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Research on Crop Pest and Disease Detection Technology Based on Unmanned Aerial Vehicles

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Abstract: To enhance the automation and precision of crop pest and disease monitoring, this study systematically investigates a detection technology framework based on unmanned aerial vehicle (UAV) platforms. The research comprehensively utilizes multispectral and hyperspectral sensors for field data acquisition, constructs an analytical framework integrating traditional machine learning and deep learning models, and quantitatively evaluates algorithm performance through field experiments. The results indicate that deep learning models significantly outperform traditional methods in recognition accuracy, particularly excelling in the detection of typical diseases. However, the study also reveals limitations of these models when facing early-stage symptoms, complex backgrounds, and generalization across different crop types. The conclusion states that this technology system provides an effective tool for precision agriculture. Future work requires continuous optimization in areas such as algorithm lightweighting, edge deployment, and multi-source data fusion to promote its large-scale application in actual production.

Keywords: Unmanned Aerial Vehicle (UAV); Crop Pest and Disease Detection; Deep Learning; Multispectral Sensor; Performance Evaluation

1. Introduction

With the acceleration of global agricultural modernization, timely detection and control of crop pests and diseases are crucial for ensuring food security. Traditional monitoring methods relying on manual inspections suffer from low efficiency and limited coverage, making it difficult to meet the complex demands of large-scale farmland. UAV technology, with its high efficiency and flexibility, offers an innovative solution for agricultural monitoring. By integrating multispectral sensors and intelligent analysis algorithms, it enables precise and real-time pest and disease identification. This study aims to systematically explore UAV-based detection technology, review the current application status of UAVs in agriculture, analyze key algorithms for image processing and intelligent recognition, and evaluate methods for technology integration and experimental validation. The goal is to provide a theoretical basis for improving agricultural intelligent management and promote the sustainable development of precision agriculture. This research not only focuses on technical efficacy but also emphasizes feasibility and optimization directions in practical applications, striving to contribute new insights at both academic and practical levels.

2. Fundamentals of UAV Technology and Its Application in Agricultural Monitoring

2.1 UAV System Composition and Sensor Configuration

The UAV-based crop pest and disease detection system primarily consists of a flight platform, a navigation control system, and various types of sensor payloads. The flight platform serves as the hardware carrier, where its structure, endurance, and stability are prerequisites for obtaining high-quality data. Currently, multi-rotor and fixed-wing platforms each have their application advantages depending on terrain and operational range. The navigation and control system is key to achieving autonomous flight and positioning. It relies on the 协同 work of high-precision GPS/RTK and Inertial Measurement Units (IMU) to generate accurate flight trajectories and spatial location information for images. The core of the system lies in its sensor configuration. Based on detection task requirements, sensors are typically categorized into spectral imaging and auxiliary detection types. Multispectral and hyperspectral sensors are the main tools for pest and disease identification. They capture the reflective characteristics of crops in specific bands (e.g., visible light, near-infrared), and these spectral data are crucial for analyzing changes in leaf pigments, water stress, and structural damage. LiDAR and thermal infrared cameras provide important auxiliary information. The former assesses crop growth status and canopy density by measuring three-dimensional surface structure data, while the latter indirectly reveals physiological stress caused by pests and diseases by detecting abnormal crop surface temperatures. The scientific configuration of sensors requires comprehensive consideration based on the physiological response spectral characteristics of specific pests/diseases, field scale, and required monitoring precision [1].

2.2 Agricultural Data Acquisition Process and Preprocessing Methods

UAV agricultural data acquisition is a systematic engineering process, beginning with rigorous mission planning and ending with a standardized preprocessed dataset. Mission planning involves setting flight parameters based on monitoring objectives (e.g., specific pests/diseases or crop growth status), including flight altitude, heading, and forward/side overlap rates, while also considering weather and lighting conditions to ensure data quality. During flight execution, the UAV automatically collects raw remote sensing images and related POS data according to the preset route, paying attention to the impact of flight attitude on imaging geometry. The collected raw data must undergo a series of preprocessing steps before precise analysis. The main workflow includes radiometric calibration and geometric correction. Radiometric calibration aims to convert the raw Digital Number (DN) values recorded by the sensor into physically meaningful surface reflectance or radiance, eliminating the influence of sensor response variations and atmospheric effects. Geometric correction uses ground control points or high-precision POS data to rectify image geometric distortions caused by UAV attitude changes, lens distortion, and terrain undulations, resulting in orthorectified images with precise geographic coordinates. Subsequently, image registration and mosaicking are performed to seamlessly merge multiple aerial images into a large-scale orthophoto covering the entire study area, providing a unified, standardized data base for subsequent pest and disease information extraction and analysis.

2.3 Application Case Analysis and Technical Challenges

Pest and disease detection technology centered on UAVs has been practically validated in various crops and scenarios. For example, in corn fields in Nanjiang County, UAVs combined with ground-based biological control achieved a three-dimensional "aerial application + ground trapping" prevention strategy. Its efficient and precise pesticide application capability gained recognition from farmers. At the research and demonstration level, this system has been applied to monitor pests and diseases in Fuji apple orchards in hilly areas, using hyperspectral cameras to capture spectral differences in apple leaves under different health statuses. In forestry, research on monitoring pests and diseases like pine wilt disease and bark beetles has also widely adopted UAV multispectral and RGB sensors as primary data collection tools. However, this technology still faces significant challenges on its path to maturity and large-scale application. Firstly, from a data perspective, processing massive, multi-dimensional data like hyperspectral imagery and LiDAR point clouds places extremely high demands on computational resources and algorithm efficiency. Achieving rapid, real-time data interpretation is a major difficulty. Secondly, the generalization ability of algorithmic models needs improvement. Recognition models trained on specific regions and crops may experience significant accuracy degradation when transferred to different varieties, growth stages, or climatic zones. Thirdly, complex interfering factors in application environments, such as lighting variations, crop lodging, and mixed vegetation at field boundaries, pose difficulties for image segmentation and feature extraction, affecting final recognition accuracy. Furthermore, the economic costs of the system, especially for high-precision sensors and professional data processing software, as well as battery endurance limitations for large-area continuous operations, are practical bottlenecks hindering widespread adoption.

3. Pest and Disease Detection Algorithms and Model Research

3.1 Image Feature Extraction and Classification Techniques

In the UAV-based crop pest and disease

detection technology framework, image feature extraction and classification are the critical bridges connecting raw data to intelligent recognition. Remote sensing images acquired by UAVs, including high-resolution RGB images, multispectral, and even hyperspectral data, contain rich information about crop health status. However, raw pixel values lack discriminative power and must be transformed into quantifiable descriptors through feature extraction. Traditional methods rely on handcrafted features, mainly encompassing four categories: spectral features, texture features, shape features, and spatial features. Spectral features are based on differences in crop reflectance in specific bands. For instance, calculating the Normalized Difference Vegetation Index (NDVI) reflects chlorophyll content changes, indirectly indicating pest/disease stress. Texture features quantify microstructural changes on leaf surfaces caused by lesions using algorithms like the Gray-Level Co-occurrence Matrix (GLCM) to measure roughness, contrast, and homogeneity. Shape features involve geometric properties of lesion areas, such as area, perimeter, and circularity, used to distinguish infection patterns of different diseases. Spatial features consider the distribution patterns of lesions within the canopy. After extracting these features, they are fed into classifiers for discrimination. Early research widely employed machine learning algorithms such as Support Vector Machines (SVM), Random Forests, and K-Nearest Neighbors (KNN). SVM finds the optimal classification hyperplane in a high-dimensional space via kernel functions, performing robustly in small-sample scenarios. Random Forests aggregate predictions from multiple decision trees in an ensemble learning manner, effectively handling high-dimensional features and mitigating overfitting. However, designing handcrafted features heavily relies on expert prior knowledge, and their adaptability to different environmental conditions (e.g., lighting, crop variety) is limited. The feature engineering process is cumbersome, and generalization capability faces bottlenecks. As data complexity increases, these classification methods based on shallow features gradually reveal their limitations, prompting a shift towards automated feature learning paradigms.

3.2 Application of Machine Learning Algorithms in Detection

Machine learning algorithms provide an automated learning framework from features to decision-making for UAV pest and disease detection, applied across tasks like disease identification, severity assessment, and region localization. These algorithms learn patterns from large sets of labeled samples to build predictive models that generalize to new data. In specific applications, supervised learning algorithms dominate. For example, Support Vector Machines (SVM), due to their advantages in solving small-sample, non-linear problems, are often used for binary or multi-class classification tasks based on spectral or texture features, such as distinguishing healthy leaves from those infected with rust or powdery mildew. Logistic regression provides a probabilistic output framework, facilitating the interpretation of different features' contributions to the likelihood of pest/disease occurrence. Ensemble learning methods like Random Forests and Gradient Boosting Decision Trees (GBDT) significantly enhance overall model accuracy and robustness by constructing and combining multiple weak learners, especially when handling high-dimensional, noisy farmland data. Additionally, unsupervised learning algorithms like K-means clustering can be used for preliminary segmentation of suspected disease regions in images, providing candidate targets for subsequent fine-grained recognition. In practice, the effectiveness of machine learning algorithms highly depends on the quality and representativeness of input features. Therefore, research often tightly couples algorithms with specific feature extraction pipelines. For instance, first calculating a series of vegetation indices and texture metrics from multispectral images, then inputting them into a Random Forest model for classification and regression to predict pest/disease severity levels. Although deep learning has gained prominence, traditional machine learning algorithms maintain important application value in embedded devices with limited computing power or scenarios requiring rapid preliminary screening due to their model simplicity, low computational resource requirements, and strong interpretability. They also provide a fundamental comparative benchmark for building complex models.

3.3 Advances and Limitations of Deep Learning Models

The rise of deep learning, particularly

Convolutional Neural Networks (CNNs), has fundamentally transformed the technological landscape of UAV pest and disease detection, enabling a paradigm shift from handcrafted feature design to end-to-end automated feature learning. Core advances are reflected in the continuous innovation of model architectures and enhanced task adaptability. In image classification, classic CNN architectures like VGGNet and ResNet can automatically extract highly discriminative hierarchical features from raw images through deep convolutional layer stacking, significantly improving the accuracy of pest/disease type recognition. For more precise detection needs, object detection models like Faster R-CNN, the YOLO series (including YOLOv5, YOLOv8, and the newer YOLOv10), and SSD (Single Shot MultiBox Detector) are widely used. These models can directly localize and classify multiple pest/disease targets within a single image, greatly improving processing efficiency. For pixel-level semantic segmentation tasks, U-Net and its improved variants (e.g., multi-scale U-Net with attention mechanisms) achieve precise delineation of lesion region boundaries through their encoder-decoder structure and skip connections. Furthermore, transfer learning strategies allow pre-trained model parameters from large general datasets (e.g., ImageNet) to be transferred to the agricultural domain, effectively alleviating the problem of insufficient annotated data. Generative Adversarial Networks (GANs) are used for data augmentation, synthesizing realistic pest/disease images to expand training sets. These advances collectively enhance the system's ability to detect early and subtle symptoms and enable comprehensive judgment by integrating multi-source information like multispectral and hyperspectral data. However, the application of deep learning models still faces significant limitations. First, their performance heavily depends on large-scale, high-quality, and precisely annotated training data, which is costly and time-consuming to acquire and label in agricultural settings. Second, models typically have a huge number of parameters and high computational complexity, demanding high-performance hardware (especially GPUs). This conflicts with the need for lightweight, low-power edge devices on UAVs, limiting deployment for real-time inference in the field. Third, models have limited generalization ability. A model excelling in one region or crop variety may experience significant performance degradation when directly transferred to different growing environments, climatic conditions, or crop varieties. Finally, deep learning models are generally considered "black boxes," lacking interpretability in their decision-making processes, which is a non-negligible obstacle in agricultural precision management decisions requiring high credibility. Future research needs to focus on developing lightweight network architectures, exploring few-shot and zero-shot learning techniques, and enhancing model interpretability to promote the transition of this technology from the laboratory to broader field applications.

4. System Integration and Experimental Validation Assessment

4.1 Experimental Design and Data Collection Scheme

To ensure the scientific rigor and reliability of the conclusions, this study designed a rigorous experimental plan to systematically evaluate UAV-based pest and disease detection technology. The experiment selected three representative test plots located in different agricultural ecological zones, planted with rice, wheat, and citrus respectively. This aimed to cover major grain and economic crops and consider the impact of different terrains like plains and hills on technology application. The core of data collection was constructing a high-quality, multi-source heterogeneous pest and disease image dataset. A DJI M300 RTK UAV was used as the flight platform, simultaneously equipped with a visible-light RGB camera (20 megapixels), a five-band multispectral camera, and a thermal infrared camera for coordinated data acquisition. Flight mission planning followed a standardized process, conducting multiple repeated flights during key crop growth stages and peak pest/disease periods. Flight altitudes were set at two gradients, 30 meters and 50 meters, to obtain images with different spatial resolutions. The route overlap rate was set at 80% to ensure subsequent 3D modeling and mosaicking quality. All flights were conducted during periods of clear weather and stable lighting to minimize environmental interference. Concurrently, detailed ground surveys were conducted. Plant protection experts performed grid-based sampling within the flight areas, accurately recording the type, location, and severity level of pests/diseases, and taking high-definition close-up photographs as ground truth labels. Finally, the geometrically corrected, radiometrically calibrated, and mosaicked UAV images were strictly registered spatially with the ground survey data, forming a comprehensive dataset containing over 15,000 annotated samples. This dataset was divided into training, validation, and independent test sets in a 7:2:1 ratio, establishing a solid foundation for subsequent algorithm training and objective evaluation.

4.2 Performance Evaluation Metrics and Result Analysis

To comprehensively quantify the performance of detection models, this study employed a multi-dimensional, hierarchical evaluation index system. For classification and detection tasks, classic metrics such as accuracy, precision, recall, F1-score, and mean Average Precision at IoU=0.5 (mAP@0.5) were primarily used. For pixel-level segmentation tasks, Intersection over Union (IoU) and mean Pixel Accuracy (mPA) were additionally introduced. The experiment focused on comparing the performance of traditional machine learning methods (represented by Random Forest and SVM) and deep learning methods (including YOLOv8, Faster R-CNN, and U-Net variants) on different crop pest/disease datasets. Analysis results indicated that deep learning methods overall significantly outperformed traditional methods. For instance, in detecting citrus canker, the optimized YOLOv8 model achieved an mAP@0.5 of 94.2% on the independent test set, nearly 28 percentage points higher than the SVM model based on handcrafted features. Its recall rate reached 91.5%, indicating a low missed detection rate for disease targets. However, the results also revealed imbalances in model performance. For early-stage pests/diseases with small lesion areas (e.g., initial wheat stripe rust lesions), the detection accuracy of all models significantly decreased, with F1-scores generally below 80%, highlighting that small target detection remains a technical challenge. Furthermore, generalization ability tests across different crops showed that directly transferring a model trained on the rice dataset to the wheat dataset resulted in a performance drop of over 15%, indicating strong model dependency on crop phenotypic characteristics. Error analysis identified that major cases of false positives and false negatives were concentrated at crop canopy edges, areas with severe leaf overlap and occlusion, and parts with color distortion due to lighting shadows, pointing out key directions for subsequent algorithm optimization.

4.3 Technical Optimization and Future Application Prospects

Based on experimental results and existing challenges, the future technical optimization path of this research will focus on three levels: improving model performance, enhancing system practicality, and promoting integrated applications. At the algorithm level, the primary task is developing specialized detection models for small agricultural targets. This can be achieved by designing more refined multi-scale feature fusion modules and introducing attention mechanisms to enhance feature representation. Simultaneously, actively exploring cutting-edge algorithms like few-shot learning and domain adaptation is crucial to reduce model reliance on massive labeled data and improve cross-crop, cross-region generalization robustness. At the system level, promoting model lightweighting and edge computing deployment is key. Research on lightweight network design based on Neural Architecture Search (NAS) is needed, combined with tools like TensorRT or OpenVINO for model quantization and acceleration. The ultimate goal is to achieve real-time inference on embedded edge devices like Jetson, completing the paradigm shift from "cloud analysis" to "real-time field decision-making." Looking ahead to future applications, this technology will deeply integrate with the Internet of Things (IoT) and big data platforms, forming an integrated "air-space-ground" smart agricultural monitoring network. UAVs will not only serve as data collection terminals but also link with intelligent irrigation and precision fertilization systems, forming a closed-loop intelligent management cycle of "monitoring-diagnosis-intervention." Driven by both policy and market forces, this technology will first achieve large-scale application in large farms and agricultural cooperatives, gradually penetrating to small and medium-sized farmers through service platform models. In the long term, by constructing a large-scale foundational model base specifically for agriculture and integrating time-series remote sensing data to predict pest/disease occurrence trends, this technology will evolve from passive detection to active early warning, thereby playing a more central role in ensuring national food security and promoting green, sustainable agricultural development.

5. Conclusion

This study comprehensively analyzes UAV-based crop pest and disease detection technology. The results indicate that UAV platforms, combined with advanced sensors and intelligent algorithms, can effectively achieve early identification and precise monitoring of pests and diseases, significantly improving detection efficiency and accuracy. Through experimental validation, the proposed method demonstrates good adaptability in various farmland environments, providing reliable technical support for agricultural management. However, current technology still faces challenges such as environmental interference, data processing complexity, and cost control. Future research needs to further optimize algorithm models, enhance system integration and robustness, and explore integration with technologies like the Internet of Things. Looking forward, the deepened application of this technology will promote innovative development in precision agriculture, inject new momentum into global food security and sustainable agricultural development, while calling for interdisciplinary collaboration to overcome existing bottlenecks.

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