Exploring the Application of Drone Imagery in Early Identification of Crop Diseases and Pests

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Abstract. Early and accurate identification of crop diseases and pests is critical to ensuring food security and sustainable agricultural development. The rapid advancement of high-resolution drone remote sensing technology provides innovative tools for early pest and disease detection. This paper explores the research progress, technical bottlenecks, and future directions of drone imagery technology in crop disease and pest monitoring. The study concludes that multi-spectral, thermal infrared and RGB sensors integrated on drone platforms can collaboratively capture centimeter-level high-resolution data. Through multi-source fusion of spectral, texture, and temporal data combined with lightweight model deployment, early spectral and morphological characteristics of crop stress caused by diseases and pests can be accurately identified, significantly improving detection accuracy compared to traditional satellite remote sensing and single machine learning methods. Case studies demonstrate that drone technology achieves 85% - 95% recognition accuracy in monitoring typical diseases such as wheat rust and rice blast while reducing field inspection costs by over 60%. This paper provides a theoretical framework and technical roadmap for precision agriculture, offering practical significance for promoting agricultural digital transformation.

Keywords: High-resolution drones; Crop diseases and pests; Multi-spectral remote sensing; Deep learning; Precision agriculture.

1. Introduction

Agriculture is the foundation of the national economy, and diseases and pests are major biological threats to food security and agricultural sustainability. According to the Food and Agriculture Organization (FAO), global crop yield losses due to diseases and pests reach 20%–40% annually, with economic losses exceeding $220 billion. In China, frequent outbreaks of rice blast, wheat scab, and other diseases in staple crops have become core challenges hindering the adoption of precision agriculture and green control technologies [1]. Traditional monitoring methods, such as manual field inspections and laboratory testing, suffer from inefficiency, high costs, and subjectivity, and often fail to achieve accurate identification during the latent or early stages of disease (e.g., abnormal leaf physiological indicators). Thus, developing efficient, non-destructive early monitoring technologies is crucial for achieving the plant protection goal of "prevention first, integrated management."

In recent years, remote sensing technology has provided new pathways for agricultural disease and pest monitoring. While satellite remote sensing offers broad coverage, its spatial resolution (typically >10 meters) and revisit cycles (e.g., 16 days for Landsat) are inadequate for small-scale, time-sensitive farmland monitoring. In contrast, drone remote sensing, with centimeter-level resolution, flexible low-altitude flight capabilities, and multi-sensor collaboration, has emerged as a vital tool for agricultural management. Drones equipped with multi-spectral, hyperspectral, and thermal infrared sensors can capture physiological and biochemical parameters (e.g., chlorophyll content) and canopy structural changes, detecting stress signals before visible symptoms (e.g., lesions, wilting) appear. Studies show that high-resolution drone imagery can identify canopy temperature anomalies and spectral reflectance changes, significantly improving disease recognition accuracy and timeliness when combined with machine learning models [2]. For example, red-edge band (705–745 nm) reflectance anomalies enable early warning of wheat powdery mildew 7–10 days in advance, with 92% accuracy [3]. Multi-spectral sensors and AI models automatically analyze rice leaf color, texture, and canopy temperature variations, improving pest (e.g., planthoppers) and disease (e.g., sheath blight) detection efficiency by over fivefold compared to manual methods [4]. Spectral-texture-temporal data fusion enhances model generalization, while thermal infrared imaging detects temperature anomalies caused by diseases (e.g., 2–3°C increase in wheat stripe rust-infected areas), achieving over 89% warning accuracy (2024 review).

This paper explores the potential and technical advantages of drone remote sensing in agricultural disease and pest monitoring. It analyzes the principles and characteristics of drone remote sensing, details its applications in early diagnosis, real-time monitoring, and precision control, and discusses challenges and future directions to provide scientific and technical references for efficient agricultural management.

2. UAV Remote Sensing Technology and Data Acquisition

The application of drone imagery in early crop disease and pest identification relies on efficient, flexible data acquisition and multi-sensor collaboration. Drones equipped with hyperspectral, multi-spectral, thermal infrared, and LiDAR sensors capture crop physiological and structural information from multiple dimensions. Hyperspectral sensors collect narrow-band reflectance spectra (400–2500 nm), detecting subtle spectral changes caused by pests or diseases, such as increased red-band (650–680 nm) reflectance due to chlorophyll decline or near-infrared (1450 nm, 1940 nm) anomalies from cellular damage. Multi-spectral sensors focus on visible (RGB) and near-infrared (NIR) bands, computing vegetation indices (e.g., NDVI, EVI) to assess crop health, offering advantages in speed and scalability. Thermal infrared sensors detect canopy temperature anomalies caused by metabolic disruptions (e.g., reduced transpiration), while LiDAR quantifies structural changes (e.g., lodging, canopy density).

Flight planning is critical for data quality. Parameters such as altitude (50–150 m), overlap rate (70%-80%), and sensor settings (band range, exposure) must be optimized based on terrain, crop type, and monitoring objectives. Data acquisition should occur under stable lighting (10 AM–2 PM) and clear skies. Multi-source data synchronization ensures temporal-spatial consistency for fusion analysis. Real-time data transmission via 5G/IoT enables dynamic monitoring. Data formats vary by sensor: HDF/LAS for hyperspectral/LiDAR and GeoTIFF for multi-spectral/thermal.

Quality control includes geometric correction (using GCPs or IMU) and radiometric calibration (using reference panels). Ground validation enhances accuracy. Advances in AI-driven autonomous flight, lightweight sensors, and edge computing enable real-time processing, supporting timely pest management.

3. Case Studies

Current research emphasizes the importance of multi-source data fusion and intelligent algorithms to improve the efficiency of agricultural disease monitoring and management.

In terms of data collection, the use of multispectral sensors (such as Sentera Quad-M) can capture changes in chlorophyll decay through the red edge band (710–750 nm) and the near-infrared band (760–900 nm). In addition, thermal imaging devices (such as FLIR Tau2) can detect temperature anomalies, thereby increasing sensitivity to early diseases [5]. This diversity of data collection allows researchers to have a more comprehensive understanding of plant health and take timely intervention measures.

In terms of algorithm application, traditional machine learning methods (such as support vector machine SVM combined with normalized vegetation index NDVI and gray level co-occurrence matrix GLCM texture features) achieved an accuracy of 87.4% in the identification of wheat stripe rust, but performed poorly in the detection of small pests, with a false negative rate of more than 25% [6]. To address these limitations, deep learning models have been introduced and have made significant progress. For example, the CBAM-enhanced version of YOLOv5s with channel attention mechanism achieved an average precision (AP@0.5) of 92.3% in corn borer detection , while U-

Net++ combined with multispectral input achieved an intersection over union (IoU) of 0.81 in rice blast segmentation . The application of these deep learning methods not only improves the accuracy of detection, but also enhances the recognition ability of complex diseases.

In terms of multi-source fusion, Li et al. fused LiDAR data with thermal imaging data, and successfully achieved an accuracy of 89.7% for cotton vascular dehydration disease by using the characteristics of canopy collapse and transpiration inhibition. This fusion of multi-source data not only improves the recognition accuracy of the model, but also provides a more comprehensive analysis perspective for different types of plant diseases.

However, current research also faces many challenges. The universality of the model remains an issue that needs to be addressed. The F1-score variation rate in different regions ranges from 15% to 30%, indicating that the performance of the model may be inconsistent under different environmental conditions. In addition, the need for real-time processing and robustness under environmental interference have not been effectively addressed. The existence of these problems limits the widespread application of intelligent algorithms in actual agricultural environments, and further research and technological breakthroughs are urgently needed.

4. Limitations and Future Directions

4.1. Existing Challenges

Currently, many agricultural monitoring systems still rely on a single sensor (such as RGB cameras), which greatly limits the ability to extract multidimensional features. A single sensor cannot fully capture the health and growth characteristics of plants, so some key diseases or growth indicators may be missed. In addition, environmental noise (such as cloud cover) will lead to an increase in radiation errors, which studies have shown can reach 12% to 18%. This not only affects the quality of the data, but may also lead to decision-making errors, further increasing the difficulty of crop management.

Under different crops and climate conditions, the performance of the model often drops significantly, with the F1-score dropping by 15% to 30%. This problem of insufficient generalization ability means that the model trained in a specific environment may not be effectively applied to other environments, thus limiting the widespread application of intelligent algorithms in agricultural management. How to improve the adaptability of the model so that it can maintain efficient recognition capabilities under various crops and climate conditions is one of the current challenges that need to be solved.

The processing method that relies on cloud computing often leads to latency problems, and the processing time may exceed 6 hours, which is extremely unfavorable to real-time decision-making. In agricultural production, timely decision-making is crucial for disease prevention and crop management. This delay prevents farmers from responding quickly to potential threats, which may lead to serious economic losses.

4.2. Future Research Directions

Future research should focus on integrating satellite, drone, and ground Internet of Things (IoT) data to achieve spatiotemporal synergy. By combining different types of data sources, changes in the agricultural environment and the growth status of plants can be captured more comprehensively, thereby improving the accuracy and efficiency of monitoring. This multimodal perception will provide a richer information basis for agricultural management and help farmers make more scientific decisions.

Develop lightweight models, using quantization techniques (such as FP32 to INT8), pruning, and knowledge distillation to adapt to embedded GPUs (such as Jetson Orin). This will significantly reduce the computational requirements of the model, enabling it to run in real time on edge devices, thereby reducing processing delays and improving decision-making speed. The application of edge

AI will make agricultural monitoring systems more flexible and efficient, able to quickly process data and respond on the spot.

Embed plant pathology models (such as pathogen diffusion models) into deep learning frameworks to enhance the model's understanding of disease transmission mechanisms. The integration of this mechanism and data can not only improve the accuracy of the model, but also provide farmers with more detailed early warning information, helping them to intervene in the early stages of the disease.

Establish technical standards and open data sets (such as "AgriPest-1M") and obtain policy support. This will provide researchers and developers with a unified reference framework and promote the exchange and cooperation of different research results. At the same time, open data sets will provide rich data resources for model training and verification, and promote the rapid development of smart agricultural technology. Through standardization, the entire industry will be able to share and use data more effectively, thereby accelerating the process of agricultural intelligence..

5. Conclusion

This paper reviews the application of high-resolution drone imagery in early crop disease and pest identification. Drone-based multi-sensor systems enable multi-source data fusion and lightweight models to capture early stress features, achieving 85%–95% accuracy and reducing inspection costs by 60%. Challenges include data quality, model generalization, and latency. Future work should focus on multi-modal sensing, edge AI, mechanism-data fusion, and standardization to advance precision agriculture and sustainable development.

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