Review Paper

Research Progress on Non-Destructive Detection of Crop Diseases Using Hyperspectral Imaging Technology

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Abstract. Spotting plant ailments without harming the crop is a cornerstone of yield and quality protection: early warning curbs chemical overuse and shields farm income. Here we outline how hyperspectral cameras pick up pre-visual leaf stress, then survey global progress that couples these image cubes to support-vector classifiers, partial-least-squares regressors and deep convolutional networks for pinpoint disease identification. analyzes the principles and classification processes of hyperspectral image recognition algorithms for crop diseases, compares the advantages and disadvantages of three deep learning algorithms [Deep Belief Network (DBN), Stacked Autoencoder Network (SAE) based on Autoencoder (AE), and Convolutional Neural Network (CNN)] in the recognition of hyperspectral images of crop diseases and pests; explains the calculation process and principles of common deep learning classification metrics; points out the problems faced in hyperspectral detection and recognition of crop diseases: different objects with similar spectra, complicated data preprocessing and feature extraction processes, small data volume, and imbalanced training data, and suggests future research directions to address these issues.

Keywords: *Hyperspectral Imaging; Crop Diseases; Non-Destructive Detection; Deep Learning; Support Vector Machine*

1. Research on Change Detection Methods Based on Spectral Trend Features and Spatial Information

1.1 Spectral Detection Methods

Both human activities and natural changes are affecting land surface changes. The land surface environment is crucial for humanity, closely related to global climate, ecological environment, and the distribution and utilization of urban resources [1]. Early on, to accurately obtain changes in land cover types, people could only collect surface information by organizing field surveys. However, this method was time-consuming, labor-intensive, and made it difficult to obtain data in areas like forests, swamps, mountains, and deserts. The emergence of remote sensing technology provided an effective means for detecting changes on the Earth's surface [2].

In 1972, the U.S. placed ERTS-1—later rebranded Landsat-1—into orbit, opening the first page of the long-running Landsat chronicle and ushering in the modern era of planetary monitoring [3]. Since then, countries worldwide have invested significant effort into developing aerial satellite technology. With the rapid development of sensor technology, computer technology, and aerospace technology, remote sensing data now exhibit the characteristics of "three multiples" (multi-angle, multi-platform, multi-sensor) [4], and image acquisition boasts advantages such as near real-time capability, short revisit times, and wide coverage [5]. As remote sensing technology continues to develop, the data applied to change detection are becoming

increasingly abundant. Common data sources include satellite optical imagery, SAR imagery, and low-altitude UAV imagery [6-8]. The advantages, disadvantages, and usage scenarios of various data types are shown in Table 1.

Table 1. Characteristics and Usage Scenarios of Common Image Data Sources

Data Type	Advantages	Disadvantages	Usage Scenarios
Satellite Optical Imagery	Periodic acquisition, rich bands, wide coverage	Susceptible to weather conditions	Land cover type detection, urban and rural construction planning
SAR Imagery	All-weather, strong penetration, unaffected by weather	Lower spatial resolution, presence of speckle noise	3D reconstruction, 3D stereoscopic studies
Low-Altitude UAV Imagery	High timeliness, high spatial resolution	Relatively small ground object coverage	Building change detection, large-scale mapping

Multi-date optical scenes from orbit remain the work-horse for change-detection studies, guiding decisions in urban sprawl analysis, precision farming, forest inventories, water budgeting, defence mapping, disaster audits and broad-scale resource surveys [9,10].

In recent years, scholars have proposed numerous change detection methods from different perspectives and made significant progress. However, due to the complexity of the natural environment, there is no universal method that can handle remote sensing images under different conditions [11-13]. While improving image spatial resolution, spectral resolution is often sacrificed, leading to large spectral differences among similar ground objects [14], while different ground objects may exhibit similar spectral characteristics. Using only single spectral feature information makes it difficult to achieve good detection results [8, 15].

Based on research into traditional optical remote sensing image change detection methods, this paper fully integrates spectral features and spatial information to enhance the reliability of change information and proposes change detection methods from both pixel-level and object-level perspectives.

1.2 Domestic and International Research Status

1.2.1 Research Status of Pixel-Based Change Detection Methods

Pixel-level change detection methods take pixels as the research object, comparing pixels at the same location in images from different times one by one, and determining whether a change has occurred based on differences in spectral features. Pixel-level change detection methods mainly include algebraic operation methods and post-classification comparison methods.

Common algebraic operation methods include difference method and ratio method. After extracting difference information based on algebraic operations, it is often necessary to set a segmentation threshold to binarize the difference image. SAMIH [16] used TM imagery from 1983 and ETM+ imagery from 2004, employing the difference method to identify changes in irrigated areas. Ralf Koller et al. [17] used pixels as the analysis unit to quantitatively analyze forest vegetation deforestation. Algebraic operation methods have small computational requirements and are easy to implement, but the detection effect depends on the segmentation threshold. Furthermore, when processing complex ground object imagery and high-resolution imagery, severe "salt-and-pepper noise" often occurs, resulting in less than ideal detection results. The post-classification comparison method involves classifying ground object categories in images from different time phases and then comparing the ground object category information pixel by pixel. This method can obtain both the changed area and the change category information. Its disadvantage is the accumulation of classification errors; if the classification accuracy is insufficient, it can seriously affect the accuracy of the change detection results.

To squeeze extra reliability and accuracy out of the process, researchers later folded in Principal Component Analysis and Change Vector Analysis, techniques that distill the spectral shift into cleaner, more interpretable axes. PCA can effectively reduce image redundancy and emphasize change information, making it widely used in multispectral data. Li Chenglong et al. [18] applied the PCA method to earthquake disaster detection work. Celik [19] used PCA to extract orthogonal feature vectors and combined them with K-means clustering to divide the feature vector space into two clusters, obtaining the final change detection result. Huang Wei et al. [20] used PCA to extract change information from images and then performed differential operations to construct a difference image. CVA performs differential operations on data from various bands under images of different time phases to solve for the amount of change at each pixel. It is a widely used unsupervised classification detection method. Zeng Zifang et al. [21] used the Otsu method to segment the difference image obtained by the CVA method. Liu Yangyang et al. [22] combined the oscillation index with the CVA method to achieve change detection in the Yangtze River Basin. Chen et al. [23] used a Support Vector Machine (SVM) to classify images and obtain pixel class membership information. Then, based on the CVA method, they performed differential operations on the posterior probability information to obtain the change category information of the pixels.

In addition to the above pixel-level detection methods, Bruzzone et al. [24] used the Expectation-Maximization algorithm for unsupervised estimation of prior probabilities and density functions of pixels. Zhu et al. [25] proposed an algorithm based on the Maximum Autocorrelation Factor and Gaussian Mixture Model to obtain difference images, effectively reducing the impact of spectral band correlation on change detection. Ashish et al. [26] explored the regularity of adjacent pixel changes based on spatial contextual information. Kusetogullari et al. [27] proposed an unsupervised change detection method for multispectral images based on a parallel binary particle swarm optimization algorithm, which has good noise immunity. Turgay [28] proposed an unsupervised change detection method for difference images using a genetic algorithm.

Although research on pixel-level change detection methods is relatively mature, many pixel-level methods are based on single spectral features and have weak noise immunity. Additionally, many pixel-level methods use direct grayscale difference operations on images in the difference information extraction step, ignoring the spatial correlation of pixels.

1.2.2 Research Status of Object-Based Change Detection Methods

Traditional pixel-level change detection methods often suffer from severe "salt-and-pepper noise" [29, 30] when processing high-resolution images, yielding unsatisfactory results [31, 32]. To solve this problem, the object-oriented concept was introduced into the field of change detection. The research target is no longer a single pixel but homogeneous region objects that are highly similar in aspects such as spectrum and texture [33, 34].

Object-oriented approaches slice the scene into spectrally uniform patches, then track how each segment evolves through time. They can more fully utilize the feature information of the image, especially when processing high-resolution images, often achieving high detection accuracy.

Junfeng Xu [3] stacked texture-shape-context descriptors on image segments and let an SVM pin down the separating hyper-plane, lifting both precision and trust in the change label. Toure et al. [35] adopted the same philosophy to chronicle Africa's urban sprawl, while Hou et al. [36] fed SLIC super-pixels into a Random-Forest engine to flag newly erected buildings in very-high-resolution scenes. Lv et al. [37] introduced an object strategy into a hybrid conditional random field model to extract spectral feature information. Pei Huan et al. [38] analyzed the Gray-Level Co-occurrence Matrix to obtain optimal GLCM texture features and detected changes in land use types based on an overall optimal segmentation strategy. Wu et al. [39] constructed an index to measure object homogeneity and tested it on GF-1 imagery and imagery obtained from Google Earth. Kindu et al. [40] used object-based image classification technology to analyze land cover type changes in Ethiopia from 1973 to 2012. Chen et al. [41] combined object-based multi-feature analysis with the change vector method, proposing an adaptive weight change vector analysis algorithm that improved the detection accuracy of high-resolution images. Wu et al. [42] proposed a binarization technique based on a Weibull mixture model to process image patches; this method showed improved accuracy compared to classical binarization methods. Zhang et al. [43] used an incremental segmentation method to segment images, selected the optimal combination of spectral

and texture features through the Optimal Index Factor method, and constructed feature spaces for images from different times. Wang et al. [44] introduced an unsupervised approach that couples cross-sharpening with segmentation to suppress false alarms triggered by viewing-angle shifts or sub-pixel mis-registration between dates. Nguyen-Thanh Son et al. [45] used an object-based image analysis method to assess changes in mangrove area within the study area by detecting Landsat images acquired from 1979 to 2013.

Compared to pixel-level methods, object-level methods perform better when processing high-resolution images, as they can more fully utilize spatial and spectral information. However, image processing accuracy is greatly influenced by the segmentation scale factor.

2. Research Progress in Hyperspectral Image-based Detection and Identification of Crop Diseases

In recent years, due to the severity of crop diseases in China, the vast affected areas, the significant proportion of grain loss, and the suboptimal effectiveness of control measures in recouping losses, disease detection in crops has become extremely important in the crop disease control process. Traditional crop disease diagnosis methods include: 1) Disease symptom observation method, which combines morphological characteristics of pathogens and past experience for identification, but it is highly subjective and heavily reliant on crop disease experts; 2) Enzyme-linked immunosorbent assay (ELISA), which can sensitively detect viral protein content in crops but is expensive and less applied in the detection of bacterial and fungal diseases in crops. With the rise of precision agriculture, imaging technology has provided new ideas for crop disease identification and has become an important technical means to replace traditional detection methods. Hyperspectral imaging technology offers advantages over traditional identification techniques in the crop disease identification process, such as being non-destructive, timely, highly accurate, and environmentally friendly. It can detect changes in internal physiological information during the early stages of crop infection, including proteins, enzymatic antioxidant indicators, amino acids, etc. Compared to other imaging technologies like machine vision and infrared thermal imaging, it has higher sensitivity for early-stage crop disease identification. This review tracks how hyperspectral snapshotting, teamed with deep-learning interpreters, is pushing rapid, zero-damage diagnosis of crop diseases.

Principle of Hyperspectral Imaging Technology for Crop Disease Detection:When crops are under disease stress, their internal physiological activities and external physical structures change, and their spectral characteristics also change accordingly. This change indirectly reflects the physiological characteristics of crops under disease stress. Therefore, changes in spectrum can be used to monitor early disease conditions in crops. The wavelength of light spans a very wide range. The human eye can only see wavelengths from 400-700 nm, which can reflect the phenotypic characteristics of crops, such as wilting, yellowing, and damage. Wavelengths below 400 nm are ultraviolet light, and those above 700 nm are infrared light; these are bands that the human eye cannot directly observe. These bands often can reflect deeper internal physiological characteristics of crops, such as protein content, water content, and changes in mesophyll cells. Hyperspectral imaging technology typically divides the visible to near-infrared light band (400~1000 nm) into dozens or even hundreds of adjacent narrow bands and performs imaging separately in each narrow band. Images reveal the canopy's surface signature; spectra expose its inner chemistry and physiological state. Therefore, hyperspectral images contain very rich information. In recent years, this technology has been widely applied in food crops, economic crops, vegetable crops, and fruits.

2.1 Research on Hyperspectral Image Recognition of Early Crop Diseases

Image recognition refers to the process of extracting image features as targets and establishing a classifier to achieve target recognition. Stable, fast, and highly accurate recognition algorithms have always been the pursuit of researchers. Recognition can be based on shape, texture, statistics, etc. Depending on the number of recognition categories, there are binary classifiers and multi-class classifiers, where multi-class classifiers are combinations of binary classifiers. A survey of the literature shows that SVM, PLSR and assorted deep nets still dominate the disease-classification toolbox for hyperspectral cubes.

Support Vector Machine is a supervised linear classifier that lifts inseparable data into a higher dimension where a single hyper-plane can split healthy from infected tissue, making it a work-horse for hyperspectral disease

tasks. Chu Xuan used hyperspectral imaging technology to study the growth of single species of mold and mixed bacteria inoculated by single-point or pour plate methods on different types of culture media and corn kernels for 1~6 days, and captured their hyperspectral images. Using Successive Projections Algorithm (SPA) to select characteristic wavelengths combined with SVM modeling, the discrimination accuracy reached over 99.5% [15]. Baek et al. captured hyperspectral cubes of rice seeds tainted with bacterial grain blight, then benchmarked SVM against LDA and QDA to pick out the discolored, infected grains.. The results showed that when using only 2 or 3 characteristic wavelengths, all classification methods achieved over 90% classification accuracy for the sample test set and validation set [16]. Bohnenkamp et al. used two measurement platforms, a ground vehicle and a UAV, and employed an SVM discriminant model to recognize hyperspectral images of wheat yellow rust. The highest recognition accuracy based on hyperspectral images from the ground vehicle and UAV platforms reached 92.3% and 83.0%, respectively [17]. Jiang Jinlin used pepper samples with different disease severity levels as detection samples. Based on hyperspectral imaging technology and SVM, she established robust grading models for three severity levels of pepper blight based on full spectrum, characteristic wavelengths, and characteristic vegetation indices. Among them, the grading model established using characteristic wavelengths and vegetation indices achieved an accuracy of 99.75% [18]. Liu Shuang, starting from the research on hyperspectral information extraction technology and recognition models for wheat scab grains, used an SVM model and a secondary classification method with SVM scatter correction to improve the classification accuracy of the test set in the SPA feature space to 88.98%. The research results showed that using hyperspectral imaging technology combined with data processing algorithms can achieve in-situ rapid visual recognition of wheat scab grains, helping to improve the detection efficiency and quantity of wheat scab and reduce the missed detection rate [19]. In the recognition of hyperspectral images of crop diseases, SVM has a solid theoretical foundation and strong generalization ability, offering unique advantages for problems involving non-linearity, small samples, and high-dimensional patterns. Combined with appropriate preprocessing and feature extraction methods, it can achieve a high recognition rate.

2.2 Partial Least Squares Regression

PLSR compresses both spectra and reference chemistry into latent vectors, then links the two blocks with a single linear model—still the go-to choice for near-infrared hyperspectral plant-disease assays [20]. Cheng's group imaged cucumber leaves hit by bacterial angular leaf spot and regressed the visible/near-infrared spectra against POD activity with PLSR, achieving r = 0.816 and RMSEP = 11.235 on the independent test set. The same study showed that the spectral-plus-chemometrics pipeline can reliably quantify POD activity before visual symptoms appear [21]. An offshoot of PLSR, Partial Least Squares-Discriminant Analysis, turns the regression into a classifier by assigning samples to the category whose latent-variable scores best match the measured spectra. Gold et al. used hyperspectral imaging technology to detect and identify pre-symptomatic characteristics of potato late blight and early blight, establishing a classification model using PLS-DA. The experimental results showed that 2~4 days before obvious symptoms appeared, hyperspectral measurements could detect and distinguish between potato late blight and early blight with an accuracy of over 80% [22]. Perez-Roncal et al. used hyperspectral imaging technology (900~1700 nm spectral range) to detect powdery mildew in black grapes and established a PLS-DA model with a combination of preprocessing methods including Smoothing (SM), Standard Normal Variate (SNV), and Mean Centering (MC), which achieved the best recognition rate. With 85.33 % cross-validated accuracy, the model showed that hyperspectral cubes plus chemometric classifiers can spot powdery mildew on black grapes long before the white mycelium is visible [23].

2.3 Hyperspectral Image Recognition Methods for Crop Diseases Based on Deep Learning

Deep learning originates from neural networks and is a branch of artificial intelligence. Compared to traditional deep neural networks, it has more hidden layers, integrates feature extraction and classification into one structure, uses deep nonlinear learning models to approximate complex functions, automatically performs layer-by-layer feature extraction from sample sets, learns the essential features of the dataset, and obtains an optimal recognition model [24]. Utilizing the powerful image classification capability of deep learning, it can automatically extract features from high-dimensional, information-rich crop hyperspectral images that are beneficial for improving classification accuracy, greatly enhancing recognition precision and robustness. The recognition process is shown in Figure 2. Currently, deep learning models used in the field of hyperspectral crop disease image recognition mainly include three models: Deep Belief Network (DBN), Stacked Autoencoder Network (SAE) based on Autoencoders (AE), and Convolutional Neural Network (CNN) [25]. The advantages and

disadvantages of these three deep learning models in hyperspectral crop image recognition are shown in Table 2.

Table 2. Advantages and Disadvantages of Three Deep Learning Models in Hyperspectral Crop Image Recognition

Aspect	Deep Belief Network (DBN)	Autoencoder Network (AE)	Convolutional Neural Network (CNN)
Advantages	Can better extract image features during unsupervised learning; explored DBN structural parameters based on complex and limited image data are greatly beneficial for future research	Can perform dimensionality reduction and solve problems of data complexity and limited samples; exhibits characteristics of unsupervised classification in practical applications; produces less reconstruction error than PCA in dimensionality reduction and feature extraction	Has obvious advantages when processing high-dimensional images like hyperspectral data; can extract internal features of images and accurately extract distribution patterns of images
Disadvantages	Network parameter settings require prior knowledge and manual experience; difficult to determine appropriate experimental parameters	SAE is not completely unsupervised; practical applications often require combination with other classifiers to achieve high recognition accuracy; requires manual labeling of samples, etc.	High recognition accuracy requires a large number of training samples; manual selection of appropriate activation functions, convolution kernels, and network hyperparameters

CNN has many applications in image classification, scene segmentation, object detection, etc., and has achieved very significant results. Among the three, CNNs have grabbed the lion's share of hyperspectral classification work, spawning a family of architectures—VGG, ResNet, GoogleNet, LeNet and their variants [26–29]. The purpose of CNN network processing is to find the parameters that minimize the loss function value. Stochastic Gradient Descent (SGD) is the core operation in this process, updating parameters along the gradient direction during computation and repeating this step until the parameters minimizing the loss function are found [30]. For plant-disease cubes, CNN pipelines now split into two streams: one that classifies pure spectral signatures, and another that lets the network learn spatial–textural cues from the image planes [31].

2.3.1 Spectral Feature-Based Classification Methods

Hyperspectral images contain rich spectral information, allowing the extraction of a one-dimensional vector composed of spectral information from each pixel. Using this one-dimensional vector for image classification is spectral feature-based classification. Wang Jiantao et al. used normal citrus leaves, sooty mold leaves, canker leaves, red spider mite leaves, and glyphosate-damaged leaves as research samples, collected hyperspectral images of 128 bands in the 400~1000 nm range, and performed preprocessing with gray board correction. They extracted spectral information from regions of interest and input it into a VGG16 convolutional neural network composed of an input layer, convolutional layers, pooling layers, fully connected layers, and an output layer. Each convolutional layer incorporated the ReLU activation function to enhance network non-linearity. The pooling layers in the model used max pooling to achieve feature dimensionality reduction and data smoothing. The fully connected layer had 512 neurons, and the output layer had 5 nodes to identify normal citrus leaves and the four other types of diseased citrus leaves. Experimental results showed that with a learning rate of 0.001 and 1000 iterations, the algorithm achieved an average accuracy of 98.75% [26]. Due to strong inter-spectral correlation and high redundancy in spectra extracted from hyperspectral images, directly inputting them into a CNN may not yield ideal recognition speed and 效果. Usually, some smoothing, denoising, and characteristic band extraction are performed on the original spectrum. Typical pre-processing tricks include Multiple Scattering Correction, Standard Normal Variate, and derivative smoothing to strip unwanted scatter and baseline drift before the spectra hit the net. Deep learning network models based on spectral feature classification have advantages such as simple network structure and small computational load but are prone to overfitting. Adjustments to the model need to be made according to actual needs.

2.3.2 Image Feature-Based Classification Methods

Each spectral band corresponds to a grayscale image, reflecting the spatial information of crop diseases in different bands. Classification using these two-dimensional grayscale images is image feature-based classification. Huang Shuangping et al. used 1467 rice panicles collected from the field as test objects, used a Gaia Field-F-V10 portable outdoor hyperspectral imager to capture hyperspectral images of rice panicles under natural light conditions, and established a deep convolutional model using GoogLeNet, optimized with the Stochastic Gradient Descent (SGD) algorithm [28]. The specific workflow is shown in Figure 4. GoogLeNet is a deep convolutional neural network model that requires large amounts of data and a labeled supervision mechanism for model training. Due to the time-consuming, labor-intensive, and high-cost process of original panicle hyperspectral data acquisition, original data was insufficient, and training data was imbalanced (positive to negative training sample ratio was about 8). Huang Shuangping et al. proposed two data augmentation strategies: The first strategy leveraged the ultra-high spectral resolution of the hyperspectral imager, randomly discarding band images and randomly shifting the brightness of the average hyperspectral image [28]. The random band discarding strategy involved randomly discarding one band's information from the 260 bands of the hyperspectral image and then calculating the average spectral image. The second strategy was random shifting of the average spectral image brightness. Since portable outdoor hyperspectral imagers capture rice panicle hyperspectral images under dynamically changing natural light conditions, the average spectral images showed significant brightness differences. To enhance the GoogLeNet model's adaptability to lighting changes, data was augmented by randomly shifting the spectral image brightness, increasing the diversity in the lighting brightness dimension, which could multiply the training data volume and increase sample diversity, improving model generalization ability. The results showed that the deep convolutional model established using GoogLeNet could well achieve accurate detection of rice panicle blast disease, overcoming the difficulties faced in disease prediction using spectral images under outdoor natural light conditions, and pushed this type of research a big step forward towards practical production applications. Due to strong inter-spectral correlation and high redundancy, the corresponding grayscale images also have these characteristics. Directly inputting them into a CNN may lead to suboptimal recognition speed. Usually, some processing like denoising, compression, and correlation reduction is performed on the images. Specific processing methods include Principal Component Analysis (PCA), Minimum Noise Fraction (MNF), band ratio calculation, etc. Deep learning models are good at processing 2D images, have strong robustness, and can extract deep, stable, and intrinsic features of images. There is also a wealth of mature algorithms and experience in real life that can be drawn upon. Deep learning network models based on image feature classification can achieve a relatively high recognition rate. However, due to limited hyperspectral image data, overfitting often occurs easily.

2.4 Model Evaluation and Performance Metrics

The performance of recognition models is usually evaluated through experimental testing, hence datasets are divided into test sets and training sets. Common division methods include the Hold-out Method [32] and Cross-Validation [33]. Both the hold-out method and cross-validation reserve a portion of samples for testing, which can lead to insufficient training samples. Although cross-validation mitigates the issue of small training samples, its computational complexity is high. Deep learning has demonstrated good performance, fast recognition, good robustness, and strong generalization ability in crop disease image recognition and classification [34]. Performance is judged with the usual machine-learning yard-stick: Acc, Recall, F1, mAP for classification, plus RMSE and MAE when continuous biochemical traits are predicted [35–40].

Accuracy and recall are relatively contradictory performance metrics; usually high accuracy implies low recall, and high recall implies low accuracy. However, in some simple tasks, both recall and accuracy can achieve high values. In some tasks, the importance placed on accuracy and recall differs. The F1-score can reflect different emphases on accuracy or recall.

3. Application Research Status of Crop Diseases and Pests Based on Hyperspectral Remote Sensing Technology

Agriculture is a pillar industry of the national economy, and crop diseases and pests seriously affect agricultural production. Abroad, the United States was the first to use remote sensing data such as Landsat and Meteorological Satellite to predict global wheat yield, with an accuracy of over 90%, allowing the United States to occupy a dominant position globally [1]. The European Union has also applied remote sensing technology to verify agricultural subsidies (CAP), providing strong support for the implementation of the Common Agricultural Policy and enhancing the international competitiveness of EU agricultural products [2]. Canada's Urthecast company is planning to build the world's first artificial satellite group integrating both optical and radar imaging, namely OptiSAR [3]. China's mapping satellite system, high-resolution satellite series, and land resource satellite series can conduct agricultural remote sensing observations, initially meeting the application needs of agricultural condition monitoring, crop classification, yield estimation, and agricultural disaster monitoring. This technology records spectra of various wavelengths and converts them into numerical forms. By detecting the spectral signals of infected plants, it masters the process and patterns of disease development, investigates and analyzes plant growth status, disease and pest situations, and growth environments, and determines plant disease and pest control plans based on the information, achieving effective management and prediction of plant diseases and pests. The principles of hyperspectral technology include the following aspects.

3.1 Hyperspectral Remote Sensing Technology

3.1.1 Spectral Data Collection and Processing

Hyperspectral instruments are used to collect spectral signals from the target area and convert them into digital signals. These digital values are related to wavelength. Mathematical models can be used to analyze and process the data to identify specific spectral characteristics produced by infected plants. These spectral signals help analyze the composition and structure of chemical substances in leaves. Under different spectral characteristics, both diseased and healthy plants emit different signals. By comparing and analyzing these different spectral signals, researchers can determine the root cause, identify spectral characteristics caused by certain diseases, pests, and nutritional deficiencies, for monitoring and predicting diseases and pests.

3.1.2 Use of Mathematical Models

The spectral signals measured by hyperspectral instruments are massive in size and change rapidly at the pixel level. Therefore, researchers need to use various mathematical algorithms and techniques to extract useful information.

3.1.3 Data Processing and Analysis

The collected spectral data is transmitted to a computer for processing and analysis through relevant software and algorithms, thereby obtaining specific spectral patterns, shapes, and other information. This helps identify different disease and pest types, the status of disease progression, and the performance of diseases under different environments.

3.1.4 Interpretation and Statistical Analysis of Monitoring Results

The collected spectral data is transformed into meaningful information. The plant's growth environment, current growth status, and disease and pest situation are classified, statistically analyzed, etc., to determine plant disease and pest control plans and strengthen environmental control and management. In practical applications, hyperspectral technology is widely used in crop detection and identification, as well as disease and pest monitoring and prediction. Hyperspectral technology can determine the planting environment and help farmers improve yield and quality by detecting the spectral characteristics of crops. This technology can rapidly and accurately detect and identify plant diseases and pests, as well as predict and control diseases.

3.2 Application Status of Remote Sensing Technology in Crop Disease and Pest Monitoring

3.2.1 Remote Sensing Data Acquisition

Sound monitoring starts with crisp imagery: spatial, spectral and temporal resolution govern every later step. Satellites, crewed aircraft and UAVs currently form the three-tier toolbox for grabbing the pictures [7]. Satellites remain the work-horse, split into high-, medium- and coarse-resolution constellations that trade pixel size for revisit frequency.

3.2.2 Remote Sensing Data Processing

Remote sensing data processing is a key step in crop disease and pest monitoring. It involves correcting, enhancing, and denoising remote sensing data to improve data quality and reduce errors. Commonly used remote sensing data processing methods include:

Geometric Correction:Correcting remote sensing images geometrically to eliminate image distortion and other errors.

Radiometric Correction:Performing radiometric correction on remote sensing images to eliminate the effects of the atmosphere, clouds, etc., reflecting the true situation of the ground surface.

Noise Filtering:Filtering noise in remote sensing images to eliminate noise interference and improve data quality.

Image Enhancement:Enhancing remote sensing images to make image features more prominent, facilitating subsequent processing and analysis.

3.2.3 Remote Sensing Monitoring Methods for Crop Diseases and Pests

Once the cubes are in hand, analysts pick one of three lenses: pixel-level, object-level or time-series, each tuned to a different scale of symptom expression. Among them, the pixel-based monitoring method is the most commonly used. It analyzes each pixel in the remote sensing image to identify different types of diseases and pests. The object-based monitoring method first identifies targets in the remote sensing image and then monitors and identifies diseases and pests. The time-series-based monitoring method detects changes in crop diseases and pests over different periods by comparing multi-temporal remote sensing images [8].

3.2.4 Application Cases

Monitoring Rice Bacterial Leaf Blight:Rice is one of China's main food crops, and bacterial leaf blight is an important disease affecting rice yield and quality. Traditional monitoring methods for rice bacterial leaf blight mainly rely on manual surveys, which are inefficient and costly. For example, Wang Huadi [10] used high-resolution Sentinel-2 satellite imagery to extract the rice vegetation index (NDVI), combined with meteorological data and ground survey data to establish a mathematical model for monitoring and predicting rice bacterial leaf blight.

Application of Remote Sensing Technology in Crop Pest Monitoring:

Cotton Red Spider Mite Monitoring:Cotton is an important economic crop in China, and the red spider mite is a major pest of cotton. Traditional monitoring methods for cotton red spider mites mainly rely on manual surveys, which involve heavy workload, low efficiency, and high cost. Remote sensing technology can monitor and predict the growth status of cotton and the distribution of red spider mites by acquiring high-resolution satellite remote sensing imagery. For example, Manavalan R [9] used high-resolution Landsat satellite imagery to extract the cotton vegetation index (NDVI), combined with meteorological data and ground survey data to establish a mathematical model for monitoring and predicting cotton red spider mite damage.

Corn Borer Monitoring:Corn is an important economic crop in China, and the corn borer is a major pest of corn. Traditional monitoring methods for corn borers mainly rely on manual surveys and trapping, but this method suffers from low efficiency and high cost. Remote sensing technology can monitor and predict the growth status of corn and the distribution of corn borers by acquiring high-resolution satellite remote sensing imagery. For example, Su Wei et al. [11] used Sentinel-2 imagery combined with PROSAIL model parameter calibration to extract the corn vegetation index (NDVI) and surface temperature, combined with meteorological data and ground survey data to establish a mathematical model for monitoring and predicting corn borers.

Fruit Tree Borer Monitoring:Fruit trees are important economic crops in China, and fruit borers are a major pest of fruit trees. Traditional monitoring methods for fruit tree borers mainly rely on manual surveys and trapping. Remote sensing technology can monitor and predict the growth status of fruit trees and the distribution of fruit borers by acquiring high-resolution satellite remote sensing imagery. For example, Zhou Bin et al. [12] used high-resolution Landsat satellite imagery and Sentinel-2 satellite imagery to extract the fruit tree vegetation index (NDVI) and land surface temperature, combined with meteorological data and ground survey data to establish a mathematical model for monitoring and predicting fruit tree borers.

To sum up, remote sensing has become a routine guard for crop health: it cuts survey time, shrinks field bills and underpins both farm income and food security. As sensors and analytics keep maturing, their watch over pests and pathogens will only widen and sharpen.

3.3 Advantages and Disadvantages

3.3.1 Advantages of Hyperspectral Remote Sensing Technology in Crop Disease and Pest Monitoring

Hyperspectral instruments harvest leaf reflectance across dozens to hundreds of narrow wavebands, giving each pixel a full optical fingerprint. This information can reflect the characteristics of crops, such as chlorophyll content and plant growth status. At the same time, the method can pick up subtle spectral signatures created by pests or disease. For example, leaves infected with viruses show reduced reflectance in the infrared band, while leaves infected with fungi exhibit different colors in the visible light band. These characteristics can be used for monitoring and identifying diseases and pests [13].

Hyperspectral remote sensing technology can monitor large areas of farmland through aerial or satellite remote sensing, without the need for manual entry into the fields, greatly improving monitoring efficiency and coverage. Simultaneously, hyperspectral remote sensing technology can acquire high-precision data, enabling comprehensive monitoring and analysis of farmland.

Because data can be gathered and processed on the fly, growers get an early warning and can treat outbreaks before major yield is lost. By stacking time-sequential cubes, the same technology charts how infections unfold and how the crop responds, giving agronomists a solid evidence base for every management decision.

Hyperspectral remote sensing technology can comprehensively monitor and analyze the growth status of crops and the occurrence of diseases and pests, providing a scientific basis for agricultural production and promoting sustainable agricultural development. At the same time, hyperspectral remote sensing technology can provide technical support and services to farmers, improving the efficiency and quality of agricultural production.

3.3.2 Disadvantages of Hyperspectral Remote Sensing Technology in Crop Disease and Pest Monitoring

Hyperspectral remote sensing technology requires professional technical support and equipment, necessitating specialists for data processing and analysis. Additionally, the data volume of hyperspectral remote sensing technology is large, requiring big data processing and storage, which involves relatively high costs.

The technique demands clear skies—cloud, fog or rain quickly erode data quality. Thick cloud, drizzle or fog scatters and absorbs key wavelengths, blurring the spectral fingerprint and weakening pest- or disease-spotting power.

Besides, the technique can stumble when separate pathogens or insects cast near-identical spectral shadows, inviting classification errors. Field scouting is still indispensable—ground-truthing spectra against visual symptoms keeps the classifier honest and cuts false calls.

Hyperspectral remote sensing technology requires professional technical support and equipment, leading to limited acceptance among agricultural practitioners. On top of that, wrangling hundreds of narrow bands demands solid spectroscopic and statistical know-how—skills that can't be picked up overnight.

3.4 Application Prospects and Urgent Problems to be Solved

As sensors, platforms and analytics mature, hyperspectral crop-health surveillance will only widen its reach. Coupled with AI and on-the-fly machine learning, the next generation of systems should sharpen discrimination, trim false positives and give growers a decision-ready map within hours of capture. Hooked into farm-wide IoT nets and tamper-proof blockchains, tomorrow's hyperspectral feeds could trigger instant phone alerts, order spare parts or schedule drone sprays—turning spectral snapshots into end-to-end, trust-verified crop protection services.

3.4.1 Data Processing Problems

Hyperspectral remote sensing technology acquires a vast amount of data, requiring effective data processing and analysis to extract useful information. Due to the complexity and diversity of agricultural diseases and pests, it is necessary to analyze and model the spectral reflectance characteristics of different crops and different diseases and pests to more accurately detect and identify them. Therefore, there is a need to develop more efficient and accurate data processing and analysis methods to improve practical application effectiveness.

3.4.2 Accuracy Problems

Hyperspectral remote sensing technology needs to achieve high-precision monitoring results in agricultural disease and pest monitoring to timely detect and predict the occurrence and evolution of diseases and pests. Currently, the accuracy of hyperspectral remote sensing technology in agricultural disease and pest monitoring needs improvement. This is mainly due to the influence of various factors, such as meteorological conditions, soil quality, and vegetation coverage. To push accuracy and trust even higher, hyperspectral cubes must be fused with weather-station logs, on-the-ground scouting, and other remote-sensing layers—blending many lines of evidence into one reliable diagnosis.

3.4.3 Application Scope Problems

Coverage is also crop-specific: every species—and often every cultivar—carries its own optical personality, so a model tuned to wheat stripe rust can slump when asked to spot citrus canker. Hence, case-by-case calibration is essential—spectral libraries and detection algorithms must be re-trained for each crop–pathogen pair before the technology can reliably move from plot to plot.

3.4.4 Practical Application Problems

Hyperspectral imaging may look like a silver bullet for crop protection, yet taking it from the lab to the field still hits practical snags—weather quirks, data overload and model drift keep trimming its real-world payoff. On many farms the method stalls for a simpler reason—growers simply don't know what a "hyperspectral cube" is or how to turn it into a spray decision. Bridging that gap will take plain-language outreach, hands-on demos and user-friendly dashboards that hide the spectroscopy and deliver only the action: when, where and what to treat.

In short, hyperspectral imaging has the muscle to revolutionize crop protection, but its on-farm muscles are still cramped by technical, economic and knowledge bottlenecks. More robust sensors, lighter data pipelines and grower-centric training are the next must-solve items on the to-do list..

In summary, hyperspectral remote sensing technology has broad application prospects in agricultural disease and pest monitoring, but there are still some urgent problems to be solved. In-depth research and exploration are needed in technology, methods, and applications to improve the application effectiveness and level of hyperspectral remote sensing technology in agricultural disease and pest monitoring.

4. Summary

International trends show satellite data are now woven into almost every step of farming, yet hyperspectral disease surveillance is still a narrow lane—most studies orbit the big staples (wheat, rice) while fruit trees, pulses or vegetables wait their turn. Expanding crop menus and cultivar-level calibrations is the evident next gear-shift. At the same time, existing monitoring methods are still far from meeting the requirements of actual production. The next research frontier is turning raw hyperspectral signals into field-ready tools: transforming reflectance with derivatives or log-shifts, distilling band-position/area metrics into custom vegetation and stress indices, and stress-testing models until one runs fast and lean enough for continent-scale, same-day pest-and-disease maps..

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