

Intelligent Detection System for Rice Pests and Diseases Based on UAV and Deep Learning

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ABSTRACT: China possesses a vast rice-planting area, and pests and diseases constitute critical factors restricting rice yield and quality. Traditional manual field inspection for pest and disease monitoring suffers from low efficiency, strong subjectivity, limited coverage, delayed prevention and control, and improper pesticide abuse. Combined with UAV remote sensing, multi-sensor acquisition and lightweight YOLO deep-learning target-detection algorithms, this paper develops the “Agri-IntelliDet” rice pest-disease intelligent detection system. A four-layer architecture including data acquisition, transmission, processing and application is constructed to realize automatic acquisition of rice-field images, intelligent identification and positioning of pests and diseases, data analysis, visual display and automatic export of monitoring reports. Adaptable to large-scale farms, household farmers, plant protection departments and agricultural research experimental plots, the system achieves a mean detection accuracy of 85%-95% in tests. It greatly improves field pest-disease monitoring efficiency and reduces pesticide input, providing technical support for green rice prevention-control, smart-agriculture implementation and national food security guarantee.

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I. INTRODUCTION

Rice is China's staple food crop, closely related to national food security and agricultural economic stability. Under high-temperature and high-humidity field conditions throughout rice growth cycles, various pests and diseases such as rice blast, sheath blight, rice planthopper and rice leaf roller readily occur. Pest-disease outbreaks cause leaf damage and reduced seed-setting rate; severe cases lead to large-scale yield reduction or even total crop failure.

Conventional manual field inspection relies on practical observation and empirical judgment by agricultural technicians and growers. This mode presents obvious drawbacks. Manual inspection is time-consuming and cannot complete full-coverage investigation over large rice fields. Identification results heavily depend on personal experience, which easily causes missed detection and misjudgment for early-stage or symptom-similar pests and diseases. Moreover, high labor cost and delayed information feedback make quantitative recording difficult, restricting precise pesticide application and regional unified prevention and control.

With the continuous advancement of smart agriculture and digital-rural construction, UAV remote-sensing and deep-learning visual-detection technologies have been widely applied in agriculture. Multi-rotor UAVs feature high flexibility, wide operating range and non-contact operation, capable of rapidly acquiring aerial images of farmland. One-stage detection algorithms represented by YOLOv8 and YOLOv10 deliver fast inference speed and great lightweight potential, suitable for target recognition under complex field conditions. Integrating UAV aerial-collection capacity with deep-learning algorithms establishes an air-ground integrated intelligent-detection system, overcoming the limitations of manual monitoring and enabling efficient, large-scale and intelligent rice pest-disease monitoring.

Foreign research on agricultural intelligent monitoring started relatively early. Researchers carry out studies on crop stress and pest-disease recognition based on UAV remote sensing and deep learning. Domestic research develops rapidly, yet most existing models contain massive parameters and cannot be deployed on airborne edge devices. Some datasets are captured at close range, inconsistent with UAV aerial perspective. The recognition performance for tiny aerial-image lesions and insects remains unsatisfactory, and few integrated engineering-oriented application systems are available. National policies promote the integration of artificial intelligence, UAV and big-data technologies with agriculture, aiming to improve intelligent pest-disease early-warning and realize green prevention with reduced pesticide consumption. Against this background, research on UAV-oriented rice pest-disease intelligent-detection systems bears important theoretical value and engineering application significance.

This study designs and implements an integrated rice pest-disease detection system. Based on dataset construction, algorithm optimization, hardware-software integration and field verification, the system realizes

automatic inspection, intelligent identification, spatial positioning and visualized output. It provides feasible technical solutions for smart rice-field management and green pest-disease prevention.



Figure 1.1 Disease Detection

II. SYSTEM DESIGN AND EXPERIMENTAL SETUP

2.1 Design Idea

Following practical, lightweight and easy-to-deploy principles, the system adopts the technical framework of “UAV data acquisition + edge/cloud intelligent analysis + visual platform display”, forming a complete business chain of “air-perception — intelligent computation — business application”. Each functional unit is modularized with unified application interfaces for data interaction. Modules can be independently debugged or collaboratively operated with favorable expandability. Balancing recognition accuracy and inference real-time performance, the system considers poor network conditions and complex farmland environments. Operation procedures are simplified and hardware deployment costs are controlled to adapt to usage habits of grassroots farmers and farm managers.

2.2 Four-layer Distributed System Architecture

Data Acquisition Layer Multi-rotor UAV serves as the perception terminal, equipped with a 12-000-20-000-pixel visible-light camera, three-axis mechanical gimbal and GPS / Beidou dual-mode positioning module. Full-coverage rice-field image acquisition is performed along pre-planned routes, synchronously recording shooting position, flight altitude and attitude information. The flight height is set from 5 m to 15 m, with forward overlap ratio of 60%-80% and side overlap ratio of 50%-60%, ensuring complete coverage and clear image details. The three-axis gimbal counteracts flight jitter to guarantee high-quality raw images for algorithm input.

Data Transmission Layer Digital image transmission, 4G/5G and WiFi are combined for hybrid transmission. Short-range operations adopt built-in digital transmission for low-latency image feedback; 4G/5G modules upload data during large-scale patrols. Local caching, breakpoint resume and data-compression mechanisms are implemented to avoid data loss caused by unstable farmland network signals.

Data Processing Layer This layer consists of edge-computing nodes and cloud servers. Lightweight YOLO models are deployed on edge terminals for real-time image inference to reduce transmission pressure. Cloud servers undertake mass-image storage, iterative model training and historical-data comparison. Image pre-processing procedures including distortion correction, illumination enhancement and denoising are executed. Pest-disease target detection, category judgment and confidence calculation are completed. Combined with GPS coordinates, pixel coordinates are mapped to actual field longitude-latitude to realize spatial positioning of pests and diseases.

Application Service Layer Composed of databases, Web management terminals and visual interactive interfaces. Databases store flight parameters, images, pest-disease categories, position coordinates and occurrence levels. Front-end interfaces support map marking, pest-disease distribution heatmaps and statistical charts. Functions including task management, data filtering, monitoring-report export and early-warning push are provided, together with prevention suggestions for end-user decision-making support.

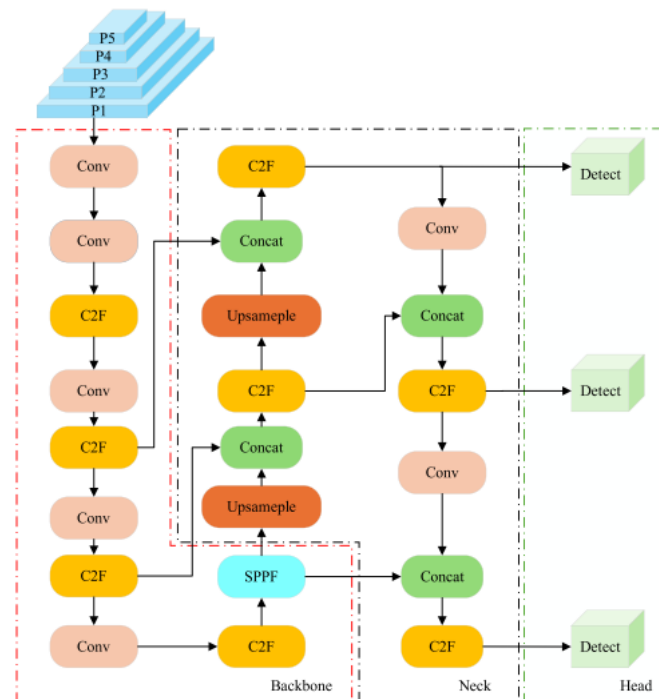


Figure 2.1 Structure of Benchmark Model

2.3 Hardware Platform Selection

The hardware platform mainly includes multi-rotor UAV body, flight-control navigation system, imaging gimbal and image-transmission communication module. Four-axis / six-axis industrial patrol multi-rotor UAV is selected, with no-load weight of 1.2-1.8 kg, effective payload of 500-800 g and single-flight endurance of 30-40 minutes. It resists wind force of grade 4-5 and supports automatic route planning, fixed-point hovering and low-power automatic return, adapting to irregular rice plots. The flight-control system realizes fixed-height and fixed-speed shooting; three-axis stabilized gimbal eliminates flight shake; high-resolution visible-light camera is equipped; image-transmission modules realize image feedback and TF-card local storage. The whole hardware is rainproof and anti-fog, adapting to high-temperature and high-humidity farmland environments, and can be deployed by single operators.

2.4 Software Platform Design

The software contains image-pre-processing module, YOLO-model training-inference module, database and visual-interaction module.

Image pre-processing: Lens distortion correction and unified image input size adjustment; adaptive brightness adjustment and filtering denoising. Data augmentation operations such as flipping, rotation, scaling and mosaic are applied to improve model adaptability against illumination variation and leaf occlusion.

The YOLO algorithm module takes YOLOv8 / YOLOv10 as baseline framework. A UAV-aerial rice-pest-disease dataset containing rice blast, sheath blight and rice planthopper samples is constructed, and divided into training set, validation set and test set at the ratio of 7:2:1. SGD / AdamW optimizer and CIOU loss function are adopted, with cosine-annealing learning-rate strategy. To solve small-target detection difficulties in aerial images, attention mechanisms are introduced to enhance feature extraction for subtle lesions and insects. Model pruning and quantization are performed for lightweight transformation. Weighted non-maximum suppression is adopted in post-processing to remove duplicate detection boxes. The model achieves mAP of 85%-95% on test sets, satisfying real-time edge-device inference requirements.

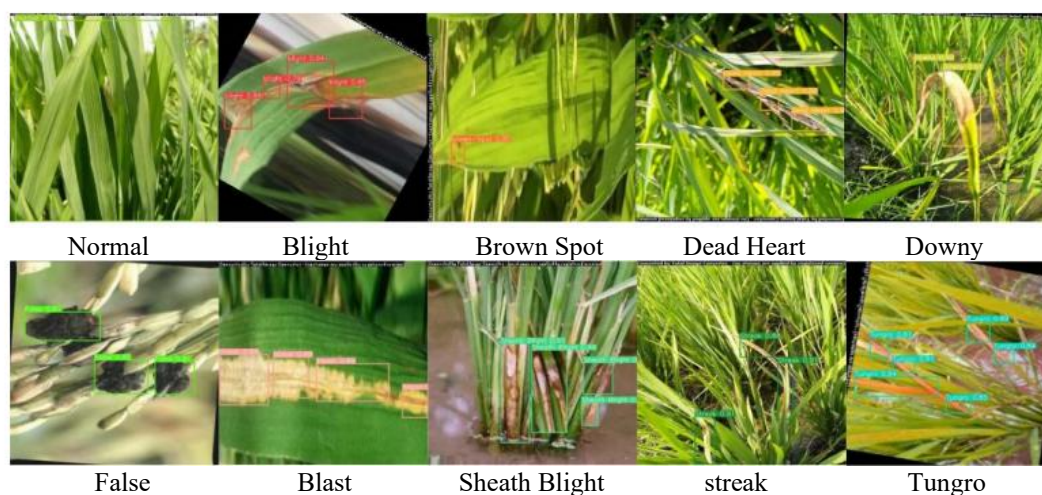


Figure 2.2 Ten different kinds disease

The visual-interaction software is developed based on PyQt. It supports single-image detection, batch-folder detection, video and camera real-time inference. Detection category, confidence and inference time are displayed on interfaces. Tables record file paths and recognition results. Monitoring reports can be summarized and exported in PDF and Excel formats.

2.5 Research and Test Process

The research strictly follows the scientific workflow: demand analysis — technical research and development — laboratory and field test optimization — application verification. User requirements are clarified through literature review and demand investigation. Hardware component selection, system integration and software-algorithm development are completed. Subsequent laboratory tests and field pilot experiments are carried out to continuously optimize model performance, hardware stability and user experience. Finally, comprehensive functional verification is implemented for practical-application scenarios.

III. RESULTS AND DISCUSSION

3.1 System Workflow

The whole operating procedure includes mission planning, image acquisition & transmission, pest-disease detection & inference, result visualization and report export.

Flight-mission planning: Farmland maps are loaded on ground-station software. Patrol areas are framed, and grid patrol routes are automatically generated. Parameters including flight height, shooting interval and image overlap ratio are configured. The UAV takes off after surrounding-environment safety confirmation.

Image acquisition and transmission: The UAV flies and shoots automatically according to pre-set routes. Images are stored on airborne memory cards and fed back to ground terminals simultaneously. The UAV returns and lands automatically after missions. Images are imported into the detection system in batches.

Pest-disease detection execution: Aerial images are imported into software, and the trained lightweight YOLO model is loaded with confidence thresholds configured. The system automatically completes image pre-processing and model inference, identifies pest-disease categories, outputs detection boxes and confidence values, and maps geographic coordinates of pest-disease locations.

Result inspection and report export: Annotated images are displayed on visual interfaces. Pest-disease points are marked on electronic maps and distribution heatmaps are generated. Pest-disease occurrence levels in different regions are counted. Monitoring reports summarizing damaged area and pest-disease types are generated and exported for archiving.

3.2 Application Scenarios and Comprehensive Benefit Evaluation

The system can be deployed in multiple agricultural production scenarios:

Routine investigation for large-scale farms: UAVs can inspect thousands of mu of rice fields within one day, generating pest-disease distribution reports to realize digital monitoring for the whole growth cycle and replace multi-person manual field surveys.

Variable pesticide-application decision-making for precision agriculture: Pest-disease positions and occurrence density are identified to divide safe zones, light-occurrence zones, moderate-occurrence zones and

severe-occurrence zones. Plant-protection UAVs are guided to apply pesticides in zones as required. Compared with full-field uniform spraying, pesticide consumption can be reduced by 20%-40%, lowering agent costs and farmland ecological pollution.

Early warning and outbreak monitoring of pests and diseases: Low-altitude high-frequency patrols capture faint early-stage lesion features. Combined with statistical recognition results, pest-disease outbreak risks are evaluated and warning messages are pushed to realize early discovery and early disposal for yield-loss mitigation.

Regional unified prevention and emergency disposal: Serving plant-protection stations and agricultural-technology extension departments, the system rapidly completes disaster investigation over contiguous county-level and township-level rice fields, generating global pest-disease electronic distribution maps to provide objective data for emergency disposal and prevention-effect evaluation.

Light-weight management for family farms and large-scale individual growers: The system features low operation thresholds. Single users can complete whole-plot patrols and inspect detection results via mobile terminals, helping small-scale growers realize scientific field management.

Monitoring for agricultural-research experimental plots: Images of experimental sub-plots are collected in a standardized manner. Diseased-plant ratio and damage degree are automatically counted to reduce manual-survey errors and provide quantitative data for variety screening and pesticide-efficacy comparison experiments.

Economic benefits: Monitoring efficiency is improved dozens of times compared with manual inspection, saving substantial field-labor costs. Zonal pesticide-application guidance reduces pesticide procurement investment.

Environmental benefits: Pesticide consumption reduction mitigates soil and water pesticide residues and supports green agricultural development.

Social benefits: Rice-field management is transformed from experience-driven mode to data-driven mode, boosting smart-agriculture construction and providing technical means for stable grain production.

3.3 System Test and Fault Handling

Laboratory and field pilot tests prove that the system runs stably under complex illumination and outdoor farmland conditions. Lightweight models realize smooth inference on edge devices. Hardware can complete standardized image acquisition under grade-4-5 wind conditions.

Various faults may emerge during field application: UAV-side faults include positioning abnormality, blurry images and corrupted materials; software-side faults contain model-loading failure, slow inference speed, missed and false detection; transmission faults include image-transmission interruption and GPS-coordinate offset. Strong sunlight, fog and weed backgrounds also interfere with recognition performance. Corresponding solutions are proposed: calibrate compass, wipe lenses and replace memory cards; verify model file paths, adopt lightweight weights and expand training datasets; inspect communication equipment; select appropriate operation time periods and enable image-pre-processing enhancement algorithms.

3.4 Sustainability Analysis

The system presents favorable sustainability in technology, economy, environment and society. Technically, model performance can be iteratively promoted with the development of computer-vision technologies. Economically, diversified application modes can guarantee stable returns. Environmentally, it promotes pesticide reduction and green crop protection. Socially, large-scale application will accelerate the digital transformation of rice-planting management.

IV. CONCLUSION

This paper designs and implements the “Agri-IntelliDet” rice pest-disease intelligent-detection system integrating UAV remote sensing and improved YOLO deep-learning algorithms. Dataset construction, algorithm optimization and hardware-software integration are completed. The system realizes full-process functions including automatic rice-field patrol acquisition, intelligent pest-disease identification and positioning, visual analysis and report export. Tests demonstrate high recognition accuracy and compatibility with diverse agricultural scenarios. It effectively addresses traditional monitoring drawbacks such as low manual-inspection efficiency, strong subjectivity and delayed prevention-control. Labor and pesticide input can be reduced, delivering practical application value for smart-agriculture development and food-security guarantee.

Currently the system mainly relies on visible-light images for recognition. Multi-spectral and thermal-infrared sensors can be introduced for multi-modal data fusion to reduce false-detection rates in future research. Automatic pest-disease severity grading models will be improved to quantify damaged area. Meteorological, soil and crop-growth-period data will be integrated to construct pest-disease risk-prediction

models for advance early-warning. Further model pruning and knowledge distillation will compress computational overhead to realize real-time on-board UAV inference. Data interfaces with plant-protection operation platforms will be opened to build the closed-loop workflow of “monitoring-identification-decision-pesticide-application-effect-verification”. Recognition capacity will be expanded for wheat, corn and other crops. Mobile mini-programs and offline-operation functions will be optimized to lower usage thresholds and promote large-scale technology popularization.

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