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Review

Research Progress of Deep Learning-Based Artificial Intelligence Technology in Pest and Disease Detection and Control

Yu Wu [1], Li Chen [1], Ning Yang [2] and Zongbao Sun [1,*]

[1] Department of Food & Biological Engineering, Jiangsu University, Zhenjiang 212013, China
[2] School of Electrical & Information Engineering, Jiangsu University, Zhenjiang 212013, China
* Correspondence: zongbaos@163.com; Tel.: +86-13913442131

Abstract

With the rapid advancement of artificial intelligence technology, the widespread application of deep learning in computer vision is driving the transformation of agricultural pest detection and control toward greater intelligence and precision. This paper systematically reviews the evolution of agricultural pest detection and control technologies, with a special focus on the effectiveness of deep-learning-based image recognition methods for pest identification, as well as their integrated applications in drone-based remote sensing, spectral imaging, and Internet of Things sensor systems. Through multimodal data fusion and dynamic prediction, artificial intelligence has significantly improved the response times and accuracy of pest monitoring. On the control side, the development of intelligent prediction and early-warning systems, precision pesticide-application technologies, and smart equipment has advanced the goals of eco-friendly pest management and ecological regulation. However, challenges such as high data-annotation costs, limited model generalization, and constrained computing power on edge devices remain. Moving forward, further exploration of cutting-edge approaches such as self-supervised learning, federated learning, and digital twins will be essential to build more efficient and reliable intelligent control systems, providing robust technical support for sustainable agricultural development.

Keywords: artificial intelligence; deep learning; pest and disease detection; pest and disease control; precision agriculture

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1. Introduction

1.1. Research Background and Significance

The escalating frequency and rapid spread of agricultural pests and diseases, driven by global climate change and agricultural structural adjustments, have emerged as critical factors impeding sustainable agricultural development worldwide. These biotic stressors not only disrupt normal crop growth but also lead to significant yield reductions and even total crop failure, posing substantial threats to global food security [1]. Traditional pest and disease detection methodologies, particularly those reliant on manual observation and mechanical inspection, have become increasingly inadequate in meeting the demands of modern agricultural production [2]. Although these conventional approaches can achieve certain levels of pest detection and control, they are generally characterized by operational complexity, low efficiency, high labor intensity, and susceptibility to subjective human factors, consequently compromising the accuracy and timeliness of detection and rendering them ineffective in addressing the increasingly complex challenges posed by agricultural pests and diseases.

In response to the inefficiencies, low accuracy, and reliance on manual labor in traditional pest and disease control methods, most research in recent years has focused on introducing artificial intelligence technologies, particularly deep learning methods, into the agricultural sector [3,4]. Artificial intelligence enables the automation and intelligentization of pest and disease detection through methods such as image recognition, machine vision, and multi-sensor data analysis, thereby significantly improving detection efficiency and reducing human intervention. In scenarios such as remote monitoring, deep learning technologies demonstrate significant advantages. Convolutional neural networks, recurrent neural networks, and the more recently emerging Transformer architectures are widely applied to the automatic recognition of crop pest and disease images. By analyzing high-resolution crop images, these models can accurately identify the types and severity of pest and disease infections in leaves, roots, fruits, and other plant parts, thereby improving diagnostic timeliness and accuracy [5]. Beyond image data analysis, multimodal data fusion has become a major focus of current research [6]. By integrating multi-source sensor data, including spectral data, climate information, soil moisture, and crop growth status, it is possible to develop a more comprehensive and intelligent pest and disease monitoring system [7]. This fusion strategy not only enhances model generalization capabilities but also provides strong support for accurate prediction and early prevention of agricultural pests and diseases. In addition to summarizing general trends, we also provide a representative overview of specific deep learning techniques applied in pest and disease detection. Convolutional Neural Networks and their variants have been widely used for image-based classification and object detection tasks due to their powerful feature extraction capabilities. Recurrent Neural Networks, particularly LSTM architectures, are employed for analyzing temporal dynamics such as disease progression and environmental fluctuations. Transformer-based models leverage self-attention mechanisms to capture global dependencies, showing strong potential in handling complex agricultural datasets. Generative approaches such as TRL-GAN enhance detection performance under small-sample conditions, while lightweight detection frameworks such as YOLO improve real-time monitoring and UAV-based applications. These representative techniques, summarized in Table 1, illustrate the methodological diversity of deep learning in agricultural pest and disease detection and control.

Table 1. Applications of Deep Learning Technology in Pest Detection and Control.

Model Name	Detection Technology	Disease Type	Research Advantage
Convolutional Neural Network [8]	Hyperspectral Imaging	Powdery Mildew	Early warning, low-cost monitoring
TARI/TANI + Unsupervised classification + Adaptive thresholding [9]	Hyperspectral imaging	Tea anthracnose	Robust against background noise, effective for automated tea disease detection
Deep Convolutional Neural Network [10]	Multispectral images	Rice Diseases	High recognition accuracy
CNN + Transformer [11]	Multispectral Images	Pine Wilt Disease	Lightweight implementation for real-time monitoring
DATS-ASSFormer [12]	Multispectral Images	Wheat rust, wheat scab, wheat yellow dwarf	Reduces dependency on manual labeling
Deep Convolutional Neural Network [13]	RGB images	Anthracnose, Downy Mildew, Powdery Mildew	High computational efficiency
Global Pooling Dilated Convolutional Neural Network [14]	RGB Images	Cucumber Leaf Diseases	Improved feature extraction ability and computational performance
Recurrent Neural Network [15]	RGB Images	Finger Millet Leaf Diseases	Applicable to small datasets or changing environments
Spatial Convolutional Self-attention Transformer [16]	RGB Images	Strawberry Diseases	Enhanced robustness and accuracy under noisy conditions

Table 1. *Cont.*

Model Name	Detection Technology	Disease Type	Research Advantage
Transformer [17]	RGB Images	Kiwi Diseases	Strong feature extraction ability
TRL-GAN [18]	RGB Images	Citrus Greening	Small sample learning, early detection
DDMA-YOLO [19]	UAV Remote Sensing	Leaf Blight Disease	Precise positioning, efficient detection
Decision tree + MTMF + NDVI [20]	UAV multispectral remote sensing	Wheat powdery mildew, wheat leaf rust	Enables spatiotemporal monitoring of disease progression
RustQNet [21]	RGB Images + Hyperspectral Resolution Multispectral	Stripe Rust Disease	Quantitative evaluation, precision spraying

Increasing research efforts apply artificial intelligence, particularly deep learning technologies, to agriculture in order to enhance the efficiency of pest and disease detection and control, thereby advancing agricultural intelligence. Deep learning enables precise, automated detection through image recognition and sensor data analysis. With continued technological progress, approaches based on deep learning—such as image recognition and multimodal data fusion—are expected to play a more significant role in improving agricultural productivity, reducing environmental pollution, and promoting sustainable agriculture.

1.2. Evolution of Agricultural Pest and Disease Detection and Control Technologies

1.2.1. Conventional Approaches to Pest and Disease Detection and Control

Within agricultural production systems, timely identification and effective management of pests and diseases remain critical to safeguarding both crop yield and quality. Conventional detection and control strategies predominantly depend on manual scouting, experiential assessment, and chemical interventions. Detection typically involves visual inspection, the deployment of trapping devices, or microscopic analysis to determine the type and extent of infestation. Control methods often encompass regular pesticide spraying, crop rotation, and manual pest removal. While these techniques are cost-effective and require minimal technological infrastructure, they are hindered by low operational efficiency, considerable subjectivity, and potential environmental hazards. With the growing demand for large-scale and precision agriculture, conventional methods can no longer meet the requirements for high efficiency and accuracy. This creates an opportunity for the integration of emerging intelligent technologies based on deep learning, forming the foundation for the transformation of pest and disease detection and control technologies [22].

Conventional pest and disease management methods can be categorized into chemical, biological, and physical controls, each characterized by unique strengths and constraints. Chemical control is extensively utilized for its fast-acting effects, yet chronic overuse of pesticides leads to a range of ecological and health hazards, including contamination of soil and water resources, biodiversity degradation, and the evolution of pesticide-resistant pests [23]. Physical control strategies aim to reduce risks by modifying environmental parameters or implementing physical barriers; however, exclusive reliance on these methods often yields suboptimal results, requiring combination with biological control and agronomic measures to combat resistance and soil-transmitted pathogens [24]. Biological control, which utilizes natural enemies or probiotic microorganisms, is environmentally sustainable but is often hampered by complex deployment, delayed impact, and limited consistency, especially when ecological conditions are unstable [25]. Consequently, relying on a single control approach is inadequate for the intricate nature of agricultural ecosystems; developing a multi-strategy, integrated control framework that combines the strengths

of chemical, biological, and physical measures is a key trend in contemporary pest and disease management. It further raises the requirements for intelligent and precision-based pest and disease detection and management technologies.

Conventional methods for pest and disease detection and control mainly depend on manual inspections, empirical assessments, and chemical treatments. While these methods are cost-effective and require limited equipment, they suffer from significant constraints, and prolonged reliance on chemical control has adverse environmental consequences. Existing research demonstrates that the swift progress of artificial intelligence and deep learning has facilitated the shift of pest and disease detection and control toward intelligent and automated systems [26]. By integrating deep learning with image recognition, remote sensing, and data fusion, pest and disease monitoring is being propelled toward intelligent and automated paradigms, markedly improving the efficiency and accuracy of control measures, and promoting the sustainable transformation of agriculture.

1.2.2. Emerging AI-Based Approaches for Pest and Disease Detection and Control

At present, artificial intelligence technology primarily relies on unmanned aerial vehicles, intelligent monitoring devices, and mobile applications to achieve efficient and real-time monitoring of pests and diseases. Deep learning technology plays a central role, with models such as CNNs, RNNs, and Transformers achieving remarkable results in image recognition and classification tasks. By leveraging machine learning algorithms, AI systems can be trained on large volumes of image data to automatically identify and classify various types of pests and diseases, thereby enabling accurate detection and early warning [27]. As shown in Figure 1, the workflow begins with data acquisition, including RGB and multispectral images collected by UAVs, satellite observations, and text-based information from agricultural databases. These heterogeneous inputs form the foundation for subsequent analysis. In the second stage, deep learning and multimodal fusion techniques (e.g., CNN, RNN, Transformer) are applied to integrate image, environmental, and textual data, with small-sample augmentation used to address data scarcity. The outputs of this stage directly support intelligent control tasks, such as pest and disease identification, forecasting and early warning, precision spraying, and biological control. Finally, the figure highlights two levels of future directions: (1) research-level innovations (left panel), such as causal reasoning models, digital twin virtual farms, multimodal integration systems, and eco-regulation modeling; and (2) system-level development (bottom panel), emphasizing the application of digital twin systems for long-term intelligent agricultural management. This design illustrates the progression from data collection to intelligent control, while pointing toward both theoretical and practical future research pathways.

Building upon this foundation, deep learning is being integrated closely with intelligent equipment, driving innovation in agricultural pest and disease control technologies [28]. Leveraging artificial intelligence, sensor networks, and data analytics, researchers develop intelligent monitoring systems with all-weather surveillance capabilities. By deploying high-precision sensors and cameras across farmland, such systems can capture real-time data on crop growth status, climate variations, and early signs of pest and disease occurrence, and transmit timely alerts to achieve prevention and control [29]. Artificial intelligence technologies, in conjunction with deep learning, are advancing pest and disease detection and control into an era of intelligence. AI-based automated monitoring, precise identification, and intelligent prediction are making agricultural pest and disease management more efficient, environmentally friendly, and sustainable.

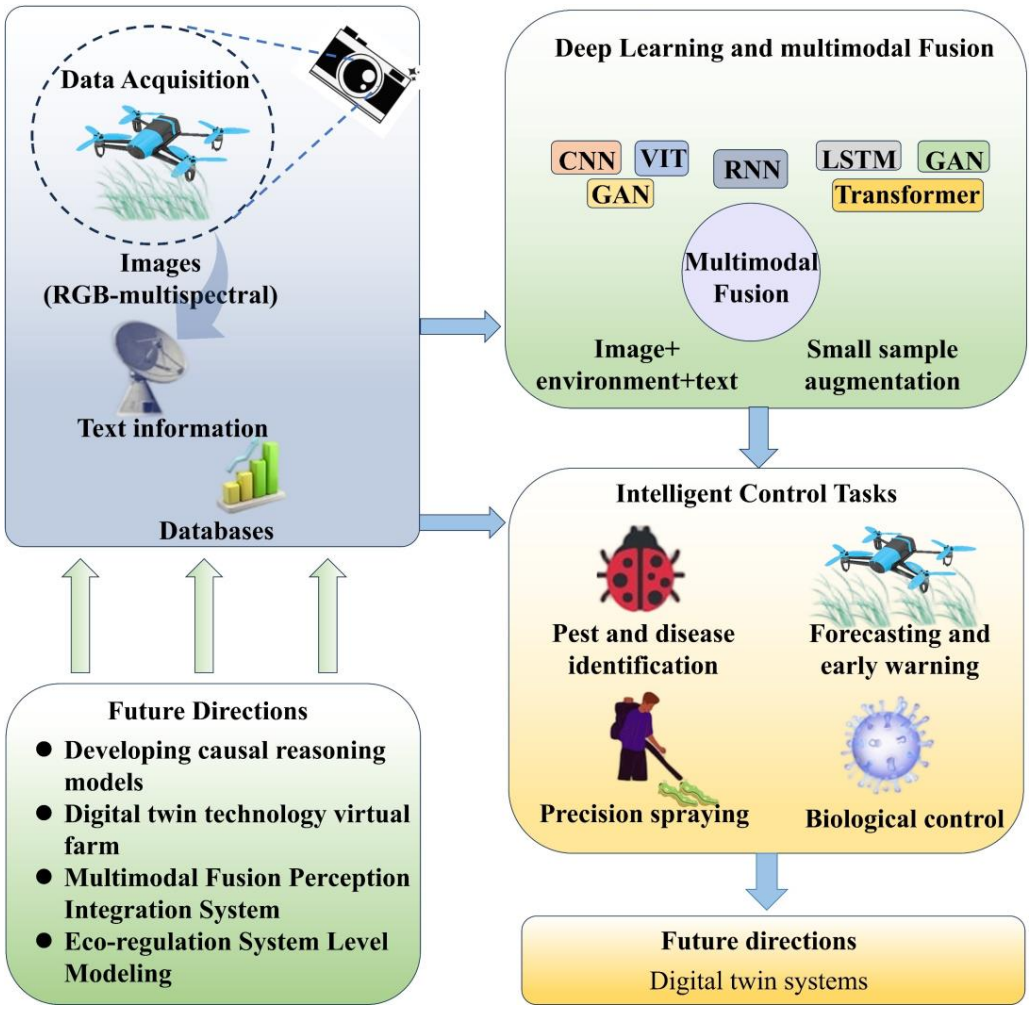


Figure 1. Application workflow of deep learning for intelligent pest and disease monitoring and control.

2. Applications of Artificial Intelligence in Agricultural Pest and Disease Identification and Detection

2.1. Deep Learning and Image Recognition Models

2.1.1. Mainstream Deep Learning Architectures

Artificial intelligence recognition technology has undergone a remarkable evolutionary trajectory. Beginning with early expert systems reliant on predefined rules, which constrained both intelligence levels and application scopes, the field has progressively transitioned toward deep learning-based intelligent models through sustained research advancements. This shift signifies continuous leaps in recognition capabilities regarding both efficiency and intelligence [30–32]. In this developmental trajectory, the introduction of mainstream deep learning architectures such as CNNs, RNNs, and Transformers served as a pivotal milestone in enabling breakthroughs for artificial intelligence in complex perception tasks.

These advanced deep learning models demonstrate broad application potential and outstanding performance in agricultural pest and disease identification tasks [33]. Figure 2 illustrates a schematic comparison of mainstream deep learning architectures applied in agricultural pest and disease detection. Convolutional neural networks are the most widely adopted architecture for agricultural pest and disease image analysis. By combining convolutional and pooling layers, CNNs automatically extract hierarchical spatial features—such as edges, lesion patterns, and texture details—from crop images. These features are then

passed through fully connected layers for classification or regression, enabling precise recognition of diseased leaves and fruits [34–36]. In contrast, recurrent neural networks are better suited for sequential agricultural data, such as disease progression curves or climate-related time series. Their recurrent structure allows hidden states to be transferred across time steps, thereby capturing temporal dependencies. Advanced variants such as LSTM further improve the ability to model long-term dependencies in dynamic agricultural environments [37]. Transformers, as a more recent innovation, employ a self-attention mechanism to model global dependencies across all input elements in parallel. This design not only accelerates computation but also enhances contextual representation, making Transformers highly effective for integrating multi-source agricultural datasets, including spectral, phenotypic, and environmental information [38]. Benefiting from the application of these deep learning technologies, agricultural pest and disease detection has evolved from static image analysis to integrated intelligent analysis incorporating environmental variables, crop growth status, and historical data, thereby significantly enhancing monitoring accuracy and adaptability. Compared with traditional pest and disease recognition methods that relied on handcrafted features or manual scouting, mainstream deep learning architectures have brought substantial improvements in classification accuracy, scalability, and automation. For example, CNN-based image classifiers consistently achieve 10–20% higher accuracy than conventional texture- or color-based algorithms in benchmark datasets, while RNNs and Transformers enable modeling of temporal and multimodal data that traditional statistical approaches cannot capture [39]. However, these advances also highlight critical knowledge gaps. Deep learning models often require large, well-annotated datasets, and their performance may degrade significantly under heterogeneous field conditions such as variable lighting, occlusion, or background interference. Moreover, computational demands limit their deployment on low-power mobile devices commonly used in agriculture.

Representative studies further highlight the potential of these architectures. Ferentinos [40] proposed a CNN-based plant leaf disease detection model, which achieved 99.53% accuracy through training on 87,848 images encompassing healthy and diseased samples from 25 plant species, providing an effective tool for early agricultural disease warning. Concurrently, Zhu et al. [41] enhanced the classification accuracy of citrus leaf diseases by integrating transfer learning with ensemble algorithms, demonstrating the robustness and efficiency of CNN models in complex background scenarios. For time-series data analysis, RNNs and their derivative Long Short-Term Memory architectures exhibit significant application prospects [42,43]. Li et al. [44] introduced a Long Short-Term Memory network model enhanced with an attention mechanism to perform multi-step forecasting of air and soil temperatures in greenhouses. Through feature-weight optimization, the long-term dependency issue was resolved, markedly increasing prediction precision and supporting intelligent greenhouse control. As deep learning advances, Ji et al. [45] developed a detection approach for green apples that combines multi-dimensional feature extraction with Transformer components. Utilizing a deformable attention mechanism for feature optimization, the method achieved substantial accuracy gains in complex orchard settings, reaching 97.12% accuracy at an intersection over union threshold of 0.5.

Although deep learning technology has demonstrated considerable potential in the field of pest and disease detection, it still faces several challenges. Convolutional neural networks require large datasets encompassing diverse conditions to function effectively; however, the agricultural environment is highly variable, and factors such as lighting, shadows, leaf overlap, and background interference may affect recognition performance, representing a major limitation. This view was validated in the study by Barbedo [46], which demonstrated that transfer learning significantly outperforms end-to-end deep

learning in plant disease classification under small-sample and high-noise conditions, and that data diversity is more critical to performance than dataset size. These directions will further promote the practical application of deep learning models in agricultural pest and disease detection.

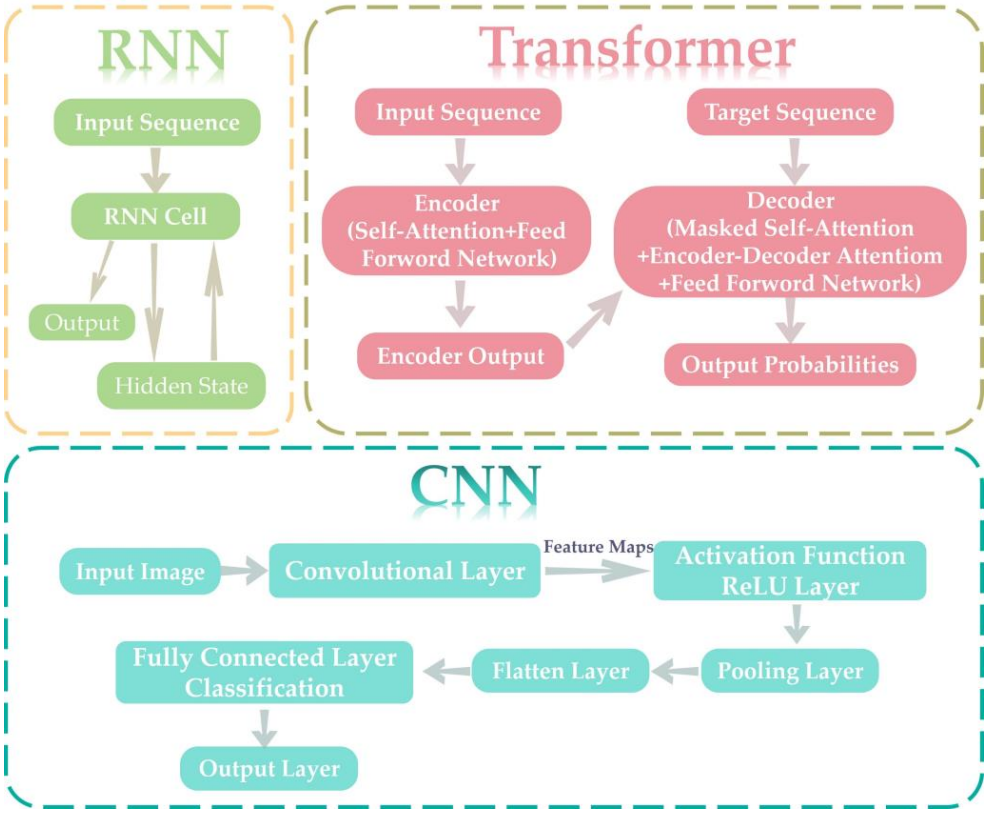


Figure 2. Schematic comparison of mainstream deep learning architectures (CNN, RNN, and Transformer) applied in agricultural pest and disease detection.

2.1.2. Image Recognition and Detection Technology

Image recognition technology holds a crucial position in the detection of agricultural pests and diseases, with its adoption greatly enhancing detection efficiency [47,48]. Building on the fundamental capabilities of mainstream architectures such as CNNs, RNNs, and Transformers, numerous deep learning-based models have been developed for pest and disease image identification. These models have established a robust theoretical framework and practical foundation for agricultural applications, demonstrating both accuracy and adaptability in complex field conditions [49]. By leveraging these architectures, pest and disease detection has progressed beyond basic image recognition, advancing toward integrated analytical frameworks that combine visual features with contextual agricultural information, thereby improving both diagnostic precision and model adaptability [50–52].

By integrating fixed cameras, UAVs, and mobile devices into a multi-source sensing network, image recognition technology can acquire and process farmland imagery in real time. When combined with cloud-deployed deep learning algorithms, it facilitates online pest and disease identification and dynamic monitoring [53,54]. Zhang and Kovacs [55] introduced semi-supervised learning to minimize annotation costs. Using deep learning methods, the system autonomously processes imagery, identifies abnormal areas, and tags probable pest and disease categories. Building on this, and targeting different crops and pest/disease categories (as presented in Table 2), the integration of diverse image processing techniques with intelligent analysis approaches has improved identification precision and timeliness.

Table 2. Application studies of deep learning-based image recognition in pest and disease detection.

Model Name	Detection Technology	Research Object	Research Advantage
Decision Tree–Based Model and Confusion Matrix Method [56]	Microscopic Imaging	Rice Pyricularia Disease	Integration of multiple features to minimize misclassification rate
Classification Model [57]	Thermal Infrared Imaging	Tea Anthracnose	Contact-free detection offering rapid response
Logistic Regression and Random Forest Classification Model [58]	Diffraction Imaging	Tomato *Botrytis cinerea* Spores	Sensitivity enhancement via integrated microfluidic enrichment
Support Vector Machine Classification Model [59]	Diffraction Imaging	*Magnaporthe oryzae* Spores	High-specificity detection capability
Support Vector Machine Classification Model [60]	Hyperspectral Imaging	Tea White Spot Disease and Anthracnose	Enables non-destructive leaf analysis
3D Convolutional Neural Network [61]	Hyperspectral Imaging	Wheat Stripe Rust	Efficient wide-area monitoring
Faster Region-Based Convolutional Neural Network [62]	Visible Light Imaging	Weeds in Cotton Field	Rapid identification and precise weed categorization
DTL-SE-ResNet50 [63]	Visible Light Imaging	Tomato Early Blight, Cucumber Downy Mildew, and Pepper Anthracnose	Accurate performance with reduced reliance on large datasets

Given the large number of models developed for pest and disease image recognition, it is not feasible to illustrate every workflow in detail. Therefore, this section presents two representative examples: Figure 3A highlights SE-ResNet50 as a typical CNN-based transfer learning workflow, while Figure 3B illustrates the Transformer framework as a representative of attention-based architectures. These were selected because they exemplify the two most influential paradigms currently applied in agricultural image recognition—transfer learning for CNN optimization and global feature modeling via self-attention. As illustrated in Figure 3A, the SE-ResNet50 model was developed by employing data augmentation and weight transfer, further optimized from the pre-trained ResNet50 architecture, and utilized for the detection of tomato powdery mildew. At the same time, the Transformer model exhibits remarkable global feature modeling ability in image recognition. As shown in Figure 3B, the model processes image data via a self-attention mechanism, extracts salient features, and produces attention maps for pest and disease detection [64]. In addition to mainstream CNN and Transformer architectures, hyperspectral imaging has shown great promise for detecting early physiological diseases in fruits. For example, Cong et al. [65] investigated chilling injury in kiwifruit, a condition difficult to recognize by the naked eye before severe damage occurs. To address the challenge of cross-variety variability in spectral characteristics, they developed a universal hybrid deep network (CDGSA-Net) optimized with a pelican optimization algorithm. The model achieved over 99% accuracy, precision, recall, specificity, and F1-score, significantly outperforming conventional ML and DL baselines. This study highlights not only the technical feasibility of integrating hyperspectral imaging with advanced deep learning but also the practical relevance for local orchard crops such as kiwifruit, where accurate and transferable detection is critical for small-scale precision management.

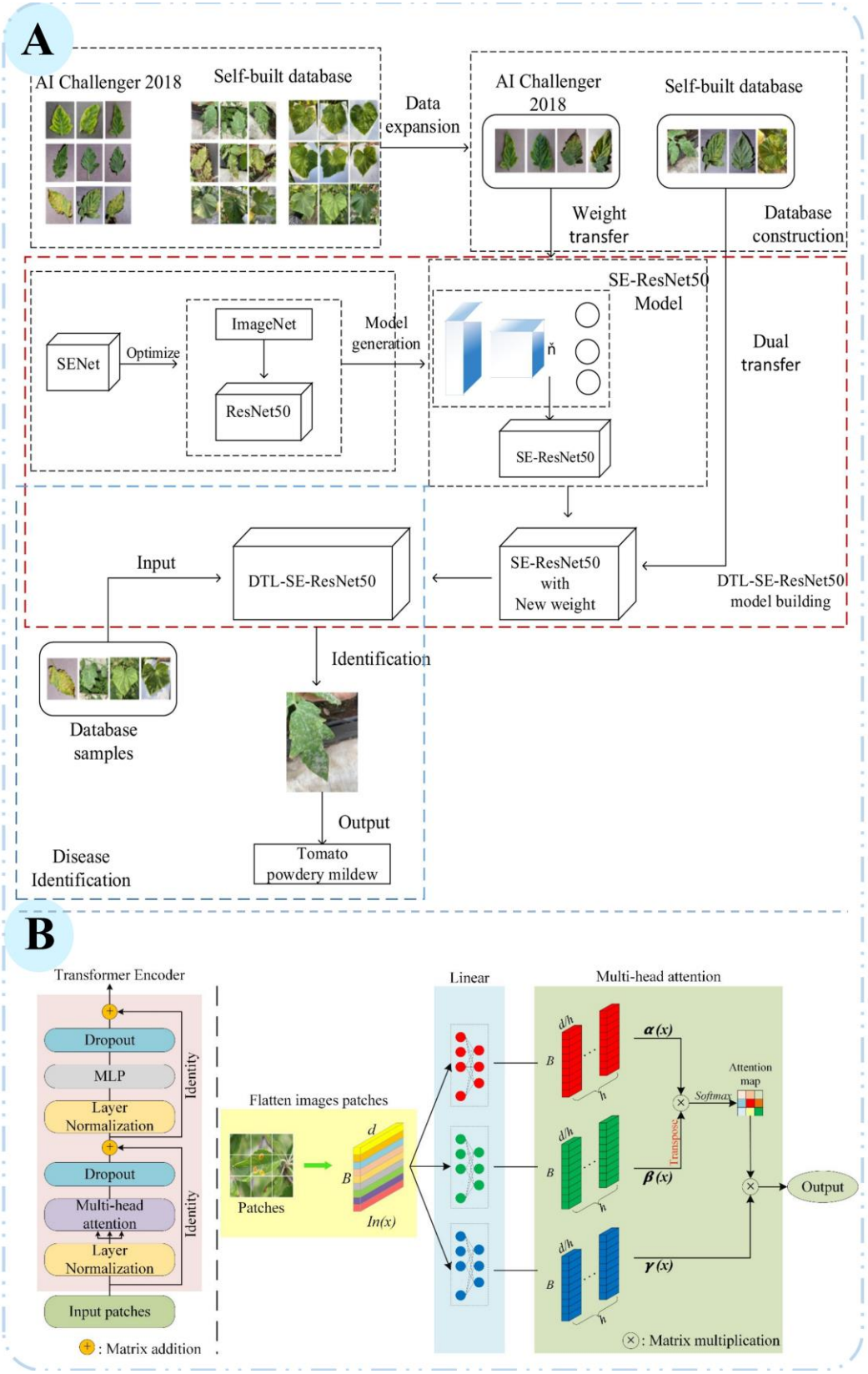


Figure 3. (**A**) A transfer learning workflow for image recognition and detection based on an improved ResNet50 combined with SENet for optimized feature extraction in deep learning; (**B**) A deep learning workflow for image recognition based on a Transformer architecture that extracts deep image features through a multi-head attention mechanism.

Significant advancements have been achieved in the application of image recognition and detection technologies for agricultural pest and disease management. Continuous innovations in model design and the fusion of diverse imaging modalities have accelerated the shift from manual diagnosis to automated and intelligent pest detection [66]. Nevertheless, substantial challenges persist during practical implementation, including pronounced image quality fluctuations in complex field environments and computational constraints during model deployment on edge devices. Future research should prioritize the development of lightweight and highly robust models, as well as the establishment of image recognition systems with real-time feedback capabilities to improve adaptability in intricate operational scenarios.

2.2. Remote Sensing and UAV Image Analysis Technology

Unmanned aerial vehicles and satellite remote sensing technologies, serving as the "Sky Eye" system for intelligent detection of agricultural pests and diseases, establish a multi-scale monitoring network through high- and low-altitude collaboration [67]. Leveraging their low-altitude, high-resolution observation advantages, UAVs overcome the constraints of satellites in atmospheric disturbance and coverage frequency, whereas satellites deliver broad-scale, periodic macro data. The integration of both enables full coverage from individual plants to regional scales, significantly enhancing the spatiotemporal efficiency of early warning, dynamic disaster assessment, and precise pest and disease control [68].

By carrying high-resolution cameras or multispectral sensors, UAVs can rapidly survey vast agricultural fields, collecting information on crop growth, disease traits, and pest distribution patterns [69–72]. Coupled with deep learning models, the system can automatically analyze these remote sensing images, rapidly detect abnormal pest and disease affected areas, and annotate potential types [73,74]. Contemporary agricultural UAVs typically carry multi-sensor payloads, including multispectral cameras, hyperspectral imaging devices, thermal infrared sensors, and light detection and ranging [75–78]. Deng et al. [79] evaluated various multispectral cameras for UAV agricultural remote sensing, assessed the effect of spatial resolution on crop monitoring, and contrasted results with the Screened Poisson reconstruction method, revealing that adding the red-edge band markedly enhanced the vegetation index's responsiveness to early crop stress. Zhu et al. [80] developed a monitoring approach for wheat Fusarium head blight that integrates UAV multispectral sensing with machine learning, using high-resolution imagery to extract canopy spectral signatures and multi-temporal data to characterize disease spatial distribution, significantly enhancing detection accuracy. Building on these advances, Gu et al. [81] applied low-altitude UAV imaging to assess narrow brown leaf spot severity in rice and evaluate fungicide efficacy under field conditions. By combining UAV imagery with disease scoring, their approach enabled accurate quantification of lesion progression and treatment effectiveness at the plot scale, demonstrating the value of UAV-based monitoring in staple crops such as rice and supporting precision field management. Additionally, combining UAV and multispectral imaging further enriched phenotypic data dimensions. Zhou et al. [82] introduced a CNN-based rice yield prediction model that enhanced prediction accuracy through multi-temporal spectral data fusion. These findings have suggested that deep learning combined with remote sensing imagery offers considerable promise, yet its high computational demands and long training times remain obstacles to large-scale agricultural deployment. Integrating deep learning with UAV-acquired remote sensing imagery has significantly advanced the automation and precision of pest and disease detection [83,84]. Wei et al. [85] achieved precise estimation of wheat canopy characteristics by integrating multi-temporal UAV-based RGB and multispectral imagery with a

CNN-LSTM deep learning model, which effectively synthesized canopy color attributes, spectral features, and spatial structural parameters. However, this approach revealed the inherent dependency of deep learning models on extensive annotated datasets. Particularly in agricultural applications, the acquisition and annotation of such data typically require substantial manual intervention, posing challenges to the model's generalizability and practical deployment. Complementing these studies, Hu et al. [86] investigated tea leaf blight detection using low-resolution UAV remote sensing images. Despite the limited image quality, tailored detection methods achieved reliable identification of symptoms in tea plantations. This highlights the practical potential of UAV-based monitoring for local crops and smallholder farms, even under resource-constrained conditions. Importantly, several deep learning-based image recognition studies originally applied to platform-independent tasks also demonstrate significant value in UAV/remote sensing contexts. For instance, Jamali et al. [87] integrated UAV-acquired high-resolution imagery with a vision transformer algorithm to map blueberry scorch virus. By leveraging multispectral and RGB sensors mounted on UAVs, the method generated spatial heatmaps of viral infection, providing crucial support for early detection and precision management. Such works illustrate how advanced architectures, when paired with UAV imaging, can overcome challenges in field environments and enhance real-time monitoring.

At the regional scale, satellite remote sensing technology serves an indispensable role in pest and disease monitoring [88]. Chang et al. [89] developed an XGBoost-based multi-scale model that fuses satellite, UAV, and ground datasets, enabling highly accurate recognition of disease spatial distribution and advancing the establishment of coordinated UAV–satellite monitoring frameworks. Nevertheless, satellite imagery remains inferior to UAV imaging in both temporal and spatial resolution, especially for small-scale crop field monitoring, where it may fail to deliver adequate precision. Consequently, the integration of UAV and satellite remote sensing offers a means to offset their respective limitations, though issues of data synchronization and fusion remain [90]. Despite these challenges, technological breakthroughs in remote sensing monitoring have significantly advanced the development of precision agriculture. Zhang et al. [91] incorporated terrain factors into a UAV-based multimodal remote sensing system and proposed an NDVI–Terrain fusion algorithm, which improved biomass prediction accuracy at the field scale, offering a novel approach. In practice, the critical challenge for achieving precision agriculture lies in efficiently merging diverse remote sensing datasets while mitigating the influence of environmental factors. Framework of UAV–satellite collaborative remote sensing integrated with deep learning models (CNN, RNN/LSTM, Transformer) for agricultural pest and disease monitoring (Figure 4). The framework consists of four modules: data acquisition (satellite reconnaissance and UAV surveys), data processing and fusion (preprocessing and multi-scale data integration), AI-powered analysis (CNN, RNN/LSTM, Transformer), and application in pest and disease detection, mapping, and early warning.

In the field of agricultural pest and disease monitoring, remote sensing and UAV-based image analysis technologies clearly outperform traditional field scouting and manual sampling by providing wider spatial coverage, faster acquisition speed, and improved objectivity. Likewise, UAV–satellite collaborative frameworks deliver greater consistency and reliability in regional monitoring than either platform alone, highlighting the practical advantages of multi-scale integration. Nevertheless, important gaps remain. Current approaches often face challenges in harmonizing data across platforms, particularly in terms of synchronization, calibration, and real-time fusion. Moreover, most studies focus on technical feasibility, while systematic comparative benchmarks that directly contrast deep learning frameworks with traditional statistical or rule-based methods under diverse field conditions are still lacking. Future studies should concentrate on boosting the efficiency of

multi-source data integration, refining deep learning models, and improving the real-time responsiveness and robustness of monitoring systems, thereby driving precision agriculture toward more efficient and intelligent development.

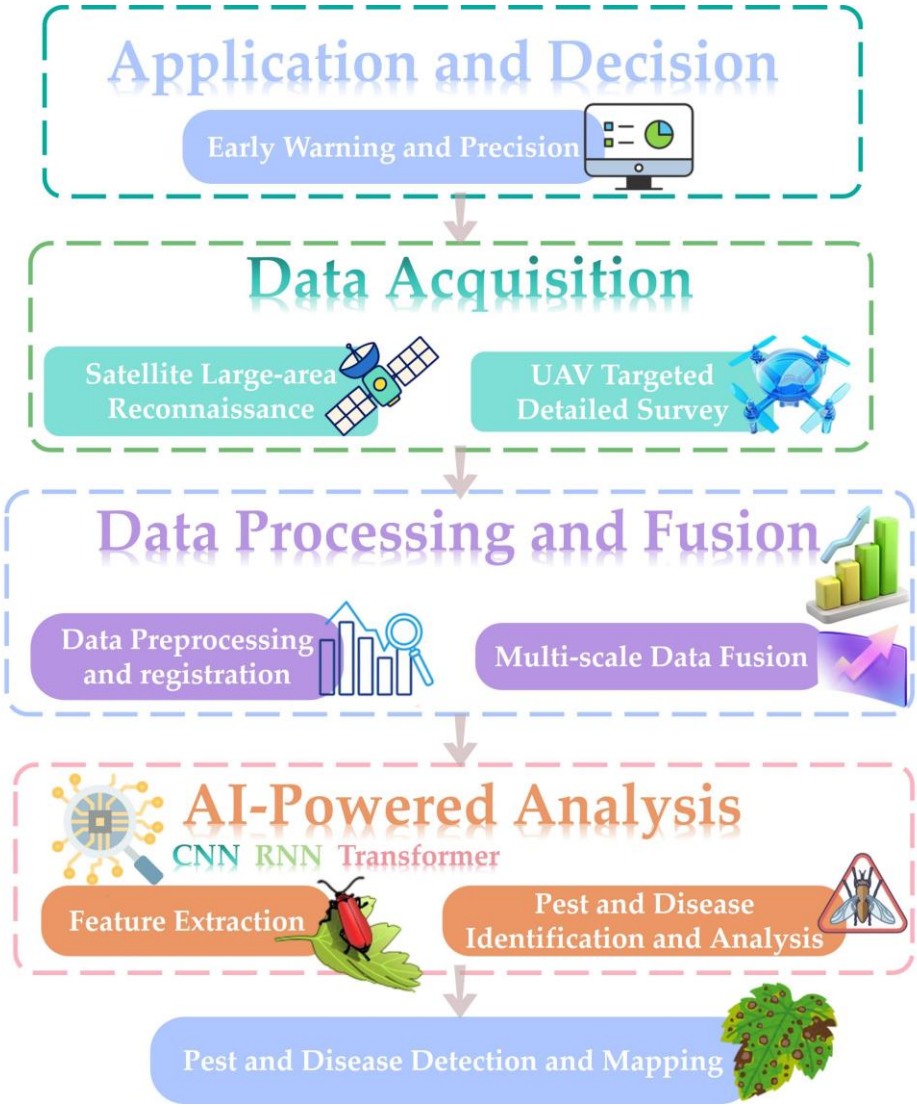


Figure 4. Framework of UAV–satellite collaborative remote sensing integrated with deep learning models (CNN, RNN/LSTM, Transformer) for agricultural pest and disease monitoring.

2.3. Internet of Things Sensors and Smart Monitoring Technologies

Within intelligent agricultural pest and disease monitoring frameworks, IoT sensors function as the "neural network" of digital farms, reshaping approaches to crop health management by enabling round-the-clock multidimensional sensing and biosignal capture [92]. Through the combination of intelligent sensing nodes and cloud-based platforms, these devices create a comprehensive monitoring network [93,94] that can continuously and accurately track greenhouse environmental parameters, optimizing greenhouse management and crop productivity, while surpassing the spatial–temporal resolution and responsiveness constraints of conventional monitoring techniques [95,96].

The application of deep learning in IoT sensor-based detection and identification has achieved remarkable advancements [97]. Gutiérrez et al. [98] designed a grapevine pest and disease diagnostic system using convolutional neural networks, which leveraged new sensing methods to categorize grapevine canopy leaves as exhibiting downy mildew, spider mite symptoms, or no symptoms, attaining an accuracy rate of 0.94. Li et al. [99]

advanced this field by creating a multimodal wearable plant sensor system that simultaneously measures critical variables—including leaf temperature, stomatal conductance, and pathogen-related molecules—and wirelessly transmitted the data to the cloud, providing early warning and real-time detection of greenhouse tomato late blight. While showcasing the promise of multimodal sensor data integration for intelligent pest and disease monitoring in agriculture, the system also highlighted challenges, including transmission latency and heavy cloud computation loads. Addressing the rapid processing and timely response demands of multi-sensor environments will require further refinement.

Continued breakthroughs in deep learning are propelling the development of smart disease monitoring systems. Guo et al. [100] proposed a system integrating temperature–humidity and optical sensors with deep learning models for batch monitoring and real-time warning of apple spoilage. Leveraging multi-source data integration, the system identifies early signs of spoilage and initiates alerts in the initial phase, enhancing storage and supply chain efficiency and mitigating financial losses. Velasquez et al. [101] introduced a diagnostic model for coffee leaf rust that combines wireless sensor networks, remote sensing, and deep learning. Utilizing weighted averages of sensor readings and image data, it precisely forecasts the progression stage of the disease, matching the accuracy of expert visual assessment. Nonetheless, the variability of data and constraints in sampling time still hinder the broader adoption of this approach, especially in areas where environmental conditions fluctuate sharply or pest and disease dynamics shift rapidly. Improving system adaptability and real-time performance will be a critical direction for future studies. In addition to greenhouse and fruit crop applications, IoT-compatible sensing and deep learning strategies have also been extended to staple crops such as wheat. For instance, Deng et al. [102] proposed a novel framework that combines a miniaturized microwave detection device with a multi-task CNN model to simultaneously analyze wheat mildew degree and aflatoxin B1 (AFB1) contamination. The system collected transmission indexes of moldy wheat samples and employed a fusion CNN-based multi-task learning strategy to achieve both qualitative classification and quantitative regression. The model attained 100% accuracy, precision, recall, and F1-score in mildew recognition, while reaching high performance in toxin quantification (RMSEP = 2.0138 μg kg^{-1}, RPD = 7.28). This study demonstrates that microwave detection integrated with deep learning can provide a rapid, non-destructive, and resource-efficient solution for food safety monitoring in wheat. Importantly, it also highlights the practical applicability of advanced sensing technologies for local crop management and smallholder farming systems, where conventional laboratory testing is often inaccessible. Beyond single-sensor data collection, IoT-based pest and disease monitoring systems increasingly integrate multimodal information with deep learning approaches. Figure 5A illustrates the process of multi-source feature fusion: near-infrared spectral features selected by algorithms such as CARS, SPA, VCPA, and VCPA-IRIV are combined with image-derived color and texture descriptors. These fused features are then analyzed using both traditional machine learning models (LDA, SVM, BPANN) and deep learning architectures (MLP, CNNX), thereby significantly enhancing the representational power of sensor data and improving recognition accuracy. In parallel, Figure 5B depicts the architecture of an IoT sensor network for agricultural pest and disease monitoring. A diverse array of sensors—including soil temperature and moisture, illuminance, environmental humidity, and wind speed—together with imaging devices (RGB and multispectral cameras) create a comprehensive real-time sensing network. Raw data are preprocessed by microcontrollers and packaged via a single-board computer before being transmitted through HTTP or SFTP protocols to remote servers and IoT platforms. This enables both local data storage and cloud-based visualization, ensuring continuity, efficiency, and robustness of greenhouse and field disease monitoring. By combining multimodal feature

extraction with IoT-based architectures, these frameworks highlight the central role of sensor fusion and intelligent connectivity in modern crop health management. This technical perspective further supports the section's emphasis on enhancing real-time capability, precision, and multi-source data integration in pest and disease monitoring.

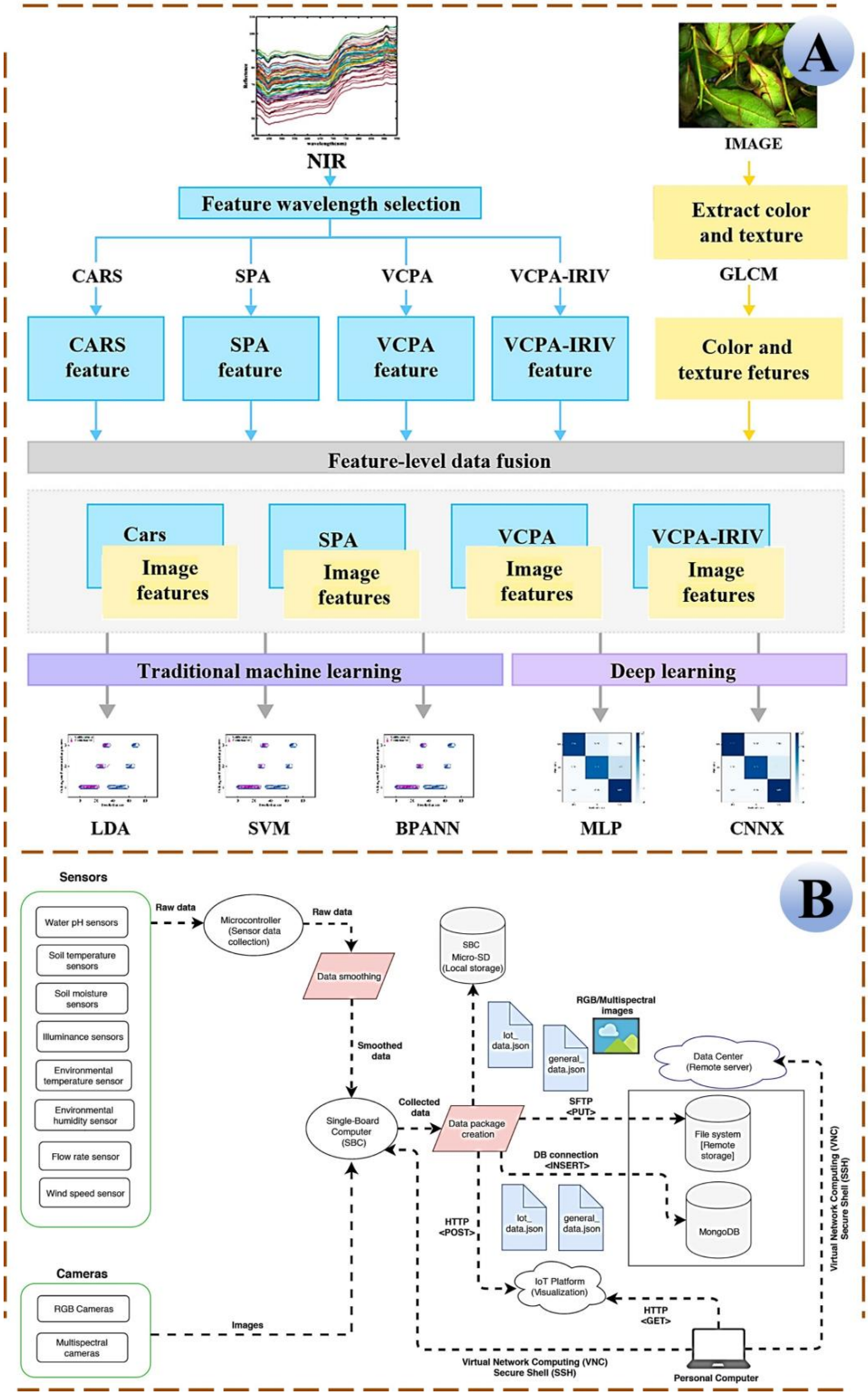


Figure 5. (**A**) Workflow of multimodal feature extraction and fusion from NIR spectroscopy and image data, combined with machine learning and deep learning models for pest and disease identification; (**B**) IoT sensor architecture integrating environmental sensors and imaging devices with data preprocessing, cloud storage, and real-time visualization for smart agricultural monitoring.

The application of IoT sensors and intelligent monitoring technologies in agriculture has substantially enhanced the precision and real-time capabilities of crop health monitoring. However, challenges persist, including high costs, technical maintenance difficulties, and inefficiencies in data processing and transmission. The integration of deep learning technologies, particularly in the processing and analysis of multi-dimensional data, has significantly advanced the intelligent monitoring and prevention of pests and diseases. Deep learning models can autonomously extract critical features from sensor data, enabling real-time identification and early warning systems, thereby markedly improving monitoring accuracy and operational efficiency. Consequently, future research should prioritize key areas such as cost-effective sensor solutions, enhanced system adaptability, reduced data transmission latency, and improved deep learning model performance with limited datasets.

2.4. Rapid Detection and Mobile Application Technologies

With agricultural pest and disease detection increasingly moving toward intelligent solutions, the combination of deep learning-driven image recognition, microfluidics, biosensors, and infrared thermal imaging offers robust capabilities for rapid in-field diagnostics. By integrating deep learning algorithms with smartphones, handheld devices, and portable analyzers, researchers have created a range of rapid diagnostic systems and platforms capable of automatically processing images and sensor readings, thereby greatly enhancing both efficiency and portability [103]. Through these mobile devices, users can rapidly access pest and disease information, leverage deep learning models for initial evaluations, and supply precise data inputs for downstream intelligent decision processes [104].

In recent years, combining image enhancement techniques with mobile-based intelligent detection has played a crucial role in enabling rapid recognition of pests and diseases in complex field environments. Advances in image enhancement algorithms have greatly improved diagnostic reliability in complex field scenarios. The end-to-end UNet architecture with optimized multi-scale pyramid structure proposed by Santos et al. [105] has greatly improved image clarity and edge detection capability in complex scenarios. Nevertheless, for low-cost, low-computing-power mobile devices, balancing image quality with real-time processing capability remains a technical challenge. Meanwhile, Raman spectroscopy, as a non-destructive analytical method, has also demonstrated great potential in agricultural residue detection. Guo et al. [106] enhanced the sensitivity of pesticide residue detection by amplifying surface-enhanced Raman scattering signals, thereby providing technical support for simultaneous multi-residue analysis. However, despite the high specificity offered by Raman spectroscopy for detection, its application in mobile devices remains constrained by equipment costs and technical complexity, posing challenges for widespread adoption in large-scale agricultural monitoring. Extending beyond a single technique, a recent comprehensive review on plant disease detection using non-destructive technologies [107] systematically summarized the principles, applications, and limitations of spectral- and imaging-based methods, including hyperspectral imaging, Raman spectroscopy, and UAV remote sensing. The review clearly highlighted that such non-destructive approaches enable rapid, accurate, and non-invasive disease identification, thereby supporting practical disease monitoring in diverse agricultural contexts, including smallholder and local crop systems. At the same time, it pointed out that future research should prioritize integrating multiple non-destructive methods, developing portable and low-cost devices, and advancing efficient data processing strategies to make these technologies more accessible and robust for field-level deployment. Together, these findings reinforce that mobile intelligent detection must balance diagnostic accuracy with affordability and adaptability to local agricultural needs.

With the improvement of mobile terminal performance and the integration of cloud computing, the deployment of deep learning models on portable devices such as smartphones is actively explored [108]. Yang et al. [109] developed a detection method for rice false smut based on mobile intelligent devices, combining rice morphological features with a support vector machine model and employing a cloud database illumination compensation algorithm to eliminate field light interference, enabling real-time recognition and upload feedback. In addition, Li et al. [110] proposed a lightweight deep learning solution by constructing a wheat pest detection model based on YOLOX, which achieved rapid identification and control recommendation delivery without relying on specialized equipment. However, the challenge lies in the model's generalization ability, especially in complex environments where frequent retraining and optimization may be required. Figure 6A presents a CNN–LSTM hybrid framework designed for mobile pest and disease detection. The CNN layers first extract local spatial features from input images (e.g., lesion textures, leaf edges), while the LSTM layers sequentially process these feature vectors to capture temporal variations across multiple image frames, thereby improving robustness in dynamic field environments. This hybrid architecture balances the lightweight computation required for mobile platforms with the ability to retain temporal context in real-time monitoring tasks. In parallel, Figure 6B illustrates a mobile intelligent detection workflow that integrates both online and offline modes. In the online mode, images captured in the field are transmitted via 5G to cloud servers, where CNN-based recognition and database matching are performed to provide rapid feedback. In the offline mode, when connectivity is limited, the mobile client employs feature extraction methods such as Histogram of Oriented Gradients (HOG) and anti-light compensation algorithms to mitigate illumination interference and ensure stable recognition. The client interface processes and displays results locally, while synchronized updates are uploaded once the network is restored. Together, these two complementary modes enhance portability, timeliness, and adaptability under diverse agricultural conditions.

Rapid diagnostic and mobile application technologies now serve as pivotal forces propelling intelligent pest and disease diagnosis in agriculture toward the goals of "low cost, high efficiency, and robust adaptability." Embedding deep learning models into mobile devices such as smartphones enables the rapid acquisition and return of pest and disease data to users, thereby greatly enhancing detection accuracy and operational efficiency [111]. Nonetheless, factors including implementation cost, timeliness, and environmental adaptability continue to limit the large-scale adoption of these technologies. Future studies should aim to lower costs and improve the generalization of models without compromising efficiency, fostering the broader deployment of intelligent pest and disease diagnostic technologies.

2.5. Multimodal Fusion and Data Analysis Technologies

Beyond image data, contemporary deep learning models are increasingly applied to processing environmental inputs such as lighting, climate, and soil conditions, achieving efficient multimodal fusion to deliver richer informational support for pest and disease detection and management in agriculture [112]. Merging plant spectral data with RGB imagery and applying coordinated multimodal analytics allows deep learning models to more precisely capture and interpret information from diverse sources [113,114], markedly enhancing the accuracy of early pest and disease detection as well as cross-spatiotemporal diagnostic performance.

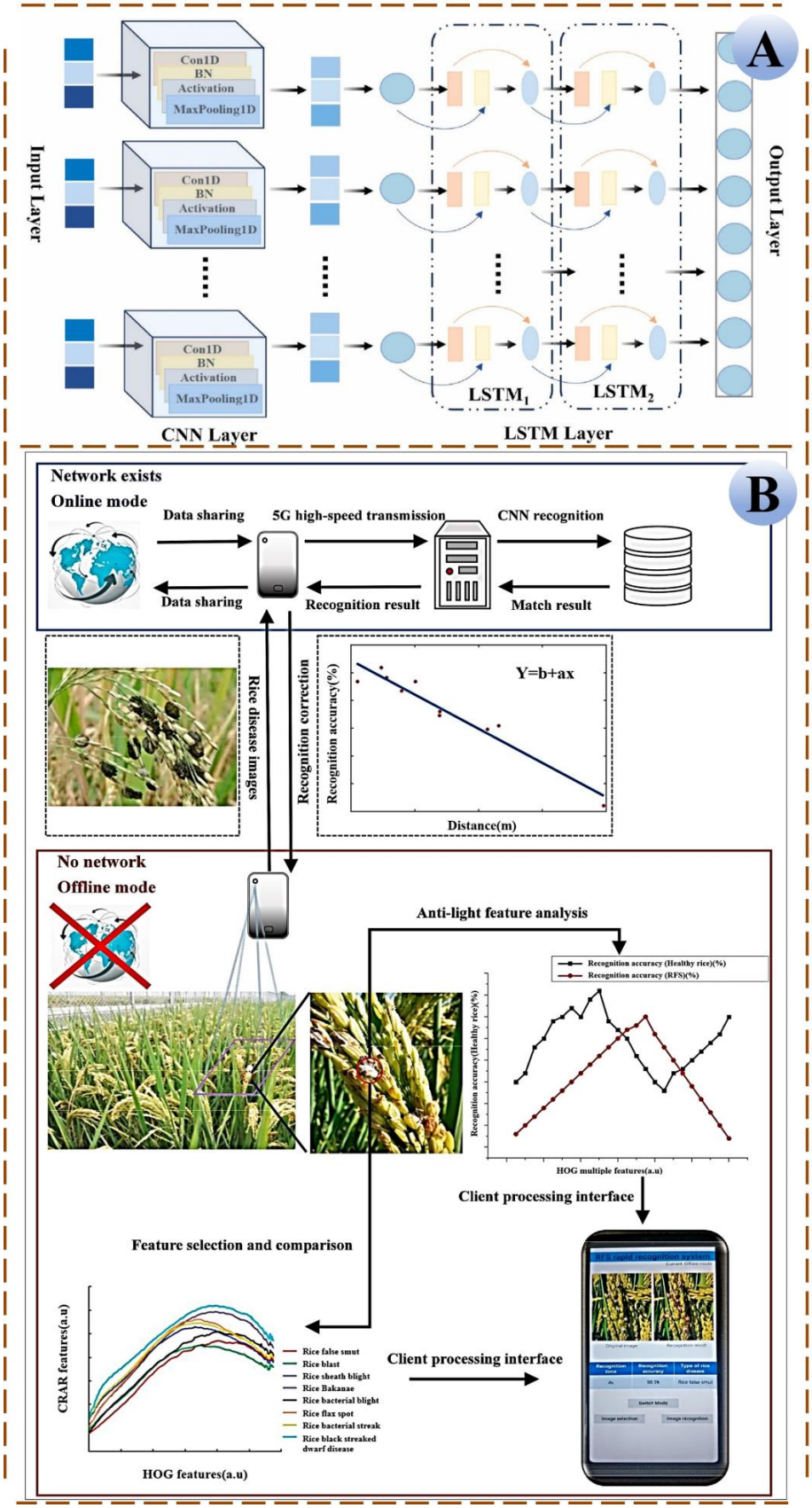


Figure 6. (**A**) CNN–LSTM hybrid architecture for rapid pest and disease detection on mobile platforms, enabling efficient feature extraction and temporal sequence modeling; (**B**) Workflow of mobile intelligent detection system integrating online and offline modes, including image capture, anti-light feature analysis, client-side processing, and cloud-based feedback for real-time field diagnostics.

In the realm of intelligent pest and disease monitoring for agriculture, multimodal data fusion combined with deep analysis is a pivotal pathway to breaking through recognition accuracy limitations [115]. With their outstanding capacity for global modeling, Transformer models are increasingly serving as the backbone for integrating multi-source, heterogeneous information. Li et al. [116] developed a multi-branch neural network framework based on parallel activation functions, integrating three heterogeneous modalities—hyperspectral leaf reflectance, canopy thermal infrared, and soil electrical conductivity. The study introduced generative adversarial networks for multimodal data augmentation, effectively enhancing model generalization and offering a new pathway for precise pest and disease identification and multi-factor diagnosis in crops. Based on this, Zhou et al. [117] proposed a multimodal interpretable model integrating image information, environmental sensor parameters, and farmers' textual descriptions, using heatmaps to visualize causal reasoning for diseases, which effectively enhanced the model's interpretability and user trust in agricultural scenarios. Furthermore, Li et al. [118] developed SugarcaneGAN, a hybrid generative neural network framework combining a lightweight CNN and a Transformer, which markedly increased data modeling efficiency under multimodal information conditions for sugarcane leaf disease detection. To improve readability and provide clearer technical context, representative figures are included. Figure 7 illustrates multimodal fusion at the feature level: image modality features are captured by CNNs, textual symptom descriptions are modeled by LSTMs, and structured knowledge embeddings are integrated to enhance interpretability and classification accuracy. Specifically, Figure 7A presents a representative multimodal framework that integrates image features, textual symptom descriptions, and knowledge embeddings. CNNs are employed to capture spatial lesion patterns from leaf images, while RNNs/LSTMs model sequential dependencies in textual data describing disease progression. These heterogeneous features are then fused with structured knowledge graph embeddings, allowing the system to enhance interpretability and achieve more accurate multi-class classification. In parallel, Figure 7B depicts the SugarcaneGAN architecture, in which residual Swin Transformer blocks embedded within an encoder–decoder pipeline refine multi-scale image features. By incorporating self-attention, the model is able to retain global dependencies during feature extraction, thereby achieving high-resolution disease detection under complex multimodal conditions.

Building on this, researchers are actively exploring the practical potential of multimodal fusion technologies in agricultural pest and disease prediction as well as fine-grained image recognition [119]. By incorporating temporal modeling and spatial segmentation mechanisms, multimodal deep models are enabling dynamic prediction of pest and disease occurrence and progression. Wang and Zhang [120] developed an interpretable pest prediction model based on meteorological data, employing an LSTM–Transformer hybrid architecture to capture long-term dependencies of meteorological factors, and integrating the SHAP algorithm to identify key influencing factors, achieving a 7-day advance warning for locust outbreaks. To clarify the mechanisms of temporal and cross-domain fusion, illustrative figures are added. Figure 8 highlights multimodal fusion at the temporal and cross-domain levels, showing how models combine meteorological and pest data with convolutional and attention-based modules to improve forecasting accuracy. As shown in Figure 8A, the model incorporates a multimodal fusion framework for meteorological and pest data, comprising three main modules: the cross-correlation feature interaction layer models intra- and inter-modal temporal relationships using multiple convolutional kernels; the feature attention layer employs an attention mechanism to focus on key variables; and the final output layer reduces the dimensionality of fused features and predicts future pest levels. Meanwhile, Zhang et al. [121] innovatively integrated diffusion models with Transformer architectures, employing multimodal attention mechanisms and editing-based

data augmentation strategies to enhance the robustness and accuracy of jujube disease detection under conditions of data scarcity and high noise. As shown in Figure 8B, the model consists of two parts: a diffusion layer, which extracts stable features and denoises them via forward diffusion and reverse reconstruction, and a Transformer module, which embeds and interactively models image and sensor data. Finally, in the multimodal fusion module, semantic alignment and unified representation are achieved, significantly enhancing the intelligent perception and discrimination capabilities of the pest and disease recognition system.

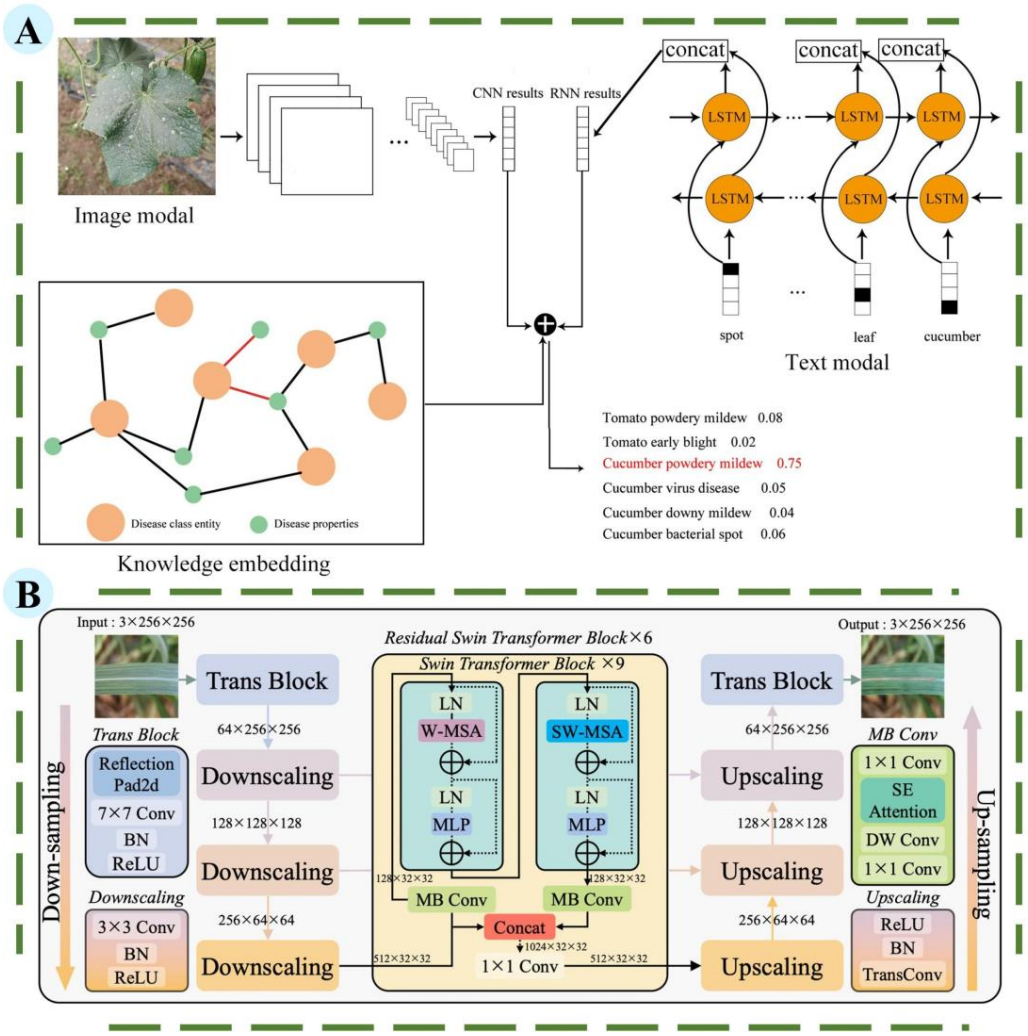


Figure 7. (**A**) Overall workflow of the model in which image modality features are extracted using convolutional and recurrent neural networks and processed through a long short-term memory network; (**B**) The encoder–decoder framework of the model that utilizes residual Swin Transformer blocks and attention mechanisms for extracting and reconstructing image features.

Although deep learning technologies have achieved remarkable progress in agricultural pest and disease detection, several critical challenges persist. Convolutional neural networks, for instance, excel in spatial feature extraction but rely on large and diverse datasets, making them vulnerable to performance drops under complex field conditions such as variable lighting, leaf occlusion, and background interference. RNNs and their LSTM variants provide advantages in temporal dynamics but are computationally demanding and prone to gradient-related issues. Transformers, while offering powerful global modeling capacity and scalability, face limitations stemming from the high cost of data annotation and difficulties in deploying large models in resource-constrained agricultural

environments. Taken together, a systematic comparison across CNNs, RNNs, and Transformers highlights their complementary strengths and inherent weaknesses, suggesting that no single architecture can fully address the diverse challenges of agricultural applications. Future research should therefore emphasize hybrid frameworks that integrate these architectures' advantages while mitigating their shortcomings, alongside efforts to standardize benchmarks and validate models across multiple agricultural scenarios. In this context, multimodal data fusion emerges as a promising pathway to overcome many of the above limitations. By integrating inputs from diverse sensors and heterogeneous data sources, multimodal deep learning models can compensate for the weaknesses of individual architectures, enabling more precise characterization of environmental dynamics and pest or disease progression. Nonetheless, challenges such as limited annotated samples, noise interference, and computational complexity remain critical bottlenecks for practical deployment. Looking ahead, the convergence of multimodal fusion techniques with advanced architectures is expected to further elevate the intelligence and automation of pest and disease detection, fostering sustained optimization of agricultural production.

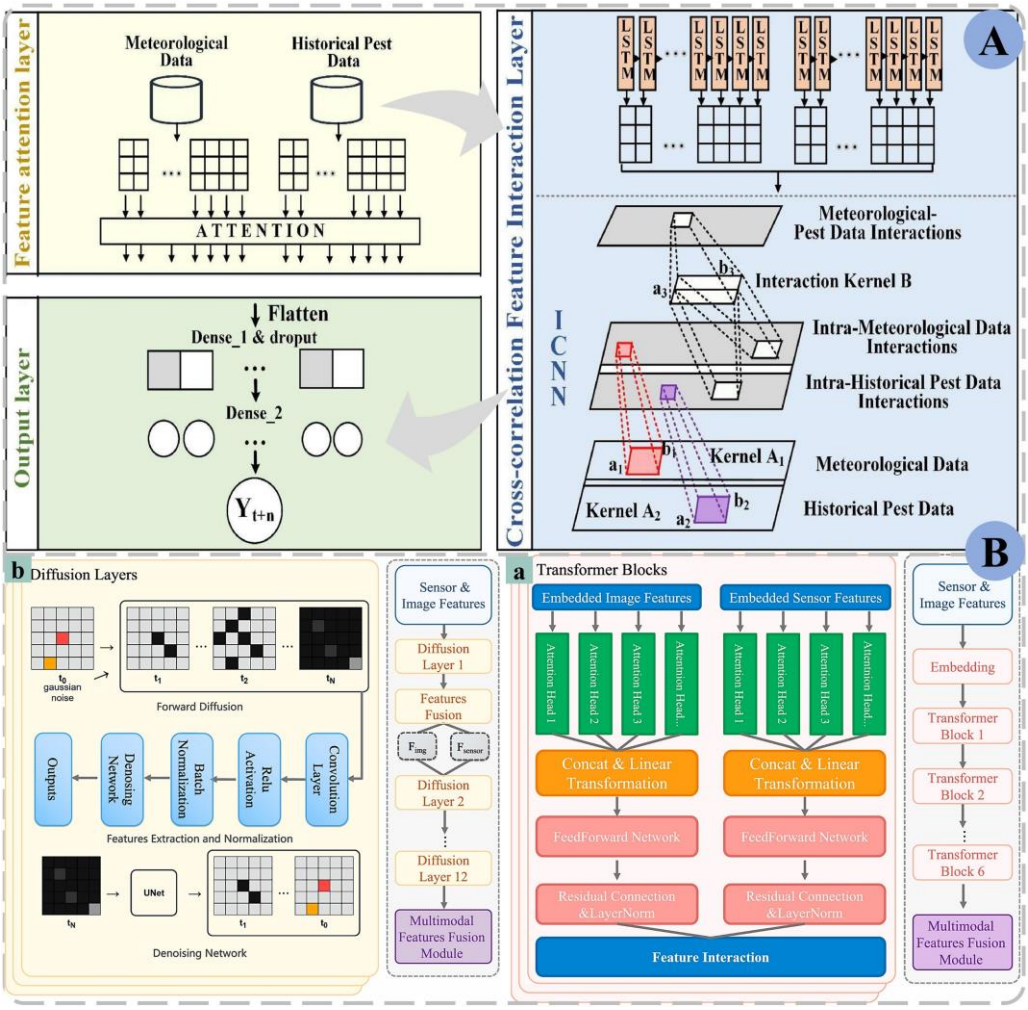


Figure 8. (**A**) Feature interaction layer of the model: processes meteorological and pest data through cross-correlation and feature interaction mechanisms. (**B**) Advanced architectures for multimodal fusion: (**a**) Diffusion Layers, which extract and denoise stable features via forward diffusion and reverse reconstruction, enhancing robustness under noisy conditions; (**b**) Transformer Blocks, which integrate embedded image features, sensor parameters, and symptom descriptions through self-attention and feedforward layers, enabling unified representation and improved classification accuracy.

3. Application of Artificial Intelligence Technologies in Agricultural Pest and Disease Control

3.1. Precision Application and Intelligent Spraying Equipment

Driven by the concept of green pest and disease control, precision application and intelligent spraying equipment technologies are gradually becoming important development directions in modern agricultural pest and disease management [122]. High-precision identification of pest and disease areas through deep learning algorithms enables quantitative spraying at the lesion and leaf levels [123]. By integrating deep learning-based image recognition and analysis technologies, intelligent spraying systems can accurately locate pest and disease areas, thereby optimizing spraying paths and controlling droplet distribution to improve spraying precision. When mounted on drones, robots, and other intelligent spraying platforms, and paired with path optimization and droplet management algorithms, these systems markedly increase operational efficiency and pesticide use efficiency [124,125].

Agricultural pest and disease management is driving ongoing technological transformation by merging deep learning with intelligent machinery. Among these, precision pesticide application relies on dynamic intelligent equipment and multi-source data modeling, enabling a shift from experience-driven to data-driven approaches while improving pesticide use efficiency and rebalancing ecological protection with control effectiveness [126,127]. For instance, Wei et al. [128] developed the lightweight YOLO-Fi object detection model, which fuses infrared and visible-light imagery to accurately identify and segment apple tree canopies. Coupled with a spray path optimization algorithm, it achieved a 47.92% reduction in pesticide use. Nonetheless, its robustness under varied environmental conditions remains limited—especially regarding generalization to different crop species, pest types, and climates. The key focus of future research will be to reduce the system's environmental dependency while maintaining operational efficiency. To better illustrate such developments, Figure 9A presents the YOLO-Fi framework as a representative example. While other object detection models are also discussed in this section, they are not shown graphically to avoid redundancy; YOLO-Fi was chosen because it exemplifies the integration of multi-source imagery with end-to-end spraying control, thereby providing a clear and representative visualization for readers. As illustrated in Figure 9A, the system integrates three core modules—data preprocessing, model construction, and precision application—employing a YOLOv9 backbone enhanced with iRMB and FasterNet components to improve performance. This framework supports end-to-end control from prescription map generation through target segmentation, route planning, and variable spraying. Recent research further emphasizes both the technical evolution and the practical applicability of intelligent spraying systems. Zhao et al. [129] reviewed the development trends of deep reinforcement learning in the intelligent transformation of agricultural machinery, underscoring its potential to optimize spraying path planning, control strategies, and adaptive decision-making in dynamic field environments. At the same time, Upadhyay et al. [130] developed and evaluated a deep learning–based smart sprayer system for site-specific weed management in row crops, employing an edge computing approach to enable real-time image processing and precision spraying directly in the field. Together, these studies highlight that advances in intelligent spraying technologies are driven not only by algorithmic innovation but also by practical considerations of economic viability and system adaptability in diverse agricultural contexts. Complementing these general advancements, recent studies have placed particular emphasis on orchard management scenarios, where crop-specific spraying requirements highlight both opportunities and challenges for intelligent systems. For example, Wang et al. [131] systematically reviewed environmental sensing technologies for targeted spraying in orchards, analyzing the operational mechanisms of lidar, ultrasonic,

and machine vision sensors and their integration with AI-based data fusion methods. Their work demonstrated how accurate canopy perception and multi-source environmental sensing can support variable-rate spraying, precise pest and disease monitoring, and targeted weed control in perennial fruit systems, while also identifying practical challenges such as sensor cost, real-time data processing, and deployment in small-scale orchards. Building on these sensing frameworks, Liu et al. [132] designed and evaluated an intelligent multi-variable spraying robot for orchards and nurseries, equipped with a swing fan structure, variable-rate control, and an improved DBSCAN-based point cloud algorithm for canopy extraction. Field experiments showed that the robot reduced pesticide dosage by up to 83% compared with conventional spraying while improving spray uniformity and canopy coverage. These results provide compelling evidence that integrating environmental sensing and robotics can achieve substantial pesticide savings and operational efficiency in localized orchard contexts, thereby balancing innovation with the specific needs of small-scale and crop-specific agricultural systems.

From current research trends, deep learning technology has been rapidly expanding along two important directions. The first is that Transformer-based vision models show marked benefits in tackling small-sample challenges in agricultural applications. Rezaei et al. [133] introduced a plant disease identification approach incorporating a meta-learning framework, which requires only five diseased leaf images per class for training to enable cross-crop disease classification. Coupled with the PMF + FA method in Vision Transformers, it attained an average accuracy of 90.12%, notably surpassing conventional CNN-based techniques. As shown in Figure 9B, the method is based on ProtoNet, incorporates a feature enhancement module to construct class prototypes, classifies small samples via Euclidean distance, and generates pseudo-labels to improve model generalization, effectively enhancing robustness and adaptability under complex environments. In addition to these equipment-oriented approaches, another emerging research direction is the convergence of digital twin technology and deep learning. Although the study by Escribà-Gelonch et al. [134] does not directly involve spraying equipment, it demonstrates how digital twins that integrate soil–crop–environment models with sensor data can provide a decision-support environment for precision agriculture. Such frameworks are expected to indirectly benefit intelligent spraying by enabling optimized irrigation, fertilization, and crop health management strategies, thereby offering a theoretical foundation for future integration with precision spraying systems. Complementing this, a comprehensive review by Zhang et al. [135] systematically examined the application of digital twin technology in agriculture, with particular attention to practical deployment challenges in crop-specific and small-scale farming scenarios. Their findings emphasize that while digital twins offer powerful tools for simulating and optimizing field operations, socioeconomic constraints, cost of deployment, and data availability remain key factors influencing their actual adoption in localized agricultural contexts. Together, these studies highlight both the technological potential and the real-world limitations of integrating digital twins into intelligent spraying systems, reinforcing the importance of balancing innovation with applicability in diverse agricultural settings.

Precision application and smart spraying systems are harnessing deep learning to enable end-to-end intelligent enhancement, spanning target detection, route planning, and variable control. The combination of multi-source sensor data and lightweight model designs in deep learning has markedly increased precision and operational efficiency. Future research should focus on optimizing system adaptability to different environments, reducing costs, and improving equipment operability, while enhancing the cross-environment generalization ability of models to further advance precision agriculture.

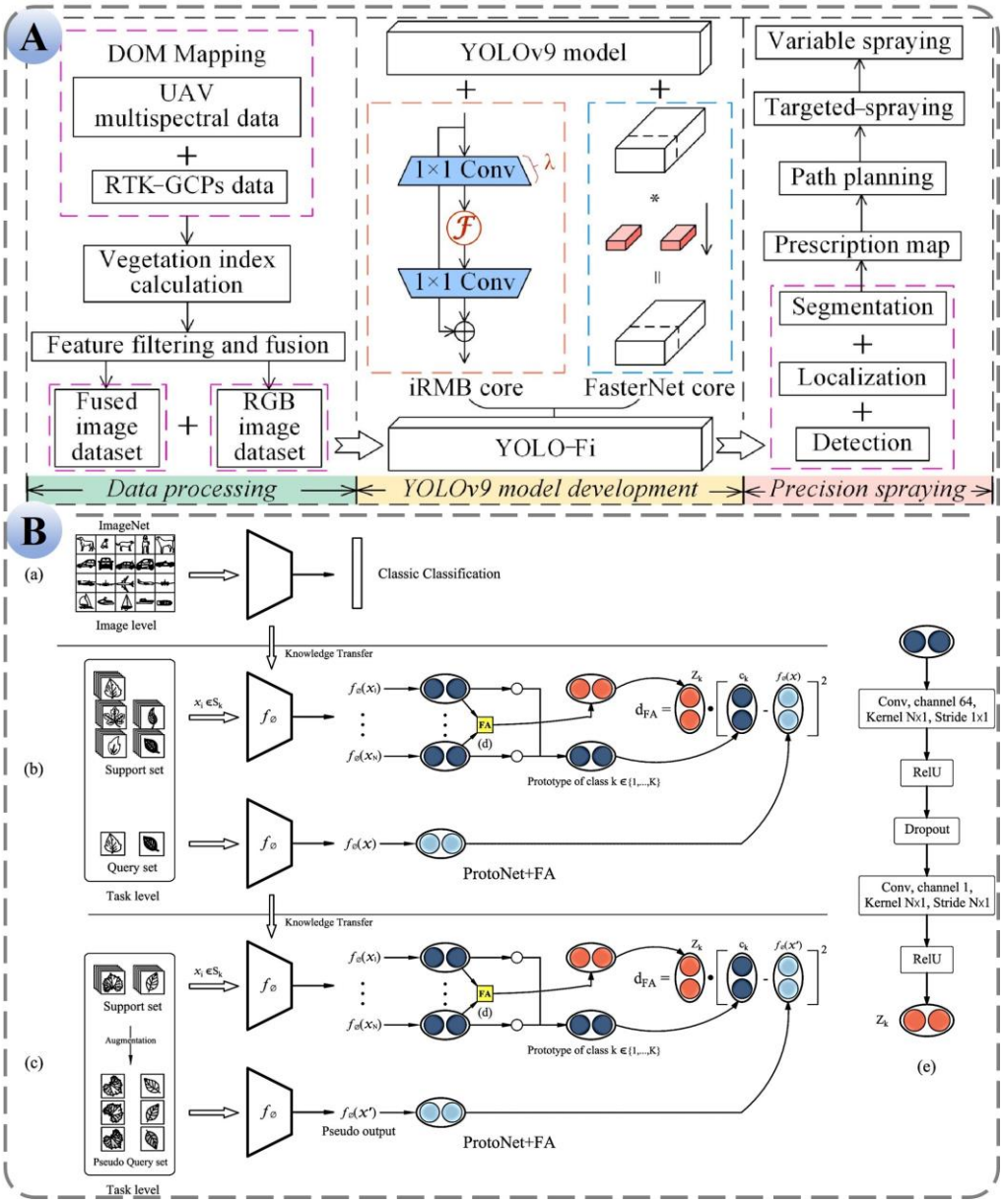


Figure 9. (**A**) Process of producing a digital orthophoto from UAV multispectral and RTKGPS data, generating an image dataset via feature filtering and fusion, and applying the YOLOv9 model with the YOLO-Fi module for detection and precision spraying; (**B**) Knowledge transfer approaches for small-sample pest and disease classification: (**a**) Classic classification workflow at the image level; (**b**) ProtoNet+FA framework using support and query sets; (**c**) ProtoNet+FA framework with pseudo-output generation to enhance model generalization; (**d**) Dotted squares represent diffusion layers or intermediate embedding modules used for feature refinement; (**e**) Dotted square showing convolutional layers (Conv, ReLU, Dropout) for feature extraction and transformation.

3.2. Smart Early-Warning and Pest Control Models

As agricultural informatization and intelligence advance, the development of efficient, reliable early-warning and control models for pests and diseases has become a critical pillar in realizing precision agriculture [136]. In this evolution, deep learning—leveraging its robust feature extraction and pattern recognition strengths—is being integrated with temporal modeling, knowledge graph construction, and causal inference, advancing pest and disease early-warning systems from static analysis to dynamic sensing and intelligent response. Through an end-to-end predictive framework, such systems can deliver high-accuracy spatiotemporal forecasts of pest and disease outbreaks using historical and

meteorological data, while refining control strategies through the incorporation of causal reasoning and expert domain knowledge [137].

As artificial intelligence technology advances, deep learning has increasingly served as the central pillar for developing intelligent early-warning models for pests and diseases [138]. At present, deep learning models built on convolutional neural networks and backpropagation have made significant breakthroughs in areas such as image recognition and natural language processing, offering new avenues for precise early warning and management of agricultural pests and diseases [139]. Barbedo et al. [140] proposed a deep learning-based plant lesion-level recognition method that achieves precise classification by extracting morphological features of local leaf lesions, effectively overcoming the misclassification issues of traditional whole-leaf recognition in complex backgrounds. Upon detecting anomalies, the system can promptly trigger alerts via its early-warning module and propose suitable control measures, thus enhancing the responsiveness to plant diseases. Apart from image recognition, deep learning concepts are also critical in other sensing domains. For instance, Chen et al. [141] developed an early detection model for rice blast in stored grain by integrating gas chromatography–ion mobility spectrometry with chemometric analysis, using variations in volatile organic compounds for non-destructive monitoring and offering a scientific basis for disease control during grain storage. Nonetheless, the high cost and operational complexity of conventional approaches—such as gas chromatography and ion mobility spectrometry—restrict their adoption in large-scale agricultural settings. Future research could explore integrating these techniques with portable sensing devices to lower costs and enhance the universality of the equipment.

On the foundation of conventional pest and disease control systems, the integration of deep learning is steadily enhancing their capacity for intelligent sensing and decision-making. By combining images, textual data, and sensor information, multimodal learning frameworks enhance the precision and environmental robustness of pest and disease recognition [142]. To avoid redundancy and maintain clarity, this section selectively illustrates representative models that demonstrate distinct technical advances in smart early-warning and pest control. In practical applications, Bi et al. [143] developed a non-destructive insect density detection system based on X-ray imaging, employing the lightweight deep model WPX-YOLO, as shown in Figure 10A. This model uses multi-layer residual fusion and feature enhancement structures to achieve high-precision, low-complexity forestry pest detection, accurately locating insect tunnels and providing efficient and reliable data for forestry pest and disease control. Nevertheless, due to the high cost of X-ray imaging equipment, how to apply this technology in small farms and low-cost environments remains a key issue for research to address. Furthermore, to address the computational limitations of mobile devices, Chen et al. [144] designed a lightweight attention-based neural network tailored for rice disease image classification on mobile platforms. Figure 10B depicts the full workflow, which includes diseased leaf image acquisition, preprocessing and augmentation, model training, and subsequent recognition with feedback. The improved MobileNet-V2 network structure effectively extracts lesion area features, and combined with transfer learning, improves model training efficiency and generalization ability, greatly enhancing the practicality and response speed of on-site agricultural disease diagnosis.

As the primary driver behind intelligent early-warning and control models, deep learning is comprehensively enabling the transformation and advancement of agricultural pest and disease monitoring frameworks. Nonetheless, the adoption of existing technologies is hindered by multiple challenges such as high costs, limited environmental adaptability, and data scarcity. Future studies should aim to refine algorithms for greater lightweight efficiency and real-time responsiveness, improve model generalization, and investigate cost-effective, high-performance devices and techniques to drive the broader deployment of intelligent early-warning and control systems in agriculture.

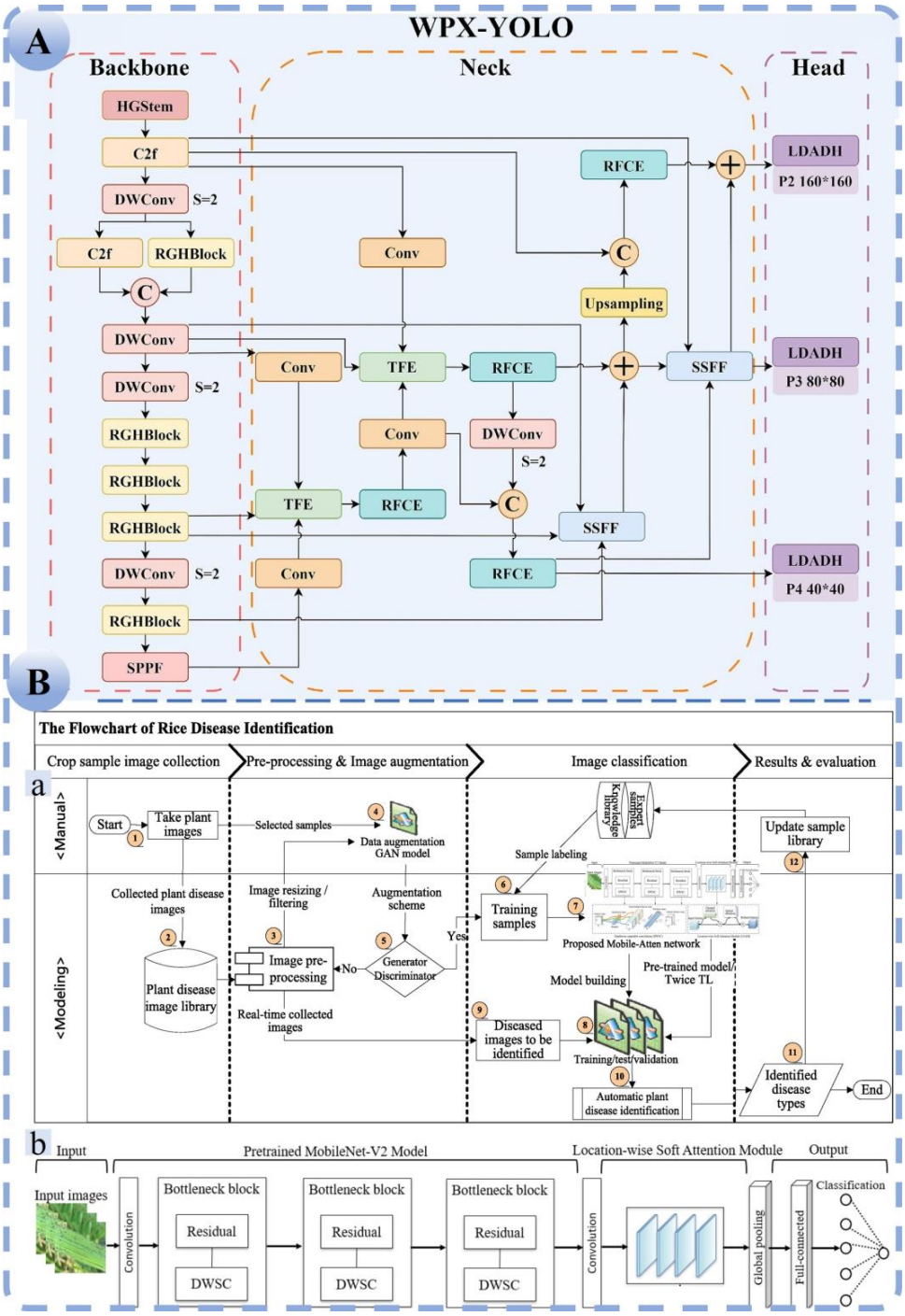


Figure 10. (**A**) Structure of the WPX-YOLO model, which performs object detection and outputs multi-scale predictions using various convolutional and feature extraction modules, The dotted squares represent the three functional modules of the framework: Backbone (feature extraction), Neck (feature fusion and refinement), and Head (multi-scale detection outputs). Each module is highlighted to illustrate its role in enhancing detection performance; (**B**-**a**) Workflow of rice disease recognition, covering the entire process from image acquisition to disease classification, including data augmentation and transfer learning, Workflow of rice disease identification. (**a**) illustrates the complete pipeline: 1 crop sample image collection, 2 taking plant images, 3 plant disease image library, 4 image resizing/blurring, 5 image pre-processing, 6 real-time collected images, 7 selected samples, 8 data augmentation using a GAN model, 9 augmentation scheme, 10 training samples, 11 model building with the proposed MobileNet-V2 + transfer learning framework, and 12 automatic disease identification.; (**B**-**b**) Image feature extraction using MobileNetV2 and a position attention module, combined with channel and spatial attention mechanisms to enhance recognition accuracy.

3.3. AI-Assisted Biological Control and Ecological Regulation

With the growing emphasis on sustainable agriculture, biological control and ecological regulation—key strategies in green pest and disease management—have progressively supplanted conventional methods dominated by chemical control [145–147]. With the rapid development of artificial intelligence technology, its deep integration into agricultural control systems has continuously expanded the spatial scale and timeliness of pest and disease management [148]. For biological control, deep learning aids in detecting crop phenotypic alterations caused by pathogenic microbes and, when integrated with high-throughput image analysis and omics datasets, facilitates intelligent selection of disease-resistant traits [149–151]. Regarding ecological regulation, deep learning leverages remote sensing images and multimodal sensor inputs to model and monitor agroecosystem structures, detect zones of beneficial organism activity, map habitat distribution and temporal changes, and support optimization of landscape configuration and crop deployment, thus enhancing the efficiency of ecological regulation [152,153].

Within biological control, deep learning technologies are providing innovative methods and tools for managing agricultural pests and diseases [154–156]. Sun et al. [157] proposed an intelligent recognition system based on an improved YOLOv5 model, focusing on the automatic detection of high-density small-target pests and the assessment of infestation levels. Optimization of the network architecture and training protocols has markedly enhanced the system's detection accuracy and real-time performance under complex field conditions, providing robust decision support for precision agriculture. While the system enhances small-object detection capability, it remains susceptible to factors such as changing illumination and background noise in real-world use, which can cause false positives and missed detections. Incorporating multimodal data fusion and adaptive learning techniques in the future could strengthen the model's generalization ability and accuracy across diverse agricultural field conditions. Mansourvar et al. [158] extended the use of deep learning in microbial ecology by creating an automated fungal interaction classification system that integrates image data with omics information, offering novel technical means for elucidating disease interaction mechanisms and informing control strategies. Ensuring accurate integration of multi-source data will be crucial for broad adoption of this technology.

Regarding ecological regulation, while deep learning applications remain in an exploratory phase, their data integration concepts have established a basis for future AI implementation. Zhang et al. [159] combined environmental variables with crop growth data to develop an ecological quality control network for American ginseng, offering a framework for standardized cultivation and quality evaluation of medicinal plants. In parallel, Graph Neural Networks present a novel pathway for the intelligent regulation of agricultural ecosystems. Unlike conventional ecological modeling methods, GNNs can accurately model nonlinear interspecies interactions and accommodate changes in dynamic environments. Anand et al. [160] developed a GNN-driven framework for predicting ecotoxicological relationships, integrating knowledge graph embeddings with graph convolutional networks to forecast the influence of ecological factors on the behavior of beneficial predatory insect populations. While the approach achieves high accuracy in ecological risk assessment, deploying it in large-scale agricultural ecosystems is challenged by computational demands and the difficulty of synchronizing heterogeneous data sources, necessitating enhancements in computational efficiency and adaptability.

As a major branch of artificial intelligence, deep learning has demonstrated enormous application potential in agriculture, particularly in the areas of biological control and ecological regulation. With AI-assisted technologies, areas such as pathogen identification, resistance screening, and ecosystem modeling have been significantly improved,

thereby effectively enhancing the precision and implementation efficiency of green control strategies. Future research should focus on improving model universality, addressing challenges in data acquisition and processing, and enhancing model stability and generalization in complex environments, so as to promote the full application of AI in sustainable agricultural development.

3.4. Green Intelligent Control Strategies for Disease-Resistant Varieties

Within sustainable agricultural pest and disease management systems, the intelligent breeding of disease-resistant varieties is transforming through the powerful impetus of deep learning technologies [161]. Compared with traditional breeding methods that rely on manual experience, deep learning can efficiently analyze crop images, genomic, and environmental data to construct intelligent analytical models integrating multidimensional "genotype–phenotype–environment" information. Such progress enhances both the detection and prediction accuracy of disease-resistance traits and shifts variety screening from phenotypic observations to molecular-level design, significantly expediting the breeding cycle [162,163].

Deep learning offers a novel methodological framework for identifying disease-resistance genes in crops. Conventional Genome-Wide Association Studies are constrained by the representational power of linear models, while genomic selection enhances breeding efficiency by combining genome-wide markers with statistical modeling. Incorporating deep learning models breaks through these constraints, leveraging nonlinear modeling to more precisely characterize the intricate associations between genes and phenotypic traits. Crossa et al. [164] systematically summarized genomic selection methods and genomic-enabled prediction models, highlighting the great potential of deep learning in complex trait prediction and laying a solid foundation for precision breeding. Leveraging results from genomic-enabled prediction models in conjunction with genomic selection can expedite gene flow in germplasm enhancement pipelines, thus improving pest and disease control and accelerating the identification of elite cultivars. Nevertheless, the integration of genomic selection and deep learning still requires more high-quality sample data in practical applications, especially in large-scale data acquisition and processing. Ma et al. [165] mapped quantitative trait loci associated with wheat stripe rust resistance and, by integrating complex genetic data derived from deep learning models, identified critical gene targets for disease-resistant breeding. Applying deep learning to genomic selection has enhanced the efficiency of breeding resistant cultivars and hastened the overall process of pest and disease management.

Intelligent breeding decision systems establish a "design–verification–optimization" closed-loop framework, providing new technical support for pest and disease control. Sarkar et al. [166] constructed a cyber-physical system and employed deep learning for the analysis of complex phenotype and genetic datasets, resulting in the creation of a modular simulation platform that supports precise resource management and fulfills the twin objectives of yield enhancement and emission reduction. These technologies have facilitated the development of disease-resistant varieties and supplied data for targeted pest and disease control, yet they face the challenge of enhancing model generalization, especially within dynamic and diverse agricultural ecosystems. Furthermore, digital twin technology—integrating IoT and multi-source data—enables dynamic simulation and optimization of agricultural processes via virtual–physical interaction, producing a dynamic representation of the full crop growth cycle and delivering more accurate decision-making support for pest and disease control. Although digital twin technology holds significant promise for agricultural management, large-scale deployment is hindered by issues like inadequate real-time data synchronization and suboptimal data quality. These problems need

to be further addressed in the future to enable its full application in agriculture [167]. In this section, four representative studies [164–167] were highlighted because they collectively cover the key spectrum of this research area—from methodological foundations to applied breeding cases, system-level frameworks, and frontier technologies—thus providing a focused yet balanced overview without unnecessary redundancy.

The application of deep learning technology in green intelligent disease-resistant variety prevention strategies has advanced the precision and intelligence of crop breeding and pest and disease management. By conducting in-depth analysis of large-scale genomic data, phenotypic information, and environmental variables via deep learning models, intelligent breeding decision systems can accurately identify disease-resistant genes and expedite the selection and optimization of superior lines. Furthermore, the integration of deep learning with digital twin technology and cyber-physical interaction models enables dynamic simulation and optimization of agricultural production processes, thereby providing a scientific basis for precision spraying, early pest and disease warning, and resource management.

4. Conclusions and Outlook

In recent years, deep learning technology has brought revolutionary progress to the field of intelligent detection and control of agricultural pests and diseases. Firstly, in terms of pest and disease detection, deep learning-based visual recognition models have significantly improved the accuracy and efficiency of identification. Combined with UAV remote sensing and satellite imagery technology, real-time dynamic monitoring of large-scale farmlands has been achieved. Secondly, the integration of lightweight models on mobile devices and IoT sensor networks has further promoted the popularization and application of early warning systems for pests and diseases. Through multi-modal data fusion technology, environmental parameters, meteorological information, and image features are integrated, greatly enhancing the diagnostic capabilities and robustness in complex agricultural scenarios. Additionally, in the field of control, deep learning-driven precision spraying systems, through object detection and path planning algorithms, optimize the spraying process, not only improving the utilization rate of pesticides but also reducing environmental pollution. Finally, intelligent early warning models, combined with historical pest and disease data and crop growth cycle analysis, can predict the risk of pest and disease outbreaks, helping decision-makers make more scientific control decisions. Deep learning-driven screening of disease-resistant genes and phenotypic analysis technologies have also accelerated the breeding of resilient crop varieties, while the intelligent management of biological control and ecological regulation provides new paths for the development of green agriculture.

Nevertheless, some important limitations remain. From a technical perspective, current deep learning models are still highly dependent on the availability of large and diverse training datasets, whereas agricultural images are often influenced by seasonal variability, illumination changes, and complex backgrounds, which may compromise model robustness. At the application level, the real-time deployment of lightweight models on UAVs, mobile devices, and IoT platforms is still challenged by limited computational resources and unstable field conditions, which restrict their large-scale adoption. Methodologically, many studies have focused on single crops or specific diseases, while systematic validation across multiple crops, regions, and growing seasons is still insufficient, limiting generalization in diverse agricultural environments. Furthermore, challenges such as noise interference in multimodal data fusion, high computational costs of advanced architectures, and the difficulty of integrating intelligent control systems into existing farming practices remain unresolved. Addressing these issues requires not only technical innovation but also the establishment of standardized datasets, collaborative evaluation frameworks, and close integration of intelligent systems with real-world agricultural management. Beyond

technical challenges, the adoption of AI-driven pest and disease management also entails potential risks and biases that affect its real-world applicability. Socioeconomic limitations, such as the high cost of advanced sensors, UAVs, and computing infrastructure, may hinder adoption in less developed regions, thereby widening the technological gap between large-scale and smallholder farms. In addition, unequal access to high-quality datasets and digital infrastructure can exacerbate disparities in the benefits gained from AI technologies. These issues highlight the importance of developing cost-effective, inclusive solutions and promoting international collaborations to ensure that the advantages of AI are equitably distributed across different agricultural contexts.

In the future, research will be extended in three main domains: technological, applicative, and ecological. On the technological front, efforts will focus on developing Transformer-driven multi-scale spatiotemporal modeling approaches to improve predictions of pest and disease dynamics, alongside causal inference models to elucidate the deep interrelations between environmental variables and disease spread. From the application perspective, efforts will aim to develop an integrated "aerospace-ground" monitoring network, leveraging digital twin technology to create virtual farms for delivering full-lifecycle precision management strategies. In the ecological dimension, cross-disciplinary collaborative platforms will be created to merge expertise from agronomy, ecology, and AI, aiming to develop interpretable and reliable intelligent decision-support systems.

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Abbreviations

The following abbreviations are used in this manuscript:

CNN	convolutional neural network
RNN	recurrent neural network
CNN-LSTM	convolutional neural network–long short-term memory network model
SE-ResNet50	squeeze-and-excitation residual network 50-layer model
SugarcaneGAN	sugarcane generative adversarial network
MobileNet-V2	mobileNet version 2
GNN	graph neural network
TRL-GAN	transformer-reinforced learning generative adversarial network
DDMA-YOLO	dual-dimensional mixed attention YOLO
DTL-SE-ResNet50	dual transfer learning squeeze-and-excitation residual network 50-layer model

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