

Design of a Precision Spraying System for Plant-Protection UAV Based on Deep Learning

Zhuohui Luo, Hainie Meng

Guangzhou Nanyang Polytechnic College, Guangzhou 510925, Guangdong, China

Copyright: © 2026 Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY 4.0), permitting distribution and reproduction in any medium, provided the original work is cited.

Abstract: Traditional plant-protection UAVs mostly adopt the extensive full-coverage spraying mode, which suffers from problems such as low pest-and-disease identification accuracy, serious pesticide-liquid waste, poor spraying uniformity, and easy farmland environmental pollution. Such systems can hardly meet the precise, green, and efficient plant-protection demands of modern agriculture. Accordingly, this paper designs a precision spraying system for plant-protection UAVs based on deep learning. Taking an embedded UAV platform as the hardware carrier, it adopts a lightweight deep-learning object-detection algorithm to realize intelligent identification of field pests and diseases as well as accurate division of operation areas. Combined with PID closed-loop control, it dynamically adjusts flight attitude and spraying parameters to complete fixed-point, quantitative on-demand pesticide application. This paper systematically elaborates the overall architecture, hardware-software design, and algorithm-optimization strategies of the scheme, and verifies system performance through field comparative experiments. The test results show that the pest-and-disease identification accuracy of this system can reach 96.2%. Its pesticide-liquid utilization rate is improved by more than 35% compared with the traditional operation mode. It can effectively reduce pesticide pollution and improve the quality and efficiency of plant-protection operations, and possesses favorable field-application value and promotion prospects.

Keywords: Plant-protection UAV; Deep learning; Precision spraying; Object detection; Intelligent plant protection

Online publication: October 21, 2026

1. Introduction

The rapid iteration of smart-agriculture and precision-plant-protection technologies promotes the transformation of traditional agricultural plant protection toward intelligence, refinement, and green development. Traditional manual plant protection features low efficiency and highly subjective pesticide application. Conventional plant-protection UAVs mostly adopt uniform full-coverage spraying, resulting in obvious problems of missed spraying, repeated spraying, and excessive pesticide application. These issues not only raise planting costs and waste pesticide resources, but also easily trigger residual pollution in soil and water bodies ^[1]. Meanwhile, field pests and diseases are judged by manual visual observation,

which brings low identification efficiency and large errors, and fails to satisfy refined plant-protection demands for large-scale farmlands. To solve the above-mentioned pain points, this paper combines lightweight deep-learning vision technology with a plant-protection UAV platform, and builds an intelligent precision-spraying system to realize automatic pest-and-disease identification, intelligent judgment of operation areas, and on-demand precision pesticide application, so as to provide technical support for green and efficient farmland plant protection.

1.1. Overall system scheme design

This system adopts a layered modular architecture, which is divided into three parts: perception layer, decision layer, and execution layer. The layers cooperate and interact with each other to independently complete the whole-process operations, including field data collection, pest-and-disease identification, parameter decision-making, and precision spraying.

The perception layer serves as the information-input terminal of the system. It consists of a high-definition onboard camera, GPS positioning module, attitude sensor, wind-speed sensor, and flow sensor. It collects key data in real time, such as field crop images, UAV position and attitude, ambient wind speed, and pesticide-liquid pipeline flow, providing complete data support for intelligent decision-making^[2].

The decision layer is the core control hub of the system, which takes an embedded main-control chip as the carrier and is equipped with a lightweight deep-learning detection model. Firstly, preprocessing operations such as noise reduction and distortion correction are performed on collected images. Then the trained model completes pest-and-disease identification and feature analysis to obtain pest-and-disease categories, distribution ranges, and hazard levels. Combined with environmental and equipment parameters such as positioning data, wind speed, and attitude, it adaptively generates optimal flight trajectories, operation heights, spraying-flow rates, and pressure parameters, and finally issues precise control instructions to the execution layer^[3].

The execution layer includes the UAV flight module and the pesticide-liquid spraying module, which are responsible for accurately executing decision instructions. The flight module adjusts the UAV's flight attitude, speed, and operation trajectory relying on the flight-control system, ensuring stable equipment operation close to crop canopies. The spraying module cooperates through booster pumps, electromagnetic regulating valves, and atomizing nozzles. It dynamically starts and stops spraying and adjusts pesticide-application dosages according to pest-and-disease distribution, so as to realize fixed-point and quantitative precision pesticide application^[4]. The three-layer architecture features clear logic and rapid response, and can realize unmanned and intelligent precision plant-protection operations.

1.2. Core system parameter indicators

Combined with plant-protection industry standards and actual field-operation requirements, this paper formulates core system-parameter indicators from three dimensions: identification performance, flight-operation performance, and spraying performance, and clarifies standards for equipment-operation accuracy and stability. Specific parameters are shown in **Table 1**.

Table 1. Core system parameter indicators

Performance Dimension	Parameter Name	Indicator Value
Identification Performance	Pest-and-disease Identification Accuracy	$\geq 96\%$
	Image Inference Speed	≤ 30 ms per frame
	Minimum Identifiable Target Size	5 mm $\times$ 5 mm
	Environmental Adaptation Range	Illumination: 300-10000 lux, slight branch-and-leaf occlusion
Flight-Operation Performance	Operation Flight Height	Adjustable 1-5 m
	Operation Flight Speed	Adjustable 1-8 m/s
	Positioning Accuracy	± 0.1 m
Spraying Performance	Pesticide-Liquid Flow Adjustment Range	0.5-5 L/min
	Spraying Uniformity Error	$\leq 8\%$
	Pesticide-Liquid Utilization Rate	$\geq 85\%$

As shown in **Table 1**, this system delivers high identification accuracy and strong environmental adaptability. Its flight-positioning and spraying-control accuracy are significantly superior to traditional plant-protection equipment. It can adapt to complex field-operation working conditions, effectively solve problems such as low operation accuracy and severe pesticide-liquid waste in traditional plant-protection work, and meet application standards for precision plant protection in modern agriculture.

2. System hardware-software design

2.1. System hardware design

The hardware system lays the foundation for stable operation of the precision-spraying system. Following the design concepts of modularization, lightweight, and high reliability, the whole system is divided into five units: main-control module, vision-acquisition module, environment-perception module, flight-control module, and precision-spraying module. Each module works independently and cooperates interactively. Under the premise of controlling equipment self-weight and volume, it guarantees the overall performance of system identification, decision-making, and execution, and satisfies lightweight-load requirements of plant-protection UAVs^[5].

The main-control module adopts the NVIDIA Jetson Nano embedded development board, which is built-in with a quad-core ARM processor and 4 GB RAM. It can meet demands for onboard real-time inference and computation of lightweight deep-learning models^[6]. It features small size, low power consumption, and favorable stability. Suitable for UAV applications, it is equipped with multiple commonly-used interfaces for good connection with various other sensors and actuators, ensuring timeliness and effectiveness of information transmission and normal operation of the whole system.

The vision-acquisition module adopts the OV2710 high-definition onboard camera, supporting 1920 $\times$ 1080 resolution and 30 fps frame rate. It possesses automatic exposure and white-balance adjustment functions and can work well under varied illumination conditions. Meanwhile, with a 120° ultra-wide field-of-view, it can cover a large farmland area in a single shot. It generates little transmission delay and can transmit clear farmland crop images to computers in real time for subsequent processing, so as to realize accurate identification of crop pests and diseases^[7].

The environment-perception module includes dual-mode GPS, MPU6050 attitude sensor, FS400 wind-speed sensor, and liquid-flow sensor. The GPS module reaches ± 0.1 m accuracy and provides position

information for fixed-point operation and path planning. The attitude sensor obtains variations in UAV pitch angle, roll angle, and heading angle to guarantee stable flight. The wind-speed sensor measures wind speed in farmlands to reduce spraying errors caused by wind. The flow sensor detects pesticide-liquid flow inside pipelines and forms spraying loops to realize accurate pesticide application.

The flight controller adopts the open-source PIX4 flight-control unit, which delivers strong stability and expandability. It can receive flight commands sent by the main-control unit and realize hovering at designated positions, flight-path execution, and attitude adjustment. Equipped with anti-interference functions against farmland wind and electromagnetic interference, it supports functions such as breakpoint-resumed flight and automatic return-to-home, greatly improving operation safety and robustness.

The precision-spraying module consists of a lightweight pesticide tank, a miniature DC booster pump, a high-precision electromagnetic regulating valve, atomizing nozzles, and pesticide-liquid pipelines. The booster pump delivers stable pressure and rapid response. The electromagnetic regulating valve supports continuous flow variation from 0.5 L/min to 5 L/min. Cooperating with hollow-cone atomizing nozzles, it achieves favorable atomizing effects and avoids waste caused by pesticide-liquid drift. It performs differentiated precision-spraying operations under system control.

2.2. System software and algorithm design

Software and algorithms constitute the key to realizing intelligent precision plant protection. They mainly include four modules: image preprocessing, lightweight pest-and-disease identification model, intelligent spraying-decision algorithm, as well as flight-and-spraying PID closed-loop control algorithm. Multiple algorithms are combined to complete the whole automated workflow ranging from image acquisition, object detection, and parameter determination to final operation, so as to improve system accuracy and automation level.

Field-acquired images are prone to noise, distortion, and low contrast caused by light, dust, leaf occlusion, and other factors. Therefore, a relatively simple preprocessing method is adopted: Gaussian filtering is used for image denoising, wide-lens distortion is corrected, and adaptive histogram equalization enhances image contrast to highlight pest-and-disease targets. It lowers computational complexity while improving image quality, facilitating subsequent accurate pest-and-disease identification by the model^[8].

Based on YOLOv5s, this paper conducts lightweight improvements under the condition of insufficient onboard computing power of UAVs. Network pruning is adopted to remove redundant convolution-layer parameters. 16-bit quantization is used to reduce model size and computation volume. A CBAM attention module is introduced to boost model performance in detecting small-size and occluded pests and diseases. On the premise of guaranteeing real-time performance, the identification accuracy under complex environments is improved.

The model is trained on a self-built farmland pest-and-disease dataset containing 28 000 images of 20 common pests and diseases of rice, wheat, fruits, and vegetables, covering field environments with different illumination intensities and varying degrees of occlusion^[9]. Transfer learning is adopted for training. A total of 300 iterations are performed with continuously adjusted learning rates and optimized loss functions. After optimization, model parameters are reduced to about half of the original size, inference speed is more than doubled, and identification accuracy rises by approximately 2.3%, satisfying real-time-inference requirements onboard UAVs.

The intelligent spraying-decision algorithm is based on the location and hazard level of identified pests and diseases. Taking wind speed, flight height, flight speed, and other factors into consideration, it adaptively adjusts optimal spraying volume, atomization area, and operation routes. Higher pesticide dosage is applied in severely diseased zones, reduced dosage for lightly-diseased zones, and spraying is stopped in disease-free zones. Meanwhile, reasonable routes are planned according to UAV battery power and remaining pesticide-liquid volume to avoid unnecessary work, improve agricultural-production efficiency, and cut costs^[10].

The system operates relying on the PID closed-loop control algorithm. During flight, attitude deviations are used to continuously adjust motor speeds for low-altitude UAV flight. For the spraying part, valve opening is adjusted according to flow rates to reduce flow deviations for reliable and accurate pesticide application. It also resists the influence of wind and airflow to improve system reliability and spraying uniformity.

2.3. System software functional-workflow design

The system software adopts modular workflow design. The whole process runs automatically without manual operation and consists of six steps: system initialization, data acquisition and preprocessing, intelligent pest-and-disease identification, operation-scheme formulation, precision pesticide spraying, as well as data saving and operation termination. Each step connects closely with clear logic.

After equipment startup, hardware detection, sensor calibration, and model loading are executed. The system stays in waiting status if no abnormality is detected. After UAV take-off, vision and perception modules simultaneously acquire images, position information, wind speed, attitude, and other data. The main-control unit preprocesses images and integrates multi-sensor information for intelligent identification and decision-making.

Preprocessed images are input into the lightweight model for pest-and-disease identification to obtain target positions and hazard levels, and misjudgment interference is eliminated. According to identification results and environmental parameters, the algorithm acquires optimal flight paths and spraying-parameter information, and issues precise control commands.

The flight-control and spraying modules receive instructions simultaneously, perform operations along preset trajectories, and implement differentiated precision pesticide application. Closed-loop control continuously adjusts operating conditions during the whole process to overcome external disturbances. Finally, the UAV autonomously returns to the base. The system saves operation information and generates reports for future reference, supporting automated plant-protection operations on large-scale farmlands.

3. System test and performance analysis

3.1. Test-scheme design

To verify the actual operational performance of the system, field comparative tests are carried out during the high-incidence period of rice pests and diseases. The test site is a large-scale rice-planting base with naturally occurring typical pests and diseases such as rice planthoppers and rice blast, conforming to real plant-protection-operation scenarios. A control group and an experimental group are set. The control group adopts the traditional full-coverage UAV spraying mode; the experimental group adopts the intelligent precision-spraying system proposed in this paper. The operation area, crop growth status, pest-and-disease distribution, and applied pesticide are kept consistent for both groups to eliminate interference from irrelevant

variables. Four indicators are mainly tested: pest-and-disease identification accuracy, pesticide-liquid utilization rate, spraying-uniformity error, and operation efficiency. Each group of tests is repeated three times, and average values are taken as final results to guarantee objective and reliable test data.

3.2. Test results and performance analysis

After completing field comparative tests, operation-performance data of equipment in both groups are counted, as shown in **Table 2**.

Table 2. Operation-performance data of equipment in two groups

Test Indicator	Traditional UAV System	Proposed Precision-Spraying System	Performance Improvement Amplitude
Pest-and-disease Identification Accuracy	78.5%	96.2%	17.7%
Pesticide-Liquid Utilization Rate	50.8%	86.2%	35.4%
Spraying-Uniformity Error	18.5%	7.2%	11.3%
Operation Time per Mu	8.2 min	6.5 min	20.7%

As can be seen from the test data in **Table 2**, the comprehensive performance of the system designed in this paper is obviously superior to that of traditional plant-protection UAVs. The pest-and-disease identification accuracy reaches 96.2%, which can accurately identify field pests and diseases and greatly reduce mis-detection and false-identification probability. The pesticide-liquid utilization rate hits 86.2%, which rises by 35.4% compared with the traditional mode, effectively cutting pesticide waste and agricultural non-point-source pollution. The spraying-uniformity error is merely 7.2 %, and operation stability is greatly enhanced. The operation time per mu is shortened by 20.7%, improving plant-protection-operation efficiency while guaranteeing operation accuracy. Tests prove that this system features prominent intelligence and precision advantages, and possesses high field practicality and promotion value.

4. Conclusion

Targeting problems including extensive operations, pesticide waste, and low identification accuracy of traditional plant-protection UAVs, this paper designs a precision-spraying system for plant-protection UAVs based on deep learning. Through a modular hardware-software architecture, lightweight deep-learning-model optimization, and multi-algorithm integrated control, it realizes automated plant-protection operations: intelligent pest-and-disease identification, accurate positioning of operation areas, and on-demand quantitative pesticide-liquid spraying. Field tests indicate that the system delivers high identification accuracy, high pesticide-liquid utilization rate, and favorable operation stability. It can effectively improve the intelligence level of farmland plant protection and meet the development demands of green agriculture and smart agriculture. Subsequent research can further optimize model generalization ability, expand functions such as multi-crop adaptation and integration of water-and-fertilizer application, and promote industrial application and popularization of intelligent plant-protection equipment.

Funding

2024 Guangdong Provincial Science and Technology Innovation Strategy Special Fund (College Student Science and Technology Innovation Cultivation) Key Project Design of Precision Spraying System for

Disclosure statement

The authors declare no conflict of interest.

References

- [1] Mei YL, 2026, Discussion on Precision Spraying Technology of Plant-Protection UAV in Liandu District, Lishui City. *Southern Agriculture*, 20(8): 216–218.
- [2] Chen WB, Fu XJ, Jiang ZW, et al., 2026, Precision Spraying System for Plant-Protection UAV Based on Improved YOLOv7. *Journal of Chinese Agricultural Mechanization*, 47(1): 167–173.
- [3] Yan Y, 2025, Research on Plant-Protection UAV Technology for Corn Pest and Disease Control. *Seed Science and Technology*, 43(23): 143–145.
- [4] Chen YF, 2025, Application Analysis of Precision-Spraying Operations for Agricultural UAVs. *China Agricultural Machinery Equipment*, 2025(12): 88–91.
- [5] Xu K, 2025, Research on Precision Control of Agricultural Plant-Protection UAV in Pesticide Spraying. *Agricultural Machinery Usage and Maintenance*, 2025(11): 74–77.
- [6] Ma DZ, 2025, Application of Plant-Protection UAV in Rice Pest and Disease Prevention and Control. *High-Quality Agricultural Products*, 2025(9): 54–56.
- [7] Li RX, 2025, Green Cultivation of Wheat and Intelligent Precision-Management Technology of Plant-Protection UAV. *Chinese and Foreign Food Industry*, 2025(16): 81–83.
- [8] Li J, Zhang YL, Zhang QZ, et al., 2026, Key Technologies of Plant-Protection UAV and Their Application in Precision Agriculture. *Research on Agricultural Mechanization*, 48(1): 286–293.
- [9] Song F, 2025, Application of Plant-Protection UAV in Fruit-Tree Cultivation. *Modern Agricultural Science and Technology*, 2025(13): 147–150 + 156.
- [10] Li YG, 2025, Research on Droplet Movement Law of Plant-Protection UAV Pesticide Application and Construction of Drift-Prediction Model, thesis, Shenyang Agricultural University.

Publisher's note

Bio-Byword Scientific Publishing remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.