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Research Progress in Agricultural Pest and Disease Diagnosis Technology based on UAV Remote Sensing

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Abstract: Crops are an important economic product in my country and an indispensable part of our daily life. Different crops such as wheat, cotton, and soybeans play their own important values. As the environment continues to change, various pests that endanger the healthy growth of crops emerge in an endless stream. The traditional technical means used by field workers to control pests and diseases on large-scale crops are inefficient and time-consuming. In recent years, with the in-depth research and development of science and technology, drone remote sensing technology has been widely used in the fields, greatly facilitating the work of workers and making traditional agriculture further develop towards smart agriculture. This paper summarizes the research progress of agricultural pest and disease identification technology based on drone remote sensing, mainly focusing on drone remote sensing technical means, algorithm models, and data sharing. Drone remote sensing identification of agricultural pests and diseases usually use a variety of technical means such as hyperspectral cameras, multispectral cameras, thermal infrared imaging, visible light imaging, and lidar. Then, the practical application of machine learning models and deep learning models in identifying pests and diseases is described in detail, and the combination of artificial intelligence and Internet of Things-enhanced systems in drone AI remote sensing agricultural data sharing is explored in the end. By analyzing existing studies, this paper summarizes the advantages and disadvantages of applying UAV remote sensing to agricultural pest and disease identification, and proposes innovative ideas, aiming to provide reference for the subsequent development of this field.

Keywords: UAV Remote Sensing; Agricultural Pest Identification; Algorithm Model; Data Sharing

1. Introduction

With the continuous growth of global population and the intensification of climate change, food security issues are becoming more and more serious. As a key factor affecting agricultural production, the monitoring and prevention of crop pests and diseases have become extremely important, because efficient and accurate pest and disease diagnosis technology can not only reduce the use of pesticides and reduce environmental pollution, but also improve crop yield and quality, thereby ensuring food security. Traditional pest and disease identification methods mostly rely on manual inspections for identification, which are inefficient, subjective, and difficult to achieve large-scale monitoring, and cannot meet the requirements of modern agriculture for efficiency and accuracy. In recent years, with the continuous advancement of remote sensing technology, UAV remote sensing, as an efficient, sensitive and high-resolution spatial big data collection tool, has shown great application potential in the identification of agricultural pests and diseases. UAV remote sensing can quickly obtain farmland images and data, and combine with advanced technical means and algorithm models to achieve accurate identification and dynamic monitoring of pests and diseases, providing strong support for the scientific prevention and control of agricultural pests and diseases. The IoT-enhanced systems integrate sensor and drone data to monitor crop growth in farmland in real time, and performs extensive data processing and rapid information transmission, thereby further implementing precision agriculture. With the rapid development of artificial intelligence and big data technology, the application potential of UAV remote sensing in pest and disease diagnosis has been further explored, laying a solid foundation for intelligent agricultural management and sustainable development.

2. UAV Remote Sensing Technology

2.1 Hyperspectral Camera

Hyperspectral cameras can provide details of crop spectral characteristics by obtaining information from hundreds or thousands of continuous and narrow spectral bands. For the identification of agricultural pests and diseases, hyperspectral cameras can capture the tiny spectral changes of crop leaves caused by pests and diseases. For example, after crops are damaged by pests and diseases, the chlorophyll content and water conditions have changed, and these changes are reflected in the changes in the reflectivity of specific bands on the hyperspectral image. Using hyperspectral data analysis, spectral features related to pests and diseases such as absorption peaks or reflection peaks in specific bands can be extracted to achieve the purpose of early identification and classification of pests and diseases. Hyperspectral cameras can accurately distinguish each wavelength and perform preventive detection on different parts of different crops. As shown in Table 1, summarizing the main crop parts measured by hyperspectral cameras at different wavelengths ranging from 300 to 14,000 nm, the typical crops targeted, and the applicable application areas.

Table 1. Crops and Application Areas Measured by Hyperspectral Cameras in Different Bands

Wavelength range	Specific wavelength (nm)	Measured crop section	Typical crop	Application area
UV band	300~400	Leaf epidermis, fruit wax layer	Grapes, Apples, Citrus	①Detection of early infection of pests and diseases ②Fruit ripeness
Blue light (visible light)	450~495	Leaf blade chlorophyll a, stomatal distribution	Wheat, Rice, Maize	①Assessment of photosynthetic efficiency ②Diagnosis of hydrogen deficiency
Green light (visible light)	500~570	Canopy structure, degree of leaf senescence	Potatoes, Cotton, Sugarcane	①Estimation of vegetation cover ②Crop senescence monitoring
Red light (visible light)	620~700	Leaf blade chlorophyll b, photosynthetically active zone	Spinach, lettuce, Tea tree	①Vegetation index NDVI calculation ②Yield prediction
Near infrared (NIR)	700~1300	Internal canopy structure, cell wall	Maize, Sorghum, Forage grass	①Water stress detection ②Biomass estimation
Short-wave infrared (SWIR)	1300~2500	Stem lignin, fruit moisture	Cotton, Potato, Dragon fruit	①Dry early stress detection ②Harvest maturity grading
Thermal Infrared (TIR)	8000~14000	Canopy surface temperature, transpiration	Rice, Wheat, Greenhouse crops	①Irrigation needs ②Disease/thermal anomaly warning
★Fluorescence band	685–740	Leaf blade photosynthesis fluorescence King signal	Corn, Tomato, Blue plum	①real-time monitoring of photosynthesis efficiency ②Photo-inhibition diagnosis

2.2 Multispectral Camera

Multispectral cameras can simultaneously collect spectral information of several specific frequency bands, including red light, green light, blue light, and near-infrared light. These bands are closely related to the growth status and health status of crops. In the process of identifying agricultural pests and diseases, multispectral cameras are often used to calculate various vegetation indicators, such as the Normalized Difference (Digital image grayscale calibration) Vegetation Index (NDVI). The occurrence of pests and diseases will cause damage to crop leaves and reduce photosynthesis, thereby causing a decrease in the NDVI value[1]. It is calculated using Normalised Difference Vegetation Index (NDVI) calculation formula in formula (1)[2], where $\mathrm{Ref}_{\mathrm{target}}$ represents the target reflectivity, that is, the electromagnetic waves reflected by the irradiated light from the leaves of crops and other parts, $\mathrm{DN}_{\mathrm{target}}$ represents the digital quantization value of the target, which is the value of the pixel corresponding to the part of the crop that reflects the electromagnetic wave in the imaging system, and $\mathrm{DN}_{\mathrm{dark}}$ represents the dark pixel. Digital quantization value is usually the pixel value output by the imaging system under no light input or extremely low light conditions, that is, it can detect the growth of crops even under low light conditions. $\mathrm{DN}_{\mathrm{white}}$ represents the digital quantization value of the white reference object, that is, the value of the corresponding pixel of the white standard reference object in the imaging system, which can measure the value of the crop part under extremely high exposure or high light reflection. $\mathrm{Ref}_{\mathrm{white}}$ represents the white reference reflectance, which is generally the reflectance of the white standard reference object with high reflectance. By monitoring the trend of NDVI changes, it can indirectly reflect the occurrence and development of pests and diseases. Multispectral cameras can also be combined with other vegetation indicators, such as leaf area index (LAI) and vegetation coverage, to further improve the recognition accuracy of pests and diseases.

Normalised Difference Vegetation Index (NDVI) calculation formula:

$$\mathrm{Ref}_{\mathrm{target}} = \frac{\mathrm{DN}_{\mathrm{target}} - \mathrm{DN}_{\mathrm{dark}}}{\mathrm{DN}_{\mathrm{white}} - \mathrm{DN}_{\mathrm{dart}}} * \mathrm{Ref}_{\mathrm{white}} \quad (1)$$

Crops reflect different health conditions due to their types, growth stages and environmental backgrounds, and the NDVI values calculated based on the index displayed by the multispectral camera are also different.

Generally speaking: NDVI>0.6: vegetation is healthy and photosynthesis is significant

NDVI 0.3~0.6: There may be mild stress or growth transition period

NDVI < 0.3: Vegetation is severely damaged, possibly affected by pests or drought

2.3 Thermal Infrared Imaging

Thermal infrared imaging technology can reflect the physiological state and the occurrence of pests and diseases by capturing the thermal radiation information on the surface of crops. When crops are damaged by pests and diseases, their physiological activities change, causing abnormal changes in surface temperature. Figure 1 shows a bird's-eye view of a drone using thermal infrared imaging technology to scan the growth status of crops in farmland. For example, pest and disease infection can cause metabolic disorders in local crop tissues and cause the temperature in the area to rise or fall. Thermal infrared imaging can monitor the temperature distribution on the surface of crops in real time, and determine the location and range of pest and disease occurrence by analyzing the temperature abnormality area[3]. Figure 2 specifically shows the drone presenting different levels of thermal infrared images of the scanned area. Compared with visible light and multispectral imaging, thermal infrared imaging is less affected by lighting conditions and can be used for monitoring at night or in low-light environments.

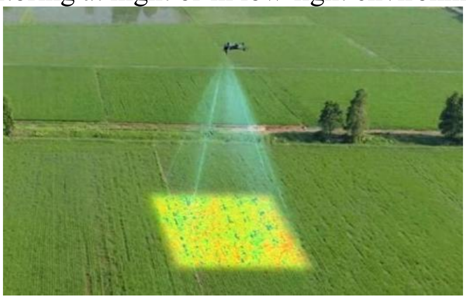

Figure 1. Drone Thermal Infrared Imaging Technology for Agricultural Field Overview

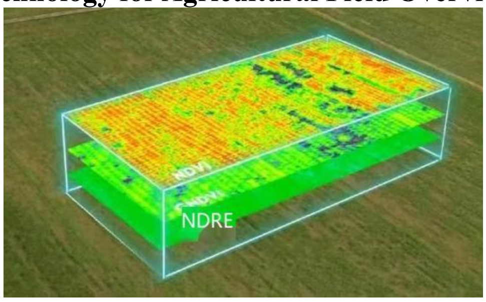

Figure 2. Different Levels of Thermal Infrared Imaging

2.4 Visible Light Imaging

Visible light imaging can intuitively show the appearance characteristics of crops by collecting color images of farmland through drones carrying visible light cameras. In terms of agricultural pest and disease identification, visible light imaging can observe the symptoms of pests and diseases such as color changes, spots, curling and wilting of crop leaves. The type and distribution range of pests and diseases can be preliminarily determined by analyzing visible light images. However, the ability of visible light imaging to identify some early or hidden pests and diseases is limited, and it needs to be combined with other technical means to improve its recognition accuracy.

2.5 LiDAR

LiDAR can obtain high-precision three-dimensional structural information[4] of the crop canopy by emitting laser pulses and measuring the return time of the reflected light. In the field of agricultural pest identification, LiDAR can provide information on crop plant height, canopy density and leaf distribution, and leaf distribution information is closely related to the health of crops. When crops are attacked by pests and diseases, they will grow abnormally, such as the height of the plants decreasing and the canopy becoming sparse. These changes can be detected through the three-dimensional data obtained by LiDAR. Table 2 summarises the working principles of lidar, the information it provides, its relationship with crop health, pest and disease detection methods, and data fusion capabilities. LiDAR also has the ability to fuse data with other sensors, such as spectral data, which helps to further improve the accuracy and stability of pest and disease detection. Table 3 summarises the performance of five different sensors under different weather conditions.

Table 2. Functions of LiDAR in Agricultural Pest Identification

Function	describe
How it works	Emit laser pulses, measure the return time of reflected light, and obtain high-precision three-dimensional structural information of crop canopies
Information provided	Crop height, canopy density, and leaf distribution information
Relationship to crop health	Leaf distribution information is closely related to crop health
Pest and disease detection methods	Detect abnormal growth caused by pests and diseases, such as plant height loss and sparse crowns, through 3D data
Data fusion capability	Data fusion can be performed with other sensors (such as spectral data) to improve the accuracy and stability of pest and disease detection

Table 3. Working Status of Different Sensor Types under Different Weather Conditions

weather conditions / Sensor type	Sunny (no clouds/few clouds)	Cloudy/overcast	Rainy weather/light rain	Foggy weather/light fog	Strong wind
Hyperspectral camera	Optimal condition 1. High signal-to-noise ratio, rich spectral details 2. Accurate identification of subtle spectral characteristics	Available but limited 1. Insufficient light causes a decrease in signal-to-noise ratio. 2. Spectral resolution and recognition accuracy decrease. 3. Partial diagnostic analysis is still possible.	Extremely poor results 1. Raindrops severely obstruct and scatter the spectral signal. 2. Water on the lens affects imaging. 3. High flight safety risk.	Not available 1. Water vapour/aerosols strongly absorb and scatter specific wavelengths. 2. Spectral information is severely distorted. 3. Penetration ability is weak.	Difficult to operate 1. Drone shaking causes blurred images/difficult stitching 2. May affect imaging stability 3. Diagnostic accuracy decreases
Multispectral camera	Excellent condition 1. Adequate sunlight, accurate calculation of vegetation indices (NDVI, NDRE, etc.) 2. Effective monitoring of stressed areas and changes in health	Good results 1. More robust to changes in light intensity than hyperspectral sensors 2. Commonly used vegetation indices still provide a good reflection of crop conditions 3. The preferred optical sensor for cloudy days	Extremely poor results 1. Raindrops severely obstruct and scatter the spectral signal. 2. Water on the lens affects imaging. 3. High flight safety risk.	Restricted 1. Fog scattering affects the visible light to near-infrared wavelength range. 2. Image blurring and reduced contrast. 3. Decreased accuracy of vegetation indices.	Difficult to operate 1. Drone shaking causes blurred images/difficulties in stitching 2. Affects spatial analysis accuracy
Thermal imaging	Excellent condition	Basically unusable 1. Clouds emit	Not available 1. Rain	Seriously restricted 1. Fog/water	Operational difficulties

	1. Accurate surface temperature information 2. Effective detection of abnormal canopy temperatures (hot spots) caused by pests, diseases, and water stress	thermal radiation, which strongly interferes with ground signals. 2. Data is severely distorted or there is no valid data.	significantly alters leaf temperature 2. Water on the lens affects temperature measurement 3. High flight safety risk	vapour absorbs and emits thermal radiation, interfering with temperature measurement. 2. The surface temperature information obtained is unreliable.	1. Wind accelerates leaf transpiration/heat dissipation, which may temporarily alter canopy temperature. 2. Drone shaking affects image stability and temperature measurement accuracy.
Visible light imaging	Optimal condition 1. High resolution and clarity 2. True colour reproduction	Good results 1. Even lighting, no strong shadows 2. Colours are slightly faded but details are well preserved	Poor results 1. Water on the lens causes blurring and glare. 2. Increased image noise and loss of detail.	Seriously restricted 1. Blurred images, reduced contrast 2. Difficulty identifying distant targets	Difficult to operate 1. Drone shaking may cause blurry images. 2. Motion artefacts may occur.
laser radar	Excellent condition 1. High point cloud quality and accurate structural information 2. Effective analysis of changes in canopy structure (height, density, gaps) (possible impact of pests and diseases)	Excellent condition 1. Active light source, unaffected by lighting conditions 2. Strong ability to penetrate thin clouds 3. Stable point cloud quality and reliable structural information	Seriously restricted 1. Raindrops reflect/scatter laser pulses, generating a large number of noise points. 2. Weak ability to penetrate raindrops, resulting in few effective echoes. 3. High flight safety risk.	Limited but usable 1. Fog/aerosols scatter lasers, attenuate signal strength, reduce point cloud density and effective detection distance. 2. However, some structural information can still be obtained.	Operational difficulties 1. Strong winds cause crops to sway violently, resulting in ‘blurred’ point clouds. 2. Affects the measurement accuracy of canopy structure parameters (such as height and gap rate).

3. UAV Remote Sensing Algorithm Model

3.1 Machine Learning Model

Machine learning models have an important impact on the identification of agricultural pests and diseases by UAV remote sensing. Common machine learning algorithms include decision trees, clustering, Bayesian classification, random forests, support vector machines, and k-nearest neighbor algorithms. These algorithms extract and analyze spectral features, texture features, and color features from remote sensing data to build pest and disease identification models. For example, the decision tree algorithm can divide the data according to different feature thresholds and gradually construct decision rules to achieve the purpose of pest and disease identification[5]. The random forest algorithm makes the model more stable and accurate based on the construction of multiple decision trees and ensemble learning. The calculation method of the support vector machine is to complete data classification by finding the best hyperplane. It shows excellent processing performance for both high-dimensional data and small sample data. In the process of establishing a machine learning model, remote sensing data needs to go through a series of preprocessing steps, including format adjustment, data cleaning, data splicing and correction, etc. Figure 3 shows the four main parts of the machine learning model for unmanned aerial vehicle remote sensing technology: common algorithms, feature extraction and analysis, model construction, and remote sensing data pre-processing, which are integrated into a general framework. Table 4 compares the characteristics of five commonly used types of algorithms: decision trees, clustering, Bayesian classification, random forests, and support vector machines.

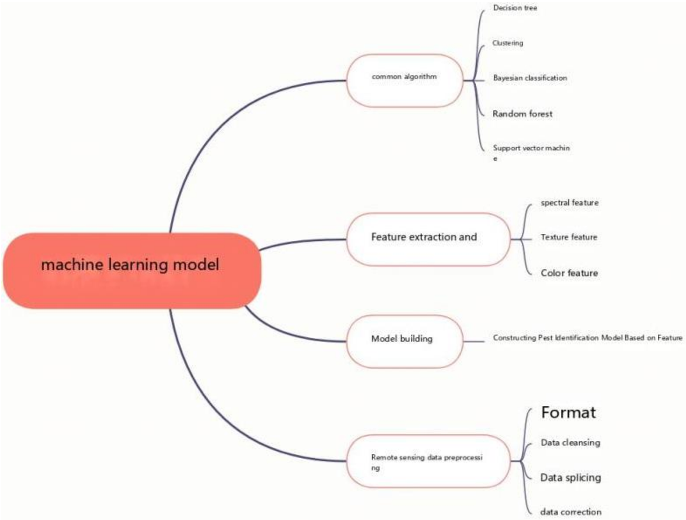

Figure 3. Main Components of a Machine Learning Model

Table 4. Different Characteristics of Five Common Algorithms

Features	Decision Tree	Clustering (K-Means)	Bayesian Classification (Naive)	Random Forest	Support Vector Machine
Type	Supervised learning	Unsupervised learning	Supervised learning	Supervised learning	Supervised learning
Work objectives	Data segmentation	Data point grouping	Probability prediction categories	High-precision classification /regression	Find the optimal surface to maximize the boundary
Training speed	Fast	Fast	Very fast	Slower	Slow
Predicted speed	Fast	Fast	Very fast	Moderate	Fast
Missing value handling	Possible	Difficult	Possible	Possible	Difficult
Feature correlation processing	Not sensitive	Sensitive	Uncertain (assumed independent)	Not sensitive	Sensitive
Capturing nonlinear relationships	Possible	Possible	Limited	Strong	Strong
Key advantages	Simple and fast	Unsupervised learning	Fast prediction	High accuracy	Strong nonlinear boundaries
Key disadvantages	Easy to overfit	Sensitive parameters/ distribution	Feature independence assumption does not hold	Slow to train	Slow to train, difficult to adjust parameters, requires preprocessing

3.2 Deep Learning Model

With the rapid growth of data, the rapid improvement of algorithms and the continuous improvement and maturity of algorithms, deep learning models have been widely used in the identification of agricultural pests by drone remote sensing. Deep learning models have strong feature learning and expression capabilities and can automatically mine deep features from massive remote sensing data. Commonly used models in deep learning include convolutional neural networks (CNN), recurrent neural networks (RNN) and their various versions. CNN has excellent image classification and target detection performance. It extracts local and global features from images through convolution and pooling with remote sensing images to achieve the purpose of accurately identifying pests and diseases[6]. The RNN method is particularly suitable for processing continuous data, such as time series remote sensing images, which can capture the dynamic changes of pests and diseases over time.

4. Drone AI Remote Sensing Enables Agricultural Data Sharing

4.1 Artificial Intelligence

Artificial intelligence technology is the core of UAV AI remote sensing agricultural data sharing. Artificial intelligence algorithms can intelligently analyze and process the massive remote sensing data collected by UAVs and extract data of great value. For example, natural language processing technology can be used to mine text from pest and disease reports and related literature to obtain knowledge on the types, patterns and prevention methods of pest and disease occurrence. At the same time, artificial intelligence can also automatically label and classify data to improve data processing efficiency[7]. In data sharing, artificial intelligence can build an intelligent data platform to uniformly manage and share data, use data mining and knowledge discovery technology to mine shared data, discover the patterns and patterns therein, and provide decision support for the identification and prevention of agricultural pests and diseases.

4.2 Internet of Things-Enhanced Systems

IoT-enhanced systems are the infrastructure and technical support for drone AI remote sensing to share agricultural data. By deploying a variety of IoT sensors in farmland, such as meteorological sensors, soil moisture sensors, and crop growth sensors, it is possible to capture the environmental conditions of farmland and crop growth data in real time. These data combined with drone remote sensing data can provide a more comprehensive understanding of the true conditions of farmland, thereby improving the accuracy of pest and disease identification[8]. Figure 4 illustrates the five specific process segments of unmanned aerial vehicle (UAV) remote sensing IoT-enhanced systems: data collection, data transmission, data processing and analysis, data sharing and application, and feedback and optimisation. These segments are implemented to achieve precise agricultural information processing and form a closed-loop connection. Through IoT-enhanced systems, data can be transmitted and shared remotely, which enables the information collected by drones and sensors to be uploaded to the cloud in real time, providing convenient access and use for agricultural researchers, management, and farmers.

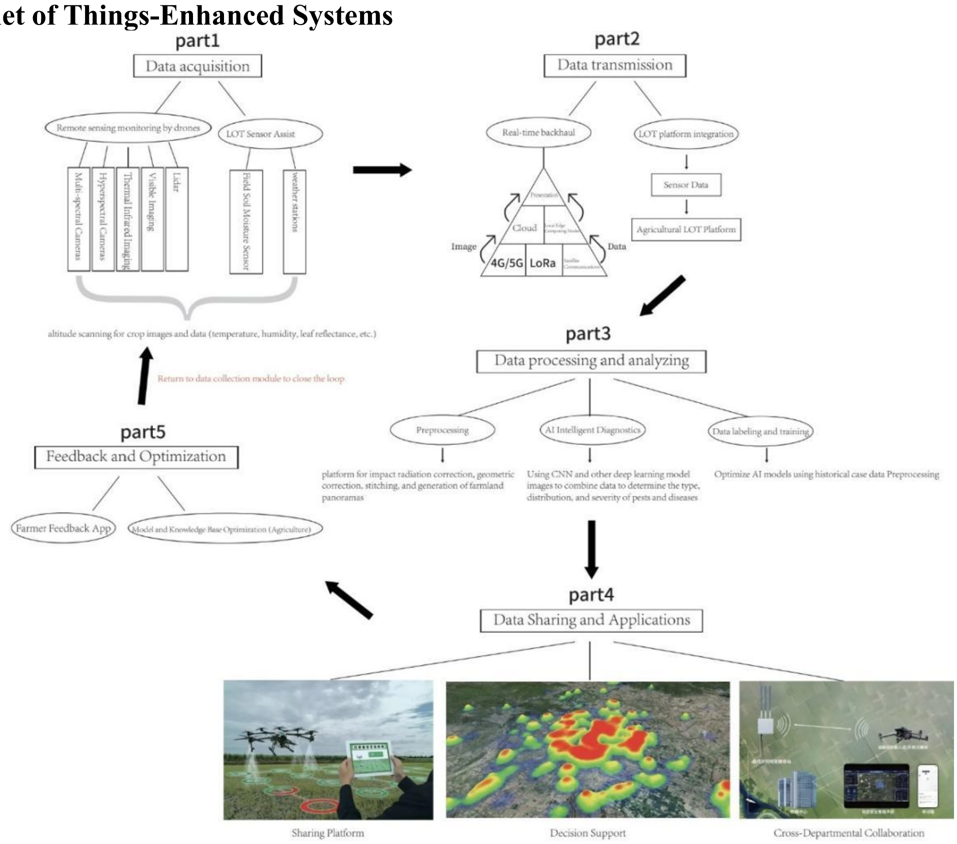

Figure 4. Process of Realizing Agricultural Data Sharing using Drone Remote Sensing IoT-Enhanced Systems

5. Advantages and Disadvantages of Current UAV Remote Sensing Research

5.1 Advantages

UAV remote sensing has many advantages for the identification of agricultural pests and diseases. First, UAVs have high imaging capabilities. UAVs have strong imaging capabilities and can obtain centimeter-level to sub-meter-level images. They can clearly observe subtle changes in crops and help to detect pests and diseases early [9] . Second, UAVs are flexible and responsive. They can be quickly deployed to designated areas and complete large-scale farmland data collection in a short period of time, which meets the timeliness requirements of pest and disease monitoring. UAV remote sensing technology can be equipped with a variety of sensors, such as hyperspectral cameras, multispectral cameras, and thermal infrared imaging. These sensors can capture rich surface data and provide all-round data support for the identification of pests and diseases.

5.2 Disadvantages

However, UAV remote sensing also has shortcomings in identifying agricultural pests and diseases. On the one hand, the endurance of UAVs is limited. Most UAVs have a flight time of only about 1-2 hours, which limits their ability to conduct continuous monitoring in large areas. On the other hand, complex weather conditions such as strong winds and rainfall will affect the flight stability of UAVs and the quality of data collection. The processing and analysis of UAV remote sensing data is very complex, especially multi-spectral, hyperspectral and lidar data, which require the support of professional technology and software[10]. The current standards and specifications for UAV remote sensing identification of pests and diseases are not yet sound, and the data processing methods and results of various research teams and units will also be different, which will affect the comparability and sharing of data.

6. Improvement Methods

In order to further enhance the role of UAV remote sensing in identifying agricultural pests and diseases, the following innovative ideas can be proposed. First, research and develop UAV technology with long endurance, such as using hydrogen fuel cells and solar-powered UAVs to extend the flight cycle of UAVs and expand their monitoring range. Second, increase the research efforts on multi-sensor collaborative technology, deeply integrate optical, lidar, thermal infrared and other multi-sensor data to improve the accuracy and reliability of pest and disease identification[11]. Unified standards and specifications for UAV remote sensing agricultural pest and disease identification have also been formulated, and data processing and analysis methods have been standardized to facilitate data sharing and exchange. At the same time, blockchain technology is combined to ensure data security and reliability, transparent sharing and traceability. Finally, strengthen cooperation with agricultural research institutions, universities and enterprises to conduct interdisciplinary research and combine UAV remote sensing technology to study agricultural biology and ecology knowledge, and gain a deep understanding of the occurrence mechanism and propagation law of pests and diseases.

7. Conclusion

The application of UAV remote sensing in agricultural pest identification has broad prospects, and research on technical means, algorithm models and data sharing continues to advance. Hyperspectral cameras, multispectral cameras, thermal infrared imaging, visible light imaging and lidar technology provide a large number of data sources for pest identification; machine learning models are combined with deep learning models to improve the accuracy and efficiency of pest identification; artificial intelligence, Internet of Things + and other technologies promote agricultural data sharing and intelligent application. However, there are still certain defects in the application of UAV remote sensing, which needs further research and improvement. The method of developing long-endurance UAVs, strengthening multi-sensor collaboration, formulating unified standards and strengthening interdisciplinary cooperation is proposed, which is expected to promote the in-depth development of UAV remote sensing in agricultural pest identification.

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