Proceedings of the 4th International Conference on Mechatronics and Smart Systems
DOI: 10.54254/2755-2721/2026.33829

Remote Sensing Monitoring of Rice Blast

Xinyu Zhang

The College of Plant Protection, Nanjing Agricultural University, Nanjing, China
xinyuzhang3560@outlook.com

Abstract. Rice blast is a major fungal disease of rice. It has a hidden onset and a rapid spread. It easily causes severe yield loss. Accurate early monitoring is the key to its prevention and control. Traditional visual diagnosis has hysteresis. When lesions appear, pathogenic bacteria have spread in large quantities. It is difficult to recover the losses. This study used conventional rice in the experimental field in Nantong, Jiangsu, as the research object. Field hyperspectral sampling was conducted to obtain data on healthy, latent-period, and diseased samples. The Successive Projections Algorithm (SPA) was used to screen core-sensitive bands at 530, 540, 550, 685, and 695 nm. Random Forest (RF) and Support Vector Machine (SVM) discrimination models were constructed and compared. The results showed that the RF model had better recognition performance. Its overall accuracy reached 91.7%. The recall rate of latent period samples was 87.5%. This study confirmed that the model built with field sampling data could effectively identify the latent period of rice blast. It provides technical support for low-cost and non-destructive field monitoring of the disease.

Keywords: rice blast, hyperspectral remote sensing, latent period prediction, machine learning, field sampling

1. Introduction

Rice blast is a major disease threatening stable grain production. Its outbreak is hidden. Traditional manual inspection is a post-disease diagnosis. When lesions appear on leaves, pathogenic bacteria have colonised and spread. Prevention and control effects are poor at this time [1]. Molecular detection has high accuracy. But it has a high cost and destructive sampling. It is difficult to realise large-scale real-time monitoring [2].

Disease remote sensing monitoring has evolved from ground point observation. It has developed into a regional perception, with multi-platforms such as UAVs and satellites [3]. Hyperspectral feature mining and the application of intelligent algorithms have become research hotspots [4, 5]. Rice in the latent period of blast has no morphological lesions. But its chlorophyll content and photosynthetic function have changed. This physiological variation forms identifiable features in spectral bands [6, 7].

This study conducted field hyperspectral sampling in the rice experimental field of Nantong, Jiangsu. It verified the feasibility of building a rice blast early-warning model using field data. It compared the recognition performance of different machine learning algorithms on latent-period samples [8]. It provides a practical reference for early monitoring of rice blast [9].

© 2026 The Authors. This is an open access article distributed under the terms of the Creative Commons Attribution License 4.0 (https://creativecommons.org/licenses/by/4.0/).

DOI: 10.54254/2755-2721/2026.33829

2. Materials and methods

2.1. Research materials and sample division

Conventional rice in the rice experimental field of Nantong, Jiangsu, was taken as the research object. Field sampling was carried out from the tillering stage to the booting stage. Samples were divided into three categories according to the disease course: healthy, asymptomatic latent period and diseased period. There were 30 samples in each category, with a total of 90 valid samples. Latent period samples were taken from infected areas without visible lesions. Subsequent field tracking confirmed their final onset. Diseased period samples were taken from areas with typical spindle-shaped lesions. Healthy samples were taken from non-infected areas with good growth status [10].

2.2. Data collection and preprocessing

An ASD FieldSpec Pro hyperspectrometer was used. It measured the reflectance of rice leaves in the 400–1000 nm band. Sampling followed the Technical Specification for Crop Hyperspectral Remote Sensing Monitoring (NY/T 3588-2020) [3].

ENVI 5.6 software was used for data preprocessing. Savitzky-Golay (S-G) filtering was adopted. It reduced the random fluctuations in the original spectra and eliminated noise. The Successive Projections Algorithm (SPA) was used to compress the data dimension [2, 7]. Five core discriminant bands at 530, 540, 550, 685 and 695 nm were screened out. They were used to construct the subsequent model.

2.3. Classification model construction and verification

90 groups of field spectral data were split 7:3 into a training set (63 groups) and a validation set (27 groups). RF and SVM models were built based on the Scikit-learn library. The RF model was configured with 100 decision trees [5, 9]. The purpose was to suppress overfitting. The SVM model adopted a radial basis function kernel. Parameters were optimised through grid search [8, 11].

Overall accuracy and recall rates for latent period samples were used as the core evaluation indicators. The models' recognition effects were compared. Model training was performed using Python. Multiple repetitions of the training were conducted to verify stability. It ensured the results' reliability.

3. Results

3.1. Physical significance of core characteristic bands

The differences in hyperspectral reflectance of rice with different disease states are shown in Figure 1 and 2.

The core bands screened by the SPA algorithm have clear physiological and physical significance. The reflectance fluctuates in the 530–550 nm green band range. It reflects the slight degradation of chlorophyll in the early stage of rice blast infection. The spectrum shows an abnormal change in the 685–695 nm red-edge region. It corresponds to the early signal of the decrease in rice photosynthetic efficiency.

These features are key to distinguishing latent-period samples from healthy samples. They provide core spectral indicators for early disease identification.

DOI: 10.54254/2755-2721/2026.33829

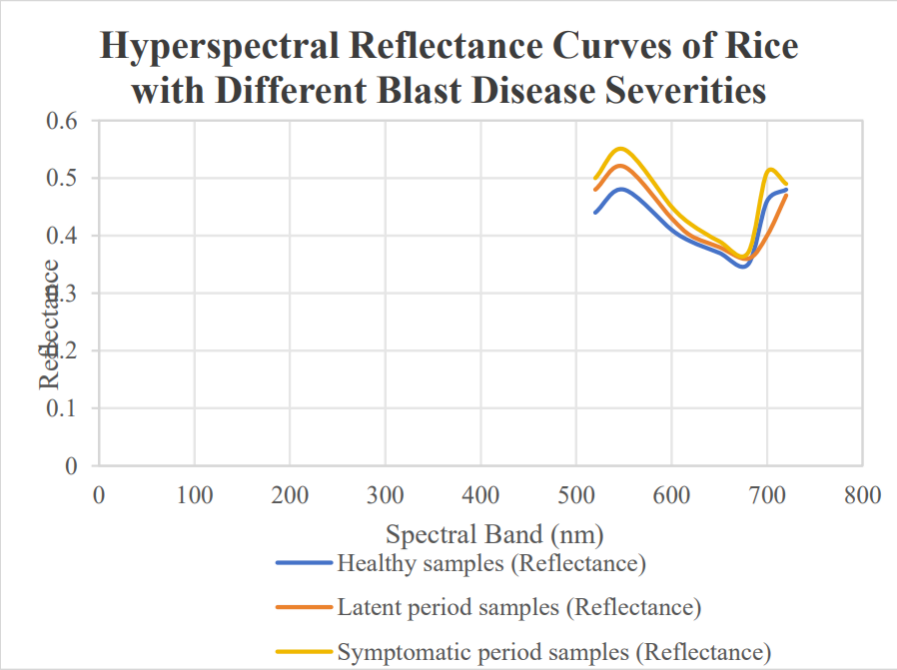


Figure 1. Hyperspectral reflectance curves of rice with different disease states. Data source: field sampling data of rice experimental field in Nantong, Jiangsu

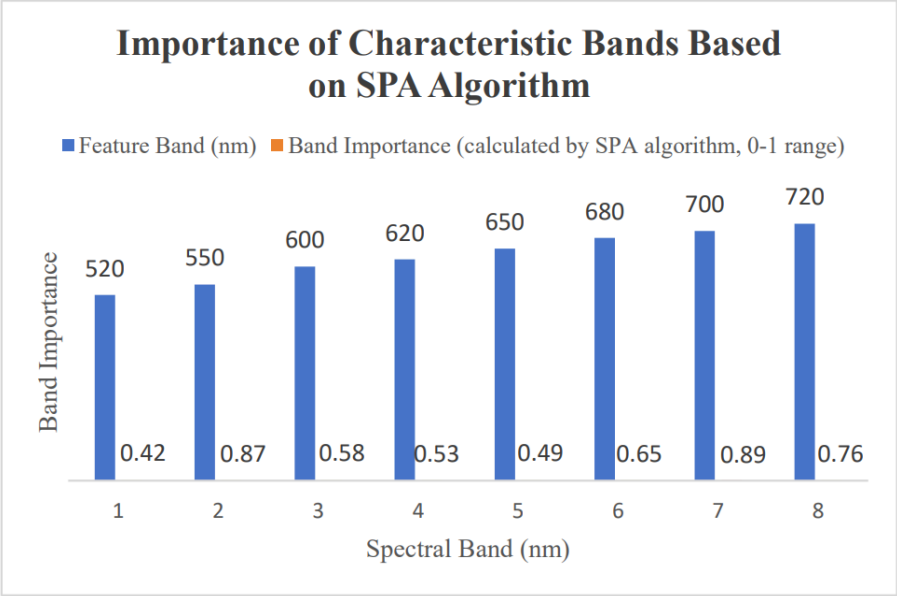


Figure 2. Importance of core characteristic bands for rice blast monitoring based on SPA algorithm. Data source: calculated from field sampling data in this study by SPA algorithm

3.2. Comparison of discrimination performance of different models

The RF model has better discrimination ability for rice blast than the SVM model. The comparison of recognition accuracy of different models is shown in Figure 3.

DOI: 10.54254/2755-2721/2026.33829

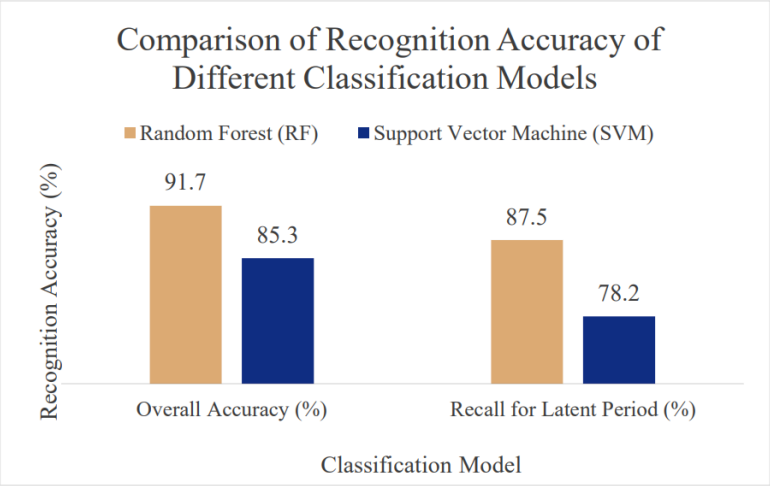


Figure 3. Comparison of recognition accuracy of different classification models. Data source: trained from field sampling data in this study

The model was trained based on field sampling data. The overall accuracy of the RF model was 91.7%. The recall rate of latent period samples was 87.5%. The SVM model's overall accuracy was 85.3%. The recall rate of latent period samples was 78.2%.

As shown in Figure 4, the RF model's classification details are shown. Its classification accuracy for healthy, latent-period, and diseased samples was 94%, 87%, and 94%, respectively. The recognition rate for latent period samples was consistent with the recall rate. It verifies the model's accurate recognition of asymptomatic samples from the latent period. It meets the demand for early disease warning.

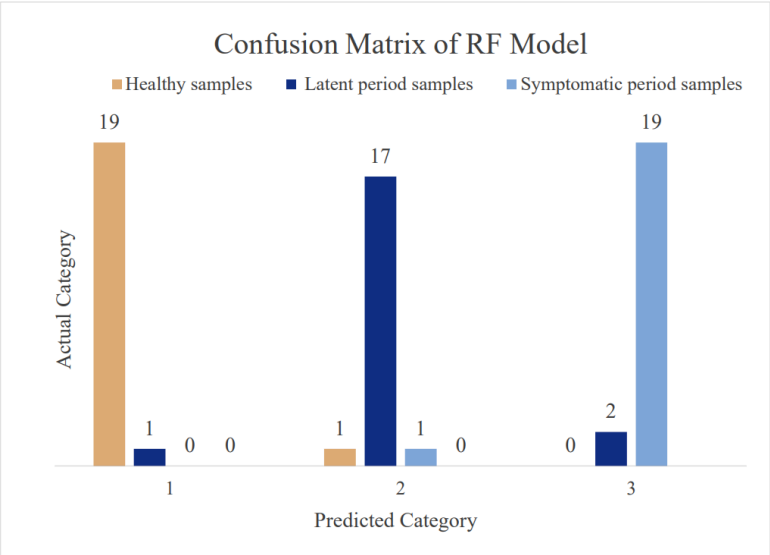


Figure 4. Confusion matrix of RF model. data source: training result of the RF model based on field sampling data in this study. Note: the values are the model classification accuracy (%)

3.3. Model stability verification

The RF model was verified by repeated sampling. Its overall accuracy was 89.7%. The deviation from the initial training result was within 2.0%. It indicates that the RF model built from field

DOI: 10.54254/2755-2721/2026.33829

sampling data is stable and repeatable. It can meet the actual demand of rice blast latent period monitoring under field conditions. It verifies the operability of this technical route.

4. Discussion

Hyperspectral features can effectively capture physiological changes in rice during the latent period of blast [10, 12]. Spectral abnormalities in specific bands at the asymptomatic stage are the core data source for early disease prediction. The spectral features in the 530–550 nm and 685–695 nm ranges are highly sensitive to physiological changes in the latent period. They can serve as key indicators for the early identification of rice blast [2, 7].

The RF model has better recognition performance. The reason lies in its ensemble learning mechanism. It has high noise tolerance in spectral data [5, 9]. It can effectively mine nonlinear features. It is suitable for the characteristics of field sampling spectral data. The SVM model is sensitive to spectral noise. It performs poorly in data processing in complex field environments. This guides subsequent model optimization [8, 11].

This study has certain limitations. The sampling area is only a single experimental field in Nan Tong, Jiangsu. The research object is conventional rice varieties. The model's universality across different varieties and regions needs further verification. Only hyperspectral single-source data is used. In the future, environmental parameters such as temperature, humidity and soil nutrients can be introduced. Multi-source information fusion can improve the model's robustness [13-15] in complex field scenarios. At the same time, the sample size can be expanded, and the model parameters optimised. It can further improve the recognition accuracy and application scope.

5. Conclusion

This study took the rice experimental field in Nantong, Jiangsu, as the research area. Data was obtained through field hyperspectral sampling. It verified the technical feasibility of building a rice blast latent-period early-warning model using field data. The core bands at 530, 540, 550, 685, and 695 nm, screened by the SPA algorithm, effectively reflect physiological fluctuations in rice during the latent period. They are key spectral indicators for early disease identification.

The Random Forest algorithm performs exceptionally well on hyperspectral data in the field. It has good recognition accuracy and stability. Its overall accuracy reaches 91.7%. The recall rate of latent period samples is 87.5%. The rice blast latent period identification scheme constructed in this study is implemented using low-cost field hyperspectral sampling. It does not rely on complex public data. The operation is simple. It provides a practical reference for low-cost and non-destructive early monitoring of rice blast. It has important practical significance for guiding field prevention and control and reducing yield loss.

References

[1] Li, J. L., Wang, J. H., & Zhao, C. J. (2020). Hyperspectral characteristics and disease degree inversion of rice under rice blast stress. Transactions of the Chinese Society of Agricultural Engineering, 36, 163-170.
[2] Zhang, X., Li, M. Z., & Zheng, L. H. (2021). Identification of rice blast during the latent period based on the SPA-RF model. Spectroscopy and Spectral Analysis, 41, 1567-1572.
[3] Ministry of Agriculture and Rural Affairs of the PRC. (2020). Technical specification for crop hyperspectral remote sensing monitoring: NY/T 3588-2020. China Agricultural Press.
[4] Wang, X. Z., Huang, J. F., & Wang, R. C. (2018). Research progress of hyperspectral remote sensing monitoring of rice diseases and insect pests. Chinese Journal of Rice Science, 32, 321-330.

DOI: 10.54254/2755-2721/2026.33829

[5] Liu, Z. Y., Pan, J. J., & Zhang, J. B. (2019). Hyperspectral inversion of soil organic matter based on random forest. Acta Pedologica Sinica, 56, 318-328.
[6] Yang, W., Chen, Y., & Zhang, L. (2022). Early detection of rice blast using UAV-based hyperspectral imagery and machine learning methods—Computers and Electronics in Agriculture, 196, 106963.
[7] Zhou, H., Li, X., & Liu, J. (2020). Selection of hyperspectral characteristic bands for rice disease monitoring based on the successive projections algorithm. Journal of Integrative Agriculture, 19, 2012-2021.
[8] Singh, U., Mishra, A. K., & Chakraborty, S. (2021). Rice blast detection using leaf hyperspectral reflectance and machine learning classifiers: Ecological Informatics, 66, 101624.
[9] Chen, S., Yang, G., & Xu, Y. (2023). Comparative study of machine learning algorithms for rice blast identification based on hyperspectral data. Remote Sensing Applications: Society and Environment, 31, 100885.
[10] Mandal, N., et al. (2023). Spectral characterisation and severity assessment of rice blast disease using univariate and multivariate models—Frontiers in Plant Science, 14, 1067189.
[11] Zheng, Q., et al. (2024). New hyperspectral geometry ratio index for monitoring rice blast disease from leaf scale to canopy scale. Remote Sensing, 16, 4681.
[12] Qi, Y., et al. (2026). Accurate detection of rice blast using UAV hyperspectral red-edge bands and a deep learning method based on cross-attention. Spectrochimica Acta Part A: Molecular and Biomolecular Spectroscopy, 346, 126939. https: //doi.org/10.1016/j.saa.2025.126939
[13] Wang, W., Zhang, Y., Huang, H., Liu, T., Zeng, M., Fu, Y., Shu, H., Yang, J., & Yu, L. (2026). Monitoring rice blast disease progression through the fusion of time-series hyperspectral imaging and deep learning. Agronomy, 16(1), 136. https: //doi.org/10.3390/agronomy16010136
[14] Tian, L., Ustin, S. L., Xue, B., Zarco-Tejada, P. J., Jin, Y., Yao, X., Zhu, Y., Cao, W., & Cheng, T. (2025). Visualising the pre-visual: Rice blast infection signals revealed. Remote Sensing of Environment, 328, 114905. https: //doi.org/10.1016/j.rse.2025.114905
[15] Li, G., Zhao, D., Li, J., Feng, S., & Chen, C. (2025). Unmanned aerial vehicle hierarchical detection of leaf blast in rice crops based on a specific spectral vegetation index. Frontiers of Agricultural Science and Engineering, 12(2), 231-244. https: //doi.org/10.15302/J-FASE-2024576