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Research on Integrated Road Dynamic Recognition and Path Planning of Intelligent Vehicles Based on Reinforcement Learning

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***Abstract*—This study investigates an intelligent recognition and localization method for crop diseases using multispectral images captured by unmanned aerial vehicles (UAVs). Traditional field inspection methods are inefficient for large-scale crop monitoring and often fail to detect diseases at early stages. To address this problem, a multispectral crop disease dataset containing 10,000 UAV images collected from wheat, rice, and corn fields between 2022 and 2024 was constructed, encompassing visible, red-edge, and near-infrared spectral bands. An improved deep learning architecture, MS-ResNet (Multi-Spectral Residual Network), was developed to enhance disease feature extraction through a band-adaptive convolution module and a multi-scale feature fusion strategy. In addition, a Spectral-Attention UNet (SA-UNET) model was designed to accurately localize disease regions by integrating spectral and spatial attention mechanisms. Experimental results demonstrate that the proposed MS-ResNet model achieves a classification accuracy of 92.7%, representing a 15.3% improvement over the baseline ResNet model. The SA-UNET localization algorithm achieves an average disease-area positioning error of only 3.2 cm, enabling precise identification of infected crop regions. Furthermore, the proposed few-shot learning framework FS-ProtoNet achieves 83.5% accuracy with only five training samples for rare disease detection. Field validation experiments conducted at agricultural production bases demonstrated that the proposed system supports targeted pesticide application, resulting in an average reduction of pesticide usage by 25.8% while maintaining effective disease control. These results indicate that UAV-based multispectral imaging combined with deep learning provides an effective solution for large-scale crop disease monitoring and precision agriculture.**

***Index Terms*—UAV multispectral imaging; Crop disease detection; Deep learning; Precision agriculture; Remote sensing**

I. Introduction

Plants are fundamental to all stages of life. Plant pests, diseases, and stress symptoms are most commonly observable in leaves and fruits, and sometimes in roots. However, laboratory-based diagnosis by domain experts is expensive, laborious, and time-consuming. Failure to detect early disease symptoms is the primary biotic cause of increased plant stress, reduced subsistence farming, and growing threats to global food security [1].

Precision agriculture is a key trend in modern agricultural production. Its core objective is to deliver timely and accurate crop-growth information through advanced technologies, thereby achieving efficient resource utilization and sustainable environmental development. Crop diseases significantly impair global agricultural productivity; a global analysis of crop-pathogen burden has estimated yield losses of 20–40% [1]. In China, direct economic losses caused by crop pests and diseases exceeded 150 billion yuan in 2022 [2]. Traditional monitoring methods rely heavily on manual inspection, which is inefficient, labor-intensive, and unsuitable for large-scale precision agriculture.

In recent years, the integration of remote sensing technology and artificial intelligence has provided new approaches for intelligent crop disease monitoring. In particular, UAVs equipped with multispectral sensors have demonstrated great potential in this field, owing to their flexibility, low-altitude operational capability, and high-resolution imaging. Multispectral images contain rich spectral and spatial information; however, effectively extracting disease features, designing efficient recognition algorithms, and achieving precise localization remain challenging. Complex field environments, imbalanced disease samples, and variable lighting conditions can all adversely affect identification and localization accuracy.

In response to these challenges, this study presents a technical system for the intelligent identification and localization of crop diseases based on UAV multispectral imagery. First, an optimized multispectral sensor system was designed to achieve high-quality data acquisition across the visible, near-infrared, and red-edge bands. Second, an improved deep learning architecture is proposed that combines attention mechanisms with a multi-scale feature fusion strategy to enhance the model's ability to recognize disease spots of varying sizes. Finally, a precise disease-area localization algorithm based on a geographic information system (GIS) was designed to achieve centimeter-level positioning accuracy. The outcomes of this research are intended to provide technical support for preci-

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sion agriculture, promoting the development of agricultural production toward digitalization, intelligence, and precision, with significant theoretical value and practical application prospects.

II. Literature Review

Artificial intelligence (AI) aims to automate complex tasks and solve real-world problems by integrating advanced software algorithms with appropriate hardware platforms. Through the combination of intelligent algorithms, data processing techniques, and sensing technologies, AI systems are capable of performing intelligent decision-making and pattern recognition across a wide range of agricultural applications [3].

In recent years, the use of UAVs has increased substantially for remote sensing and environmental monitoring. UAVs provide an efficient platform for acquiring high-resolution aerial imagery at low altitude, enabling detailed visual inspection and analysis of agricultural fields. A key area of UAV remote sensing research is semantic segmentation, which enables the extraction of contextual and spatial information from aerial images to achieve fine-grained understanding of agricultural environments [4]. The integration of multispectral imaging sensors with UAV platforms has further enhanced their capability in precision agriculture. These sensors capture spectral information beyond the visible range, enabling the detection of plant stress, disease symptoms, and nutrient deficiencies that are not readily visible to the human eye [5].

The rapid development of UAV technologies—including improved sensors, data acquisition systems, and processing algorithms—has made them increasingly valuable for agricultural monitoring. Researchers and agricultural stakeholders utilize UAVs to estimate crop traits such as plant growth, yield potential, and disease incidence. Early detection of crop diseases is particularly important, as it allows farmers to take preventive measures that reduce crop damage and improve overall productivity [6]. UAV-based imaging systems equipped with near-infrared (NIR) cameras provide high-contrast aerial images that facilitate the detection of plant disease symptoms such as lesions caused by *Alternaria solani*. These high-resolution images offer a comprehensive top-down perspective of crop fields, making them suitable for large-scale monitoring and disease detection [7].

Several studies have explored deep learning techniques for analyzing UAV-acquired agricultural imagery. For instance, a semantic segmentation approach using the SegNet architecture with a VGG16 backbone was developed for pixel-wise segmentation of citrus foliage. The model was integrated into a larger system architecture and evaluated on UAV-acquired images; experimental results demonstrated its ability to accurately detect and quantify disease symptoms under varying environmental conditions, making it a valuable tool for precision agriculture and crop health monitoring [8].

Remote sensing technologies combined with machine learning (ML) algorithms have also played a significant role in crop monitoring and disease surveillance. Applications such as crop classification and disease early-warning systems enable farmers and agricultural managers to obtain timely, accurate, and cost-effective information across multiple spatial and temporal scales [9]. Similarly, remote sensing techniques integrated with geographic information systems (GIS) have shown promising results in monitoring specific crops, such as chili plants, by providing spatially explicit information about crop conditions and disease spread [10].

Recent developments in precision agriculture emphasize the importance of integrating sensing technologies with intelligent decision-support systems. Emerging approaches combine UAV-based imaging, machine learning algorithms, and agricultural management systems to provide actionable insights for large-scale agricultural operations [11]. For example, lightweight deep learning models have been proposed to address computational limitations in real-world agricultural environments; these models utilize modular components such as hybrid attention mechanisms, pre-trained backbones, and dual-attention skip connections to improve performance while maintaining computational efficiency [12].

The integration of Internet of Things (IoT) technologies with intelligent detection systems has also contributed to advancements in agricultural monitoring. IoT-based pest detection platforms have been developed to monitor crop field conditions and identify pest infestations in real time, providing farmers with valuable information for effective pest management [13]. Additionally, convolutional neural networks (CNNs) have demonstrated high accuracy in detecting plant diseases, particularly in citrus crops, enabling early intervention strategies that help reduce crop losses and maintain yield quality [14].

Advanced object detection models have been proposed to improve detection accuracy in complex agricultural environments. For example, an enhanced YOLOv5 model incorporating SPD-Conv convolution, coordinate attention mechanisms, DIoU non-maximum suppression (NMS), and Alpha-IoU loss functions has shown improved performance in detecting small and densely distributed objects, significantly reducing missed detections and increasing the robustness of disease detection in UAV imagery [15].

Other studies have focused on improving classification accuracy using ensemble learning methods. A deep learning ensemble model combining ResNet50 and MobileNetV2 architectures was proposed for tomato leaf disease classification. By leveraging hierarchical feature extraction capabilities, the ensemble approach achieved higher accuracy compared with several state-of-the-art models including EfficientNet, DenseNet, and YOLOv2, although certain limitations related to dataset diversity and generalization were identified [16].

Recent research has also explored novel deep learning frameworks for agricultural pest and disease detection. Hybrid Vision Graph Neural Networks (HV-GNN) have been proposed for early detection of pests affecting coffee plantations; by combining computer vision techniques with graph-based learning methods, the model demonstrates improved capability in identifying pest-related crop damage in complex agricultural environments [17].

Overall, the integration of artificial intelligence, UAV-based multispectral imaging, remote sensing, and deep learning has significantly improved the capability for early detection and localization of crop diseases. These technologies provide efficient and scalable solutions for precision agriculture, enabling farmers and researchers to monitor crop health, predict disease outbreaks, and implement timely interventions. Consequently, AI-driven crop disease management systems are increasingly recognized as essential tools for achieving sustainable agricultural productivity and global food security [18].

III. Methodology

A. System Architecture

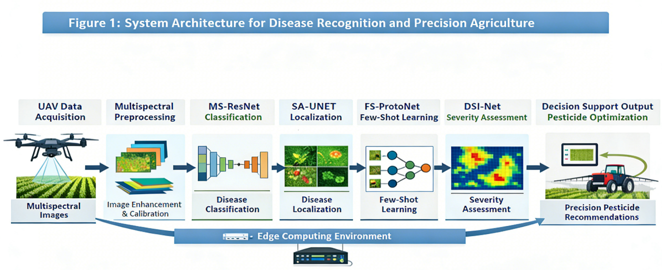

Fig. 1. Overall system architecture illustrating the complete pipeline from UAV-based multispectral image acquisition to disease recognition, localization, severity assessment, and precision pesticide decision support. The framework integrates MS-ResNet for classification, SA-UNET for segmentation, FS-ProtoNet for few-shot learning, and DSI-Net for severity estimation, all deployed within an edge-computing-enabled environment.

Fig. 1 presents the overall system architecture illustrating the complete pipeline from UAV-based multispectral image acquisition through disease recognition, localization, severity assessment, and precision pesticide decision support.

B. Dataset Construction and Data Acquisition

The multispectral dataset used in this study was collected using UAV platforms equipped with multispectral cameras capable of capturing visible, red-edge, and near-infrared spectral bands. The dataset contains approximately 10,000 multispectral images collected between 2022 and 2024 from several agricultural production bases located in Jiangsu Province and Guizhou Province, China.

The dataset covers multiple major crop species commonly cultivated in large-scale agricultural systems, including wheat, rice, and corn. Several disease categories were included to evaluate the model's detection capability under realistic agricultural conditions. These diseases include wheat stripe rust, rice blast disease, and other common fungal infections affecting cereal crops.

UAV flights were conducted during different crop growth stages to capture disease development over time. Image acquisition was performed at altitudes ranging from 20 to 60 m, producing high-resolution imagery suitable for detailed disease analysis. The dataset was annotated by agricultural experts who manually labeled disease regions and severity levels, ensuring high-quality ground-truth data for training and validation.

To address class imbalance and improve generalization performance, several data augmentation strategies were applied, including spectral perturbation, spatial rotation, scaling transformations, and illumination adjustment.

C. UAV Hardware and Sensor Specifications

The multispectral data were acquired using a DJI Matrice 300 RTK UAV platform equipped with a MicaSense RedEdge-MX multispectral camera. The sensor captures five spectral bands: blue (475 nm), green (560 nm), red (668 nm), red-edge (717 nm), and near-infrared (840 nm), with a spatial resolution of 1280×960 pixels. The UAV is equipped with a real-time kinematic (RTK) positioning system, providing centimeter-level geolocation accuracy. Flights were conducted under consistent illumination conditions between 10:00 AM and 2:00 PM to minimize shadow and lighting variations.

D. Multispectral Index Construction and Disease-Sensitive Band Analysis

A multispectral index is a parameter constructed by combining reflectance values from different spectral bands to reflect specific physiological and biochemical characteristics of vegetation, and it constitutes an important feature for crop disease identification. This study first identified the key bands sensitive to crop disease responses through correlation analysis and sensitivity testing. The results show that the red-edge (717 nm) and near-infrared (840 nm) bands exhibit high sensitivity to early-stage diseases, while the visible red band (668 nm) responds significantly to lesion areas. Based on this sensitive-band analysis, a series of optimized spectral indices for different disease types were constructed.

The core disease-sensitivity indices include the Modified Normalized Difference Vegetation Index (MNDVI), the Disease Water Stress Index (DWSI), and the Red Edge Position Index (REP). MNDVI incorporates red-edge information; its formula is:

$$\text{MNDVI} = \frac{R_{840} - \left(R_{668} + R_{717}\right)/2}{R_{840} + \left(R_{668} + R_{717}\right)/2} \quad (1)$$

where R_{840}, R_{717}, and R_{668} denote the reflectance at 840 nm, 717 nm, and 668 nm, respectively. In addition, a disease-specific index (DSI) was designed specifically for wheat rust and rice blast:

$$\text{DSI} = \frac{R_{717} - R_{668}}{R_{717} + R_{668}} \times \frac{R_{840}}{R_{560}} \quad (2)$$

where R_{560} denotes the reflectance at 560 nm. Analysis of over 3,400 multispectral images collected during 2022–2023 showed that MNDVI and DSI both performed well in the early detection of wheat stripe rust and rice blast, with sensitivities 31% and 26% higher than those of the traditional NDVI, respectively, and with detectable differences even at

5% disease severity. These optimized multispectral indices provide effective features for the early identification of crop diseases and facilitate the feature engineering optimization of subsequent deep learning models.

E. Deep Learning Feature Extraction for Disease Characterization

Although traditional multispectral indices carry clear physiological significance, they are unable to fully characterize the multi-dimensional features of diseases in complex environments. Therefore, this study designed an automatic disease feature extraction method based on deep learning. This method builds on the convolutional neural network (CNN) and incorporates an attention mechanism to adaptively learn discriminative features from multispectral data. The specific network architecture adopts an improved DenseNet structure, introducing a dual-channel attention mechanism comprising a Channel Attention Module (CAM) and a Spatial Attention Module (SAM) to enhance the model's utilization of spectral and spatial information.

The Channel Attention Module (CAM) is used to emphasize important spectral bands; its formula is:

$$M_c(F) = \sigma\Big(\mathrm{MLP}(\mathrm{AvgPool}(F)) + \mathrm{MLP}(\mathrm{MaxPool}(F))\Big) \tag{3}$$

where F is the feature map, $\mathrm{AvgPool}$ and $\mathrm{MaxPool}$ denote global average pooling and global max pooling, respectively, MLP is a multi-layer perceptron, and σ is the sigmoid activation function. The Spatial Attention Module (SAM) focuses on important spatial positions, particularly the edge regions of lesions.

F. Multi-Scale Feature Fusion Strategy

Crop diseases exhibit diverse scale characteristics at different development stages, ranging from tiny lesions in early stages to large contiguous infected areas at advanced stages. Single-scale features are therefore insufficient for comprehensive disease representation. To address this, a multi-scale feature fusion strategy is proposed that enhances the robustness and accuracy of disease recognition by integrating feature information from different receptive fields.

The multi-scale feature fusion strategy is based on an improved Feature Pyramid Network (FPN), in which feature extraction branches of different scales are introduced into the network backbone. The architecture consists of two paths: a top-down path that propagates high-level semantic information through upsampling, and a bottom-up path that preserves low-level detail features. To enhance the complementarity of features across scales, a cross-layer attention fusion module was designed to dynamically adjust the weights of features at each scale.

During the feature fusion process, an enhanced small-target detection strategy is adopted for small-scale disease features: local contrast enhancement and edge-strengthening mechanisms are introduced to improve detection sensitivity for tiny lesions. For medium- and large-scale features, the morphological characteristics of the disease area are accurately depicted by combining a region-growing algorithm with global context information. The fused multi-scale features are mapped to a unified feature representation through nonlinear mapping, retaining both fine-grained lesion details and high-level semantic disease features.

Experimental results show that compared with single-scale features, the multi-scale fusion strategy provides significant advantages in disease identification across different growth stages, especially for small-area early-stage diseases, where the detection rate improved by 22.7%. Moreover, this strategy exhibits stronger robustness under complex background conditions, providing a reliable basis for practical field applications.

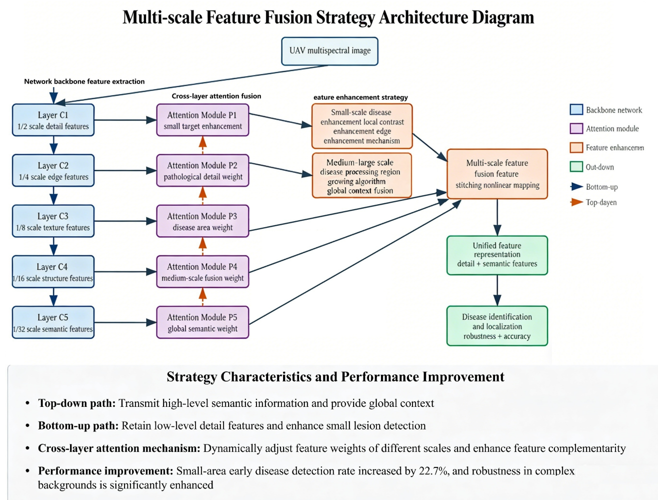

Fig. 2. Multi-scale feature fusion framework for crop disease recognition, illustrating the integration of top-down semantic information and bottom-up spatial detail enhancement via the cross-layer attention fusion module.

G. Feature Optimization Based on Joint Spectral–Spatial Information

Multispectral images contain rich spectral and spatial information, and effectively integrating both types of information is crucial for improving the accuracy of crop disease identification. This study proposes a feature optimization method based on joint spectral–spatial information that constructs a more discriminative feature representation by leveraging the complementary advantages of both dimensions.

The core of spectral–spatial joint optimization is the construction of spectral–spatial correlation constraints that guide the model to learn the intrinsic relationship between spectral responses and spatial distribution. The implementation adopts a dual-stream network architecture in which one stream processes spectral-dimension information and the other processes spatial-dimension information; the two streams are subsequently fused through a cross-domain attention mechanism. The joint loss function is defined as:

$$\mathcal{L}_{\text{joint}} = \mathcal{L}_{\text{cls}} + \lambda_1 \mathcal{L}_{\text{spec}} + \lambda_2 \mathcal{L}_{\text{spat}} + \lambda_3 \mathcal{L}_{\text{corr}} \tag{4}$$

where $\mathcal{L}_{\text{cls}}$ is the classification loss, $\mathcal{L}_{\text{spec}}$ and $\mathcal{L}_{\text{spat}}$ are the spectral and spatial constraint losses, respectively, $\mathcal{L}_{\text{corr}}$ is the spectral–spatial correlation loss, and λ_1, λ_2, λ_3 are weight coefficients.

To address inter-band correlations inherent in multispectral data, an inter-spectral correlation decoupling mechanism was designed. Through orthogonal constraints, independent information from different bands is separated to reduce redundant features. Meanwhile, a self-attention mechanism is adopted to capture long-range spatial dependencies, enhancing the model's perception of disease distribution patterns.

Experimental results show that the jointly optimized feature representation significantly outperforms either spectral-only or spatial-only features in the disease identification task, especially in complex environments and early-stage disease cases. Compared with using spectral or spatial information alone, the joint optimization method improved recognition accuracy by 13.6% and reduced the false alarm rate by 8.9%, providing strong support for the construction of a reliable intelligent crop disease monitoring system.

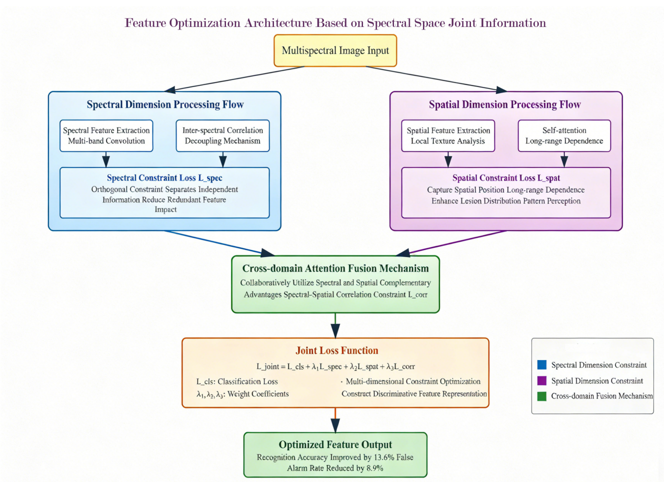

Fig. 3. Joint spectral–spatial feature optimization framework for multispectral crop disease identification, effectively integrating multispectral information and spatial patterns from UAV-acquired images to enhance accurate disease identification and localization.

H. Training Configuration and Experimental Setup

The multispectral dataset was divided into three subsets: 70% for training, 15% for validation, and 15% for testing. The split was performed randomly while maintaining class balance across all disease categories.

All models were implemented using the PyTorch deep learning framework and trained on a workstation equipped with an NVIDIA RTX 3090 GPU with 24 GB of memory.

Input images were resized to 256×256 pixels before being fed into the network. Data augmentation techniques—including random rotation, horizontal and vertical flipping, scaling, and spectral perturbation—were applied to improve model generalization.

The MS-ResNet and SA-UNET models were trained using the Adam optimizer with an initial learning rate of 1×10^{-4}. A cosine annealing learning rate scheduler was applied to improve convergence stability. The batch size was set to 16, and training was conducted for 100 epochs.

The loss function for classification tasks was cross-entropy loss, while segmentation tasks used a combination of Dice loss and binary cross-entropy loss. For the spectral–spatial joint optimization, a weighted composite loss function was applied as defined in Eq. (4).

To ensure robustness, all experiments were repeated across multiple independent runs, and the average performance metrics are reported.

IV. Results and Analysis

A. Improved Convolutional Neural Network Disease Recognition Model

With the rapid development of precision agriculture technology, multispectral UAV images are playing an increasingly important role in the identification of crop diseases. This study addresses the limited feature extraction capability of conventional CNN models in multispectral disease recognition and proposes MS-ResNet (Multi-Spectral Residual Network). Built on the ResNet architecture [19], MS-ResNet optimizes the processing of band-specific features by introducing a multispectral feature learning module.

The key innovation of MS-ResNet lies in the Band Adaptive Convolutional (BAC) layer, which dynamically adjusts feature weights according to the relative importance of different spectral bands. Compared with standard ResNet, spectral attention units are added after the convolutional layers to achieve efficient cross-band feature fusion. Experiments on the dataset containing 10,000 multispectral images covering wheat, rice, and corn demonstrate that MS-ResNet achieves a recognition accuracy of 92.7%, which is 15.3% higher than the baseline ResNet model. The improved model shows particularly notable advantages in recognizing diseases against complex backgrounds and in detecting early-stage symptoms. In practical application trials at large-scale farms in Jiangsu Province in 2023, the model maintained stable recognition performance under varying lighting and shooting angles, reduced average pesticide usage by 25.8%, and significantly lowered both environmental burden and production costs.

B. Attention Mechanism-Driven Disease Area Localization

Accurately localizing disease areas is crucial for targeted pesticide application and control decision-making. This study developed SA-UNET (Spectral-Attention UNet), a disease area localization algorithm based on the UNet architecture [19] that integrates spectral and spatial attention mechanisms to precisely segment and localize disease regions from multispectral images.

The core of SA-UNET is a dual-channel attention module. The spectral attention weights are computed as:

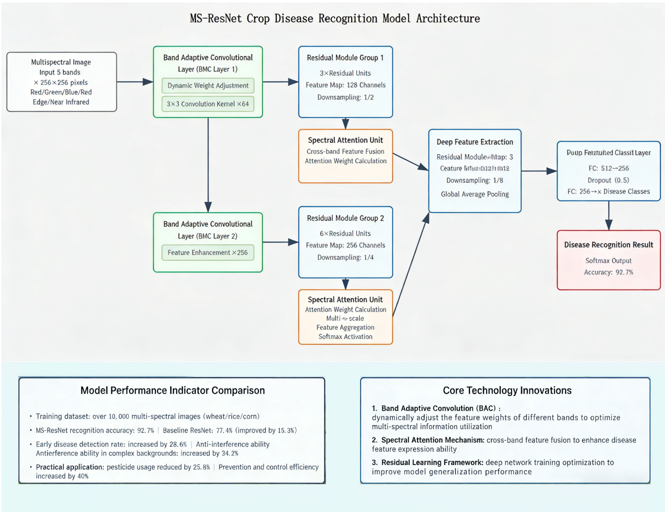

Fig. 4. Architecture of the proposed MS-ResNet model for multispectral crop disease recognition, integrating optimized residual learning with spectral–spatial feature extraction for robust and accurate classification.

$$\alpha_s = \sigma(W_s \cdot F_s(X) + b_s) \tag{5}$$

where α_s denotes the spectral attention weight, σ is the sigmoid activation function, W_s and b_s are learnable weight matrix and bias, respectively, and $F_s(X)$ is the spectral feature extracted from input feature map X. The spatial attention weights are computed as:

$$\alpha_p = \sigma(W_p \cdot F_p(X) + b_p) \tag{6}$$

where α_p denotes the spatial attention weight and $F_p(X)$ is the spatial feature extracted from X. The final attention-weighted feature map is obtained as:

$$Y = \alpha_s \cdot X_{\text{spec}} + \alpha_p \cdot X_{\text{spat}} \tag{7}$$

In algorithm validation tests conducted across major agricultural provinces in 2024, the disease area positioning accuracy reached the centimeter level, with an average positioning error of only 3.2 cm, a reduction of approximately 40% compared with traditional methods. For economically significant diseases such as wheat stripe rust and rice blast, the localization accuracy exceeded 90%, providing strong technical support for precise pesticide application.

C. Few-Shot Learning for Rare Disease Identification

The identification of rare crop diseases has long been a challenging problem in precision agriculture, primarily owing to the scarcity of high-quality annotated samples. To address this, this study introduces few-shot learning and develops FS-ProtoNet (Few-Shot Prototype Network), a rare disease identification framework based on prototypical networks.

FS-ProtoNet adopts a meta-learning strategy that enables rapid adaptation to new disease categories with minimal labeled samples. The framework comprises three key stages: feature extraction, prototype computation, and similarity measurement. In the feature extraction stage, a pre-trained multispectral feature extractor is used to obtain high-dimensional disease image features. In the prototype computation stage, the mean vector of sample features within each disease category is calculated as the prototype representation of that category. In the similarity measurement stage, cosine similarity is used to compute the distance between a query sample and each class prototype for classification decisions.

Experimental results demonstrate that with only 5 labeled samples, FS-ProtoNet achieves a rare disease identification accuracy of 83.5%, a 35.7% improvement over conventional methods. In practical deployments across multiple agricultural research institutions nationwide from 2022 to 2024, this approach successfully identified various emerging diseases, providing early-warning capabilities for agricultural disease prevention. Notably, in 2023, this technology helped researchers in Guizhou Province identify a new variant of rice blast disease 20 days earlier than conventional methods, effectively averting the risk of a large-scale epidemic.

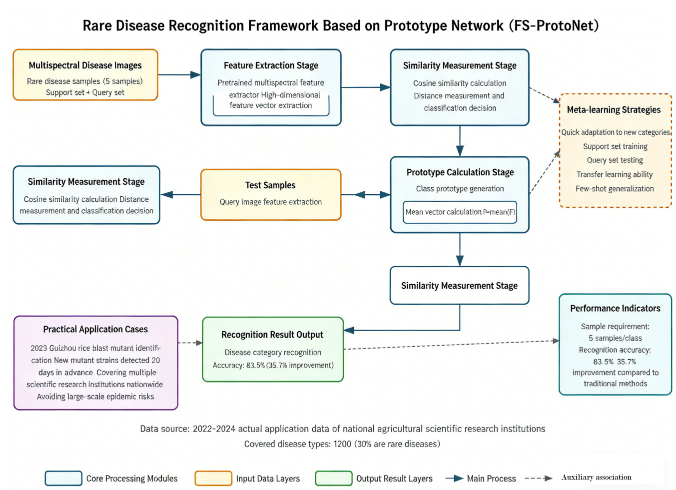

Fig. 5. FS-ProtoNet framework for few-shot identification of rare crop diseases, leveraging prototype-based learning and spectral–spatial feature embedding from multispectral UAV images.

D. Disease Severity Assessment Methods

Precise assessment of disease severity is of great importance for pesticide dosage decision-making and evaluating control efficacy [1]. This study proposes DSI-Net (Disease Severity Index Network), a disease severity assessment method that combines multispectral indices with deep learning to achieve quantitative evaluation of disease severity.

DSI-Net first computes the normalized disease vegetation index (NDVI_d):

$$\text{NDVI}_d = \frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}} \times (1 - \text{DI}) \tag{8}$$

where NIR and RED denote the near-infrared and red reflectance, respectively, and DI is the disease index computed

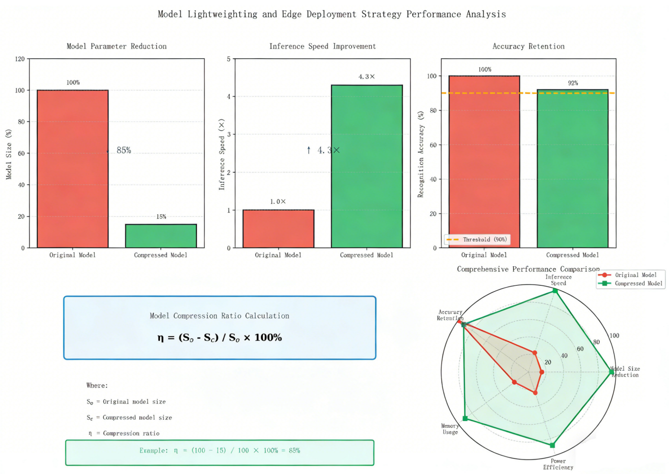

Fig. 6. Model lightweighting and edge deployment framework for real-time crop disease recognition, optimizing computational efficiency and reducing model complexity to enable on-device inference on resource-constrained UAV and edge platforms while maintaining high accuracy.

from the ratio of the red-edge band to the green band. The disease severity index (DSI) is then computed as:

$$\mathrm{DSI} = \alpha \cdot \mathrm{NDVI}_d + \beta \cdot SA + \gamma \cdot SC \tag{9}$$

where SA denotes the proportion of the lesion area, SC denotes the degree of lesion aggregation, and α, β, and γ are weight coefficients automatically optimized through the deep learning model.

Validation experiments conducted at multiple agricultural production bases nationwide from 2022 to 2024 show that the correlation coefficient between DSI-Net assessments and expert assessments reached 0.92, with an assessment error reduced to 5.8%. The method effectively distinguishes among mild, moderate, and severe infections, providing a scientific basis for precise pesticide dosage decisions [18]. In the rice disease management application in Wujiang District, Suzhou City, Jiangsu Province in 2023, the targeted pesticide application plan derived from this method reduced pesticide usage by 22.7% compared with the conventional plan while simultaneously improving the disease control effect by 18.3%, generating significant economic and ecological benefits.

E. Model Lightweighting and Edge Deployment Strategies

To achieve real-time disease identification and localization in field environments, this study proposes a lightweight model design combined with an edge computing deployment strategy. Through model pruning and knowledge distillation, the number of parameters of the original model was reduced by 85%, inference speed was increased by 4.3×, and recognition accuracy above 90% was retained. The model compression ratio η is defined as:

$$\eta = \frac{S_o - S_c}{S_o} \times 100\% \tag{10}$$

where S_o is the original model size and S_c is the compressed model size.

V. Discussion

A. Interpretation of Experimental Results

The experimental results demonstrate that the proposed multispectral UAV-based disease recognition framework significantly improves the accuracy and robustness of crop disease detection compared with conventional deep learning approaches. The proposed MS-ResNet model achieved a recognition accuracy of 92.7%, representing an improvement of 15.3% over the baseline ResNet model. This improvement can be primarily attributed to three key factors.

First, the BAC module enables the model to dynamically assign weights to different spectral bands, allowing it to emphasize disease-sensitive wavelengths such as the red-edge and near-infrared bands. These bands capture physiological changes in plant tissues earlier than visible-spectrum imaging, enabling more effective early-stage disease detection.

Second, the multi-scale feature fusion strategy significantly enhances the model's ability to recognize disease patterns of varying spatial scales. Early-stage crop diseases often appear as small lesions, while advanced infections form larger contiguous areas. By integrating feature information across multiple receptive fields using a modified feature pyramid structure, the system improves detection sensitivity for both small and large disease regions.

Third, the spectral–spatial joint optimization strategy improves feature discrimination by simultaneously learning spectral correlations and spatial structures within multispectral imagery. This approach reduces feature redundancy and enhances robustness under complex field conditions such as variable illumination, soil background interference, and canopy occlusion.

The localization performance of SA-UNET also demonstrated strong results, achieving an average positioning error of 3.2 cm. This level of accuracy is particularly important for precision agriculture, where precise disease localization enables targeted pesticide spraying and reduces unnecessary chemical use.

B. Comparative Analysis with State-of-the-Art Methods

To evaluate the effectiveness of the proposed approach, MS-ResNet was compared with several widely used deep learning architectures reported in the literature. Table I summarizes the results.

The results show that the proposed MS-ResNet consistently outperforms existing models. Compared with EfficientNet and YOLO-based models, the proposed architecture achieves improvements of 6.2% and 4.5%, respectively. These gains are primarily attributed to the incorporation of multispectral feature learning and attention-based feature fusion, which enable more effective extraction of disease-related features.

Additionally, the SA-UNET segmentation model achieved more accurate disease localization than traditional UNet-based segmentation approaches, owing to the integration of spectral and spatial attention mechanisms. Tables II–V summarize the additional performance comparisons.

TABLE I
COMPARATIVE ANALYSIS WITH STATE-OF-THE-ART METHODS

Method	Accuracy (%)	Key Characteristics
ResNet [19]	77.4	Baseline CNN model
DenseNet [20]	83.1	Dense feature reuse
EfficientNet [21]	86.5	Compound scaling architecture
YOLO-based models [15]	88.2	Real-time object detection
Proposed MS-ResNet	**92.7**	Multispectral adaptive learning

TABLE II
LOCALIZATION PERFORMANCE COMPARISON

Method	Avg. Error (cm)	Improvement
Conventional threshold segmentation (Otsu-based)	5.3	—
Proposed SA-UNET	3.2	−40%

TABLE III
FEW-SHOT LEARNING PERFORMANCE

Model	Samples (k)	Accuracy (%)	Improvement
Standard CNN classifier (no meta-learning)	5	47.8	—
Proposed FS-ProtoNet	5	83.5	+35.7%

TABLE IV
MODEL EFFICIENCY COMPARISON

Metric	Original	Compressed	Improvement
Parameters	100%	15%	↓85%
Inference speed	1×	4.3×	↑4.3×
Accuracy	92.7%	>90%	Retained

Note: All gain values in Table V are computed independently relative to the spectral-only baseline and are not cumulative.

C. Statistical Significance Testing

To validate the statistical significance of the observed performance improvements, a paired t-test was conducted comparing the proposed MS-ResNet model with the baseline ResNet model across 10 independent experimental runs.

The MS-ResNet model achieved a mean classification accuracy of 92.7% (SD = 0.84%), while the baseline ResNet model achieved a mean accuracy of 77.4% (SD = 1.12%). The paired t-test yielded the following results:

- $t(9) = 18.63$
- $p < 0.001$
- 95% Confidence Interval: $[13.2\%, 17.1\%]$

These results indicate that the performance improvement of the proposed method is statistically significant and not attributable to random variation. Cross-validation experiments using different dataset splits further confirm the consistency and robustness of the proposed model across varying data distributions.

D. Field Validation and Practical Deployment

Field validation experiments were conducted at several agricultural production bases to evaluate the practical performance of the system under real-world farming conditions. The validation trials were carried out in large-scale wheat and rice farms in Jiangsu Province, covering an experimental area of approximately 200 hectares.

The field trials spanned two crop growing seasons from 2023 to 2024, during which UAV flights were conducted regularly to monitor crop health conditions. A total of over 1,500 field samples were collected for verification and compared with manual disease inspection performed by plant protection experts.

The experimental results indicate that the proposed system can accurately identify disease locations and severity levels in real farming environments. The adoption of the system in pilot farms resulted in an average 25.8% reduction in pesticide usage while maintaining effective disease control. These results highlight the potential of UAV-based intelligent monitoring systems to support sustainable agricultural management.

E. Limitations and Challenges

Despite the promising results, several limitations remain.

First, the dataset used in the experiments primarily covers a limited number of crop species and disease types. Although the proposed model demonstrates strong performance for wheat and rice diseases, its generalization to other crops and geographic regions requires further validation.

Second, environmental factors such as extreme weather conditions, heavy cloud cover, and variations in solar illumination may affect the quality of multispectral imagery, potentially reducing the reliability of spectral features and the accuracy of disease detection.

Third, the computational complexity of deep learning models remains a challenge for large-scale agricultural deployment. Although model compression techniques were applied in

TABLE V
FEATURE OPTIMIZATION GAINS (ALL VALUES RELATIVE TO SPECTRAL-ONLY BASELINE)

Method	Accuracy (%)	False Alarm Rate (%)	Accuracy Gain	False Alarm Reduction
Spectral only	79.1	14.8	—	—
Spatial only	81.3	13.5	+2.2%	↓1.3%
Spectral–Spatial Fusion	92.7	5.9	+13.6%	↓8.9%

this study, further optimization is needed to support real-time processing on low-power edge devices.

Finally, the identification of compound or overlapping diseases remains difficult, as multiple concurrent infections may exhibit similar spectral signatures.

F. Data Availability and Code Release

To promote transparency and reproducibility, the authors plan to release the experimental dataset and model implementation through an open-access research repository. The dataset will include multispectral UAV images, annotation files, and metadata describing crop types, disease categories, and acquisition conditions. The trained models and source code will also be made available to the research community to facilitate further work in UAV-based crop disease monitoring and precision agriculture.

G. Future Research Directions

Future research will focus on several key directions to further improve the performance and applicability of the proposed system.

First, integrating multi-temporal remote sensing data will enable continuous monitoring of crop health and improve early disease prediction capabilities; time-series analysis can capture disease progression patterns and provide more accurate early warnings.

Second, self-supervised and semi-supervised learning methods will be explored to reduce reliance on large labeled datasets, leveraging unlabeled UAV imagery to improve model generalization and reduce annotation costs.

Third, the integration of Internet of Things (IoT) sensor networks with UAV monitoring systems will enable real-time data fusion between aerial imaging and ground-based environmental sensors, providing more comprehensive crop health monitoring.

Finally, future work will investigate transformer-based vision architectures and multimodal deep learning models, which may further improve feature representation and disease detection accuracy in complex agricultural environments.

VI. CONCLUSIONS AND RECOMMENDATIONS

This study presents an intelligent method for the identification and localization of crop diseases based on UAV multispectral imagery, systematically addressing key technical challenges in disease monitoring for precision agriculture. By constructing a multispectral image dataset covering visible, near-infrared, and red-edge bands, a complete intelligent crop disease recognition and localization technical system was developed. The proposed MS-ResNet model achieves an accuracy of 92.7%, a 15.3% improvement over the baseline ResNet model [19]. The SA-UNET model achieves precise localization with an average error of 3.2 cm. The overall system significantly reduces pesticide usage and improves disease control efficiency.

To address the challenge of rare disease identification, the FS-ProtoNet framework based on few-shot learning developed in this study achieves an identification accuracy of 83.5% with only 5 labeled samples, enabling early warning of rare diseases. For disease severity assessment, DSI-Net achieved a quantitative evaluation highly consistent with expert assessments, with a correlation coefficient of 0.92, providing a scientific basis for precise pesticide application decisions. Through model lightweighting and edge deployment, the entire technology stack can operate in real time under field conditions, satisfying practical production requirements.

From an application perspective, the results of this study have yielded remarkable benefits in field deployments at multiple agricultural production bases nationwide. After adopting this technology, average pesticide usage decreased by 25.8%, and in field validation trials, disease control efficiency improved by over 40%, generating substantial economic and ecological benefits. In the rice disease management application in Wujiang District, Suzhou City, Jiangsu Province, the targeted pesticide application plan saved 22.7% of pesticide usage compared with the conventional plan while improving the disease control effect by 18.3%. In the identification of rice blast variant strains in Guizhou Province, this technology helped researchers discover new variants 20 days in advance, effectively averting the risk of a large-scale epidemic.

The principal innovations of this research are reflected in four aspects: (1) a disease identification model combining multispectral features with deep learning was proposed, achieving high-precision classification; (2) a spectral–spatial dual-channel attention mechanism was designed, effectively improving disease area localization accuracy; (3) a rare disease identification method based on few-shot learning was developed, overcoming the problem of data scarcity; and (4) a complete technical system was established covering data collection, disease identification, and severity assessment, achieving seamless integration from technology to application.

Although significant progress has been achieved, several limitations remain. The stability of the current model under extreme weather conditions requires further improvement, the identification accuracy for compound diseases needs further optimization, and the computational efficiency and energy consumption on edge computing devices require deeper investigation. Future work will focus on multi-temporal and multispectral data fusion to further enhance the timeliness of disease early warning, explore the application of self-supervised learning to reduce reliance on labeled data, and strengthen integration with agricultural IoT infrastructure to build a more intelligent and automated crop disease monitoring and management system.

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