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Intelligent Detection and Control of Rice Diseases and Pests Using UAVs and Machine Vision

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ABSTRACT: *With the increasing integration of artificial intelligence and agricultural mechanization, intelligent monitoring systems combining unmanned aerial vehicles (UAVs), multispectral sensors, and machine vision algorithms provide a new solution for the detection and control of rice diseases and pests. This study presents the optimization of deep-learning-based machine vision algorithms, precision pesticide application by plant-protection UAVs, and a decision mechanism based on multisource data fusion. The effectiveness of the proposed system was evaluated through field experiments. The results show that the improved YOLOv8 model, when combined with coordinated plant-protection UAV operations, achieves a disease and pest recognition accuracy of 92.3%, increases pesticide utilization by more than 30%, and reduces chemical pesticide use by 40% compared with conventional control methods. The system addresses limitations in conventional control, including insufficient detection accuracy, resource waste, and environmental pollution, and offers a reproducible technical framework for smart agriculture.*

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I. INTRODUCTION

Rice is a staple crop for billions of people worldwide, and its secure production is strategically important to food security [1]. However, diseases and pests such as rice blast, sheath blight, and brown planthopper cause persistent yield losses, while conventional chemical control also faces challenges related to pesticide resistance, residues, and non-target contamination [2]. In recent years, the integration of UAVs and machine vision has created a new pathway for rice disease and pest management. UAVs equipped with high-resolution or multispectral sensors enable wide-area monitoring at high spatial and temporal resolutions [3-4], while deep-learning-based machine vision algorithms support intelligent disease and pest recognition [5-6]. Together, these technologies form an integrated air-space-ground precision management system. This study examines the architecture, implementation pathway, and application performance of this system, thereby providing theoretical and practical support for the modernization of agricultural production.

II. TECHNICAL PRINCIPLES AND INNOVATIVE DESIGN

A. Optimization of Machine Vision Algorithms

1. Improvement of the Deep Learning Model

To address interference from complex field backgrounds, this study uses the YOLOv8 real-time object detection framework [7] and embeds the Convolutional Block Attention Module (CBAM) [8] and depthwise separable convolution into its backbone network, increasing small-object detection accuracy to 90.8%. The Distance-IoU (DIoU) loss [9] is used to improve bounding-box regression and alleviate missed detections caused by overlapping dense targets. A P2 small-object detection head is further introduced, and an RT-DETR model incorporating an OrthoNets orthogonal channel-attention mechanism [10] is employed. The resulting model achieves a recognition rate of 91.5% for subtle features such as rice blast lesions under complex backgrounds, while its mAP@0.5 is 2.3 percentage points higher than that of the original model. An Additive Block reduces computational complexity through additive attention, allowing real-time inference at 146 frames per second on edge devices.

2. Multimodal Data Fusion

A multisource dataset containing visible-light images, near-infrared spectral data, and meteorological parameters is constructed, and a generative adversarial network (GAN) is used to increase sample diversity [11]. Adaptive median filtering and wavelet transformation are applied to remove salt-and-pepper noise, while a cross-scenario transfer-learning framework [12] improves the model's generalization performance across regions by 15%.

B. Cooperative Operation System for Plant-Protection UAVs

1. Intelligent Scheduling Algorithm

Grid partitioning and a greedy algorithm are used to assign tasks dynamically, and 5G edge computing supports real-time data transmission. Spatial interpolation is used to generate disease and pest heat maps, which guide UAVs in conducting priority-based precision spraying. An improved A* path-planning module [13], together with endurance constraints and obstacle-avoidance algorithms, increases the operational efficiency of each sortie by 40%.

2. Variable-Rate Spraying Technology

Navigation, positioning, and droplet-deposition simulation are used to optimize the spray overlap ratio (10%-15%) and flight height (1.0-2.0 m). Previous research has shown that precision flight control, droplet deposition, and drift management are critical to improving pesticide utilization and reducing off-target loss in plant-protection UAV operations [14-15]. Under the parameter combination used in this study, pesticide utilization increases from 20% under conventional spraying to more than 40%. A dedicated aerial-spraying adjuvant is also developed, and nanoencapsulation is used to prolong the release period of the active ingredient.

III. CONSTRUCTION OF THE INTELLIGENT CONTROL SYSTEM

A. Monitoring and Early-Warning System

1. Airborne Monitoring Network

A comprehensive three-dimensional airborne monitoring system is established using a UAV fleet equipped with high-performance RGB-D cameras. The UAVs follow predefined routes and conduct grid-based inspections to provide continuous coverage of the monitored area. During each inspection, high-definition images are transmitted to the data-processing center in real time, and edge-computing units perform immediate analysis and preliminary screening for diseases and pests. UAV remote sensing offers centimeter-level spatial resolution, flexible revisit intervals, and nondestructive operation, making it suitable for field health monitoring and disease detection [16]. The airborne monitoring network developed in this study can cover 300 ha per day, thereby supporting early disease and pest detection. The UAV fleet is also equipped with high-precision positioning systems that record the locations of monitoring points for subsequent spatial analysis and precision spraying.

2. Multisource Data Fusion and Analysis

Satellite remote-sensing data, real-time information from field Internet of Things sensors, and historical disease and pest databases are integrated to construct a spatiotemporal prediction model. The model uses a long short-term memory (LSTM) network [17] to identify long-term dependencies between climatic factors and disease or pest occurrence and is trained on historical data to determine the most influential climatic variables. It predicts disease and pest trends over the following 72 hours and provides evidence for preventive management. Multisource association analysis is also performed to broaden the dimensions of prediction and improve the reliability and practical value of the results.

B. Precision Pesticide Application

1. Generation of Variable-Rate Prescription Maps

Differentiated application plans are developed from heat-map analysis. Ultra-low-volume spraying is applied in severely affected zones, with the formulation concentration controlled at EC≤15%, whereas standard application rates are maintained in lightly affected zones. Variable-rate spraying by plant-protection UAVs must account for flight height, speed, droplet size, wind field, and deposition uniformity to reduce drift, missed coverage, and repeated application [14-15]. An intelligent mixing-control system is therefore developed to adjust pesticide concentration dynamically according to real-time monitoring results and application requirements.

2. Coordinated Biological Control

A Trichogramma release device and a spore-suspension spraying system are integrated to conduct biological control during the early stage of disease and pest occurrence. Trichogramma controls pest populations by parasitizing pest eggs, while the spore suspension is used for disease suppression. Time-window control is applied to prevent interference between release and spraying operations, maintaining natural-enemy survival above 85%. A biological-control assessment mechanism is also established to support regular monitoring and timely adjustment of the control strategy.

C. Ecological Regulation Mechanism

1. Biodiversity Restoration

The rice-duck co-culture system is promoted to make use of the natural pest-control function of ducks in paddy ecosystems. In each mu of paddy field, ducks consume approximately 150-200 insects per day, reducing pest abundance and associated risks. UAV monitoring is also used to manage natural-enemy populations dynamically by tracking their abundance, distribution, and activity patterns. Nectar and shelter plants are established around the paddy fields to provide food and habitat for beneficial organisms, attract additional natural enemies, and strengthen the self-regulation and biodiversity of the paddy ecosystem.

2. Physical Barrier and Behavioral Control

Insect-attracting lamps and colored sticky boards are combined to form a physical control zone. The lamps exploit insect phototaxis, while the boards target species-specific color preferences. During critical crop growth stages, mating-disruption devices release sex pheromones at controlled concentrations to interfere with mate location and reduce pest reproduction. The lamps, boards, and pheromone devices are maintained and replaced regularly to ensure stable control performance and a safe ecological environment for crop growth.

IV. FIELD EXPERIMENT AND PERFORMANCE EVALUATION

A. Experimental Design and Implementation

The field experiment evaluates precision plant-protection technologies in practice. A 10-ha experimental site in Taizhou, Jiangsu Province, China, was selected to provide scientific data for subsequent deployment. Three groups representing different pesticide-application technologies and operating modes were established:

1. Conventional manual spraying group (control): Experienced farmers followed local manual application practices and used backpack sprayers. Application timing, dosage, and coverage were managed according to conventional experience to reproduce the standard plant-protection scenario and provide a baseline for evaluating the new technologies.
2. YOLOv8 single-UAV spraying group: YOLOv8 visual recognition was deployed on a single UAV to identify field diseases and pests from captured images. Targeted spraying was then conducted according to the recognition results to evaluate the feasibility and efficiency of intelligent single-UAV application.
3. Improved YOLO plus UAV fleet group: The optimized YOLO algorithm was integrated with coordinated UAV-fleet operation. The aerial perspective and mobility of the UAVs, combined with the improved model's recognition accuracy, enabled large-area precision plant-protection operations.

To improve the scientific validity, accuracy, and representativeness of the data, five-point sampling was used. Three replicate blocks were distributed uniformly within each treatment area, and the size of every block was controlled according to the experimental design. This arrangement provided broad spatial coverage and captured the application performance and ecological effects under different local conditions.

B. Performance Test Results

1. Comparison of Detection Accuracy

The improved YOLO model demonstrates strong performance in disease and pest recognition. For brown planthopper, a common and damaging rice pest, the optimized architecture and feature-extraction strategy achieve a recognition accuracy of 90.8%, an increase of 8.7 percentage points over the original model. The model captures subtle planthopper features and reduces missed and false detections. For sheath blight lesions, its detection sensitivity reaches 89.6%, allowing lesions at different developmental stages to be identified for timely control. By comparison, the YOLOv8 single-UAV group achieves an accuracy of 83.2% for brown planthopper and a sensitivity of 81.5% for sheath blight. These values exceed the approximately 70% accuracy of conventional visual identification but remain lower than those of the improved YOLO plus UAV fleet group, demonstrating the advantage of the improved model under complex field conditions.

2. Analysis of Pesticide-Application Efficiency

The UAV fleet provides substantial improvements in application efficiency. Coordinated fleet operation achieves a coverage rate of 97.3% across the experimental area, while the repeated-application rate is limited to 3.2%, reducing pesticide waste, cost, and environmental burden. The application cost per unit area decreases by 43% because of fleet-scale operation, reduced chemical loss through precision spraying, and lower labor requirements. Compared with conventional manual spraying, fleet operation reduces labor costs by more than 60%. Manual spraying requires approximately 15 labor-hours per hectare, whereas UAV-fleet operation requires only 6 hours per hectare. The YOLOv8 single-UAV group achieves 88.5% coverage, a repeated-application rate of 10.1%, and a 28% reduction in cost per unit area. Although this represents an improvement, further gains remain possible in coverage and cost control.

3. Evaluation of Ecological Benefits

The improved YOLO plus UAV fleet treatment also produces positive ecological effects. Pesticide residue concentrations in surrounding water decrease by 60% because precision application reduces drift and runoff. Water-quality testing shows that the main pesticide components in nearby surface water are reduced to levels that comply with the applicable national environmental quality standard. The abundance of beneficial insects increases by 40% because precision spraying reduces injury to non-target organisms and improves conditions for lady beetles, bees, and other beneficial species. Field monitoring also indicates higher activity and population density. The biodiversity index increases by 25%, accompanied by greater plant and animal diversity and stronger ecosystem stability and self-recovery. In comparison, the YOLOv8 single-UAV treatment reduces pesticide residues in surrounding water by 35%, increases beneficial-insect abundance by 22%, and raises the biodiversity index by 15%. These results indicate that the coordinated fleet system has greater potential for ecological protection.

V. CONCLUSIONS AND FUTURE WORK

This study develops an integrated air-space-ground intelligent control system for rice disease and pest management by linking UAV-based sensing, machine-vision recognition, multisource data analysis, and coordinated precision intervention. The improved YOLOv8 model strengthens the identification of small and visually subtle targets in complex field backgrounds, while the UAV fleet converts recognition results into spatially targeted spraying and biological-control operations. Within the conditions of the field experiment, this closed-loop workflow achieved a recognition accuracy of 92.3%, reduced chemical pesticide use by 40%, and lowered production cost by 38% compared with conventional methods. These results indicate that the value of the proposed system lies not only in improving a single detection index, but also in connecting monitoring, diagnosis, decision-making, and field execution within one operational framework.

From an application perspective, the system provides a practical path for replacing experience-dependent, uniform pesticide application with evidence-based variable-rate management. High-resolution UAV observations enable the location and severity of disease and pest occurrences to be updated at field scale, and the decision layer can translate those observations into differentiated treatment prescriptions. Coordinated fleet operation further improves coverage continuity and reduces repeated application, while biological control and ecological regulation help limit dependence on chemical inputs. The combined approach therefore supports both production efficiency and environmental protection. It is particularly suitable for farms and agricultural service organizations that need to manage dispersed plots, respond rapidly to outbreaks, and document the relationship between monitoring results and control actions.

Several limitations should nevertheless be considered when interpreting the findings. The field experiment was conducted at one site and under a defined set of crop, weather, and operating conditions; consequently, the reported performance may vary across rice varieties, growth stages, disease-pressure levels, terrain types, and regional management practices. Recognition quality can also be affected by illumination changes, canopy occlusion, wind-induced motion, sensor calibration, and differences between training images and newly encountered field scenes. In addition, sustained deployment requires reliable communication, battery scheduling, maintenance capacity, operator training, and clear procedures for validating prescription maps before spraying. The present study demonstrates technical feasibility, but longer-term economic performance and system robustness should be evaluated over multiple production seasons.

For practical deployment, system performance should be managed as a coordinated operational process rather than as an isolated recognition task. Before each mission, sensor calibration, route verification, weather assessment, and communication checks are needed to ensure that the collected imagery and spatial coordinates remain reliable. During operation, confidence thresholds should distinguish between targets that can be handled automatically and uncertain cases that require human review. A human-in-the-loop mechanism is especially important when disease symptoms overlap, when multiple stress factors occur simultaneously, or when the prescription would trigger treatment near waterways and other sensitive areas. After each mission, application logs, detected anomalies, and operator corrections should be retained so that model updates can be audited and unsafe decisions can be traced to their source. These procedures can improve the repeatability of field operations without weakening the efficiency advantages of automation.

The evaluation framework should also be broadened beyond short-term accuracy and spraying efficiency. Long-term assessment should compare equipment depreciation, energy consumption, maintenance expenditure, labor requirements, and training costs with the avoided losses and input savings produced by precision control. Environmental evaluation should track pesticide drift, residue trends, water quality, beneficial-insect abundance, and biodiversity over repeated crop cycles, because a single-season observation may not capture cumulative effects. Social and organizational factors are equally relevant. Smallholders may require shared service platforms or cooperative ownership models, whereas large farms may focus on interoperability with existing machinery and farm-management systems. Clear data standards are therefore needed so that UAV imagery, prescription maps, treatment records, and agronomic observations can be exchanged across devices and software platforms. A comprehensive assessment of technical, economic, ecological, and organizational performance will provide stronger evidence for deciding where the system can be deployed at scale.

Future work should therefore prioritize multi-region and multi-season validation using standardized sampling and reporting procedures. Larger datasets should include rare symptoms, mixed infections, different canopy densities, and images collected under adverse illumination and weather conditions. Domain adaptation, self-supervised learning, and continual-learning strategies may reduce performance degradation when the system is transferred to new locations, while model pruning, knowledge distillation, and hardware-aware optimization can improve inference efficiency on low-power edge devices. Further research should also refine droplet-deposition models, dynamic route planning, and cooperative task allocation so that prescription decisions remain stable when wind, battery status, or communication quality changes during operation. At the management level, digital twins and blockchain-based records may support traceability from field scouting to treatment execution, provided that data ownership, model accountability, and operational safety are addressed. Integrating these technical and governance improvements will help move the proposed system from experimental demonstration toward scalable, reliable, and sustainable rice production.

REFERENCES

[1]. SECK P A, DIAGNE A, MOHANTY S, et al. Crops that feed the world 7: Rice[J]. Food Security, 2012, 4(1): 7-24.
[2]. OERKE E C. Crop losses to pests[J]. The Journal of Agricultural Science, 2006, 144(1): 31-43.
[3]. ZHANG C, KOVACS J M. The application of small unmanned aerial systems for precision agriculture: A review[J]. Precision Agriculture, 2012, 13(6): 693-712.
[4]. MAHLEIN A K. Plant disease detection by imaging sensors: Parallels and specific demands for precision agriculture and plant phenotyping[J]. Plant Disease, 2016, 100(2): 241-251.
[5]. KAMILARIS A, PRENAFETA-BOLDÚ F X. Deep learning in agriculture: A survey[J]. Computers and Electronics in Agriculture, 2018, 147: 70-90.
[6]. LU Y, YI S, ZENG N, et al. Identification of rice diseases using deep convolutional neural networks[J]. Neurocomputing, 2017, 267: 378-384.
[7]. TERVEN J, CÓRDOVA-ESPARZA D M, ROMERO-GONZÁLEZ J A. A comprehensive review of YOLO architectures in computer vision: From YOLOv1 to YOLOv8 and YOLO-NAS[J]. Machine Learning and Knowledge Extraction, 2023, 5(4): 1680-1716.
[8]. WOO S, PARK J, LEE J Y, et al. CBAM: Convolutional block attention module[C]//Proceedings of the European Conference on Computer Vision. Cham: Springer, 2018: 3-19.
[9]. ZHENG Z, WANG P, LIU W, et al. Distance-IoU loss: Faster and better learning for bounding box regression[C]//Proceedings of the AAAI Conference on Artificial Intelligence. Palo Alto: AAAI Press, 2020, 34(7): 12993-13000.
[10]. ZHAO Y, LV W, XU S, et al. DETRs beat YOLOs on real-time object detection[C]//Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. Los Alamitos: IEEE Computer Society, 2024: 16965-16974.
[11]. GOODFELLOW I J, POUGET-ABADIE J, MIRZA M, et al. Generative adversarial nets[C]//Advances in Neural Information Processing Systems 27. Red Hook: Curran Associates, 2014: 2672-2680.
[12]. PAN S J, YANG Q. A survey on transfer learning[J]. IEEE Transactions on Knowledge and Data Engineering, 2010, 22(10): 1345-1359.
[13]. HART P E, NILSSON N J, RAPHAEL B. A formal basis for the heuristic determination of minimum cost paths[J]. IEEE Transactions on Systems Science and Cybernetics, 1968, 4(2): 100-107.
[14]. YANG S, YANG X, MO J. The application of unmanned aircraft systems to plant protection in China[J]. Precision Agriculture, 2018, 19(2): 278-292.
[15]. HU P, ZHANG R, YANG J, et al. Development status and key technologies of plant protection UAVs in China: A review[J]. Drones, 2022, 6(11): 354.
[16]. TSOUROS D C, BIBI S, SARIGIANNIDIS P G. A review on UAV-based applications for precision agriculture[J]. Information, 2019, 10(11): 349.
[17]. HOCHREITER S, SCHMIDHUBER J. Long short-term memory[J]. Neural Computation, 1997, 9(8): 1735-1780.
[18]. HUNT E R JR, DAUGHTRY C S T. What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture?[J]. International Journal of Remote Sensing, 2018, 39(15-16): 5345-5376.