

Article

Evaluation of an Automated Severity Classification Framework for Rice BLB at a Regional Scale Using Multispectral UAV Imagery

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Abstract

Rice bacterial leaf blight (BLB), caused by the bacterium *Xanthomonas oryzae* *pv.* *oryzae*, severely damages leaves during rice growth, leading to reduced yield or even death. This study aimed to develop an automated identification and assessment method for rice BLB based on multispectral UAV imagery to overcome the limitations of in-field inspection methods. By obtaining multispectral image data of rice fields and extracting color features (CFs), texture features (TFs), and vegetation indices (VIs) of rice canopy using image processing techniques, three algorithms, namely, Support Vector Machine (SVM), Random Forest (RF), and Back Propagation Neural Network (BPNN), were utilized to establish a monitoring model for the severity levels of rice BLB. The classification results of several models are compared, with the overall Correct Identification Rate (CIR) of the three-feature fusion classification algorithm generally higher than the other two. Among the three algorithms, the RF algorithm performs the best, with a CIR reaching 93.4% and a Kappa coefficient of 0.91. The BPNN algorithm follows, with a CIR of 82.1% and a Kappa coefficient of 0.76, showing moderate effectiveness. Lastly, the SVM algorithm performs the poorest, with a CIR of 65.1% and a Kappa coefficient of 0.54. A rice BLB large-scale detection framework based on unmanned aerial vehicle (UAV) images was designed, and a graphical user interface (GUI) was developed using Python language to achieve automated processing from image input to final recognition results, achieving good results.

Keywords: BLB; UAV; multispectral imagery; multi-source feature fusion



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1. Introduction

Rice is one of the main cereal crops in China, but due to its complex growth environment, it is particularly susceptible to diseases and pests. Among them, rice bacterial leaf blight (BLB) is a common disease in rice production, severely affecting yield and quality [1,2]. Traditional visual inspection methods for monitoring rice BLB in large rice fields are inefficient and costly, making it difficult to detect the occurrence and spread of diseases in a timely manner [3,4]. With the advancement of agricultural practices and technology, the application of unmanned aerial vehicle (UAV) technology in agriculture is

becoming increasingly widespread [5–8]. In the monitoring and control of agricultural diseases and pests, the application of multispectral UAV technology provides unprecedented opportunity for improved technical support for agricultural production [9,10]. Zhang et al. (2018) found that extracting color features (CFs) from RGB images could qualitatively detect infected areas, but had poor effects on diseases of different levels, while vegetation indices (VIs) extracted from multispectral images could better quantify different levels of rice sheath blight (ShB) [11]. Zhang et al. (2011) found significant differences in the original spectral reflectance and first-order derivative reflectance of rice neck blast in different spectral regions under different disease severity [12]. Due to the superior nonlinear problem-solving ability of the Back Propagation Neural Network (BPNN) model, better accuracy was achieved. In the detection of rice diseases and pests using UAV multispectral data, spectral features or VIs are often extracted as input features for classifiers [13–15]. Chen et al. (2023) developed a support vector machine (SVM) regression model using vegetation indices extracted from UAV multispectral images, achieving high accuracy in monitoring different severity levels of cotton disease [16]. Zhang et al. (2024) developed two new spectral indices based on data from multiple sensors, and the constructed feature set achieved an accuracy of over 90%, realizing efficient monitoring of rice blast [17]. In terms of algorithms, researchers have conducted a series of studies on disease classification using various classification algorithms to build models in order to improve classification accuracy and prediction accuracy [18,19]. Luo et al. (2019) used spectral features of rice blast at different levels to establish rice blast classification prediction models using clustering methods, BPNN, and probabilistic neural networks, with results showing that the model based on the probabilistic neural network performed the best [20]. Singh et al. (2015) used the K-means clustering algorithm to segment infected parts of leaves and extracted texture features (TFs) as input for the support vector machine (SVM) classifier, with results showing that SVM could more accurately classify rice blast, achieving an accuracy of 82% [21]. Feng et al. (2021) used Partial Least Squares (PLS), Random Forest Regression (RFR), and Support Vector Machine Regression (SVR) algorithms to build a wheat powdery mildew disease index prediction model, with results showing that RFR exhibited high prediction accuracy under single-source and multi-source data modeling [22].

The above researchers have conducted a series of explorations in the field of rice disease and pest detection applied to rice and other crops; however, most of these studies are limited to the application of single features or algorithms. This study integrates three features, including VIs from multispectral images, and TFs and CFs from RGB images, to develop an automated recognition and assessment method for rice BLB based on multispectral UAV images. By obtaining multispectral image data of rice field areas and using image processing techniques to extract TFs, CFs, and VIs from rice canopy, this study employs SVM, RF, and BPNN algorithms for classification and recognition, establishing a monitoring model for the severity levels of rice BLB. This enables rapid and accurate identification of different severity levels of rice BLB in rice fields to meet the demand for precise pesticide application.

2. Materials and Methods

2.1. Experimental Field

The main experimental site of this study is located in experimental fields in Zhucun Street, Zengcheng District, Guangzhou City, Guangdong Province (23° 17' 33'' N, 113° 49' 45'' W). The experimental area belongs to the subtropical maritime monsoon climate of South Asia, characterized by mild climate, abundant sunshine, and ample rainfall, with an annual sunshine duration of around 1906 h and rainfall of 1800 mm. Rice infected with BLB

under natural conditions is the focus of this study, with the variety being Simiao. The rice was transplanted into the experimental fields in early April and harvested in early August.

2.2. Acquisition of Unmanned Aerial Vehicle Imaging Multispectral Data

The unmanned aerial vehicle low-altitude remote sensing (UAV-LARS) system used in this study is the DJI Phantom 4 Multispectral version (P4M, SZ DJI Technology Co., Ltd., Shenzhen, China), as shown in Figure 1. From June 2022 to July 2023, multispectral images of the study area were acquired using the multispectral camera on the UAV. The weather was clear, with wind speeds below 3 m/s and a temperature of approximately 30 °C, during the peak period of rice BLB. For the classification monitoring of BLB infection levels at the plot scale, the UAV was flown at an altitude of approximately 15~20 m, with the camera shooting angle set at -90° to capture images of rice plants at different levels of BLB infection.



Figure 1. DJI Phantom 4 Multispectral.

2.3. Data Processing

2.3.1. Preprocessing of Plot-Scale Data

The P4M camera comprises one visible light and five multispectral monochrome sensors, capable of simultaneously capturing six images: RGB, Blue, Green, Red, RedEdge (RE), and Near-Infrared (NIR). The single-band camera records pixel brightness values, also known as Digital Number (DN), influenced by factors like solar angle, cloud shadows, and exposure time, making them inadequate for directly assessing crop growth conditions. Hence, conversion to reflectance is necessary to ensure the robustness of the established model. The reflectance formula for a specific band (denoted as X) is shown in Equations (1) and (2). Finally, the reflectance formula for each band is obtained in Equation (3).

$$X_{ref} = \frac{X_{reflected}}{X_{incident}} = \frac{X_{camera}}{X_{LS}} \times \rho_x \quad (1)$$

$$\rho_x = \rho_{NIR} \times \frac{pCam_x}{pLS_x} \quad (2)$$

$$X_{ref} = \frac{X_{camera}}{X_{LS}} \times \rho_{NIR} \times \frac{pCam_x}{pLS_x} = \frac{\rho_{NIR} \times pCam_x}{X_{LS} \times pLS_x} \times X_{camera} \quad (3)$$

where X_{ref} , $X_{reflected}$, and $X_{incident}$, respectively, represent reflectance, incident light quantity, and reflected light quantity on the X band. X_{camera} represents the image signal value, X_{LS} represents the photosensitive signal value of the band light intensity sensor, and ρ_x represents the parameter for converting between the image signal value and the photo-sensitive signal value. $pCam_x$ and pLS_x , respectively, represent the camera conversion coefficient and the photoelectric conversion coefficient of the light intensity sensor for the x -th band. The parameters can be obtained by reading the metadata of the band images. Finally, the image undergoes processes such as camera position error correction, exposure time correction, distortion correction, and image fusion to obtain X_{ref} .

Due to the distinct physical positions and exposure settings among individual cameras within the P4M system, the acquired images of different spectral bands suffer from spatial misalignment, which prevents direct and reliable extraction of image features. Direct stacking of the raw R, G, and B band images without geometric alignment yields the result shown in Figure 2, where three distinct colored bands are clearly visible as a result of misregistration. Thus, it is necessary to register the two images to align them. Taking NIR band image as the reference, the images of the B, G, R, and RE bands are aligned to the reference image. Alignment involves two parts: the phase difference caused by the physical position difference between different bands, and the offset caused by the exposure time difference between cameras. The positional offset (in pixels) of each band camera relative to the reference band camera is stored in the metadata. With this information, the initial alignment of the five bands can be achieved. The specific process is illustrated in Figure 3. Subsequently, the edges of each band image can be extracted using a Sobel filter, followed by alignment improvement using the Enhanced Correlation Coefficient (ECC) Maximization algorithm. After registering each band, the results are shown in Figure 4. After preprocessing such as cropping the registered images, a total of 1054 multispectral images with dimensions of 200×200 pixels and varying degrees of BLB infection were obtained.

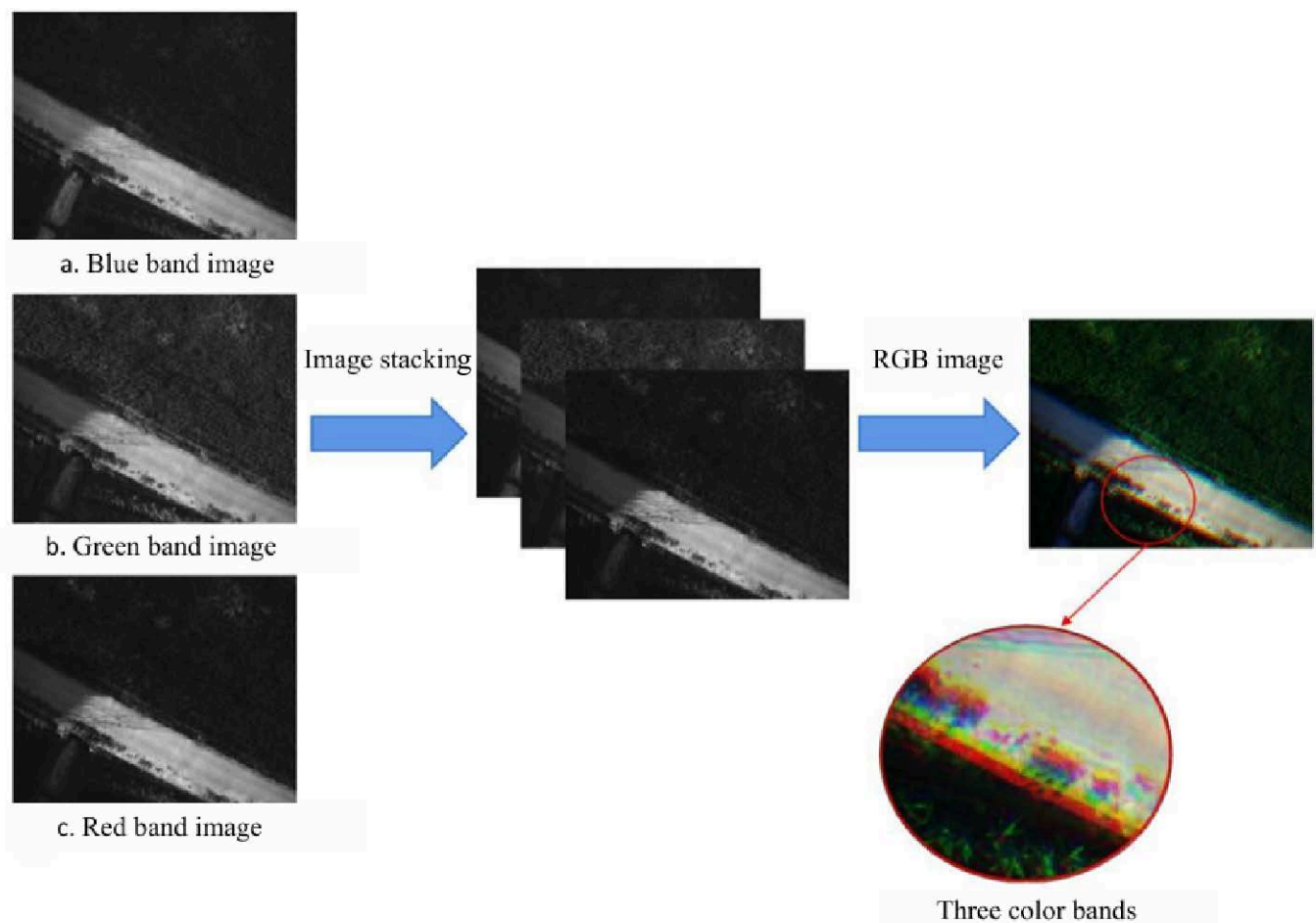


Figure 2. Multispectral band image fusion results without processing.

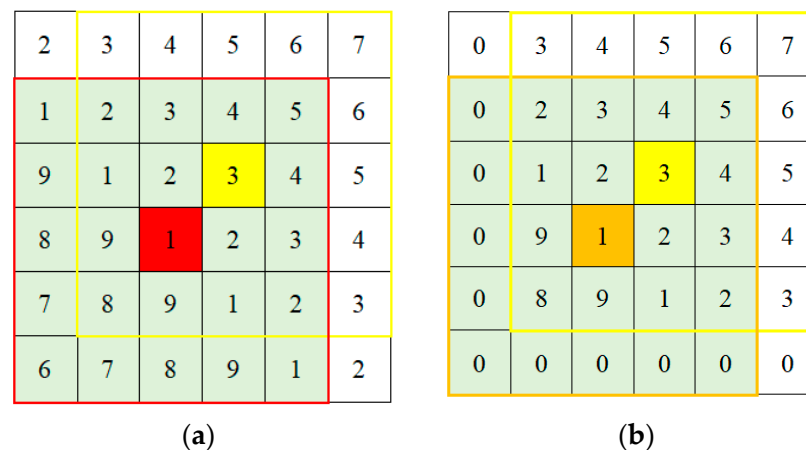


Figure 3. Flow chart of alignment of multispectral images in various bands. Note: The red box represents the reference image (NIR band); the yellow box represents the image to be aligned; the orange box represents the registered image. (a) Phase difference between two bands images; (b) aligned image.



Figure 4. Multispectral band image registration and fusion results. (a) RGB image after registration; (b) reference image.

2.3.2. Feature Extraction and Selection

In terms of disease and pest detection, the HSV color space of images is conducive to the extraction of disease feature information, and the recognition accuracy of BLB monitoring model constructed by fusing TFs and CFs reaches over 80%. To further improve the accuracy of BLB monitoring, this study utilizes UAV multispectral images to fuse TFs, CFs, and VIs. The monitoring model is built using SVM, RF, and BPNN algorithms. Firstly, convert the RGB three-band image to the HSV color space. Extract the first and second moments of the image as CFs using Equations (4) and (5), where H_P , S_P , and V_P represent the H, S, and V color components of the image, μ_H , μ_S , and μ_V represent the first moments of the HSV components, and δ_H , δ_S , and δ_V represent the second moments of the HSV components, respectively. Secondly, using the Gray-level Co-occurrence Matrix (GLCM), contrast (CON), correlation (COR), energy (EN), and homogeneity (HO) texture features are extracted from the R, G, B components of the image. GLCM parameters are set with three different distances and four different angles, resulting in a total of 144 texture features.

Finally, 33 VIs were obtained based on the commonly used VIs for crop pest and disease monitoring, and a total of 183 features were obtained [23–29].

$$\mu_H = \frac{1}{N} \sum_{p=1}^N H_p, \mu_S = \frac{1}{N} \sum_{p=1}^N S_p, \mu_V = \frac{1}{N} \sum_{p=1}^N V_p \quad (4)$$

$$\delta_H = \left[\frac{1}{N} \sum_{p=1}^N (H_p - \mu_H)^2 \right]^{1/2}, \delta_S = \left[\frac{1}{N} \sum_{p=1}^N (S_p - \mu_S)^2 \right]^{1/2}, \delta_V = \left[\frac{1}{N} \sum_{p=1}^N (V_p - \mu_V)^2 \right]^{1/2} \quad (5)$$

In this study, dimensionality reduction is applied to TFs and VIs, extracting 10 features each, which are then combined with CFs to form a total of 26 features as input for the model. Based on RF, the importance of features in monitoring BLB infection levels is determined. Features with importance scores ≥ 0.01 are selected. Subsequently, Autoencoder (AE) is employed to extract 10 TFs, achieving dimensionality reduction of TFs, as detailed in our previous work [30]. For the 33 VIs, the top 10 most important features are directly extracted as sensitive VIs for BLB, with their respective sorting, names, and formulas detailed in Table 1.

Table 1. Sorting, names, and formulas for 10 VIs sensitive to BLB.

Number	Names of VIs and Abbreviation	Calculation Formula
1	Visible Atmospherically Resistant Index (VARI)	$(G - R) / (G + R - B)$
2	Green Red Ratio Index (GRII)	G / R
3	Atmospherically Resistant Vegetation Index (ARVI)	$(NIR - (2R - B)) / NIR + (2R - B)$
4	Normalized Pigment Chlorophyll Index (NPCl)	$(RE - B) / (RE + B)$
5	Red Green Ratio (RGR)	R / G
6	Green Red Vegetation Index (GRVI)	$(G - R) / (G + R)$
7	Modified Green Red Vegetation Index (MGRVI)	$(G^2 - R^2) / (G^2 + R^2)$
8	Rededge Red Ratio Index 2 (RRI2)	RE / R
9	Carotenoid Reflectance Index 2 (CRI2)	$1 / G - 1 / NIR$
10	Normalized Red RE (NormRRE)	$RE / (NIR + RE + G)$

2.3.3. Model Establishment and Evaluation

This study utilizes UAV multispectral images to construct SVM, RF, and BPNN classification models for BLB severity levels based on features including CFs + TFs, VIs, and CFs + TFs + VIs. Subsequently, the results of each classification model are compared. Confusion matrix, Correct Identification Rate (CIR), and Kappa coefficient are employed as evaluation metrics for classification results. The confusion matrix is a commonly used intuitive evaluation method for qualitative model assessment, representing the correspondence between predicted and actual categories in a matrix table format. The confusion matrix for this study is presented in Table 2.

Table 2. Confusion matrix of prediction.

Predicted Severity Level	Actual Severity Level				Actual Total
	H	HR	M	S	
H	T_{00}	F_{01}	F_{02}	F_{03}	$T_{00} + F_{01} + F_{02} + F_{03}$
HR	F_{10}	T_{11}	F_{12}	F_{13}	$F_{10} + T_{11} + F_{12} + F_{13}$
M	F_{20}	F_{21}	T_{22}	F_{23}	$F_{20} + F_{21} + T_{22} + F_{23}$
S	F_{30}	F_{31}	F_{32}	T_{33}	$F_{30} + F_{31} + F_{32} + T_{33}$
Total Forecast	$T_{00} + F_{10} + F_{20} + F_{30}$	$F_{01} + T_{11} + F_{21} + F_{31}$	$F_{02} + F_{12} + T_{22} + F_{32}$	$F_{03} + F_{13} + F_{23} + T_{33}$	N

The CIR refers to the percentage of correctly identified samples out of the total number of samples, with higher values closer to 1 indicating better classification performance and higher discrimination accuracy, as calculated in Equation (6). The Kappa coefficient is a

statistical measure used to assess the consistency between classifier predictions and actual observations in classification problems. It typically ranges from -1 to 1 , where a value of 1 indicates perfect agreement between classifier predictions and actual observations, 0 indicates agreement equivalent to random guessing, and values less than 0 indicate lower consistency than random guessing, potentially indicating significant inconsistency. The specific formula for the Kappa coefficient is provided in Equation (7).

$$CIR = \frac{T_{00} + T_{11} + T_{22} + T_{33}}{N} \times 100\% \quad (6)$$

$$Kappa = \frac{N \times \sum_{i=1}^4 x_{ii} - \sum_{i=1}^4 (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^4 (x_{i+} \times x_{+i})} \quad (7)$$

where N represents the total number of samples, x_{ii} represents the sum of diagonal elements in the confusion matrix, and x_{i+} and x_{+i} represent the sum of rows and columns in the confusion matrix, respectively.

3. Results and Analysis

3.1. BLB Infection Severity

In this study, manual threshold segmentation was applied to RGB images to create mask images of BLB. These mask images were then multiplied by the RGB images to obtain BLB lesion images. Subsequently, the lesion images were converted to grayscale and binarized. Finally, the ratio of non-zero pixels to total pixels in the binarized images was calculated as the infection rate of BLB. Based on the infection rate, the severity of BLB was categorized into four levels: healthy (H) with an infection rate of 0% , healthy-relatively infected (HR) with an infection rate ranging from 0% to 15% , moderate infection (M) with an infection rate ranging from 15% to 30% , and severe infection (S) with an infection rate exceeding 30% . Samples of different infection levels are illustrated in Figure 5. The infection rates of BLB were calculated for all images, resulting in the classification of 1054 images into four groups: Group 1 representing H, comprising 272 images; Group 2 representing HR, comprising 270 images; Group 3 representing M, comprising 222 images; and Group 4 representing S, comprising 290 images. These images were divided into training and validation sets in an 8:2 ratio, with 842 and 212 images, respectively.

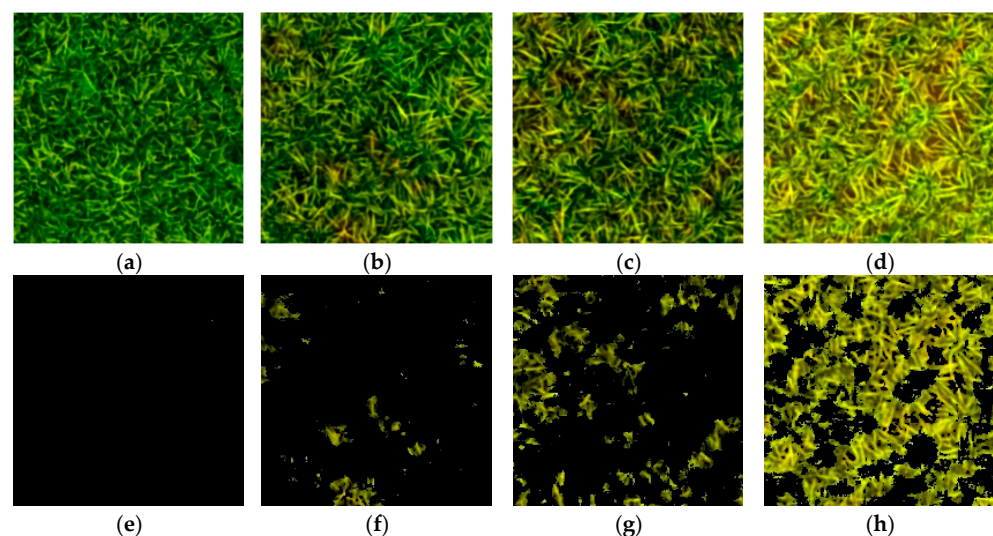


Figure 5. Samples of four infection levels in BLB. (a) RGB images (H), (b) RGB images (HR), (c) RGB images (M), (d) RGB images (S), (e) infected leaf (H), (f) infected leaf (HR), (g) infected leaf (M), (h) infected leaf (S).

3.2. Classification Model for BLB Infection Severity

The extracted 26 features, including CFs, TFs, and VIs, were used as variables to establish classification models for BLB infection severity using SVM, RF, and BPNN methods.

3.2.1. SVM-Based Classification Model

SVM is a classic supervised learning algorithm applicable to binary and multiclass problems. Its core concept is to find an optimal hyperplane in the feature space to effectively classify data while maximizing the margin of separation for the classification boundary. SVM's strong classification capability and flexible application scope make it one of the preferred algorithms for solving various classification problems. In this study, using CFs + TFs fusion features, VIs, and CFs + TFs + VIs fusion features as input feature variables, the "leave-one-out" cross-validation method was employed to construct the SVM prediction results, as shown in Table 3. The CIR and Kappa coefficients of the three classification models are 62.7%, 44.3%, and 65.1%, and 0.50, 0.25, and 0.54, respectively. Although the results are not ideal, it can be observed that the fusion of CFs + TFs + VIs can effectively improve the accuracy of the classification model.

Table 3. Confusion matrix based on three SVM classification models for predicting accuracy.

Input Features	Classification	Actual Severity Level				Actual Total	CIR/%
		H	HR	M	S		
CFs + TFs	H	42	8	4	0	54	77.8
	HR	11	26	17	0	54	48.1
	M	4	14	22	4	44	50
	S	0	4	13	43	60	71.7
	Total Forecast	57	52	56	47	212	62.7
VIs	H	30	14	1	9	54	55.6
	HR	7	19	8	20	54	35.2
	M	8	7	12	17	44	27.3
	S	11	9	7	33	60	55
	Total Forecast	56	49	28	79	212	44.3
CFs + TFs + VIs	H	45	8	1	0	54	83.3
	HR	10	26	15	3	54	48.1
	M	3	13	26	2	44	59.1
	S	2	2	15	41	60	68.3
	Total Forecast	60	49	57	46	212	65.1

3.2.2. RF-Based Classification Model

The core idea of RF lies in constructing each decision tree by randomly selecting feature and sample subsets, which enhances the model's diversity. This randomness helps reduce overfitting and improves the model's generalization ability. Additionally, since each tree is trained independently, RF can effectively handle high-dimensional and large-scale datasets. The performance of the RF classification model can be seen in Table 4. The CIR and Kappa coefficients for the three classification models were 87.8%, 86.8%, and 93.4%, and 0.84, 0.82, and 0.91, respectively. All three models had a CIR of over 85%, indicating satisfactory results, which can provide a basis for classifying rice BLB severity levels. The RF classification model based on the fusion of CFs + TFs + VIs can effectively improve the accuracy of the classification model to over 90%.

Table 4. Confusion matrix based on three RF classification model for predicting accuracy.

Input Features	Classification	Actual Severity Level				Actual Total	CIR/%
		H	HR	M	S		
CFs + TFs	H	40	6	0	8	54	74.1
	HR	2	48	0	4	54	88.9
	M	4	0	40	0	44	90.9
	S	0	0	2	58	60	96.7
	Total Forecast	46	54	42	70	212	87.8
VIs	H	50	3	1	0	54	92.6
	HR	7	45	2	0	54	83.3
	M	2	3	38	1	44	86.4
	S	0	4	5	51	60	85.0
	Total Forecast	59	55	46	52	212	86.8
CFs + TFs + VIs	H	52	2	0	0	54	96.3
	HR	6	48	0	0	54	88.9
	M	0	2	42	0	44	95.5
	S	0	4	0	56	60	93.3
	Total Forecast	58	56	42	56	212	93.4

3.2.3. BPNN-Based Classification Model

BPNN consists of multiple layers of neurons, typically including input, hidden, and output layers. Its training process is achieved through the backpropagation algorithm, which adjusts the weights and biases in the network using gradient descent to minimize the loss function. BPNN can learn and approximate various complex nonlinear function relationships, demonstrating strong expressive power. The performance of the three BPNN classification models can be seen in Table 5. The CIR and Kappa coefficients for the three classification models were 73.6%, 75.9%, and 82.1%, and 0.65, 0.68, and 0.76, respectively. While there is an improvement compared to the SVM results, the performance is still relatively low. Only when the three types of features are fused does the accuracy reach above 80%, providing guidance for the prevention and control of rice BLB. This is because BPNN is prone to getting stuck in local optima, sensitive to initial weights and learning rates, and as the network depth increases, issues such as vanishing or exploding gradients during training become more pronounced.

Table 5. Confusion matrix based on three BPNN classification models for predicting accuracy.

Input Features	Classification	Actual Severity Level				Actual Total	CIR/%
		H	HR	M	S		
CFs + TFs	H	42	7	5	0	54	77.8
	HR	5	37	12	0	54	68.5
	M	3	8	30	3	44	68.2
	S	0	4	9	47	60	78.3
	Total Forecast	50	56	56	50	212	73.6
VIs	H	44	7	3	0	54	81.5
	HR	5	39	10	0	54	72.2
	M	0	7	32	5	44	72.7
	S	0	6	8	46	60	76.7
	Total Forecast	49	59	53	51	212	75.9
CFs + TFs + VIs	H	46	5	2	1	54	85.2
	HR	5	43	6	0	54	79.6
	M	0	5	37	2	44	84.1
	S	0	2	10	48	60	80.0
	Total Forecast	51	55	55	51	212	82.1

3.2.4. Model Results and Analysis

This study investigates the performance of three different feature combinations in the classification of rice BLB using SVM, RF, and BPNN algorithms, namely, CFs + TFs, VIs, and CFs + TFs + VIs.

- (1) Analysis based on SVM classification model. Under the combination of CFs + TFs, the classification accuracy of the H level reached 77.8%, the highest among the three levels. The classification accuracies of HR and M levels were 48.1% and 50%, respectively, relatively low. The classification accuracy of the S level reached 71.7%, showing good performance. Under the VIs, the classification accuracies of the four levels were 55.6%, 35.2%, 27.3%, and 55%, showing poor performance. Under the combination of CFs + TFs + VIs, the CIR reached 65.1%, slightly higher than when using CFs + TFs or VIs alone. The classification accuracy of the H level was 83.3%, the highest among the three combinations. The classification accuracy of the HR level remained at 48.1%, showing stable performance without significant improvement. The classification accuracies for the M and S levels were 59.1% and 68.3%, respectively, higher than when using CFs + TFs or VIs alone, indicating that using multiple features can improve the identification accuracy of rice BLB, especially for H level.
- (2) Analysis based on RF classification model. Under the combination of CFs + TFs, the classification accuracy of the H level was 74.1%, showing good classification accuracy. The classification accuracy of the HR level reached 88.9%, indicating high accuracy. The classification accuracy of the M level was 90.9%, and the classification accuracy of the S level reached 96.7%, showing excellent performance. Under the VIs, the classification accuracy of the H level was 92.6%, showing excellent performance, while the classification accuracies of HR, M, and S levels were 83.3%, 86.4%, and 85.0%, respectively, lower than the CFs + TFs combination, but still at a high level. Under the combination of CFs + TFs + VIs, the classification accuracy of the H level reached 96.3%, the highest among the three combinations, showing outstanding performance. The classification accuracy of the HR level was 88.9%, similar to the CFs + TFs combination, the classification accuracy of the M level was 95.5%, significantly higher than when using VIs or CFs + TFs alone, and the classification accuracy of the S level was 93.3%, lower than the CFs + TFs combination, but still good. The comprehensive use of CFs + TFs + VIs can significantly improve the accuracy of classification, indicating that different feature combinations perform differently in the classification of different severity levels; thus, using multiple features can improve the robustness and accuracy of classification.
- (3) Analysis based on BPNN classification model. Under the combination of CFs + TFs, the classification accuracies of H, HR, and M levels were 77.8%, 68.5%, and 68.2%, respectively. The classification accuracy of the S level reached 78.3%, the highest among the three levels. Under the VIs, the classification accuracies of H, HR, and M levels were 81.5%, 72.2%, and 72.7%, respectively, slightly higher than the CFs + TFs. The classification accuracy of the S level was 76.7%, slightly lower than the CFs + TFs. Under the combination of CFs + TFs + VIs, all four severity levels were effectively improved, reaching 85.2%, 79.6%, 84.1%, and 80.0%, respectively.

In summary, in terms of overall classification accuracy, the classification accuracy of the three feature fusion algorithms is generally higher than the first two. It indicates that the comprehensive use of multiple features such as CFs, TFs, and VIs can effectively improve the robustness and accuracy of rice BLB classification. Among the three algorithms, the RF algorithm performs the best, with a maximum CIR of 93.4% and a Kappa of 0.91; followed by the BPNN algorithm, with a CIR of 82.1% and a Kappa of 0.76, with moderate effectiveness; and finally, the SVM algorithm, with a CIR of 65.1% and a Kappa of 0.54,

showing relatively poor performance. Therefore, in the classification of rice BLB, the RF algorithm performs the best, with high classification accuracy and stability, and can be used as the preferred algorithm for application. The next best is the BPNN algorithm, while the SVM algorithm performs relatively poorly.

3.3. Application Design of Rice BLB Infection Level on a Large Scale

By using multispectral UAV remote sensing imagery to capture large-area images of rice fields, combined with computer vision and machine learning techniques, early detection and accurate diagnosis of rice BLB can be achieved. This study designs an application for rice BLB detection based on large-scale UAV images. A graphical user interface (GUI) is developed using Python 3.8 to automate the entire process, from image input to final identification results.

3.3.1. Building DOM for Large-Scale Rice Fields

Prediction of rice BLB infection levels at a large scale requires first stitching together the acquired continuous multispectral image data to form a complete image of the rice field area. P4M flight parameters were set with a flight altitude and speed of 18 m and 3 m/s, respectively, with longitudinal and lateral overlaps of 85% and 80%, respectively. Imaging was conducted between 10:00 and 16:00 local time, targeting the rice experimental area. To mitigate the effects of sunlight variations on the images, calibration images were captured before and after each flight at a height of 5 m above the ground with a diffuse reflectance panel having a reflectance rate of 95%, as shown in Figure 6a. DJI Terra (V3.6.8) was used for preprocessing the UAV multispectral images, including initialization processing, radiometric correction using the diffuse reflectance reference panel, feature point matching, etc., resulting in the generation of a multispectral UAV digital orthophoto map (DOM) with a ground sample distance (GSD) of 0.9 cm, as depicted in Figure 6b.

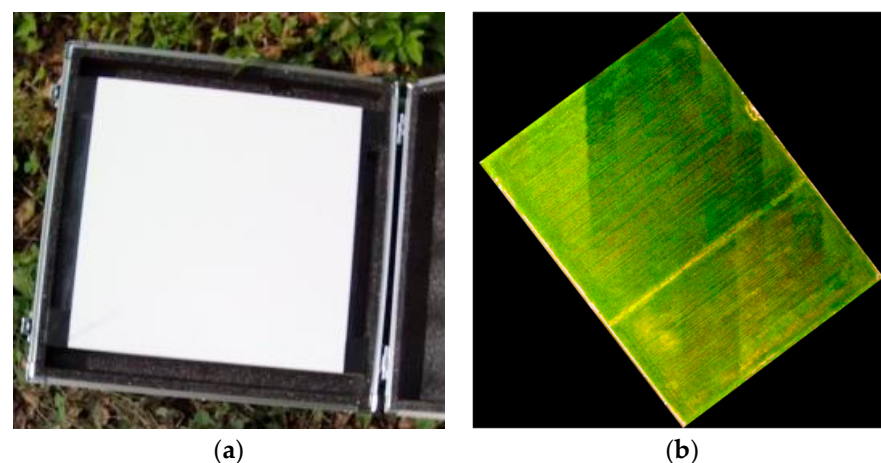


Figure 6. DOM of rice paddies infected with BLB. (a) Diffuse reflection reference board; (b) rice paddy DOM.

3.3.2. Design and Implementation of the BLB Recognition Application GUI

To facilitate user operation, the system's GUI was developed using the Tkinter library in Python. The interface provides a simple and intuitive workflow, as shown in Figure 7. It includes the following main functional modules:

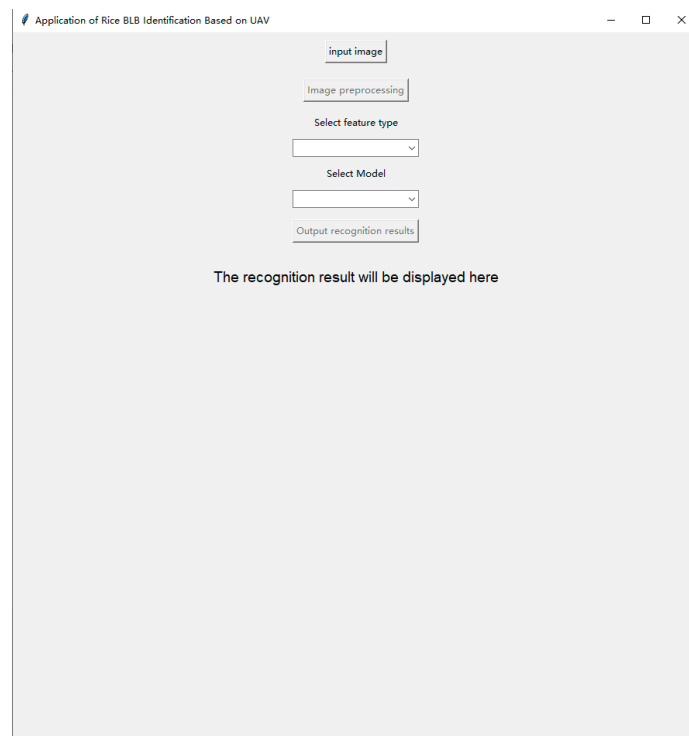


Figure 7. Application interface for identifying the severity level of BLB at the regional scale.

Image Input Module. Users can upload image files stored locally (e.g., JPEG, PNG, or TIF formats) through the GUI. In this study, the input images are the DOM images of rice fields captured by UAVs.

Image Preprocessing Module. To improve processing efficiency and convert large-area rice field images into a format suitable for feature extraction, the system resizes and crops the input images. First, the input image size is adjusted to be a multiple of 200×200 pixels. This ensures that subsequent image cropping is uniform and avoids processing issues caused by irregular image sizes. Then, the adjusted image is divided into several 200×200 -pixel sub-images, which are used as input for feature extraction and model classification.

Feature Selection Module. The system offers two feature extraction options: CFs + TFs, and CFs + TFs + VIs. Users can select the appropriate feature extraction method from the GUI, and the system will automatically extract the corresponding features from each sub-image.

Model Selection Module. Based on the selected features, users can choose the corresponding model for recognition. The system provides two pre-trained classification models: CFs + TFs + RF1 and CFs + TFs + VIs + RF2.

Recognition Result Display Module. After feature extraction and model classification, the system stitches together the classification results of each sub-image to reconstruct the complete large-area image. The final recognition results are displayed using color coding or markers, allowing users to visually observe the distribution of diseased areas in the rice field.

3.3.3. System Recognition Result Analysis

Figure 8 shows the visualization of the severe levels of rice BLB as manually classified, and the results of the best-performing RF classification model. The dataset was manually divided into four severity levels: H, HR, M, and S, with sub-images assigned different colors—red, green, blue, and yellow—corresponding to each severity level. These colored sub-images were then reassembled into a large-area image based on their cropping se-

quence, as shown in Figure 8a. Figure 8b displays the large-area rice field distribution map of BLB severity, generated by the system. The features and model used for classification were based on the three-feature fusion RF classification model. A comparison of the results shows that the system can accurately classify the severity levels of BLB in rice fields at the regional scale. As shown in Table 6, this study quantitatively compares the proportion of pixels between manual division and system recognition for BLB severity levels. The statistical results demonstrate a high degree of consistency, with absolute differences for individual samples ranging from 1.4% to 2.2%. This indicates that our system achieves excellent overall segmentation accuracy, exhibiting only minor deviations in edge details.

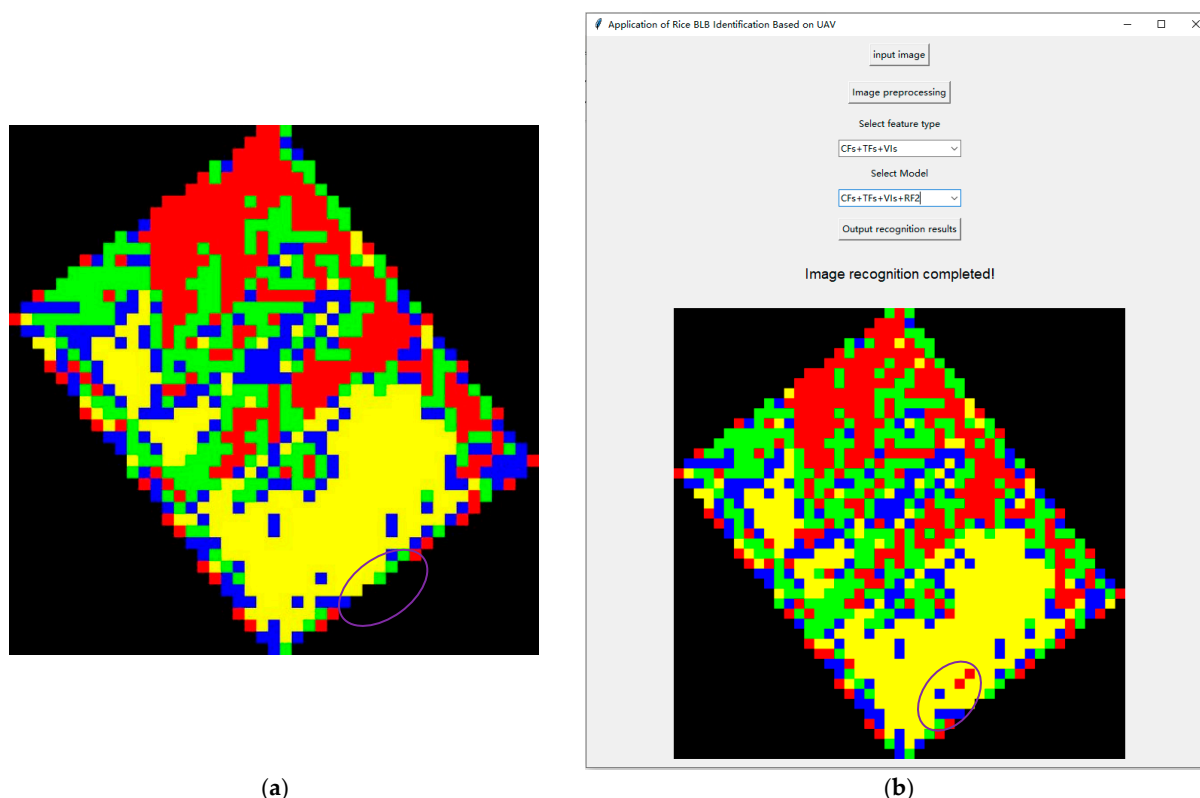


Figure 8. Comparison between manual partitioning results and system recognition results. The purple circle denotes a typical region with inconsistent classification results between our system’s output and manual annotation. Despite such minor local differences, the two maps show excellent overall agreement. (a) Manual division results; (b) system recognition results.

Table 6. Pixel percentage of rice BLB severity levels from manual division and system recognition.

Classification Method	Proportion of Red Pixels/%	Proportion of Red Pixels/%	Proportion of Red Pixels/%	Proportion of Red Pixels/%
Manual division	25.5	24.6	17.6	32.3
System recognition	26.9	26.8	15.7	30.6
Absolute difference	1.4	2.2	1.9	1.7

4. Conclusions

This study utilized multispectral image data of rice fields and employed image processing techniques to extract CFs, TFs, and VIs of rice canopies. Three machine learning algorithms, SVM, RF, and BPNN, were used for classification and identification, resulting in the establishment of a monitoring model for severe levels of rice BLB. The following conclusions were drawn:

1. The comprehensive utilization of CFs, TFs, and VIs significantly enhances the accuracy and robustness of rice BLB classification. Differences in classification results were observed among different severity levels when comparing the performance of various algorithm combinations under different feature sets.
2. Under the CFs + TFs combination, the SVM algorithm achieved a total CIR of 65.1%, which was slightly lower than its performance under the other two feature combinations. The RF algorithm exhibited the highest total CIR of 93.4%, demonstrating superior classification accuracy and stability. Meanwhile, the BPNN algorithm had a total CIR of 82.1%, ranking in the middle among the three algorithms.
3. Classification accuracy was generally lower under the VIs, indicating that utilizing VIs alone for classification is ineffective. The combination of CFs, TFs, and VIs showed promising classification results across all algorithms. Among them, the RF algorithm performed the best in rice BLB classification, exhibiting the highest classification accuracy and stability, and can be considered the preferred algorithm for application.
4. A UAV-based application for detecting rice BLB on large-area images has been developed, automating the entire process from image input to final recognition results. The system can automatically identify and assess the severity of rice BLB, significantly improving detection efficiency and reducing labor costs.

The results of this study demonstrate the importance of using a classification algorithm that integrates multiple features for accurate rice BLB recognition. The UAV-based system for detecting rice BLB not only efficiently processes large-scale rice field images, but also offers flexible feature extraction and model selection options, aiding agricultural experts in disease monitoring and precise diagnosis. Future research could explore additional feature combinations or optimized algorithm models to further enhance the accuracy and practicality of rice disease classification.

5. Discussion

With the advancement of agricultural modernization, traditional disease detection methods have gradually failed to meet the demands of precision agriculture. Remote sensing technology has become an essential instrument in modern agricultural disease management due to its efficiency and real-time capabilities [31,32]. Although remarkable progress has been made in research on remote sensing-based detection of rice diseases, the field still faces common technical bottlenecks including limited datasets, poor cross-scale adaptability, and high barriers to practical deployment [33–36]. Gulo et al. (2025) [37] constructed a machine learning model using color and texture features to achieve high-precision identification of rice diseases. However, their research was based on single-leaf images, making it difficult to apply to field-scale mapping and UAV pesticide spraying operations [37]. In contrast, Logavitool et al. adopted deep learning to perform pixel-level segmentation of BLB with outstanding accuracy, yet the method imposes heavy demands on labeled datasets and computing power, hindering its large-scale promotion [38].

In this study, multi-feature fusion and a lightweight graphical user interface (GUI) design are adopted. While retaining high accuracy for disease severity grading, the proposed approach drastically lowers the threshold for field application and enables end-to-end automatic monitoring. Future work will further expand the coverage of disease categories, integrate environmental and meteorological data, and incorporate Internet of Things (IoT) devices to improve model generalization capability. This will provide transferable technical support for large-scale precise monitoring of rice diseases.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author, due to their being part of an ongoing study.

Conflicts of Interest: Author Kanmo Chen was employed by the company Zhanjiang High-Tech Low-Altitude Economic Development Co., Ltd. The remaining authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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