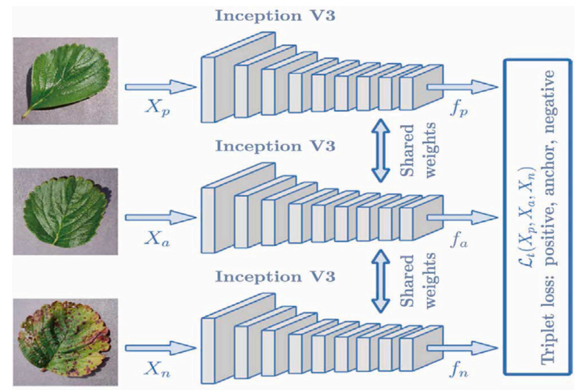


Fig. 6. Illustration of the three-headed Siamese network based on Triplet loss (Argüeso et al., 2020).

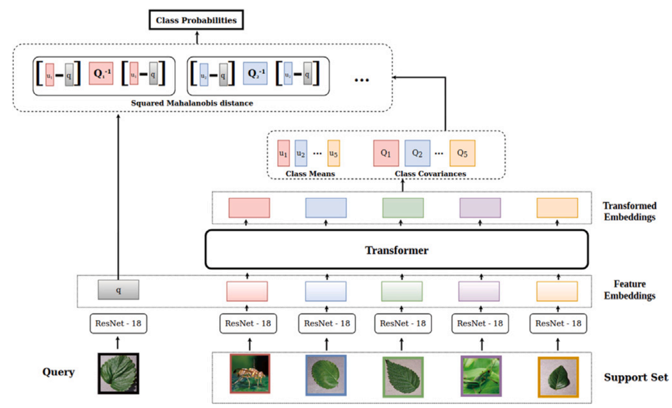


Fig. 7. Illustration of a metric learning architecture (Nuthalapati and Tunga, 2021).

enhanced this approach by integrating Deep Adversarial Metric Learning with triplet networks, where DAML generates challenging negative samples, achieving notable results in plant disease recognition. Additionally, Tassis and Krohling (2022) combined triplet networks with prototypical networks for biotic stress classification in coffee leaves, achieving a 0.79% accuracy improvement and significantly enhanced leaf damage severity estimation. Shafik et al. (2023) advanced crop disease recognition by integrating triplet networks with matching networks, mapping small datasets to a shared embedding space and using cosine similarity for classification.

Further enhancements involve incorporating additional information into distance metrics. Nuthalapati and Tunga (2021) used a class covariance-based metric to automatically categorize pests, plants, and diseases by calculating similarity on transformed embeddings, as shown in Fig. 7. Wang et al. (2022b) developed the DHBP model, leveraging hierarchical bilinear pooling to integrate multi-level features, improving the detection of subtle plant disease variations. Yang et al. (2022) introduced a fine-grained classification approach based on inter-class similarity analysis, significantly outperforming random selection methods in plant disease identification. Wang et al. (2023b) combined a Siamese network with convolutional layers and attention modules for sample-sparse learning in crop leaf disease recognition. Lin et al. (2024) proposed a Feature Representation Enhancement Network for tobacco anomaly recognition, employing global pooling and Gaussian calibration to normalize feature distributions, effectively identifying various tobacco diseases with limited samples.

2.5. Applications of few-shot learning in agriculture

FSL has shown considerable promise in various agricultural applications, particularly in plant disease recognition, pest identification,

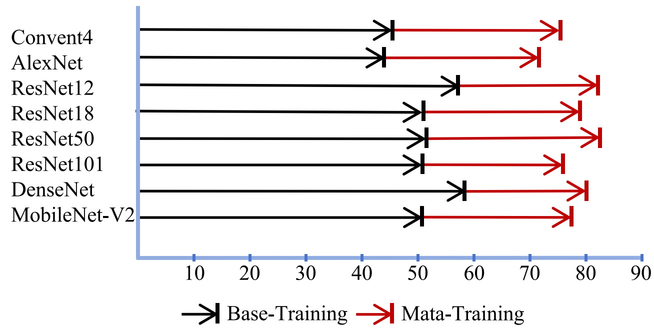


Fig. 8. The comparison of model performance between data-driven training and meta-learning approaches in few-shot learning tasks (Lin et al., 2022).

and fruit detection and classification. These areas often face challenges such as data scarcity and high annotation costs, which hinder the performance of traditional machine learning models. FSL, with its ability to generalize effectively from a small number of labeled samples, has proven to be a powerful tool in addressing these challenges.

2.5.1. Plant disease recognition

Plant diseases can significantly reduce crop yield and quality, making early and accurate detection essential for effective management. FSL has proven particularly useful in plant disease recognition, especially when labeled data is scarce. For example, HongLin et al. proposed a Meta-Baseline FSL-based network that integrates Cascaded Multi-Scale Feature Fusion and Channel Attention (Lin et al., 2022). This approach addresses the issues of limited feature representation and poor generalization inherent in traditional FSL models when applied to plant disease images. Yang et al. proposed a cross-domain few-shot learning framework with a Brownian distance covariance module to improve domain adaptation, achieving 63.95% accuracy in 1-shot and 80.13% accuracy in 5-shots in cross-domain tasks (Yang et al., 2024). As a result, the method enhances both classification accuracy and robustness, demonstrating the power of FSL in real-world agricultural applications. In fact, as shown in Fig. 8, the results indicate that when the model is trained solely on image data, the recognition accuracy ceases to improve due to the limited data. However, by incorporating meta-learning in the FSL framework, leveraging task-specific data, the accuracy can be further improved by approximately 20% to 30%, illustrating the potential of FSL-based meta-learning to overcome data scarcity and enhance model performance.

2.5.2. Pest identification

Pest identification is a critical task in agricultural management, but it is often hindered by the diversity of pest species and the limited availability of labeled data. FSL, particularly through meta-learning techniques, has been leveraged to overcome these obstacles. For instance, meta-learning algorithms such as Matching Networks, Prototypical Networks, and Relation Networks have shown success in pest identification, where rapid convergence and strong generalization are essential for effective identification across different species with limited data (Lin et al., 2022; Rezaei et al., 2024). These methods facilitate the training of models that can generalize well to unseen pest species, even when only a few labeled samples are available. By addressing the constraints imposed by small datasets, FSL is enabling more accurate and scalable pest monitoring solutions in agriculture.

2.5.3. Fruit detection and classification

Traditional methods for fruit maturity detection and disease classification often struggle with the challenges posed by data scarcity and high annotation costs. In contrast, FSL utilizes its remarkable ability to generalize from limited labeled data to achieve efficient and accurate classification. For example, Muhammad Ahmed et al. developed an FSL-based avocado maturity detection system that uses microwave imaging to capture internal fruit characteristics (Ahmed et al., 2024). By applying an FSL model, their method achieved an accuracy rate of 80% to 96%, outperforming traditional methods in scenarios with limited data. Additionally, Sivasubramaniam Janarthan et al. proposed a lightweight framework for citrus disease classification based on deep metric learning, which can accurately detect diseases even with scarce data (Janarthan et al., 2020). This framework not only outperforms existing algorithms in terms of model size and detection time, but it also shows significant potential for deployment on resource-constrained devices, such as mobile phones, offering practical solutions for in-field disease detection.

These advancements highlight how FSL can significantly improve the efficiency of fruit detection, disease recognition, and pest monitoring in agriculture. Its ability to deliver scalable and practical solutions in data-limited environments offers clear advantages, such as reduced dependency on large annotated datasets and enhanced generalization across different agricultural contexts. However, FSL also presents potential limitations, including sensitivity to the quality and diversity of the few labeled samples available, which may hinder its performance in highly variable or complex agricultural scenarios. Nevertheless, when effectively implemented, FSL contributes greatly to the advancement of precision agriculture, enabling timely interventions, better crop management, and ultimately more sustainable farming practices.

2.6. Advantages and challenges of few-shot learning

Table 3 summarizes characteristics of different FSL methods. FSL addresses the challenge of training models on limited data. It is particularly relevant in agricultural applications where obtaining a large dataset of labeled instances, such as diseased or pest-infested crops, can be difficult and resource-intensive. The advantages of FSL include the ability to generalize from a small number of examples, reducing the need for extensive manual labeling, and the potential to adapt quickly to new or rare types of pests and diseases. This is crucial for timely and accurate identification, which can lead to more effective pest management strategies and reduced crop losses.

However, FSL also faces several challenges. One of the primary challenges is the risk of overfitting, where the model becomes too specialized to the limited examples it was trained on, and thus performs poorly on unseen data. Additionally, the quality and diversity of the small dataset can significantly impact the model's performance. Ensuring that the few examples are representative of the broader population is critical.

3. New technology in modeling and training

The latest advancements in agricultural pest and disease recognition are driven by numerous innovative architectures and novel technical strategies. This section delves into three key areas of development, as shown in Table 4. First, it explores the potential of GANs and Transformers in pest and disease detection, highlighting their structural advantages and application potential. Secondly, it examines new training paradigms, including unsupervised, self-supervised, and semi-supervised learning, which offer more efficient solutions for model training with limited labeled data. Lastly, it discusses the research on Large Language Models (LLMs), addressing their untapped potential in agricultural applications. These technological advancements collectively provide more efficient and accurate solutions for pest and disease management strategies. While these approaches differ in their technical focus—GANs aim to enhance or reconstruct training data distributions, Transformers focus on efficient feature modeling, and training paradigms and LLMs center on how learning is structured and data is utilized—they are by no means isolated. On the contrary,

Table 3
A summary and classification of algorithms commonly used in the monitoring of plant diseases and pests with few-shot learning.

Direction	Solutions	Methods	Datasets	Subjects	Tasks	Metric	Year	Refs.
Few-shot Learning	Parameter Optimization	multi-task learning	private	cucumbers	identification	F1-Score:94.81%	2023	Cao et al. (2023)
		Initial parameter optimization	private	pines	identification	F1-Score:98.5%	2022	Li et al. (2022b)
		Spatial Structure Optimizer	private	cotton	identification	Accuracy:95.13%	2021	Liang (2021)
		joint optimization	private	strawberries	detection	F1-Score:84.0%	2022	Liu et al. (2022b)
		Initial parameter optimization	public	apple, wines, strawberries	segmentation	IoU:82.9%	2023	Zhou et al. (2023c)
		Initial parameter optimization	public	diverse plants	identification	Accuracy:89.90%	2019	Ren et al. (2019)
		Initial parameter optimization	public	diverse plants	identification	Accuracy:91.4%	2020	Argüeso et al. (2020)
		Initial parameter optimization	private	teas	identification	Accuracy:100%	2020	Wu (2020)
		Initial parameter optimization	public	diverse plants	detection	F1-Score:99.63%	2022	Mehedi et al. (2022)
		Initial parameter optimization	private	teas	identification	Accuracy:90%	2019	Hu et al. (2019)
		multi-task learning	public	diverse plants	identification	Accuracy:75.06%	2022	Wang et al. (2022b)
		Spatial Structure Optimizer	public	diverse plants	identification	Accuracy:95.32%	2019	Wang and Wang (2019)
		Initial parameter optimization	public	orange	identification	Accuracy:53.4%	2020	Zhong et al. (2020)
	Data Augmentation	Generating Models	public	wines	identification	Accuracy:97.5%	2023	Chen and Wu (2023)
		Generating Models	private	rice	detection	Accurary:91.83%	2023	Haruna et al. (2023)
		Generating Models	private	teas	identification	Fl-Score:90.41%	2023	Hu and Fang (2022)
		Generating Models	public	diverse plants	identification	Accuracy:97.84%	2020	Bi and Hu (2020)
		Generating Models, transformation	private	maize	detection	mAP:95%	2023	Song et al. (2023)
		transformation	private	orange	detection	mAP:79.8%	2022	Li and Lee (2022)
		Diffusion Models	private	orange	identification	Accuracy:94.8%	2023	Li et al. (2023a)
		transformation	public&private	diverse plants,cucumbers, potatoes	identification	Accuracy:99.2%	2023	Abbas et al. (2023a)
		Generating Models	private	cucumbers	identification	Accuracy:99.75%	2022	Wang et al. (2022a)
		transformation	private	wheat	identification	F1-Score:97.86%	2022	Gao et al. (2022)
		Generating Models, transformation	private	cucumbers	identification	Accuracy:96.11%	2021	Zhang et al. (2021)
		transformation	private	pepper	identification	Accurary:91.79%	2023	Pratap and Kumar (2023)
		transformation	public&private	diverse plants, orange	identification	Accuracy:92.90%	2024	Mu et al. (2024)
		transformation	private	cotton	identification	Accuracy:92.19%	2023	Zhang et al. (2023c)
	Metric Learning	Siamese Network	private	wines, maize, wheat	detection	Accuracy:96%	2020	Goncharov et al. (2020)
		Siamese Network	public&private	tomato	identification	Accuracy:96.97%	2022	Thuseethan et al. (2022)
		Siamese Network	private	apple	identification	F1-Score:93.19%	2023	Zhang et al. (2023d)
		Triplet loss	public&private	diverse plants	identification	Accuracy:91.4%	2020	Argüeso et al. (2020)
		Siamese Network	private	crop	identification	Accuracy:97.8%	2021	Uzhinskiy et al. (2021)
		Triplet loss	public&private	diverse plants	identification	Accuracy:99%	2021	Afifi et al. (2020)
		Triplet Network	private	coffee	identification	Accuracy:96.03%	2022	Tassis and Krohling (2022)
		Siamese Network	private	cane	identification	F1-Score:91%	2021	Shafik et al. (2023)
		Mahalanobis	public&private	diverse plants	identification	Accuracy:88.5%	2021	Nuthalapati and Tunga (2021)
		bilinear pooling	public	diverse plants	identification	Accuracy:75.06%	2022	Wang et al. (2022b)
		similarity analysis	public&private	diverse plants	segmentation	Accuracy:93.87%	2022	Yang et al. (2022)
		Siamese Network	private	apple, potatoes	identification	Accuracy:98.03%	2023	Wang et al. (2023b)
		Task Adaptation	public&private	diverse plants, cigarette	identification	Accuracy:81.8%	2024	Lin et al. (2024)

Table 4
The current status and advancements of new technology-driven algorithms for plant disease and pest detection.

Direction	Solutions	Methods	Datasets	Subjects	Tasks	Metric	Year	Refs.
New Technology in Modeling and Training	New Network Framework	GAN	private	wines	identification	Accuracy:98.70%	2020	Liu et al. (2020)
		GAN	private	tomato	identification	Accuracy:90.62%	2022	Tao et al. (2022a)
		GAN	private	tomato	identification	Accuracy:97.63%	2022	Salmi et al. (2022)
		Transformer	public	diverse plants	identification	Accuracy:97%	2023	Gole et al. (2023)
		Transformer	private	diverse plants	detection	Accuracy:97.98%	2021	Chohan et al. (2020)
		Transformer	private	diverse plants	identification	Accuracy:93.6%	2023	Li et al. (2023d)
		Transformer	private	strawberries	identification	Accuracy:99.1%	2023	Li et al. (2023b)
		Transformer	private	apple	identification	Accuracy:96.85%	2022	Li and Li (2022)
		Transformer	private	orange	identification	Accuracy:96.3%	2023	Li et al. (2023a)
		Transformer	private	apple	segmentation	IoU:87.40%	2023	Lu et al. (2023b)
		Transformer	private	apple	detection	mAP:73.4%	2023	Lv and Su (2024)
		Transformer	private	cucumbers	detection	mAP:84.9%	2022	Li et al. (2022a)
		Transformer	private	rice	detection	mAP:88.6%	2023	Huang et al. (2023b)
		Transformer	private	crop	segmentation	Accuracy:73.70%	2023	Wang et al. (2023a)
		Transformer	private	diverse plants	detection	F1-Score:89.5%	2023	De Silva and Brown (2023)
	New Training Paradigm	self-supervised	private	canola	detection	Accuracy:94.38%	2022	Gong et al. (2022)
		self-supervised	public	crop	identification	Accuracy:74.69%	2022	Liu et al. (2022a)
		self-supervised	private	strawberries	detection	Accuracy:90.8%	2022	Liu et al. (2022b)
		self-supervised	public	diverse plants	identification	Accuracy:90.52%	2023	Zhao et al. (2023)
		self-supervised	private	orange	detection	Accuracy:92.33%	2024	Thien et al. (2024)
		Semi-supervised	public&private	tomato	identification	Accuracy:90.62%	2022	Tao et al. (2022a)
		unsupervised	private	celery	identification	Accuracy:95.29%	2024	Agarwal et al. (2024)
		unsupervised	private	pine	identification	Accuracy:97.74%	2022	Santos et al. (2022)
		unsupervised	public&private	wines	identification	Accuracy:96.13%	2022	Jin et al. (2022)
		unsupervised	private	tomato	identification	Accuracy:86.1%	2020	Nazki et al. (2020)
		unsupervised	private	wheat	detection	Accuracy:94.66%	2023	Zhang et al. (2023b)
		unsupervised	private	tomato	identification	Accuracy:95.6%	2023	Uppada and Kumar (2023)
		unsupervised	private	pines	identification	Accuracy:91.35%	2023	Wan et al. (2022)
		unsupervised	private	tomato	detection	Accuracy:96.25%	2019	Wang et al. (2019)
		unsupervised	private	tomato	segmentation	Accuracy:96.40%	2022	Wu et al. (2022)
	LLM	GPT-4	private	orange	identification	Accuracy:94.5%	2023	Qing et al. (2023)
		ITLMLP	private	cucumbers	identification	Accuracy:94.84%	2023	Cao et al. (2023)
		Intelligent Agricultural Q&A System	private	rice, wheat,potatoes, cotton	detection	Accuracy:94%	2024	Lu et al. (2024)

they are highly complementary: GANs can enrich sample diversity for self- or semi-supervised learning frameworks; Transformers can be paired with LLMs to integrate visual and textual cues; and LLMs, in turn, can serve as semantic-level reasoning modules to boost overall system intelligence. Together, these advances address core challenges such as data scarcity, structural complexity, and generalization, and point towards a more unified, integrative direction for building robust, deployable AI systems in agricultural pest and disease management.

3.1. New network framework

The advent of advanced deep learning methodologies has significantly transformed agricultural pest and disease identification, with two prominent approaches, GANs and Transformer models, playing a pivotal role in this shift, as shown in Fig. 9. These models offer unique advantages in addressing key challenges such as limited training data and complex disease detection tasks. We explore these two methodologies in detail, highlighting their individual contributions to improving pest and disease recognition.

3.1.1. GANs in pest and disease recognition

GANs have demonstrated the capacity to produce highly realistic synthetic data through the dynamic interplay between generator and discriminator components. This process not only enriches the training dataset but also mitigates the challenge of scarce training imagery. Liu et al. introduced a GAN-driven data augmentation approach for the detection of grapevine leaf diseases, effectively addressing overfitting issues, and enhancing diagnostic precision (Liu et al., 2020).

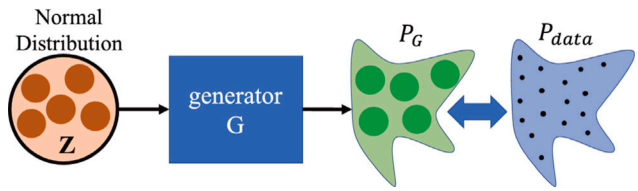


Fig. 9. Illustration of basic form of generative modeling (Liu et al., 2020).

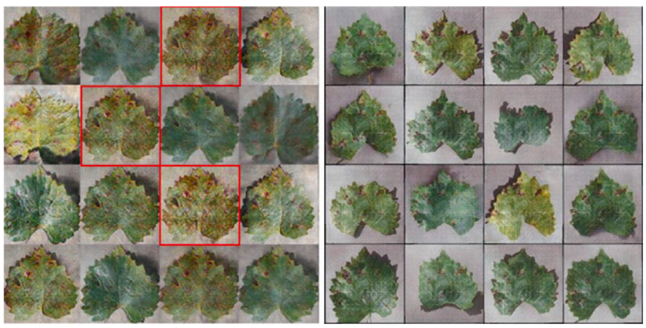


Fig. 10. Visualization of Black Rot Grape Leaf Images Generated Using GANs (Liu et al., 2020).

Fig. 11. (A) Original image, (B) YOLOV5 detection results, (C) YOLOV5-CBAM-C3TR detection results. Colored bounding boxes represent different types of apple leaf diseases: Alternaria blotch (red), Gray spot (pink), and Rust (orange). Lv and Su (2024).

As shown in Fig. 10, the visualization of Black Rot grape leaf images generated using GANs demonstrates the feasibility of using generative models for data augmentation to improve disease detection. Similarly, Tao et al. presented a semi-supervised GAN framework for tomato leaf disease recognition, improving model performance by generating novel, unlabeled data (Tao et al., 2022a). Salmi et al. developed a GAN-based image enhancement technique that refines image quality to better delineate disease characteristics (Salmi et al., 2022).

3.1.2. Transformer models in pest and disease recognition

Transformer models excel at capturing the global contextual dependencies within an image through a self-attention mechanism, enhancing the fidelity and efficiency of feature extraction. Gole et al. developed a compact visual Transformer architecture, TrIncNet, which surpasses traditional CNNs and ViT models in accuracy for plant disease identification. Additionally, it is compatible with IoT devices (Gole et al., 2023). Hirani et al. conducted a comparative analysis of CNNs and Transformer networks, revealing that the latter achieved an impressive 97.98% accuracy on the validation dataset, an improvement of 2.4% over the custom CNN (Chohan et al., 2020). Li et al. engineered a streamlined Transformer-based network that, through parameter reduction, achieved both efficiency and accuracy in disease recognition (Li et al., 2023d). Furthermore, they proposed a method for strawberry disease identification that leverages the Transformer module to capture long-range feature dependencies, thereby improving recognition efficiency and accuracy (Li et al., 2023b). The academic community has also delved into the exploration of Transformer variants and enhanced architectures. Li et al. proposed the ConvViT model, which integrates convolutional and Transformer structures to efficiently extract features from diseased crop regions (Li and Li, 2022). Kong et al. proposed the FICformer framework, which integrates fuzzy Bayesian imputation with a dimension-temporal cross-attention architecture to address missing data in agricultural sensor streams, significantly improving forecasting accuracy in decision support systems (Kong et al., 2024). Li et al. evaluated the efficacy of Denoising Diffusion Probabilistic Model, Swin Transformer, and transfer learning in enhancing the performance of small-sample disease diagnostics in citrus (Li et al., 2023a). Lu et al. introduced the MixSeg network, a hybrid model combining CNN, Transformer, and multilayer perceptron elements for the semantic segmentation of apple leaf diseases (Lu et al., 2023b). Lv and Su developed a Transformer-augmented YOLOV5 model for apple leaf disease detection, which optimizes the attention mechanism for improved accuracy (Lv and Su, 2024). The visualization results, as shown in Fig. 11, further illustrate the model's enhanced performance in accurately identifying apple leaf diseases. Li et al. combined YOLOv5 with Transformer to enhance the detection of small disease targets in cucumbers (Li et al., 2022a). Huang et al. presented a Transformer-based model for the real-time detection of insect eggs in paddy fields, integrating YOLOv5s and Swin Transformer to significantly boost detection precision and performance (Huang et al., 2023b). Wang et al. introduced PAST-Net, which employs a Swin Transformer and path aggregation model for efficient instance segmentation of tomato anthracnose (Wang et al., 2023a). De Silva and Brown investigated the potential of a hybrid CNN-Transformer approach to elevate the accuracy of plant disease detection (De Silva and Brown, 2023). Liu et al. developed an Efficient Swin Transformer for plant disease detection, incorporating a selective token generator and feature fusion aggregator to reduce tokens (Liu and Zhang, 2025). Their model cut parameters by 21% and achieved 80.14% precision on the PlantDoc dataset. Similarly, Ting Zhang et al. added residual skip connections to a Swin Transformer for cotton pest classification, raising accuracy from 94.6% to 97.4% (Zhang et al., 2024). These studies illustrate that transformer adaptations can substantially boost agricultural recognition performance, albeit with added model complexity.

3.2. New training paradigm

The advent of deep learning and image processing technologies has facilitated the application of self-supervised, semi-supervised, and unsupervised learning methodologies in this domain. These approaches address the limitations of traditional supervised learning, which often requires large, labeled datasets that are costly and time-consuming to create. In contrast, recent state-of-the-art methods such as PotCapsNet have demonstrated the effectiveness of supervised learning in quickly and objectively detecting late and early blight on potato leaves. This method, while still based on traditional supervised learning, significantly improves detection speed and accuracy, setting a new standard in the field (Gupta et al., 2024a). Nonetheless, the high demand for labeled data remains a key challenge that motivates the exploration of alternative learning paradigms.

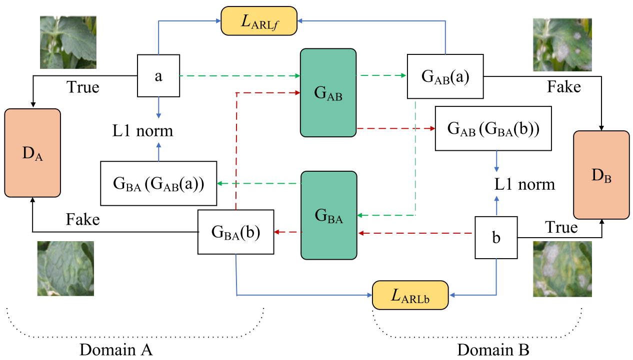


Fig. 12. Illustration of an approach using a GAN (Nazki et al., 2020).

3.2.1. Self-supervised learning

Self-supervised learning, which leverages unlabeled data to develop general feature representations, has emerged as a powerful solution to the dependence on large-scale labeled datasets. For instance, Gong et al. (2022) introduced U3-YOLOXs, an innovative deep target detector that improves the identification of sub-healthy regions in oilseed rape through self-supervised pre-training. Liu et al. (2022a) proposed a self-supervised transformer-based pre-training approach using Latent Semantic Mask Self-Encoder, which significantly enhances classification performance for pest and disease detection in agricultural contexts. Similarly, Liu et al. (2022b) developed a self-encoder co-optimization strategy integrated with a self-supervised classifier, which improved the precision and robustness of strawberry anomaly detection in hyperspectral imagery. Zhao et al. (2023) demonstrated improvements in plant leaf disease recognition by utilizing self-supervised learning combined with domain adaptation techniques. Additionally, Thien et al. (2024) introduced a self-supervised pre-training method for the detection of anthracnose disease in citrus fruit trees using deep learning.

3.2.2. Semi-supervised learning

Semi-supervised learning strategies capitalize on the synergy between limited labeled data and extensive unlabeled data, thereby enhancing recognition accuracy through the optimization of the model's predictive capabilities on unlabeled datasets. For example, Tao et al. (2022a) presented a semi-supervised learning method that employs GANs, which has led to a notable increase in disease recognition accuracy. By utilizing the available labeled data effectively while incorporating vast amounts of unlabeled data, semi-supervised approaches can achieve high accuracy with fewer labeled examples.

3.2.3. Unsupervised learning

Unsupervised learning methods are particularly adept at managing unlabeled data, as evidenced by their applications. For instance, Agarwal et al. (2024) utilized unsupervised multivariate analysis to monitor root rot in flat-leaved parsley. Santos et al. (2022) employed unsupervised machine learning to analyze remote sensing imagery for effective monitoring of leaf drop caused by leaf-cutting ants in Brazilian eucalyptus forests. Jin et al. (2022) introduced GrapeGAN, a novel GAN architecture designed to accurately identify grape leaf diseases. Nazki et al. (2020) proposed an unsupervised approach using GANs for image transformation to enhance plant disease recognition by enriching the training dataset with synthetic samples, thereby improving classification accuracy. Zhang et al. (2023b) introduced the Rotating YOLO Wheat Detection Network and the unsupervised Simple Spatial Attention Network to enhance the detection accuracy of wheat blast, as shown in Fig. 12. Uppada and Kumar (2023) successfully distinguished between healthy and diseased tomato plants using unsupervised neural network techniques for image preprocessing and feature fusion. Wan et al. (2022) proposed an unsupervised learning method based on drone imagery to monitor tree discoloration caused by pine wood nematode disease using a decision fusion technique. Wang et al. (2019) developed an Anomaly Removal-Assisted Classifier GAN for hyperspectral imaging analysis, facilitating early detection of tomato spotted wilt virus. Wu et al. (2022) introduced DS-DETR, a model that employs unsupervised pre-training and an enhanced Transformer structure for effective segmentation and assessment of tomato leaf diseases.

In summary, unsupervised, semi-supervised, and self-supervised learning methods have demonstrated significant potential in improving the accuracy and robustness of pest and disease recognition. These advanced methods can train models more effectively with limited labeled data, addressing a key challenge in agricultural technology. In the future, these methods are expected to expand their influence in the field of agricultural applications, thereby enhancing the convenience and efficiency of agricultural production. This will ultimately lead to more efficient and sustainable agricultural practices, reducing costs and increasing productivity.

3.3. LLMs in pest and disease recognition

In recent years, significant advancements in computational power have catalyzed the rapid evolution of LLMs that possess tens of billions of parameters. Utilizing the Transformer architecture (Vaswani et al., 2017), these models have demonstrated proficiency in a spectrum of natural language processing tasks, including inference, summarization, translation, and human-like text generation. Notably, models such as Bidirectional Encoder Representations from Transformers (BERT) (Devlin et al., 2018) and the Generative Pre-trained Transformer (GPT) (Brown et al., 2020) family have been extensively evaluated across various sectors, including healthcare, finance, and education, where they have yielded remarkably significant outcomes (Sharma et al., 2023). Meanwhile, the application of large-scale language models in agriculture is gaining momentum. Early applications have focused on enhancing human–computer interaction, data processing, as well as hardware design and control (Li et al., 2023e). For instance, a conversational robot has been developed, leveraging ChatGPT-3.5, to facilitate plant disease analysis (Kuska et al., 2024), thereby simplifying information retrieval and interaction with data systems. In the realms of poultry farming and fruit cultivation, the capabilities of GPT-4.0 in data quality monitoring and structured processing of graphical data have been explored (Lu et al., 2023a). Additionally, a tomato picking robot has been designed with the aid of ChatGPT-3.0 (Stella et al., 2023), which has significantly improved the visual recognition module of the robot.

In the domain of agricultural pest and disease detection, which is a classic image recognition/classification challenge, the deployment of LLMs is primarily approached from three angles: multimodal capability, inference, and generalization. A study (Qing et al., 2023) constructed an end-to-end multimodal language model for citrus pest and disease detection, integrating YOLOv5 and GPT-4. This model capitalizes on YOLO's visual understanding as well as GPT-4's logical reasoning to address complex issues such as semantic comprehension, unclassified bootstrapping, and data contamination, which are typically challenging for traditional deep learning models in agricultural data processing. Another study (Cao et al., 2023), grounded in cucumber disease recognition, combines the text-image multimodal language model CLIP (Radford et al., 2021) with the data enhancement technique from MoCov3 (He et al., 2020) to achieve both multimodal contrast learning and self-supervised contrast learning on a small dataset. This research has demonstrated that the incorporation of LLMs can significantly enhance the models' generalization and accuracy in recognition tasks. Furthermore, a novel architecture has been proposed that amalgamates traditional image models like YOLO and CNN with the BERT and ChatGPT-3.5. This architecture aims to fulfill the requirements for unified monitoring and analysis of multi-category pest and disease conditions across various crops and to address expert Q&A in agricultural intelligent systems. The ability of LLMs to process and map across different modalities of data effectively manages the integration of diverse data structures, including images, texts, and knowledge graphs. Notably, spectral data offer unique advantages in agricultural pest and disease recognition by capturing biochemical changes that are imperceptible to the human eye. Future multimodal fusion research should explore synergistic analysis methods integrating spectral data with visual and textual modalities. For instance, early fusion strategies can combine hyperspectral band features with RGB image features at the input level, while late fusion approaches can perform weighted decision-making based on spectral classification and visual detection results. Previous studies (Bauriegel et al., 2011; Patil and Kumar, 2022) have demonstrated that spectral-visual collaborative analysis enhances model sensitivity to early disease manifestations, such as chlorophyll content abnormalities.

These studies underscore the untapped potential of large-scale language models in agriculture. As the application of these models becomes more sophisticated and agricultural data is standardized both qualitatively and quantitatively, there is a promising future for LLM-based agricultural image classification/recognition systems. These systems hold the potential to surpass current specialized deep learning systems, which are characterized by limited interactivity and generalization capabilities (Cao et al., 2022).

4. Lightweighting

Lightweight networks are neural architectures designed for computational efficiency and minimal resource consumption, making them ideal for deployment on devices with limited processing power, such as smartphones or IoT-based sensors in agricultural settings (Howard et al., 2017; Tan et al., 2019). In the context of pest and disease recognition, where on-site, real-time inference is often crucial, these compact models have become increasingly important. Recent research has explored a diverse range of lightweight solutions—ranging from manually designed backbones like MobileNet and ShuffleNet, to streamlined variants of Transformers and YOLO architectures—each tailored to balance performance with hardware constraints. To further reduce model complexity, additional techniques such as network pruning, quantization, and knowledge distillation are commonly applied. These strategies vary in where and how they act: some reconfigure the model architecture from the ground up, while others compress or fine-tune pre-trained networks. Despite their differences, these approaches are often used in combination—models built with lightweight blocks can be further compressed and distilled to create highly efficient pipelines suitable for field deployment. As summarized in Table 5, these advances together represent a layered and complementary toolkit for bringing deep learning into real-world agricultural environments.

4.1. Lightweighting with attention mechanisms

The integration of attention mechanisms in deep learning, especially within image recognition tasks, has significantly advanced model performance, particularly in agricultural pest recognition. An attention mechanism is a computational approach that allows a model to assign different levels of importance to different parts of the input—much like how humans tend to focus on the most relevant regions in a scene. Attention mechanisms help address model simplification challenges by enhancing the model's ability to focus on the most relevant image regions, akin to human visual attention. For instance, Alirezazadeh et al. improved Convolutional Neural Network (CNN) performance in plant disease classification by incorporating the Convolutional Block Attention Module into their model (Alirezazadeh et al., 2023). Similarly, Bhujel et al. demonstrated how attention mechanisms can reduce computational load and parameter count in lightweight CNNs while maintaining accuracy (Bhujel et al., 2022). Further, Bao

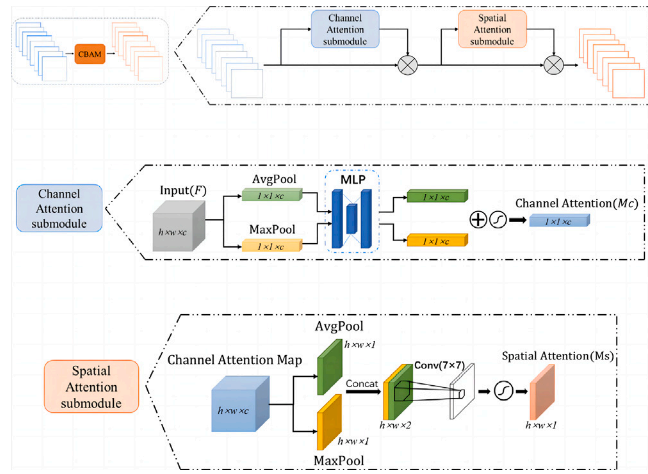


Fig. 13. Illustration of three common lightweighting attention mechanisms (Bao et al., 2021).

et al.'s SimpleNet model combines attention mechanisms with a streamlined architecture for efficient wheat spike disease recognition (Bao et al., 2021), as shown in Fig. 13. Other notable contributions include Chelloug et al.'s MULTINET, which integrates multi-agent deep reinforcement learning with attention mechanisms to enhance model accuracy and efficiency (Chelloug et al., 2023).

While attention mechanisms significantly enhance recognition accuracy, their computational overhead must be carefully managed to align with lightweight design objectives. To address this challenge, researchers have developed various strategies, including computationally efficient attention modules such as CBAM and ECA, sparse attention mechanisms, and the integration of depthwise separable convolutions as an alternative to full self-attention (Woo et al., 2018; Wang et al., 2020a; Martins et al., 2020). Li et al. (2023d) demonstrated that lightweight CNNs with optimized attention mechanisms can effectively balance efficiency and accuracy. Additionally, techniques such as pruning (Zhang et al., 2020), quantization (Zhou et al., 2019), and knowledge distillation (Cho and Hariharan, 2019) further reduce computational demands without sacrificing model performance. These optimizations have paved the way for more efficient applications of attention mechanisms in agricultural tasks. For instance, Chen et al. achieved improved recognition of subtle lesion characteristics by integrating transfer learning, null convolution, and SPP modules into potato and rice disease recognition models (Chen et al., 2023a, 2021b). Additionally, Zhang et al. enhanced disease detection in various crops by leveraging attention-guided deep multiscale CNNs and innovative attention operations (Zhang et al., 2022c, 2023a). Zheng et al. introduced Rice-YOLO, a YOLOv8-N variant that incorporates a customized detection head, deep-supervision branches, and dynamic up-sampling, specifically optimized for rice-pest detection. The design delivers substantially higher accuracy than earlier detectors, albeit with a modest increase in architectural complexity (Zheng et al., 2024). Other studies, including Feng et al.'s DFFANet for real-time rice blast segmentation (Feng et al., 2022) and Zhou et al.'s attention-based models for tomato and rice disease recognition (Zhou et al., 2023a,b), exemplify the growing impact of attention mechanisms. Collectively, these advancements underscore the critical role of attention mechanisms in driving smart agricultural technologies by enabling faster, more precise pest and disease identification, ultimately enhancing agricultural productivity.

4.2. Lightweighting with new module

With advancements in deep learning technology, agricultural pest and disease identification has made significant progress. However,

Table 5
A summary of lightweighting model algorithms commonly used for plant disease and pest detection.

Direction	Solutions	Methods	Dataset	Subject	Task	Metric	Year	Refs.
Light-weighting	Attention Mechanisms	Convolutional Block Attention	public	tomato	identification	Accuracy:97.2%	2022	Bhujel et al. (2022)
		lightweight attention	public	rice	segmentation	Accuracy:99.67%	2021	Feng et al. (2022)
		Convolutional Block Attention	private	rice, wheat, coffee	identification	Accuracy:98.32%	2022	Li et al. (2023d)
		multiscale attention	public	potatoes	identification	Accuracy:97.73%	2022	Zeng et al. (2022b)
		coordinated attention	private	maize	identification	Accuracy:98.47%	2022	Zeng et al. (2022a)
		double-factor weight attention	private	apple	detection	Accuracy:99.5%	2022	Zhang et al. (2022c)
		effective channel attention	private	rice	identification	Accuracy:96.6%	2023	Zhou et al. (2023b)
		Coordinate Attention	private	crop	identification	Accuracy:98.4%	2023	Zheng et al. (2023)
	New Module	Convolutional autoencoder	private	diverse plants	identification	Accuracy:98.35%	2024	Bedi et al. (2024)
		Dise-Efficient	public	diverse plants, pests	identification	Accuracy:99.80%	2023	Guan et al. (2023)
		Inception-CNN	private	maize	identification	Accuracy:98.97%	2022	Haque et al. (2022)
		MobileNet	private	potatoes	identification	Accuracy:93%	2022	Kang et al. (2023)
		VLDNet	public	diverse plants	identification	Accuracy:98.13%	2023	Li et al. (2023f)
		MixSeg	private	apple	segmentation	Accuracy:98.22%	2023	Lu et al. (2023b)
		MLP-Mixer	private	cotton, maize	detection	Accuracy:98.43%	2024	Maurya et al. (2024)
		LWCNN	public	rice	identification	Accuracy:99.7%	2023	Ning et al. (2023)
		GLD-Det	private	guava	detection	Accuracy:98%	2023	Mustak Un Nobi et al. (2023)
		lightweight-2D-CNN	public	diverse plants, tomato, cotton	detection	Accuracy:97%	2023	Peyal et al. (2023)
	YOLO	Lightweight Components	private	wheat	detection	mAP:97.15%	2024	Gao et al. (2024)
		feature fusion	private	cucumbers	detection	mAP:84.9%	2022	Li et al. (2022a)
		Lightweight Components	private	rice	detection	mAP:93.7%	2023	Jia et al. (2023)
		pruning	private	fruit	detection	Accuracy:94.0%	2022	Lan et al. (2022)
		feature fusion	private	cucumbers	detection	Accuracy:98.3%	2023	Li et al. (2023g)
		Lightweight Components	private	orange	detection	mAP:92.5%	2023	Luo et al. (2023b)
		Lightweight Components	private	vegetables	detection	mAP:92.91%	2024	Wang and Liu (2024)
		other	private	tomato	detection	mAP:98.3%	2021	Wang et al. (2021a)
	Other Technologies	knowledge distillation	private	fruit	segmentation	IoU:89.33%	2024	Cai et al. (2024)
		network compression	private	apple	identification	Accuracy:99.40%	2021	Chao et al. (2021)
		pruning	private	tomato	identification	Accuracy:99.06%	2023	Chen et al. (2023b)
		pruning, knowledge distillation	private	diverse plants	detection	Accuracy:94.24%	2022	Dai and Fan (2022)
		network compression	private	pepper	identification	Accuracy:97.87%	2023	Dai et al. (2023)
		knowledge distillation	public	diverse plants	detection	mAP:74.8%	2023	Hu et al. (2023)
		network compression	public	diverse plants, pests	identification	Accuracy:83.80%	2023	Kong et al. (2023)
		pruning	private	fruit	detection	Accurary:94.0%	2022	Lan et al. (2022)
		network compression	private	diverse plants, pests	detection	Accuracy:97.2%	2022	Rangarajan et al. (2022)
		network compression	private	apple	segmentation	Accuracy:99.29%	2024	Wang et al. (2024)
		pruning	private	litchi	detection	Accuracy:88.6%	2023	Xiao et al. (2023)
		pruning	private	wheat	detection	F1-Score:94.13%	2022	Zhang et al. (2022b)

traditional deep learning models often have high parameter counts and computational complexity, which poses significant challenges in resource-limited agricultural environments. To address these issues, researchers have developed various lightweight network structures and optimization techniques to enhance the efficiency and applicability of these models. The following review covers recent advancements in the design of lightweight networks and optimization strategies for pest and disease identification.

4.2.1. Design and improvement of lightweight networks

The literature presents several innovative approaches in the realm of plant disease recognition using lightweight and efficient deep learning models. One such framework is "PDSE-Lite" (Bedi et al., 2024), which combines convolutional self-encoders with few-sample learning to reduce manual data annotation while providing accurate disease severity assessments. In Chen et al. (2020), a modified MobileNetV2, coupled with classification activation map techniques, is used to develop a lightweight network for disease recognition. This model shows promising performance on both public and local datasets, demonstrating its potential for mobile device deployment in plant disease monitoring. Similarly, the TRInCNet model (Gole et al., 2023) introduces a custom Trans-Inception module to replace traditional Multilayer Perceptron layers, reducing parameter count and enhancing accuracy. The Dise-Efficient model (Guan et al., 2023), based on an improved EfficientNetV2, achieves a model size of just 13.3 MB while improving accuracy on the PlantVillage dataset from 99.71% to 99.80% using dynamic learning rate decay and transfer learning.

Further advancements include an improved lightweight network combined with Choquet fuzzy integration for soybean leaf disease recognition, augmented by CycleGAN for feature space enhancement (Hang et al., 2024). The MDSD dataset (Haque et al., 2022), comprising 1,760 images of maize leaves, supports a lightweight CNN model that outperforms DenseNet121 by 3.48% in accuracy. In Kang et al. (2023), a Django-based system integrates a lightweight CNN for potato leaf disease recognition. RegNet (Li et al., 2021a) leverages transfer learning for apple leaf disease identification, while VLDNet (Li et al., 2023f) utilizes 1×1 convolution and inexpensive linear operations for efficient feature extraction. MixSeg (Lu et al., 2023b) integrates CNNs, transformers, and MLPs for semantic segmentation of apple leaf diseases. The multi-plant disease recognition model in Ma et al. (2023) employs maximum grouping convolution to reduce computational requirements, and the GLD-Det model (Mustak Un Nobi et al., 2023) enhances MobileNet for real-time papaya leaf disease detection. Lastly, a lightweight 2D CNN architecture for diagnosing 14 classes of tomato and cotton diseases has been implemented in a smartphone application in Peyal et al. (2023).

However, the pursuit of lightweight models in plant pest and disease recognition presents inherent trade-offs between accuracy and efficiency. While models like Micro-YOLO demonstrate significant parameter reduction and computational efficiency without compromising detection quality (Hu and Li, 2021), there remains a fundamental challenge in balancing performance with resource constraints. Moreover, the impact of hardware-specific limitations cannot be overlooked. For instance, ShuffleNet (Zhang et al., 2018), despite its theoretical efficiency, exhibits performance degradation on ARM-based processors due to hardware mismatches, while MobileNets suffer from quantization-induced accuracy losses due to dynamic range fluctuations. These challenges highlight the need for hardware-aware optimization strategies in agricultural applications, ensuring that lightweight models not only reduce computational burdens but also maintain robustness when deployed on real-world edge devices.

4.2.2. Lightweight technology application and optimization

The application and optimization of lightweight technology are also discussed. The Choquet fuzzy integration technique, as highlighted in Hang et al. (2024), significantly improves the accuracy and robustness of soybean disease recognition when combined with an improved lightweight network. A lightweight meta-integration method for plant disease detection on IoT devices is proposed in Maurya et al. (2024), achieving excellent classification performance across three datasets. The summary in Ning et al. (2023) outlines the application of CNN techniques for rice disease recognition and discusses model enhancements focusing on accuracy, speed, and lightweighting. A real-time lightweight deep learning method based on MobileNet for the detection of papaya leaf disease is introduced in Mustak Un Nobi et al. (2023).

An increasing number of tasks focused on pest recognition are embracing novel lightweight network architectures. These models not only enhance recognition accuracy but also substantially diminish the

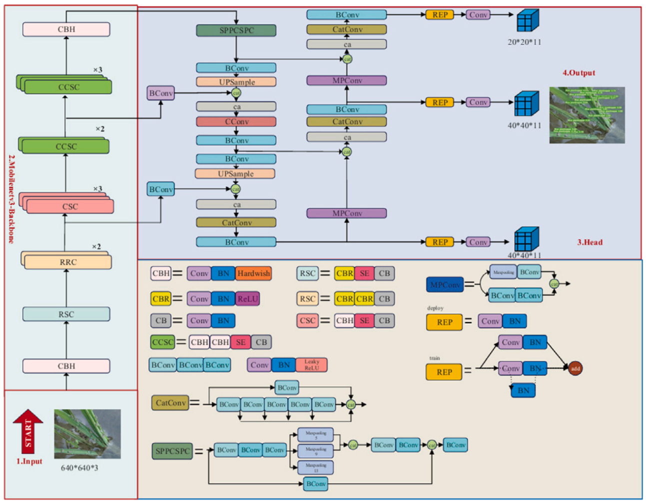


Fig. 14. Illustration of lightweighting with YOLO (Jia et al., 2023).

parameter count and computational complexity of the model, offering a viable avenue for real-time detection and identification of agricultural pests and diseases. As technological advancements persist, the incorporation of lightweight network structures within the realm of agricultural pest recognition is anticipated to proliferate steadily.

Furthermore, real-time indicators are critical for evaluating the efficiency of lightweight models deployed on low-computing-power devices. The forecasting framework proposed in Shoukourian and Kranzlmüller (2020) leverages LSTM networks to predict power-efficiency-related KPIs, such as cooling efficiency and system inlet temperature. These real-time evaluations enable dynamic adjustments to optimize power consumption and operational performance. Similarly, the L-Net model in Shen et al. (2024) demonstrates the feasibility of lightweight CNNs in resource-constrained environments, ensuring real-time inference with minimal computational overhead. These approaches highlight the importance of integrating real-time performance metrics—such as inference latency and power consumption—into the development of lightweight neural networks for agricultural pest and disease detection. By incorporating such considerations, future lightweight architectures can further enhance their adaptability and efficiency in real-world agricultural applications.

4.3. Lightweighting with YOLO

In the realm of object detection algorithms, the You Only Look Once(YOLO) framework is distinguished by its exceptional speed and accuracy in object recognition within images. This paper aims to evaluate the strategies employed by various YOLO architectures to achieve a lightweight neural network for pest recognition, focusing on the utilization of YOLO structures.

4.3.1. Utilization of lightweight network components

Gao et al. (2024) introduced a modified YOLOv5s model that replaces the original backbone network with the lightweight MobileNetV3 and SPPF networks. Additionally, the C3 module was replaced with C3Ghost, which streamlines the model without compromising detection performance. Li et al. (2024b) proposed the CCG-YOLOv5n model, integrating a lightweight CARAFE up-sampling module and GSConv for feature fusion, thereby reducing the model's parameter count and computational complexity. Hong et al. (2022) replaced the YOLOv4 backbone with MobileNet, significantly reducing the network's parameters and complexity. Deng et al. (2023) explored two enhanced detection models, YOLOv5 and YOLOv7-tiny, which incorporate the Ghost module and Convolutional Block Attention Module with SIoU to enhance learning capabilities and precision. Li et al. (2024a) presented the GhostNet_Triplet_YOLOv8s algorithm, which integrates a lightweight GhostNet structure into the YOLOv8s backbone, simplifying the architecture and accelerating detection speed. Hu et al. (2023) proposed a lightweight detection algorithm for YOLOv5s, replacing the original CSP module with Faster-C3 to reduce the parameter count. Jia et al. (2023) developed a rice pest and disease identification model using the YOLOv7 algorithm, leveraging MobileNetV3 and incorporating the coordinate attention mechanism and SIoU loss function to enhance accuracy, as shown in Fig. 14. Luo et al. (2023b) introduced Light-SA YOLOV8, which employs a FasterNet block for simplification. Wang and Liu (2024) proposed the YOLOv8n-vegetable model, replacing some C2f modules with the lightweight C2fGhost module.

4.3.2. Feature fusion and multi-scale detection for network lightweighting

Li et al. (2022a) proposed the MTC-YOLOv5 network, integrating lightweight coordinate structure attention and a multiscale training strategy, along with a feature fusion network to reduce computational demands (Kong et al., 2021). Huang and Wu (2023) enhanced the YOLOV4-Tiny model by adding Squeeze-and-Excitation and Spatial Pyramid Pooling modules, followed by depthwise convolution to reduce model size. Lin et al. (2023) introduced YOLOTobacco, an improved YOLOX-Tiny network, utilizing hierarchical mixed-scale units for inter-channel interaction and feature refinement. Li et al. (2023c) developed an apple leaf disease detection method based on an enhanced YOLOv5s model, employing a bidirectional feature pyramid network for efficient multi-scale feature fusion. Li et al. (2023g) proposed the MG-YOLO algorithm for rapid detection of gray mold spores, incorporating a weighted bidirectional feature pyramid network, and optimizing the neck with GhostCSP using a lightweight network.

4.3.3. Pruning and quantization techniques

Lan et al. (2022) introduced a new lightweight model, Swin-T YOLOX, combining the YOLOX detection network with the Swin transformer backbone. A model layer pruning technique was employed to refine the Swin transformer's multilayer structure.

4.3.4. Knowledge distillation approaches

Huang et al. (2023c) devised two strategies to construct four distinct lightweight student models: YOLOR-Light-v1, v2, and Mobile-YOLOR-v1, v2, using the YOLOR model as the teacher. A multi-stage knowledge distillation method was implemented to bolster the lightweight models' performance. Additional methods include (Wang et al., 2021a), which proposed an improved target detection algorithm for early real-time detection of tomato pests and diseases based on YOLOv3. This approach utilized convolutional decomposition to achieve network lightweighting, reduce model size and parameters, and optimize the loss function's mini-objectives with a balancing factor.

4.4. Lightweighting with other technologies

Crop pest and disease identification is a crucial aspect of agricultural production. Traditional expert diagnosis, while cost-effective, can be labor-intensive and time-consuming. With the advent of computer vision technology, research has shifted towards utilizing image processing and deep learning techniques for more efficient identification. These modern approaches often surpass the efficacy of traditional methods. Neural networks have been highly successful in various machine vision tasks, including image classification and object detection. However, training such models typically requires

substantial computational resources and large datasets. Deploying deep neural networks on lightweight devices, such as smartphones, is challenging due to constraints on resources and power consumption. To address this, model compression techniques are employed to reduce model size while maintaining inference capabilities. Common methods include knowledge distillation, mesh compression, and pruning.

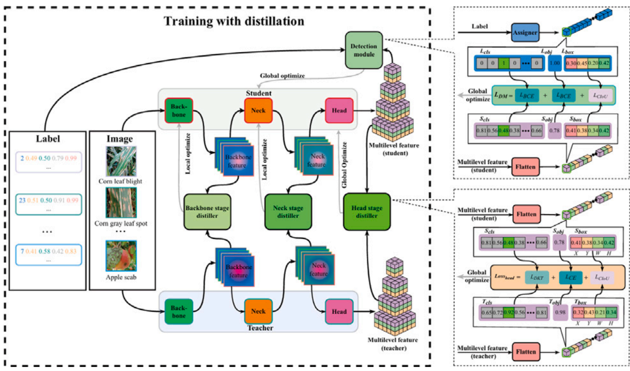


Fig. 15. Illustration of lightweighting with distillation (Huang et al., 2023c).

4.4.1. Lightweighting neural networks using knowledge distillation

Knowledge distillation is an effective model compression technique that enhances the performance of a smaller, lightweight model, known as the student model, by leveraging supervisory signals from a larger, more accurate teacher model. In recent research, the Fast-SegFormer (Cai et al., 2024) employs a multi-resolution KD strategy to support real-time fruit defect detection, enhancing distillation by increasing the teacher model's input resolution. Another study (Hu et al., 2023) integrates a Faster-C3 module into YOLO V5, reducing the model's parameter count and employing channel-wise KD during training. As shown in Fig. 15, MSKD (Huang et al., 2023c) is a multi-stage KD approach that guides the student model's learning across various stages, while OSPS-MicroNet (Tharani Pavithra and Baranidharan, 2024) represents a lightweight CNN model derived through KD.

4.4.2. Lightweighting neural networks using network compression

Network compression involves reducing the parameter count or computational footprint of a network by altering its architecture or employing quantization techniques, thereby accelerating operations without compromising performance. In one study, the SE_Xception (Chao et al., 2021) network was utilized for plant leaf disease recognition, with findings indicating that width compression has a lesser impact on performance compared to depth compression, achieving a 39:1 parameter compression ratio with high classification accuracy. The GoogLeNet-EL (Dai et al., 2023) model, based on Inception V1, modifies convolution kernel sizes across layers to achieve network compression, reducing computational complexity and memory requirements. The LCA-Net (Kong et al., 2023) incorporates a feature fusion module to optimize the network structure, minimizing parameter count and computation. Studies (Rangarajan et al., 2022; Wang et al., 2024) have also demonstrated the effectiveness of network compression in creating lightweight models.

4.4.3. Lightweighting neural networks using pruning

Pruning is a model compression technique that involves training a neural network and then removing weights below a certain threshold to create a sparser network, followed by fine-tuning to restore accuracy. A study featuring LBFNet (Chen et al., 2023b) for tomato leaf disease identification demonstrated that pruning can halve the model size from 6.85 MB to 3.46 MB with only a 1.4% decrease in accuracy. The YOLO V5-CAcT (Dai and Fan, 2022) network, based on the efficient YOLO V5, combines pruning with KD to achieve lightweight status. The YOLOv7-MGPC (Xiao et al., 2023) network substitutes its original backbone with GhostNetV1 and employs channel pruning to reduce parameter size from 36.5 MB to 7.8 MB. Swin-T YOLOX (Lan et al., 2022) introduces a new lightweight model utilizing layer pruning to reduce the Swin Transformer's multi-layer structure, achieving a two-thirds reduction in size with a slight improvement in accuracy. The study (Hu et al., 2020) focuses on pruning insignificant weights and convolution kernels in CNNs, while ASFL-YOLOX and DF-UNet (Li et al., 2022c; Xu et al., 2023; Zhang et al., 2022b) have successfully implemented pruning strategies to enhance their models.

4.5. Advantages and challenges of lightweighting

In the realm of agricultural research, particularly within the domain of AI-based pest and disease identification, the development and deployment of lightweight models have garnered significant attention. Lightweight models are advantageous due to their reduced computational requirements, which enable them to be efficiently executed on edge devices with limited processing power, such as those commonly found in remote agricultural settings. These models are designed to minimize the size and complexity of the neural network architecture, thereby facilitating faster inference times and lower energy consumption. This is particularly beneficial for real-time pest and disease detection, where swift and accurate identification is crucial for timely intervention and management. However, the creation and optimization of lightweight models also present several challenges. One of the primary concerns is maintaining accuracy while reducing model complexity. The trade-off between model size and performance is a delicate balance to strike, as overly simplified models may not capture the nuances necessary for precise identification. Additionally, the generalization capabilities of lightweight models across diverse datasets and environmental conditions must be rigorously tested to ensure reliability.

5. Advancements in deployment and hardware

Deploying plant pest and disease recognition technologies presents several key challenges, including ensuring the timeliness of data collection, ensuring compatibility between models and hardware, and addressing limitations in computational resources, as outlined in Table 6. This section delves into these challenges and explores how technologies such as drone-based remote sensing, Field-Programmable Gate Arrays (FPGAs), and other embedded systems, along with IoT strategies like cloud computing, edge computing, and cloud–edge collaboration, can effectively address these issues. These deployment technologies vary considerably in terms of latency tolerance, power consumption, and computing capacity: drone and embedded systems emphasize portability and autonomy; edge computing offers low-latency, offline inference; while cloud-based and collaborative models enable large-scale computation and storage but rely on stable connectivity. Despite these differences, they are often integrated within a unified system to strike a balance between performance and practicality. For example, lightweight models can be deployed on edge devices for instant field diagnosis, while more complex analyses are offloaded to the cloud as needed. While these technologies differ in their data processing and resource requirements, they complement the earlier-discussed methods, ensuring that pest and disease recognition systems remain both scalable and practical for deployment in real-world agricultural settings. By leveraging these innovations, the efficacy and practicality of pest and disease recognition technologies can be significantly enhanced, making them viable for large-scale agricultural applications.

5.1. Drone remote sensing technology

Drone remote sensing technology is an advanced method that integrates various sensors, such as high-resolution CCD cameras, multi-spectral imagers, and infrared scanners, on drone platforms to capture geographic information. This technology offers several advantages: high-resolution image capture, flexible deployment, and cost-effective operation (Meivel and Maheswari, 2021). It excels in the early detection of crop pests and diseases by analyzing vegetation spectral features to accurately identify affected areas. The basic process is shown

Table 6
A summary of commonly used hardware technologies and deployment methods for plant disease and pest detection.

Direction	Solutions	Methods	Datasets	Subjects	Tasks	Metric	Year	Refs.
Deployment and Hardware	Drone Remote Sensing Technology	Unmanned Aerial System	*	Corn & Soybean	Monitoring	R^2=0.81	2020	Chang et al. (2020)
		Remote Sensing	Private	Various Crop Types	Detection	R^2 = 0.811%	2023	Abbas et al. (2023b)
		Unmanned Aerial Vehicles	Private	Potato	Prediction	MAE:11.72	2018	Duarte-Carvajalino et al. (2018)
		Unmanned Aerial Vehicles	Private	Corn	Monitoring	Accuracy:98.50%	2022	Zhang et al. (2022a)
	FPGA and Embedded Systems	FPGA & CNN	Public	Plants	Identification	Accuracy:95.24%	2023	Luo et al. (2023a)
		SSD Network	Private	Jujube	Detection	mAP:97.1%	2024	Yin et al. (2024)
		FPGA System	*	Plants	Monitoring	*	2010	Zhang et al. (2010)
		Embedded Sensing	Private	Crop	Monitoring	Accuracy:97.75%	2022	Zhang et al. (2010)
	Edge Computing and Cloud-Edge Collaboration	Real-time Detection System	Private	Cherry Fruit	Detection	Accuracy:92.7%	2024	Uygun and Ozguven (2024)
		Edge Computing	Private	Longan Crops	Identification	mAP:95.24%	2021	Chen et al. (2021a)
		Edge Computing	Public	Cashew Trees	Detection	Accuracy:98.0%	2023	Rajagopal and MS (2023)
		Cloud Computing & IoT	Private	Crop	Identification	Accuracy:89.0%	2024	Dong et al. (2024b)

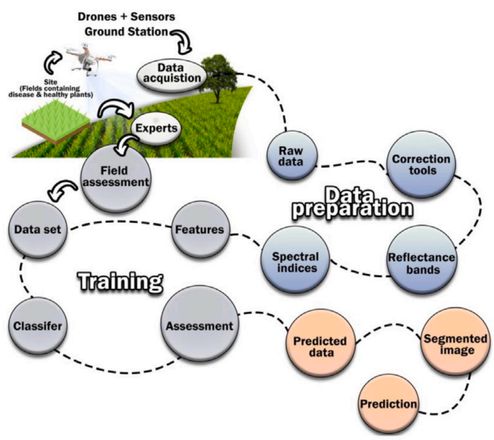


Fig. 16. Illustration of the drone detection technology (Abbas et al., 2023b).

in Fig. 16. Drone remote sensing can quickly collect large amounts of high-quality data, providing strong support for accurate recognition and timely, effective control measures, playing a crucial role in agricultural production. Multispectral/hyperspectral sensors mounted on unmanned aerial vehicles (UAVs) can simultaneously capture spatial, spectral, and temporal information of crops. Such spectral–spatial multimodal data can facilitate feature interaction through attention mechanisms (Hong et al., 2021), enhancing the model's capability to identify concealed pests and diseases. For example, Chang et al. developed a drone system capable of capturing far-red Sun-Induced Fluorescence and hyperspectral reflectance, providing higher spatial and temporal resolution crop monitoring for precision agriculture (Chang et al., 2020). Alessandro et al. demonstrated the effectiveness of drones equipped with thermal imaging cameras in measuring the Crop Water Stress Index of grapevines, combining traditional physiological measurement methods to optimize irrigation practices and reduce disease spread related to water stress (Matese et al., 2018). Additionally, Duarte-Carvajalino et al. studied the use of drones equipped with multispectral imaging systems combined with machine learning algorithms to assess the severity of late blight in potatoes. Their research showed that combining multispectral imaging with machine learning algorithms can accurately predict diseases, facilitating timely control measures (Duarte-Carvajalino et al., 2018). Zhang et al. used drone-based multispectral images and supervised and unsupervised methods to detect banana wilt disease, providing new avenues for early pest and disease detection and monitoring in agriculture (Zhang et al., 2022a). Tao et al. utilized drone multispectral imaging technology combined with machine learning algorithms to monitor cotton bollworm damage on summer maize, demonstrating that optimized drone datasets and RF models can reliably identify maize damage at field scale (Tao et al., 2022b).

5.2. FPGA and embedded systems

The advancement of deep learning has introduced many high-precision models to the field of plant pest and disease recognition, but due to geographical and environmental constraints on farms, large high-performance computing devices are often impractical in agricultural settings. In modern smart agriculture, FPGA and embedded systems offer low-power and high-precision solutions. The underlying architecture is shown in Fig. 17. Recent research shows that these technologies have significant advantages in real-time pest and disease detection and agricultural management. For instance, Luo et al. proposed an FPGA-accelerated Convolutional Neural Network for real-time plant pest and disease recognition. Their lightweight network 'LiteCNN' with only 176 K parameters and 78.47M floating-point operations, achieved a high accuracy rate of 95.24% on resource-constrained edge devices through knowledge distillation training, meeting precision needs in production processes while maintaining low energy consumption (Luo et al., 2023a). Yin et al. proposed a high-precision date tree pest and disease spot detection method based on Solid-State Drive, called JujubeSSD. This method performed excellently in detecting disease spots on date trees and is suitable for practical agricultural needs (Yin et al., 2024). Zhang et al. designed a remote monitoring and control system for plant pests and diseases based on Digital Signal Processor and FPGA. This system achieved accurate diagnosis and effective control of plant diseases and pests by efficiently processing image and video data. The use of ultra-low-power FPGA chips and optimized data acquisition circuits reduced overall costs. The system also designed two data compression and transmission strategies to meet different user needs and improved video transmission quality through the H.264 encoding standard (Zhang et al., 2010). Sharma et al. proposed an intelligent agriculture solution integrating AI and embedded sensor technologies. This solution assesses wheat crop nitrogen status by analyzing crop images captured under different lighting conditions, applying HSI color normalization and optimization processing. Subsequently, genetic algorithms and artificial neural networks are used for efficient pest and disease recognition (Sharma et al., 2022).

5.3. Cloud computing, edge computing, and cloud-edge collaboration

In modern agriculture, leveraging computational resources is crucial for enhancing the efficiency and accuracy of crop management. Recent research indicates that combining cloud computing, edge computing, and cloud–edge collaboration can effectively optimize resource utilization and system performance. Specifically, complex tasks requiring substantial computational resources can be handled in the cloud, while tasks with high real-time requirements can be processed on edge devices, achieving efficient collaboration.

Cloud computing offers robust computational and storage resources, enabling large-scale data processing and complex model training. In contrast, edge computing handles real-time data processing near the data source, reducing latency and enhancing responsiveness. The synergy between cloud and edge computing capitalizes on both architectures, efficiently allocating computational tasks and ensuring seamless collaboration between cloud platforms and edge devices. These technological frameworks are particularly valuable in smart agriculture, where they support precise data processing, rapid responses, and improved crop management efficiency.

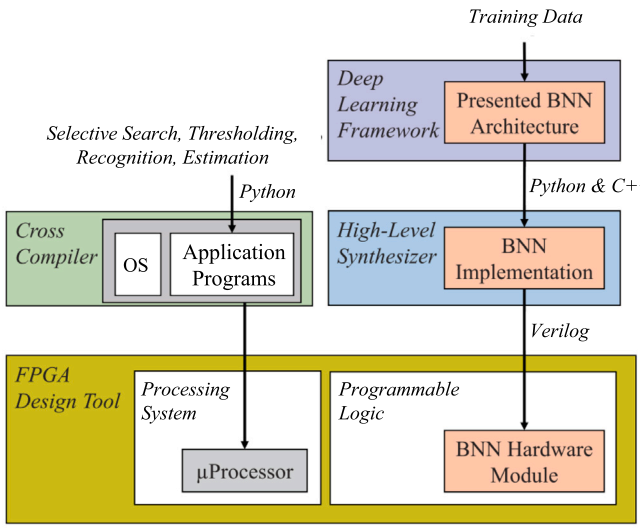


Fig. 17. Design flow for implementing the FPGA-based system architecture (Huang, 2021).

Various studies illustrate the application of cloud–edge collaboration in smart agriculture. For example, Sriveni et al. introduced a cloud-based model that uses IoT-enabled drones with sensors and cameras to monitor crop health and detect pests in real time. Data is transmitted to the cloud for storage, analysis, and visualization, empowering farmers with precise decision-making tools (Dholu and Ghodinde, 2018). Similarly, Tahsin et al. demonstrated the efficacy of edge computing for pest detection by deploying trained YOLOv8 models on smartphones for real-time recognition of cherry fruit diseases, reducing cloud dependency and improving detection speed (Uygun and Ozguven, 2024). Additionally, Chen et al. developed an edge-intelligent pest detection system utilizing drones with cameras and Tiny-YOLOv3 models on the NVIDIA Jetson TX2 platform, achieving efficient pest detection while optimizing pesticide usage (Chen et al., 2021a). Further advancements include AI-driven drone systems proposed by Manoj Kumar R and Bala Murugan MS for disease detection in cashew plantations (Rajagopal and MS, 2023), and Mo et al.'s integration of edge computing and IoT technologies for environmental monitoring, ensuring stable long-distance data transmission and precise pest recognition (Dong et al., 2024b).

In summary, deploying drone remote sensing technology, FPGA and embedded systems, as well as cloud computing, edge computing, and cloud–edge collaboration can effectively enhance the practicality of deep learning models in the field of plant pest and disease recognition, providing more accurate, efficient, and intelligent solutions for agricultural production.

6. Perspectives and future developments

The application prospects of AI technology in agriculture are increasingly expansive. The integration of AI not only introduces innovative methods for pest and disease recognition and monitoring to traditional agriculture but also provides robust support for the advancement of precision agriculture. This section adopts a comprehensive, end-to-end perspective to examine the key stages in the plant pest and disease recognition process, including data collection, model training and optimization, and deployment. We analyze the limitations of current technologies in these stages and propose future directions for the development of technologies in each phase, covering areas such as more effective few-shot learning methods, task-specific algorithm design, multimodal information fusion, and agricultural embodied intelligence. The goal is to provide scientific guidance and technical support to achieve more efficient agricultural production.

6.1. Towards more effective few-shot learning methods

FSL has garnered significant attention in the field of plant pest and disease recognition due to its ability to effectively learn from limited labeled datasets. Given the high cost and time-consuming nature of data collection in agriculture, few-shot learning presents an important strategy for overcoming these barriers. Looking ahead, the future development of few-shot learning will focus on the following key directions:

6.1.1. Leveraging large-scale pre-trained models to extract prior knowledge, and utilizing strategies such as knowledge distillation and contrastive learning, to align a small amount of data with extensive expert knowledge for downstream tasks.

6.1.2. With the increasing ease of data acquisition, the application scenarios for few-shot learning will gradually shift towards addressing the high costs associated with data labeling. Future research may lean towards the development of transductive few-shot learning methods, which incorporate additional unlabeled data through various means, utilizing LLMs to generate domain-specific textual knowledge in agriculture, or employing diffusion models to generate supplementary image data. By combining these unlabeled data with a limited number of labeled samples, models can achieve improved recognition accuracy and generalization ability.

6.1.3. Current few-shot learning methods typically evaluate model performance using fixed shot settings, such as 1-shot, 2-shot, 4-shot, or 8-shot, which do not fully reflect the practical requirements of real-world applications. In actual agricultural scenarios, models are often trained using all available data. Therefore, future research needs to establish a more reasonable definition for few-shot learning, with a greater focus on the long-tail distribution of different categories within the sample range. Additionally, more scientifically rigorous evaluation methods are needed to assess the effectiveness of these approaches in practical applications.

6.2. Task-specific algorithm design

Current research and applications in plant pest and disease recognition primarily follow two key methodologies. The first involves constructing pest-specific datasets and refining existing models to address particular recognition tasks. The second leverages pre-trained image models, adapting them to new scenarios through techniques such as transfer learning or few-shot learning to achieve satisfactory accuracy. However, existing approaches often overlook the temporal dynamics of pest and disease progression. Detection requirements vary significantly between early-stage infections, characterized by subtle physiological changes, and late-stage manifestations, which involve visible tissue damage (Sankaran et al., 2010).

Future algorithmic advancements will increasingly focus on agricultural task-specific requirements. By explicitly modeling the temporal progression of symptoms, customized algorithms can be tailored to specific pest types, crop species, and environmental conditions (Dong et al., 2024a). For example, temporal symptom progression models may dynamically adjust detection sensitivity thresholds according to crop growth stages. Early-stage detection may require sub-millimeter lesion analysis using hyperspectral sensors (Khaled et al., 2018), whereas late-stage monitoring focuses on recognizing large-scale infestation patterns across multiple fields. Integrating deeper biological and ecological insights into these models will enhance their generalization ability and adaptability. By analyzing pest lifecycles and propagation patterns, more effective recognition and prediction strategies can be developed. Empirical studies and case analyses, based on extensive data collection from specific crops and pest species, will play a crucial role in validating these specialized algorithms.

Task-specific algorithms will offer greater flexibility and efficiency. In real-world deployment, they can mitigate performance bottlenecks caused by hardware constraints while accounting for geographical and climatic variations, leading to more precise detection outcomes. Moreover, these specialized algorithms should be lightweight and scalable, enabling seamless adaptation to diverse hardware configurations and ensuring real-time processing capabilities. By effectively addressing these challenges, plant pest and disease recognition technology can be finely tuned to meet the evolving demands of modern agricultural production.

6.3. Integration of multimodal information

In the current field of plant pest and disease recognition research, computer vision technology is widely applied due to its dominance in single-modal data recognition. However, multimodal information fusion is rapidly demonstrating its potential to enhance recognition accuracy and comprehensiveness. It enriches data sources for pest and disease analysis by integrating Geographic Information Systems, meteorological data, and crop growth data. For example, satellite imagery provides macro-level information on crop coverage and health status, while meteorological data reflect micro-level environmental conditions. Combining these data sources improves the accuracy of predicting pest and disease trends and better assesses their potential impact on agriculture. Integrating multimodal information like soil moisture, temperature, and crop growth stages can achieve higher precision and personalization in pest and disease management. This management reduces chemical pesticide use, promotes ecological protection, and increases crop yields. In the context of global climate change, multimodal information fusion technology can monitor and analyze the impact of climate change on crop health in real-time, supporting timely adjustments to pest and disease management strategies. This capability is crucial for addressing extreme weather events and emerging plant pests and diseases. Current multimodal fusion research in plant pest and disease recognition still faces challenges such as the high dimensionality of spectral data and difficulties in cross-modal alignment. Future work should focus on exploring lightweight spectral feature extraction methods and designing adaptive fusion architectures to balance the accuracy and deployment efficiency of multimodal models.

6.4. Agricultural embodied intelligence

Embodied Intelligence refers to the concept where intelligence is deeply integrated with a physical body, emphasizing the interplay between an entity's cognitive processes and its ability to interact with the environment through sensory input and motor actions. The rapid development of agricultural embodied intelligence is positioning agricultural robots as key players in enhancing production efficiency and accuracy. Particularly in pest and disease detection, these robots offer novel solutions for modern farming practices. By integrating a range of sensors and intelligent algorithms, agricultural robots enable real-time crop monitoring and early identification of diseases and pests. Typically equipped with high-definition cameras, multispectral or hyperspectral sensors, and sometimes LiDAR, these robots capture detailed image and spectral data. Analyzing this data allows them to detect early symptoms, such as leaf discoloration and structural abnormalities. Noteworthy examples include RobHortic, a remote-controlled robot for detecting pests in horticultural crops using near-sensing technology, GNSS-based geo-location, and multispectral imaging systems (Cubero et al., 2020). Likewise, specialized robots like the VineRobot, designed for vineyards, employ stereo imaging for autonomous navigation and crop monitoring (Diago et al., 2016).

The operational capabilities of these robots extend to flexible and precise actuation systems, which are crucial for adapting to diverse crop types and field conditions. The design of robotic end-effectors ranges from gripping and cutting to suction-based mechanisms, tailored for specific agricultural tasks (Cheng et al., 2023; Gupta et al., 2024b). Additionally, numerous control systems incorporate advanced algorithms to enable autonomous navigation, path planning, task execution, and real-time target detection. Despite their promise, agricultural embodied intelligence faces challenges related to environmental variability and technological maturity, with cost-effectiveness also limiting broader adoption. As technologies advance and costs decline, agricultural embodied intelligence is expected to play an increasingly pivotal role in pest management, advancing precision agriculture practices.

7. Conclusions and outlook

The integration of AI into plant pest and disease recognition is driving significant progress in modern agriculture, offering practical solutions to long-standing challenges such as data scarcity, high annotation costs, and the demand for real-time monitoring. In particular, methods based on few-shot learning have shown promise in enabling accurate pest identification from limited labeled data, while recent developments in network architectures and lightweight models have enhanced the adaptability of AI systems in resource-constrained environments. Technologies such as GANs, Transformers, and LLMs are redefining how representations are learned, and hardware advances like drone-mounted sensors and edge computing are expanding the scope of in-field deployment.

Nevertheless, several critical limitations remain that must be addressed to unlock the full potential of AI in this domain. The trade-off between model complexity and inference efficiency continues to challenge deployment in field settings, particularly where energy and hardware resources are limited. Current models often achieve high accuracy at the cost of increased computational demands, highlighting the need for further research into hardware-aware architecture design, model compression, and energy-efficient inference strategies. Equally pressing is the issue of data limitations: most existing datasets are either too small, too domain-specific, or collected in overly controlled environments, resulting in limited generalizability across crops, regions, or seasons. Improving data quality and diversity—through collaborative dataset construction, domain adaptation techniques, or semi-supervised and synthetic data approaches—will be critical to building more robust models. Moreover, real-world scenarios demand a higher level of adaptability than most existing AI systems can currently offer. Environmental variability, such as seasonal shifts, pest life cycles, and background complexity, often reduces model robustness. Future research should therefore explore temporal modeling and cross-season adaptation, as well as the integration of multimodal inputs—such as combining RGB, thermal, and hyperspectral data with contextual sensor inputs—to support more resilient inference. Finally, while many technical challenges persist, it is equally important to promote interdisciplinary collaboration among agronomists, computer scientists, and policymakers to ensure that technological advances align with practical needs and sustainable practices.

By refining model architectures, expanding data access, and enhancing deployment robustness, AI will be better positioned to play a transformative role in pest management. This, in turn, will contribute meaningfully to the broader goals of agricultural sustainability and global food security.

CRediT authorship contribution statement

Xinda Liu: Writing – original draft. **Qinyu Zhang:** Investigation. **Weiqing Min:** Writing – review & editing. **Guohua Geng:** Writing – review & editing. **Shuqiang Jiang:** Writing – review & editing.

Declaration of competing interest

The undersigned authors hereby declare that there are no conflicts of interest to disclose in relation to the submitted work. Authors also confirm that none of them have personal relationships, affiliations, or involvements with any individual or organization that could influence the integrity or impartiality of the research presented in the manuscript.

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Data availability

No data was used for the research described in the article.

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