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Intelligent Agricultural Pest and Disease Diagnosis System Based on Multispectral UAVs and Edge Computing

Xuejian Li[1*], Zhonghui Li[1], Zunbao Feng[1], Pengbo Geng[1], Kehui Yan[1], Anqi Yan[1]

[1]College of Mechanical and Vehicular Engineering, Changchun University, 130022, Changchun, China
[*]Corresponding Author:Xuejian Li

ABSTRACT: *As China's primary industry closely tied to people's livelihoods, agricultural pest and disease control strategies vary significantly across regions due to differences in climate, cultivation techniques, and crop types. Pests and diseases severely impact crop yields, particularly in impoverished areas where delayed control measures can result in loss rates ranging from 30% to 100%. This not only causes substantial economic losses for farmers but also threatens socioeconomic stability. Therefore, achieving timely detection and precise control of pests and diseases is of paramount importance. To enhance control effectiveness, modern scientific methods are gradually replacing traditional approaches. Among these, drone-based remote sensing monitoring has gained widespread adoption due to its robust environmental adaptability and image capture/analysis capabilities. This system leverages drone remote sensing technology to achieve automatic identification of pest and disease outbreaks and their types, while supporting remote online monitoring for timely countermeasures. Integrating hardware and software design, the system employs machine vision and deep learning technologies to perform preprocessing tasks such as image annotation, adjustment, and data augmentation. This enables model construction for detection and classification. Field experiments validate the system's high stability, strong adaptability, and detection accuracy meeting design requirements, demonstrating its capability for real-time remote monitoring and pest/disease identification across multiple regions.*

Keywords*: *drone remote sensing technology; pest and disease detection; Python; deep learning

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I. Challenges and Innovations in the Work

Precise monitoring of crop pests and diseases is a critical component in ensuring food security and sustainable agricultural development[1]. Traditional manual inspection methods are inefficient and incapable of large-scale monitoring. In contrast, unmanned aerial vehicle (UAV) remote sensing technology offers a new solution for pest and disease monitoring due to its high efficiency, flexibility, and multi-scale observation capabilities. In recent years, advancements in high-resolution multispectral sensors and deep learning algorithms have demonstrated the immense potential of UAVs in early pest and disease identification and severity assessment[2]. Research indicates that visible light, multispectral, and thermal infrared sensors mounted on UAV platforms can effectively capture physiological changes in crop canopies[3]. Combined with machine learning methods, they enable precise pest and disease identification with accuracy rates exceeding 85%. Current technology is feasible for field applications. By optimizing flight parameters, sensor configurations, and algorithmic models, it is possible to establish a standardized, intelligent UAV-based monitoring system for crop pests and diseases.

However, due to the small size, high density, and environmental dependence of pest and disease imagery, detection poses greater challenges compared to other tasks like vehicle or pedestrian detection[4]. These challenges manifest in three key areas: environmental conditions affecting drone imaging, extremely small target areas at long distances, and dynamic interference from complex backgrounds.

1. Environmental Impact on UAV Imaging

UAV remote sensing for crop pest and disease monitoring is susceptible to adverse weather conditions like strong winds and rain, resulting in blurred images[5]. Simultaneously, data collection demands precise solar illumination—intense sunlight causes overexposure, while overcast skies reduce spectral feature contrast. For instance, the detection rate of wheat powdery mildew lesions decreases by 25% under intense midday sunlight. Furthermore, diseases affecting lower leaves within dense crop canopies are easily obscured. For example, corn borer larvae burrowing inside stalks are difficult to observe directly.

2. Ultra-Small Target Area Due to Long Distance

Pest and disease individuals are typically minute, with body colors highly similar to their hosts or surroundings, granting them exceptional concealment. This poses significant challenges for manual identification and monitoring. Therefore, when using drones to collect pest and disease datasets, it is essential to leverage their aerial photography advantages while ensuring target recognition accuracy. This is achieved through optimal flight altitude and swath design, enabling large-scale, efficient monitoring.

3. Dynamic Interference from Complex Backgrounds

Dynamic interference from complex backgrounds significantly reduces UAV detection accuracy for crop pests and diseases. Moving foliage, light shadows, and crop sway can easily be confused with pest/disease features, leading to false positives or false negatives. Simultaneously, continuous background changes increase computational load for image recognition, impacting the real-time performance of detection algorithms. Environmental factors like wind may also disrupt stable UAV flight, causing angle shifts or blurred images that further degrade data quality[6]. The combined effect of these interference factors poses significant challenges to achieving precise and efficient pest and disease detection in complex agricultural environments.

Multirotor drones demonstrate remarkable innovative value in crop pest and disease detection, primarily manifested in three aspects: First, by integrating hyperspectral imagers and multi-sensor fusion systems, they enable molecular-level spectral identification of early pest and disease characteristics, elevating detection accuracy to sub-centimeter precision[7]. Second, the innovative integration of edge computing and 5G transmission technology establishes an integrated “air-ground” real-time monitoring network, reducing field response times from days with traditional methods to minutes[8]. Finally, the application of deep learning algorithms overcomes technical barriers in tracking pest and disease dynamics within complex agricultural environments, enabling comprehensive health assessments throughout the crop growth cycle[9]. These technological innovations not only substantially enhance the timeliness and accuracy of pest and disease early warning systems but also provide a scalable technical framework for constructing smart agricultural monitoring systems.

II. System-Wide Solution Argumentation and Design

2.1 Design of the Overall System Solution

2.1.1 Technical Specifications to be Achieved by the System

Based on practical requirements, the drone inspection system must meet the following fundamental specifications:

1. Autonomous flight and stationary patrol
2. Multispectral + visible light data acquisition
3. Real-time pest and disease identification (edge computing)
4. Cloud-based data synchronization and visualization

2.1.2 Overall System Design Proposal

Throughout the system design process, a specific hardware circuit design solution was proposed based on the characteristics of drone inspection and image recognition principles. The overall system design encompassed five key components: the drone platform, sensor array, edge computing unit, communication module, and cloud management platform. The relationships between these systems are illustrated in Figure 2-1[10].

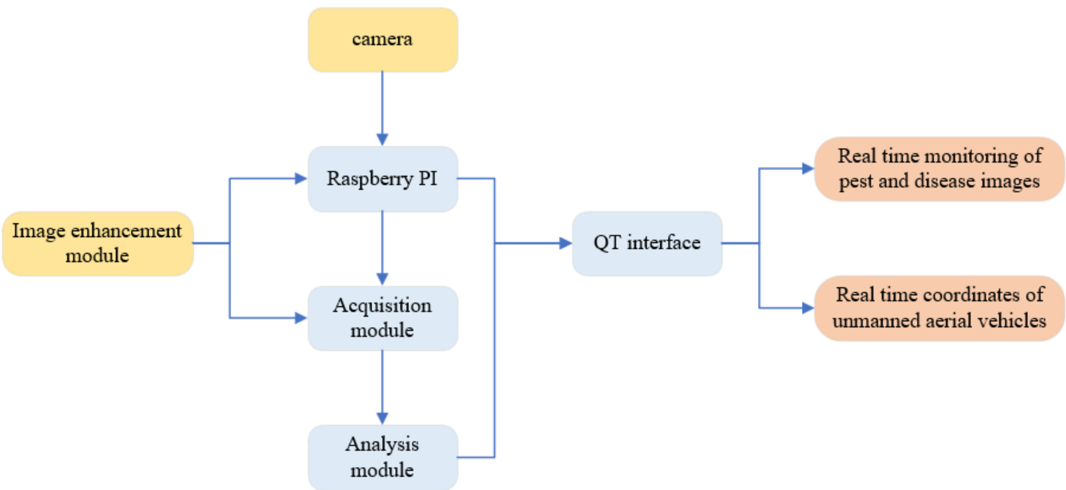

Figure 2-1 System Overall Design Scheme

Throughout the entire workflow, this system employs a highly integrated UAV platform equipped with a multi-modal sensor array (including a high-resolution visible light camera, a five-band multispectral camera, and high-precision environmental sensors). This enables all-weather, multi-dimensional data collection in complex agricultural environments, ensuring reliable operation under diverse conditions to meet practical demands. Real-time image analysis is then performed by the edge computing unit deployed on the UAV. Finally, the processed data is promptly transmitted to the cloud management platform via the communication module, enabling users to access the data in real time.

2.2 Unmanned Aerial Vehicle System Design

The UAV platform, as the foundational premise of the entire design, must ensure reliable operation across diverse environments, including adverse weather conditions such as rain and high winds. The UAV platform designed herein comprises a frame, a power system, and a flight control and navigation system. It integrates a high-energy-density battery pack to maximize power-to-weight ratio, features a high-efficiency brushless motor drive system, and employs aerodynamically optimized propeller design. Flight control is managed by the main flight control module, while a GPS positioning module enables precise targeting of inspection areas[11].

2.2.1 Selection of the Primary Flight Control Module

In unmanned aerial vehicle (UAV) system design, the flight control module serves as a core subsystem whose performance directly determines the aircraft's stability and reliability. An optimized flight control system not only ensures stable flight under diverse complex environmental conditions but also provides precise attitude reference for mission payloads, thereby guaranteeing efficient data acquisition. Particularly when confronting extreme conditions such as gust disturbances and electromagnetic interference, advanced flight control algorithms significantly enhance system robustness and mission success rates through real-time state estimation and adaptive adjustments[12].

This article employs the Pixhawk 6C as the primary flight controller module for the aircraft, with the wiring definition diagram shown in the figure.

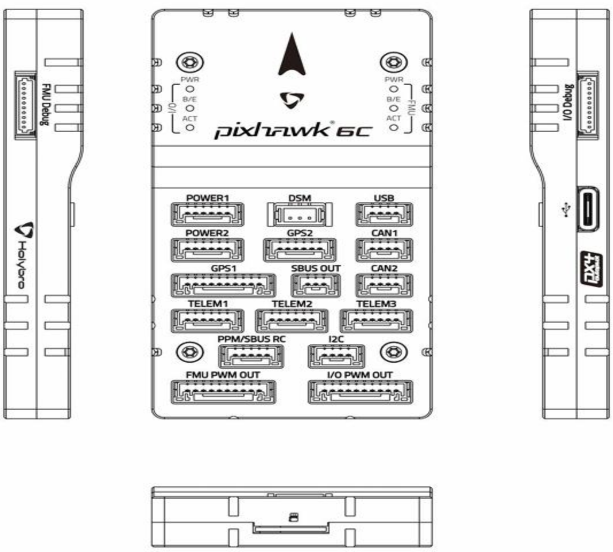

Figure 2-2 Primary Flight Control Module

The Pixhawk 6C, as the latest upgrade in the Pixhawk® flight controller series, continues the line's legacy of exceptional performance and reliability. At its core lies the STMicroelectronics® STM32H743 high-performance microcontroller, paired with Bosch® & InvenSense® high-precision sensor technology. This combination ensures flexible control while further enhancing system stability. This controller features an Arm® Cortex®-M7 core-based H7 processor operating at up to 480MHz, with 2MB flash memory and 1MB RAM, enabling efficient processing of complex flight control algorithms. Additionally, the Pixhawk 6C incorporates a high-performance, low-noise IMU (Inertial Measurement Unit). Its innovative IMU redundancy design significantly enhances system fault tolerance while optimizing costs, ensuring stable drone operation in harsh environments.

In summary, based on the Pixhawk 6C's outstanding flexibility, stability, and efficiency for real-time processing, this paper selects the Pixhawk 6C flight controller as the primary flight control module for the UAV platform.

2.2.2 Positioning Module Design

In drone applications for agricultural pest and disease monitoring, the stability of the flight system and positioning accuracy directly impact data collection efficiency and quality. To ensure stable flight in complex field environments and accurately capture spatial location data of pest and disease outbreaks—thereby significantly boosting operational efficiency and fully leveraging UAV technological advantages—this study integrates a high-precision GPS positioning module into the flight control system. This module not only delivers centimeter-level positioning data but also collaborates with the flight control system to enable autonomous route planning and precise hovering. This provides reliable spatial information support for rapid pest and disease identification and targeted control measures[13].

Figure 2-3 Positioning Module

The NEO-M8 is a high-performance concurrent GNSS module manufactured by U-blox, specifically designed for devices requiring multi-system reception capabilities (GPS, Galileo, GLONASS, and BeiDou). Building upon the strengths of previous NEO series products while incorporating technological advancements, this module supports multiple satellite systems to deliver enhanced positioning accuracy and navigation capabilities. Its core features include high-precision positioning, low-power modes, and compatibility with diverse application software.

2.3 Edge Computing Unit Selection

In drone pest and disease detection applications, the Raspberry Pi 4B 8GB stands out for its balanced performance, expandability, and cost advantages. Compared to the NVIDIA Jetson Nano, while the Jetson Nano offers stronger GPU acceleration, the RPi 4B 8GB's 8GB memory is better suited for processing high-resolution images and multi-sensor data at a lower cost. Compared to x86 platforms like the Intel NUC, the RPi 4B consumes less power (3-7W), making it more suitable for drone endurance requirements. Meanwhile, embedded solutions such as the STM32MP1 struggle to meet real-time AI inference demands due to limited computational power. Furthermore, the RPi 4B's extensive interfaces (GPIO, USB 3.0, CSI camera) facilitate integration with various agricultural sensors, reducing system complexity.

Figure 2-4 Raspberry Pi

The RPi 4B 8GB achieves an optimal balance between performance, power consumption, and cost, fully meeting the requirements of most pest and disease detection scenarios. Its 8GB memory ensures smooth operation of lightweight AI models like TensorFlow Lite, while its low-power design extends drone operational time. The mature Linux ecosystem and ROS support further streamline development workflows, making it an ideal choice for agricultural drone detection systems. For specialized scenarios requiring higher performance, the Jetson series may be considered; however, the RPi 4B 8GB remains the most cost-effective and easiest-to-deploy solution.

2.5 Sensor Types

The optical sensor system mounted on the drone includes multispectral/hyperspectral cameras (capturing crop reflectance data in the visible-near infrared spectrum), thermal imaging cameras (monitoring leaf temperature anomalies), LiDAR (constructing 3D canopy models), and high-resolution RGB cameras (providing intuitive visible light imagery). Fusion of these multi-source data provides comprehensive information support for pest and disease detection[14].

The multispectral/hyperspectral camera analyzes crop reflectance characteristics in specific bands (e.g., red edge, near-infrared) to calculate key metrics like NDVI (Normalized Difference Vegetation Index). Healthy leaves strongly reflect near-infrared light (700-1300nm) due to high chlorophyll activity, whereas crops affected by pests or diseases exhibit significantly reduced near-infrared reflectance caused by cellular structure damage. By establishing NDVI threshold models (e.g., healthy crops NDVI > 0.6, diseased areas NDVI < 0.3), early latent diseases can be quantitatively identified. Hyperspectral imaging primarily measures reflected light after interaction with matter, making it a surface measurement technique. When sunlight serves as a broad-spectrum light source, it is typically mounted on unmanned aerial vehicles (UAVs) and manned aircraft to scan large areas.

Figure 2-5 Applications of Multispectral Cameras

III. Software Design and Process

The software development is built on the Ubuntu system, with the camera transmitting 1080P HD image video streams via USB. The image processing module is developed using C++ and OpenCV 3.3.1. The system interface is designed and developed using the Qt Creator 5 IDE.

The overall design scheme is as follows:

1. The camera captures images of agricultural pests and diseases and transmits them to the RPi 4B 8GB development board for algorithm processing;
2. In low-visibility environments with complex weather conditions, the image enhancement module performs preprocessing on the images;
3. The detection module analyzes time-series images to identify targets suspected of being agricultural pests or diseases;
4. The recognition module conducts secondary identification on detected suspicious targets to confirm they are indeed pests or diseases;
5. The display panel shows real-time images of detected pests/diseases along with their coordinates.

3.1 Design of the UAV Data Acquisition Module

This agricultural pest and disease detection drone system integrates advanced flight control modules and high-precision positioning modules. It autonomously plans optimal flight paths, precisely locates target crop areas, and automatically adjusts to the optimal shooting altitude. During operations, the drone's high-resolution imaging system captures multispectral imagery of designated areas, storing and transmitting data in real time. The system employs intelligent task scheduling algorithms to ensure orderly imaging of collection points.

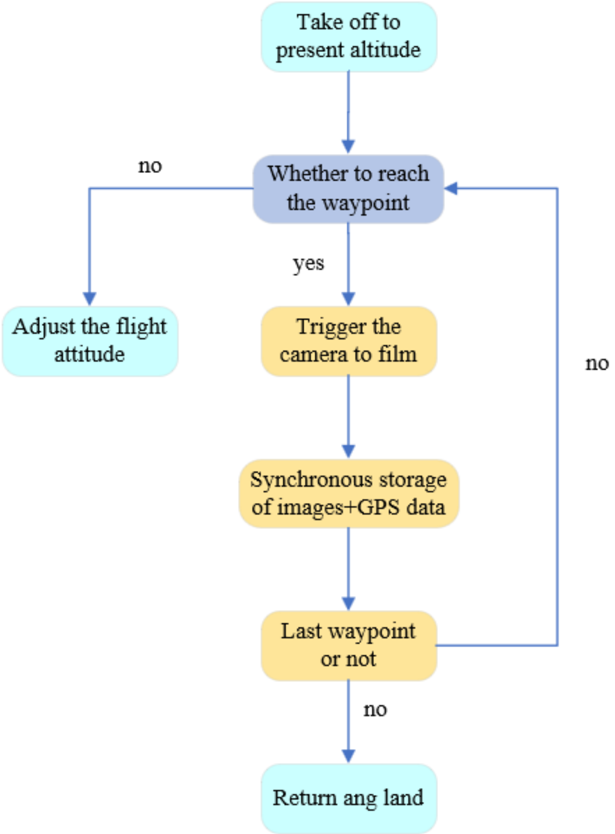

Figure 3-1 Drone Data Collection Flowchart

When detecting abnormal conditions such as low battery power, insufficient storage space, loss of communication signal, or poor lighting conditions, the embedded safety management system immediately triggers a multi-level emergency response mechanism. This includes safeguards such as automatic return-to-home, protective data storage, and task suspension pending further instructions, ensuring flight safety and data integrity.

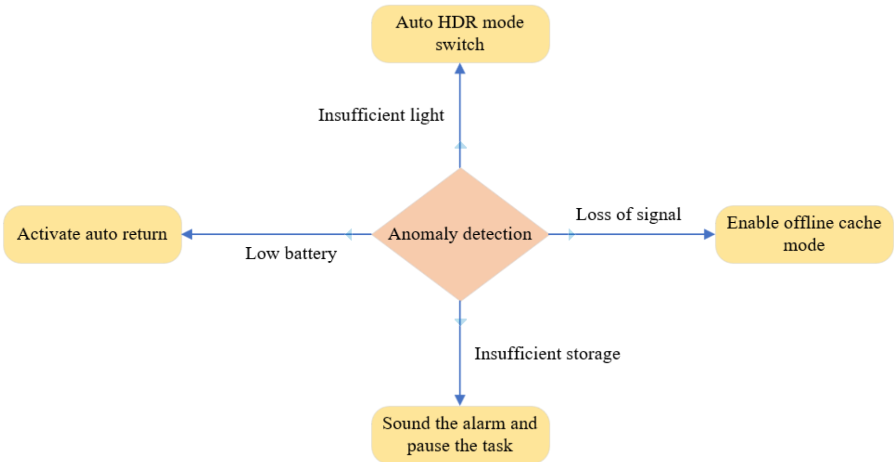

Figure 3-2 Anomaly Detection Processing

3.2 Intelligent Pest and Disease Analysis

In modern precision agriculture, intelligent recognition technology based on the YOLO (You Only Look Once) deep learning algorithm provides an efficient and accurate solution for detecting crop pests and diseases. Employing a one-stage detection architecture, it divides images into grids and directly predicts bounding boxes and class probabilities, achieving millisecond-level recognition. By training the YOLO model using annotated datasets of pest and disease images collected by drones, the model can automatically extract features such as color, texture, and shape of diseases while maintaining high accuracy in complex field environments.

The intelligent pest and disease analysis system based on the YOLO deep learning framework demonstrates significant technical advantages in agricultural detection. Beyond achieving millisecond-level image processing efficiency, it overcomes limitations of traditional detection methods by simultaneously identifying and classifying multiple pest and disease targets (such as leaf spot disease, aphids, spider mites, etc.) during a single scan, with recognition accuracy exceeding 90%. The system precisely locates pest and disease outbreak areas through advanced bounding box regression algorithms. Utilizing GPS modules mounted on drones, it achieves centimeter-level coordinate mapping, annotating detection results in real-time on digital farm maps to provide spatial decision-making support for subsequent precision pesticide application or manual intervention. By integrating NDVI vegetation indices with YOLO detection results, it enables quantitative assessment of pest and disease severity.

As shown in the figure above, this study constructed an intelligent analysis system for drone remote sensing imagery based on the YOLO deep learning framework. Through a multi-stage processing workflow, the system achieves precise detection and visual representation of agricultural pests and diseases. The system first performs standardized preprocessing on multi-source imagery data collected by drones, then employs an optimized YOLO model for efficient inference, and finally generates intuitive visual outputs through spatial statistical analysis.

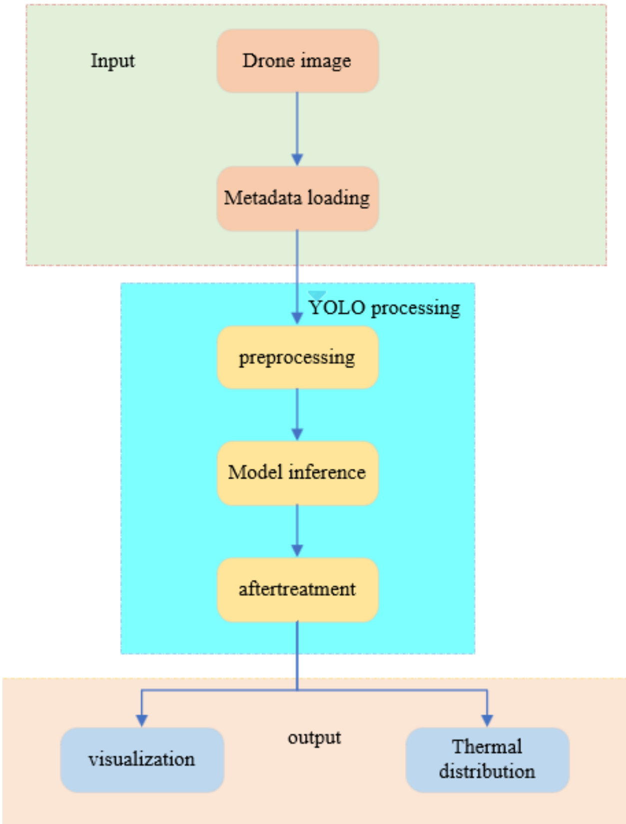

Figure 3-3 Analysis Flowchart

3.3 Image Enhancement Module Design

In drone-based agricultural pest and disease detection systems, this study proposes an efficient multimodal image enhancement scheme to improve image analysis accuracy and meet real-time processing demands. By integrating “adaptive illumination correction + multispectral NDVI enhancement + edge sharpening," this approach effectively addresses core challenges in complex field environments: light station adaptability issues, difficulties in early pest and disease identification, and bottlenecks in detecting minute targets.

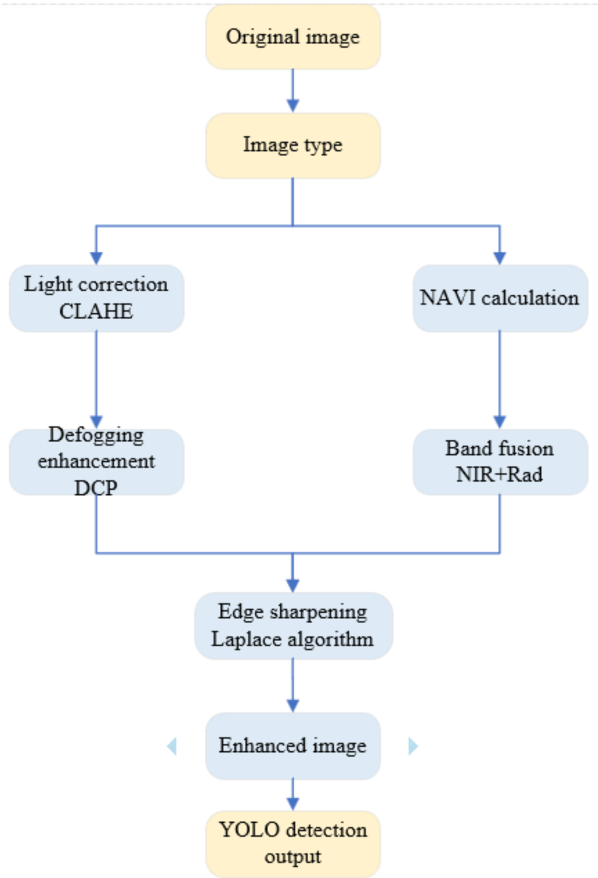

Figure 3-4 Image Enhancement Algorithm Design Process

Light correction achieves histogram equalization by segmenting images into blocks, preventing excessive global enhancement. This enhances contrast between diseased spots and healthy leaves, making wheat rust lesions more distinct, for example. The specific formula is as follows:

$$Lout(x,y) = CLAHE(Lin(x,y), clip_{limit} = 2.0, tile_{size} = 8 \times 8)$$

Multispectral NVDI enhancement highlights diseased areas by calculating vegetation indices using near-infrared (NIR) and red light bands. Early disease zones appear red in the false-color image. The specific formula is as follows:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

The principle of fog enhancement relies on dark-channel priors to estimate atmospheric light components, thereby reconstructing fog-free images. This process eliminates haze interference and enhances image clarity. The specific formula is as follows:

Calculate Dark Channel:

$$J^{dark}(x) = min_{y \in \Omega(x)} \left(min_{c \in \{r,g,b\}} J^c(y) \right)$$

Estimated transmittance:

$$t(x) = 1 - \omega \cdot J^{dark}(x)$$

IV. System Testing and Error Analysis

4.1 UAV Stability Testing

Agricultural drones face severe challenges from complex meteorological conditions during operations. Compared to traditional ground-based agricultural machinery, while drones are free from soil constraints, their low-altitude flight characteristics (typically operating at 2-10 meters) make them highly sensitive to meteorological disturbances. Specifically: - Wind speeds exceeding 5 m/s can cause flight path deviations and reduced positioning accuracy (RTK positioning errors increase 3-5 times); During hovering operations, excessive wind speeds drastically reduce image capture resolution, severely compromising pest and disease identification accuracy. More critically, sudden gusts may cause the aircraft to roll over, resulting in equipment damage and pesticide waste. The indirect losses from delayed crop protection are incalculable. To ensure operational safety and economic viability, a comprehensive stability testing system must be established after drone assembly and before field deployment. This system should include: static stability testing on a six-degree-of-freedom platform. This multidimensional, end-to-end testing approach ensures test results accurately reflect the drone's environmental adaptability while optimizing equipment configuration from a total lifecycle cost perspective. Ultimately, it achieves the optimal balance between operational efficiency and risk-cost control.

During hover stability testing, the drone is first flown to a specific altitude for hovering. Artificial disturbances are then applied to simulate real-world interference factors. A mobile phone records the entire process from disturbance onset to stability recovery. Recovery time is calculated by analyzing video frame rates. Through PID parameter optimization, center-of-gravity adjustments, and propeller enhancements, recovery time can be reduced by 30-40%, ultimately achieving an optimal balance between interference resistance and flight stability.

The above experiments were conducted in a safe and open environment, with the following results:

Table 4-1 Hover Stability Test

Number of tests	Maximum offser（m）	Recovery time（s）	Attitude angle fluctuation（°）
1	0.52	1.8	4.2
2	0.48	1.6	3.9
3	0.55	2.0	4.5
Mean value	0.52＋0.03	1.8＋0.2	4.2＋0.3

Table 4-2 Static Air Test

Wind speed（m/s）	Wind direction（°）	Lateral displacement（m）	Height fluctuation range（m）	Increase in battery power consumption（%）
3	0	0.12	0.05	＋8
5	45	0.35	0.12	＋15
8	90	1.08	0.30	＋28

Based on the above results, the agricultural drone meets the stability requirements specified in ISO 21384-3, satisfies design specifications, and is suitable for agricultural pest and disease detection.

5.4 Progressive Two-Factor Authentication

To validate the feasibility of the proposed system, this study employs an incremental validation strategy, conducting systematic experimental evaluations in phases.

Ground-based Static Image Detection Verification

First, we constructed an annotated dataset comprising eight typical rice pests and diseases (bacterial wilt, leaf streak disease, rice blast, brown spot disease, heart rot, dew disease, sheath blight, and Southeast Asian rice field disease). By controlling variables such as lighting conditions, shooting angles, and leaf lesion coverage, we evaluated the system's robustness in complex agricultural scenarios. The detection results are shown in the table below.

Table 4-3 Test Results

Types of pests and diseases	Precision P(%)	Recall rate R(%)	Average detection accuracy mAP@50 (%)
Wilt disease	86.3	79.7	88.1
Leaf spot disease	77.6	74.3	81.0
Brown spot disease	89.0	89.7	91.9
Withered heart disease	85.9	82.9	89.8
Droplet disease	93.9	95.2	97.7
Sheath rot	87.2	85.7	88.9
Southeast asian rice field disease	81.4	68.4	80.4
Rice blast disease	93.2	93.8	97.3

Test results demonstrate that this system exhibits outstanding performance in ground-based pest and disease detection, proving effective against multiple types of pests and diseases. This lays a solid foundation for its application in unmanned aerial vehicle (UAV) systems.

Verification of Dynamic Scene Transfer for Drones

Addressing the scarcity of publicly available datasets in the field of drone-based rice pest and disease detection, this study systematically collected field data to construct a specialized dataset, Sagittaria, tailored for this research. Detection results are presented in Tables 4–4.

Table 4-4 Test Results

Types of Pests and Diseases	Precision (%)	Recall rate (%)	Average detection accuracy $mAP_{@50}$ (%)
Sagittaria	95.4	95.8	96.3
Sagittaria-flower	92.5	91.7	94.6

In summary, this study addresses key technical challenges in intelligent drone-based detection of rice pests and diseases by proposing a high-precision detection model and constructing a specialized dataset. The system's outstanding performance was first validated using static ground-based imagery. Subsequently, the algorithm was optimized for dynamic drone detection requirements, enabling real-time detection of multiple concurrent pest and disease outbreaks. The system's reliability and superiority were further demonstrated through field validation using Sagittaria plants.

V. Conclusion

As a major agricultural nation, China's food security and social stability are directly tied to the prevention and control of crop pests and diseases. Traditional manual inspection methods are inefficient and struggle to address widespread, sudden pest and disease outbreaks, leading to significant crop losses. To address this challenge, this paper designs a crop pest and disease detection system based on drone remote sensing technology and deep learning. By integrating hardware and software, the system enables real-time detection, precise identification, and remote online monitoring of pests and diseases, providing an efficient, intelligent solution for modern agriculture.

The core design philosophy centers on deploying multi-modal sensors on a drone platform, integrated with edge computing and cloud management, to establish a comprehensive pest and disease monitoring system. The hardware components primarily include the drone platform, sensor array, edge computing unit, and communication module. The Pixhawk 6C serves as the primary flight controller, featuring a high-performance STM32H743 microcontroller and redundant IMU design to ensure stable flight in complex environments. The positioning module utilizes the NEO-M8 GNSS module, supporting concurrent multi-satellite systems and delivering centimeter-level positioning accuracy, laying the foundation for spatial distribution analysis of pests and diseases. The edge computing unit employs the Raspberry Pi 4B 8GB, leveraging its robust computational power and extensive interfaces to enable image acquisition, preprocessing, and real-time AI inference. The communication module employs a 4G/5G primary link with a satellite backup link working in tandem, ensuring real-time data transmission and system reliability.

Software-wise, the system leverages Python and deep learning technologies to build a comprehensive image processing and analysis workflow. First, multispectral and high-resolution images captured by the drone undergo preprocessing (including annotation, adjustment, and data augmentation) before being fed into a deep learning model based on the YOLO algorithm for pest and disease detection and classification. The single-stage detection architecture of the YOLO algorithm achieves millisecond-level recognition with over 90% accuracy. Concurrently, the system integrates NDVI vegetation index analysis to detect latent diseases early, providing scientific basis for precision pesticide application. Additionally, an image enhancement module was developed, employing adaptive illumination correction, multispectral NDVI enhancement, and edge sharpening techniques to significantly improve image quality in complex environments.

To ensure system stability and reliability, the team conducted comprehensive testing. Drone stability tests, including hover stability assessments and wind field simulations, validated the drone's interference resistance. Results showed lateral displacement of only 0.35 meters at 5m/s wind speeds, with a recovery time of 1.8 seconds—fully meeting agricultural application requirements. Performance testing of edge computing devices demonstrated that the Raspberry Pi 4B achieved a processing latency of 39 milliseconds and power consumption of 4.2W for single-frame pest detection tasks, meeting real-time processing demands.

System error analysis revealed the impact of multi-source errors, including motion blur, multispectral registration errors, and small target detection errors. To address these challenges, the team proposed a hardware-algorithm co-optimization solution: hardware-wise, adopting high-precision IMU modules and expanding multispectral bands; algorithm-wise, introducing Transformer-based multi-scale feature fusion networks and temporal convolutional networks (TCN) with dynamically adjusted detection thresholds, significantly improving recognition accuracy during seedling and mature stages.

The successful development of this system provides efficient and precise technical means for modern agricultural pest and disease control, with advantages manifested in four key aspects: First, UAV remote sensing technology enables large-scale, rapid farmland monitoring, significantly boosting operational efficiency. Second, the integration of deep learning models and multispectral analysis allows for early detection and precise localization of pests and diseases, providing scientific basis for targeted pesticide application. Third, the edge computing and cloud-linked architecture ensures real-time data transmission and processing, enabling farmers to implement timely control measures. Finally, the system's stable performance in complex environments demonstrates its robust adaptability, making it suitable for agricultural regions with varying climates and geographical conditions. These features collectively form an efficient, precise, real-time, and adaptable modern agricultural monitoring solution.

Through innovative hardware configurations and advanced algorithmic models, this drone-based pest and disease detection system successfully addresses the inefficiencies, imprecision, and lack of real-time capability inherent in traditional agricultural pest monitoring. Its stability, accuracy, and efficiency have been thoroughly validated in practical testing, providing robust support for the intelligent advancement of modern agriculture. Looking ahead, with further technological optimization and expansion, this system is poised to become a vital component of smart agriculture, making greater contributions to ensuring food security and promoting sustainable agricultural development.

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