Classification Of Rice Leaf Blast Severity Using Hyperspectral Imaging

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Abstract

Rice leaf blast is prevalent all over the world and is a serious threat to rice yield and quality. Hyperspectral imaging is an emerging technology applied in plant disease research. In this paper, the standard deviation (STD) of the spectral reflectance of whole leaves was calculated and a support vector machine (SVM) model was built to classify the degree of rice leaf blast at different growth stages. The average accuracy of the full-spectrum-based SVM model at jointing stage, booting stage and heading stage was 97.78%, 92.63% and 92.20%, respectively. The STD of the spectral reflectance of the whole leaf differed not only within samples with different disease grades, but also those with the same disease level. Compared with the raw spectral reflectance, the STD of which performed better in assessing rice leaf blast severity.

Introduction

Rice is one of the main grain crops worldwide. In China, rice accounts for approximately one-quarter of the total crop planting area and one-third of the grain yield [1]. Rice blast (*Magnaporthe grisea*), which is one of the most severe diseases in China [2], is a major cause of economic loss. Since the 1990s, the annual occurrence area of rice blast in China has been at least 3.8 million hm^2 on average, and the annual loss has been up to several hundred million kilograms [3]. Accurate evaluation of rice blast severity is of great significance to improve rice productivity and realize precision agriculture.

By now, disease scouting and phenotyping techniques mostly depend on human visual ratings [4–6]. The eye serves as a remote sensing device, and combined with the relevant parts of the brain serves as an image analysis system [7], which works extremely rapidly to capture, analyse and comprehend images [8]. The process allows individuals to both identify the type and calculate the quantity of diseased tissue on a particular leaf or plant [9]. Human visual ratings rely on rater capacity, rater credibility, and can be prone to human inaccuracy, subjectivity, and inter/intra-rater variability [10–12]. Hence, a novel and more stable method is needed.

Hyperspectral imaging (HSI) is an emerging means of assessing plant vitality, stress parameters, nutrition status, and diseases [13]. Hyperspectral imaging can overcome the aforementioned shortcomings, producing digital measurements that can be easily shared and quickly analysed with semi-automated procedures in a repeatable and objective manner [14]. Hyperspectral imaging has been used for the assessment of plant disease severity in wine grapes, barley, and sugar beet among others [13, 15, 16]. A series of data processing methods have been used in previous studies, such as raw spectra [17, 18], difference spectra [19, 20], ratio spectra [21], derivative spectra [22, 23] and vegetation indices [24–26]. All of them have achieved good results. However, to our knowledge, the standard deviation (STD) of spectral reflectance has not been used in grading rice leaf blast severity until now.

In this study, hyperspectral images of rice leaves were obtained by a ground-based hyperspectral imaging system, the average spectral reflectance of whole leaves and of different regions of the leaf were extracted by ENVI 5.6. The STD of spectral reflectance of whole leaves was calculated automatically using ENVI 5.6. To avoid the possibility of occasionality, full-spectrum-based SVM models were built using the STD dataset in three different growth stages. The classification effect was evaluated by the overall classification accuracy, the micro F1 value and the macro F1 value. All of these values were compared with those of the raw spectra, which was treated as a reference.

Results

Spectral characterization of leaves with different forms of lesions. Leaves with different forms of lesions showed various colours and structures in the hyperspectral images. Their spectral reflectance were also different (Fig. 1). The chronic form consisted of three parts: a yellow margin, red transition area and white centre. The spectral reflectance of the lesion centre was higher than that of the transition area and margin in the entire region and that of healthy tissues in most regions. The spectral reflectance of margins had a higher value than that of healthy tissues in the visible region, but the opposite in the near-infrared (NIR) region (Fig. 1a). The brown spot form had only one red centre. The spectral reflectance of healthy tissues was higher than that of diseased areas in the whole region, except in the wavelength range around 600–700 nm (Fig. 1b). The white spot

form also had only one centre, but its colour was white. The spectral reflectance of healthy tissues was lower than that of diseased areas in the visible region, but the opposite in the NIR region (Fig. 1c).

Reflectance differences for diseased versus healthy leaves. There were some differences in raw spectral reflectance among leaves of the five levels at three growth stages, but the differences were not obvious. Compared with the former, that of the STD was more evident (Fig. 2). In the visible region, the differences in raw spectral reflectance between diseased leaves and healthy leaves were positive. With the increase in disease degree, the differences also increased; while in the NIR region, the differences in raw spectral reflectance between diseased leaves and healthy leaves were negative. With the increase in disease degree, the absolute value decreased. The intersection of the difference spectra and Y axis gradually moved to the longer wavelengths with increasing of disease degree. The differences in STD between diseased leaves and healthy leaves were positive in the whole region, and the value increased with increasing disease degree (Fig. 3).

Assessment of rice leaf blast severity. The classification models performed well in assessing rice leaf blast severity (Table 1). All the three measures for the classification models constructed by the STD dataset were higher than those of raw spectral reflectance at all three growth stages. Generally, misclassification occurred between adjacent disease degrees (Table 2). Samples were prone to being misclassified as samples of level 1 and level 3.

Table 1
Measures for classification models at different stages

growth stage	sample	training set	testing set	average accuracy		mico F1 value		macro F1 value	
				raw	STD	raw	STD	raw	STD
jointing stage	level 0	7	3	\	\	\	\	\	\
	level 1	14	6	\	\	\	\	\	\
booting stage	level 2	10	5	\	\	\	\	\	\
	level 3	6	3	\	\	\	\	\	\
heading stage	level 4	1	1	\	\	\	\	\	\
	total	38	18	88.89%	97.78%	0.7222	0.9444	0.7647	0.9497
	level 0	12	6	\	\	\	\	\	\
	level 1	35	14	\	\	\	\	\	\
	level 2	10	4	\	\	\	\	\	\
	level 3	19	9	\	\	\	\	\	\
	level 4	13	5	\	\	\	\	\	\
	total	89	38	85.26%	92.63%	0.6316	0.8158	0.5583	0.7153
	level 0	11	4	\	\	\	\	\	\
	level 1	31	14	\	\	\	\	\	\
	level 2	14	6	\	\	\	\	\	\
	level 3	24	10	\	\	\	\	\	\
	level 4	16	7	\	\	\	\	\	\
	total	96	41	87.32%	92.20%	0.6829	0.8048	0.5974	0.8006

Table 2
Performances of the classification models at different growth stages

growth stage	sample	raw spectral reflectance						Standard deviation					
		level 0	level 1	level 2	level 3	level 4	true	level 0	level 1	level 2	level 3	level 4	true
jointing stage	level 0	3	0	0	0	0	3	3	0	0	0	0	3
booting stage	level 1	1	5	0	0	0	6	0	6	0	0	0	6
heading stage	level 2	0	1	2	2	0	5	0	0	5	0	0	5
	level 3	0	0	1	2	0	3	0	0	1	2	0	3
	level 4	0	0	0	0	1	1	0	0	0	0	1	1
	prediction	4	6	3	4	1	18	3	6	6	2	1	18
	level 0	2	4	0	0	0	6	6	0	0	0	0	6
	level 1	0	13	0	1	0	14	0	14	0	0	0	14
	level 2	0	3	0	1	0	4	0	4	0	0	0	4
	level 3	0	3	0	5	1	9	0	2	0	7	0	9
	level 4	0	0	0	1	4	5	0	0	0	1	4	5
	prediction	2	23	0	8	5	38	6	20	0	8	4	38
	level 0	2	2	0	0	0	4	4	0	0	0	0	4
	level 1	2	12	0	0	0	14	1	12	1	0	0	14
	level 2	0	6	0	0	0	6	0	2	3	1	0	6
	level 3	0	2	0	7	1	10	0	1	1	7	1	10
	level 4	0	0	0	0	7	7	0	0	0	0	7	7
	prediction	4	22	0	7	8	41	5	15	5	8	8	41

Discussion

In this study, the STD of the whole leaf reflectance was calculated and used for grading rice leaf blast severity at three growth stages. The results showed that the model using the STD dataset performed significantly better than that using raw spectral reflectance, it was capable of classifying rice leaf blast severity using the STD of spectral reflectance of whole leaves. The proposed data processing method was derived from physiological phenomena that were visible to the naked eye, making it more intuitive and convincing. To our knowledge, this was the first time this method was used to classify rice leaf blast severity.

In theory, there are four forms of lesions in field conditions, with the names of acute form, chronic form, white spot form and brown spot form [27]. However, only the last three forms of lesions were found in this study. This was because lesions of the acute form could convert to the chronic form under suitable conditions [27]. Different forms of lesions had diverse effects on leaves. For example, lesions of chronic form produced conidia, while the other two did not [27]. If a lesion had no spore production, it would not affect the possible disease cycle in the future, making it hard to predict the following pathological process. As a result, until now, the assessment of rice leaf blast still focussed on one single disease cycle, rather than a consecutive process.

The spectral characterization of rice leaf blast revealed that the reflectance varied not only within a single lesion, but also among different forms of lesions. For the centre of chronic form lesions, the reflectance was extremely high. This may have

been caused by the degradation of photosynthetic pigments within this area [28]. Steinkamp et al. [28] identified a boundary zone that separated diseased tissue from healthy tissue and divided it into an inner region and an outer region. Leucker et al. [29] mapped the two regions to transition areas and margins. Although both of the aforementioned studies were conducted to investigate sugar beet *Cercospora* leaf spot (CLS), they still provided a reasonable explanation for the phenomenon in this study. Oerke et al. [20] also characterized the spectral signatures of healthy tissue and CLS lesions of five sugar beet genotypes. In their study, different spectral signatures of lesions were caused by differences in CLS resistance of diverse genotypes. However, in this study, they were caused by different forms of lesions under the same level of resistance. Despite the similar profiles of spectral reflectance in the two studies, the pathogenic mechanisms of the two diseases may be drastically different.

For the difference spectra of STD, there was a transition from mild (levels 1 and 2) to moderate (level 3) and to severe (levels 4) disease according to the peak locations. The mild samples had three peaks, located at 551, 675 and 747 nm. The moderate samples presented four peaks, a peak was located at 495 nm, and the other three peaks were the same as the former. Compared with the moderate samples, the severe samples displayed three peaks again, with the peak located at 551 nm excluded and the other three remained. Interestingly, the peak locations of both mild samples and severe samples were part of the moderate ones. It was still unknown why this phenomenon appeared. In contrast, the difference spectra of raw spectral reflectance only had one peak at all disease levels and growth stages, located at 700nm.

The pure SVM classifier combines spectral features with spatial features by kernel function [30], which utilizes the characteristics of HSI to some extent. Average accuracy evaluates the average per-class effectiveness of a classifier; micro F1 value indicates the relations between data's positive labels and those given by a classifier based on sums of per-text decisions; and macro F1 value indicates the relations between data's positive labels and those given by a classifier based on a per-class average [31]. Most misclassifications occurred between samples with adjacent disease levels. Two reasons may have accounted for this. On the one hand, a single leaf may contain various forms of lesions and their areas are different from each other. Despite having the same disease level, a fluctuation in spectral reflectance still exists. On the other hand, biological heterogeneity was another prime factor for classification inaccuracy [32]. It occurred not only within different leaves, but also within a single leaf. This may result from the unbalanced distribution of water, solid matter and air between veins and mesophyll [33].

Although we have demonstrated the feasibility of classifying rice leaf blast using STDs, some problems still exist. First, there was too much human work involved in processing hyperspectral images, making it hard to inspect large numbers of samples. Second, the experiment was conducted under controlled environment, it remains difficult to extend these results to field condition. In the future, the possible improvements in these two aspects will be investigated.

Materials And Methods

Plant materials

In this study, Mongolian rice, which is a rice variety susceptible to rice blast, was used. To get closer to the actual production situation, the field was naturally infected and all the test samples were directly obtained from field. The experimental field was located in Gengzhuang at an experimental base of Shenyang Agricultural University (122° 73' E, 40° 98' N). The planting area was about 1000m². The rice seeds were acquired and placed in a seedling shed on April 3rd, 2021 for seedling cultivation and sown on May 25th. Basal application of fertilizer was performed at a rate of 270-80-130 kg/ha (urea-potassium sulfate-superphosphate) with an additional application at a rate of 50 kg/ha (urea) at tillering stage. To prevent the effect of insect pests on the experiment, 5 g of chlorpyrifos 74% wettable powder (Shanghai Nongle Agricultural Chemical Co., Ltd., Shanghai, China) was mixed with 10 kg of water to form a solution, which was sprayed with a T20 UAV system (SZ DJI Technology Co.,Ltd., Shenzhen, China) on June 1st, July 1st and August 1st. The first leaf blast symptoms were found in early July. Approximately one week later, a serious increase in rice leaf blast was observed. Twelve diseased rice plants and 2 healthy rice

plants were randomly selected from the field for each sampling. They were transferred to a hyperspectral imaging room using a barrel (diameter of 42 cm, depth of 50 cm), and hyperspectral images of rice leaves were acquired the next day.

The samples in this study were acquired at three growth stages, and all samples were divided into a training set and testing set in a ratio of 7:3. Rice leaves acquired at jointing stage were used as the first experimental samples, which were collected on July 13th. A total of 55 samples were collected, including 10 samples of level 0, 20 samples of level 1, 15 samples of level 2, 9 samples of level 3 and 1 sample of level 4. 38 of the samples were selected for training and 18 for testing (only one sample of level 4 existed, so it belonged to both the training set and testing set simultaneously). Rice leaves acquired at booting stage were used as the second experimental samples, which were collected on July 27th. A total of 127 samples were collected, including 18 samples of level 0, 49 samples of level 1, 14 samples of level 2, 28 samples of level 3 and 18 samples of level 4. 89 of the samples were selected for training and the remaining 38 were selected for testing. Rice leaves acquired at heading stage were used as the third experimental samples, and were collected on August 12th. A total of 137 samples were collected, including 15 samples of level 0, 45 samples of level 1, 20 samples of level 2, 34 samples of level 3 and 23 samples of level 4. 96 of the samples were selected for training and the rest 41 for testing.

Hyperspectral Imaging

The imaging system consisted of a high-sensitivity EM285CL EMCCD camera (Raptor Photonics, Antrim, Northern Ireland), a stand-mounted ImSpector V10E imager (Spectral Imaging, Oulu, Finland), a scanning stage that can move horizontally, a desktop computer with Spectral-Image software (Isuzu Optics, Hsinchu, China) for controlling the imager and the scanning stage during the process of image collection, and an IT 3900 halogen light source (Ocean Optics, Dunedin, FL, USA) to provide stable illumination. The ImSpector V10E imager collected 472 wavebands over a spectral range of 400–1000 nm. The angle of the left and right linear emitters was adjusted to a vertical orientation of 45° to enable their emitted light rays to converge on a coincident line just below the camera lens. The objective lens of the camera was set at an aperture of f/1.4. The distance between the camera lens and the scanning stage was set to 300 mm, and the focus was manually adjusted to guarantee image definition. The exposure time was manually adjusted according to the lighting environment to ensure sufficient incident radiation intensity. The speed of the scanning stage was set to 1.2 mm/s, with the aspect ratio set to the default. Leaves were carefully removed from each rice stem, placed flat on the stage, and gently affixed with double-sided adhesive. Five columns of rice leaves were placed parallel on the scanning stage per imaging run. Great care was taken to not exert any pressure on the leaves. If the length of a rice leaf exceeded 400 mm, which was the maximum sliding distance of the scanning stage, it was cut into two or more sections with the integrity of the diseased area ensured. Images were captured using Spectra-Image software, and the hyperspectral data cubes were saved onto an external hard drive.

The original hyperspectral images were corrected for dark current and uneven light intensity distribution each time before further processing [34]. First, a white board with high reflectance was scanned as a 100% standard. The value of the Max DN was adjusted to 3,600, which was 80% of the maximum value. The bright field of the white board was recorded at this point. After covering the lens cap, the dark field of the white board was read. The white board was then removed, and samples were situated directly below the camera on the scanning stage, with the exposure time adjusted and other parameters unchanged so that the Max DN value was still at 3600. After covering the lens cap, the dark field of the sample was documented. The corrected sample image was calculated as follows:

$$R = \frac{R_s - R_{sd}}{R_{bw} - R_{bd}}$$

1

where R is the corrected sample image, R_s is the original hyperspectral image of the sample, R_{sd} is the hyperspectral image of the dark field of the sample, R_{bw} is the hyperspectral image of the bright field of the white board, and R_{bd} is the hyperspectral image of the dark field of the white board.

Classes Of Disease Severity

The outline of rice leaves were manually drawn using the ROI tool under ENVI 5.6 (ITT Visual Information Solutions, Boulder, USA), rice leaf area was selected as a ROI and the number of pixels it contained was counted automatically and recorded as N_1 ; the number of pixels contained in diseased areas was calculated in the same way and recorded as N_2 . The degree of rice blast on a leaf was determined by the percentage of lesion area to the whole leaf area, that is, the value of $(N_2 / N_1) \times 100\%$. The classification standard refers to [35] and is as follows:

Level 0: no visible lesions

Level 1: up to 2% of the leaf showing rice blast symptoms

Level 2: 2–5% of the leaf showing rice blast symptoms

Level 3: 5–10% of the leaf showing rice blast symptoms

Level 4: 10–20% of the leaf showing rice blast symptoms

Level 5: over 20% of the leaf showing rice blast symptoms

Since samples of level 5 were only found under extremely severe conditions, just five classes (level 0-level 4) of samples were discriminated in this study.

Analysis Of Hyperspectral Dataset

HSI Analyzer (Isuzu Optics, Hsinchu, China) was used to normalize the hyperspectral images against the known values of the white reference standard. The whole rice leaf was selected as a region of interest (ROI) and was manually drawn using a ROI tool. The average spectral reflectance R_w was extracted after the ROI was selected using the same tool. The STD of R_w at each wavelength was calculated as follows.

$$\text{STD} = \sqrt{\frac{\sum_{j=1}^n (R_j - R_w)^2}{n - 1}}$$

2

where R_j is the spectral reflectance of pixel j , R_w is the average spectral reflectance of the whole leaf, and n is the number of pixel contained in the whole leaf.

Construction Of The Classification Model

The STDs of spectral reflectance and raw spectral reflectance were classified into different disease degrees by a non-linear SVM [36]. The classification results of the former were compared to those of the latter, which acted as the baseline accuracy. The applied SVM used the radial basis function (RBF) as the kernel function to determine non-linear discriminant functions. As a supervised method, it relied on training data. In this study, randomly selected samples were chosen as the training set and the rest were assigned to the testing set. To build the optimal SVM model, the penalty parameter of the error term C and the kernel parameter g were optimized using a 5-fold grid-search optimization [37]. The range of C was set as 10^N ($-10 \leq N \leq 10$, the step of N is 0.1), and that of g was 10^M ($-15 \leq M \leq 5$, the step of M is 0.1). The best penalty parameters were determined by the highest cross validation accuracy of the training set. The performances of the SRR-SVM models were evaluated by the average accuracy, micro F1 score, and macro F1 score of the testing set [31]. LIBSVM 3.23 [38] was used to construct models,

it is available at <https://www.csie.ntu.edu.tw/~cjlin/libsvm/index.html>. The data analysis and model construction were conducted with MATLAB 2016b (The Math Works, Natick, USA).

The authors state that all methods were carried out in accordance with relevant guidelines in the method section.

Declarations

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Authors' contributions

ZGH formulated the research problem and designed approaches. ZGH, FS, ZDX and GZH performed the experiments. ZGH collected data, developed the processing workflow and performed the data analytics. XTY and TYW provided the equipment and sites for experimentation. ZGH wrote the manuscript. All authors read and approved the final manuscript.

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References

1. National Bureau of Statistics. China Statistical Yearbook. (China Statistics Press, 2020).
2. Fu, Q., & Huang, S. W. Original Colour Pictures of Diagnosis and Control of Rice Diseases and Insect Pests. (JinDun Press, 2005).
3. Sun, S. R., & Sun, G. C. Research status and prospect of rice blast in China. *Plant Protection Technology and Extension*. **3**, 39–40(1996).
4. Nagasubramanian, K. et al. Plant disease identification using explainable 3D deep learning on hyperspectral images. *Plant Methods*. **15**, 98(2019).
5. Lowe, A., Harrison, N., & French, A. P. Hyperspectral image analysis techniques for the detection and classification of the early onset of plant disease and stress. *Plant Methods*. **13**, 80(2017).
6. Ali, M. M., Bachik, N. A., Atirah Muhadi, N., & Yusof T. N. T. Non-destructive techniques of detecting plant diseases: A review. *Physiol Mol Plant P*. **108**, 101426(2019).
7. Nilsson, H-E. Remote sensing and image analysis in plant pathology. *Annu Rev Phytopathol*. **15**:489–527(1995).
8. Hubel, D. H. Eye, Brain and Vision. (W. H. Freeman, 1995).
9. Bock, C. H., Poole, G. H., Parker, P. E., & Gottwald, T. R. Plant disease severity estimated visually, by digital photography and image analysis, and by hyperspectral imaging. *Crit Rev Plant Sci*. **29**, 59–107(2010).
10. Akintayo, A. et al. A deep learning framework to discern and count microscopic nematode eggs. *Sci Rep*. **8**, 9145(2018).
11. Naik, H. S. et al. A realtime phenotyping framework using machine learning for plant stress severity rating in soybean. *Plant Methods*. **13**, 23(2017).
12. Zhang, J. et al. Computer vision and machine learning for robust phenotyping in genome-wide studies. *Sci Rep*. **7**, 44048(2017).

13. Knauer, U. et al. Improved classification accuracy of powdery mildew infection levels of wine grapes by spatial-spectral analysis of hyperspectral images. *Plant Methods*. **13**, 47(2017).
14. Hennessy, A., Clarke, K., & Lewis, M. Hyperspectral classification of plants: a review of waveband selection generalisability. *Remote Sens*. **12**, 113(2020).
15. Thomas, S. et al. Quantitative assessment of disease severity and rating of barley cultivars based on hyperspectral imaging in a non-invasive, automated phenotyping platform. *Plant Methods*. **14**, 45(2018).
16. Reynolds, G. J., Windels, C. E., MacRae, I. V., Laguette, S. Remote sensing for assessing *Rhizoctonia* crown and root rot severity in sugar beet. *Plant Dis*. **96**, 497–505(2012).
17. Gui, J. S., Fei, J. Y., Wu, Z. X., Fu, X. P., & Diakite, A. Grading method of soybean mosaic disease based on hyperspectral imaging technology. *Information Processing in Agriculture*. <https://doi.org/10.1016/j.inpa.2020.10.006>(2020).
18. Wang, H. G. et al. Application of hyperspectral data to the classification and identification of severity of wheat stripe rust. *Spectrosc Spect Anal*. **27**(9), 1811–1814(2007).
19. Kobayashi, T., Kanda, E., Kitada, K., Ishiguro, K., & Torigoe, Y. Detection of rice panicle blast with multispectral radiometer and the potential of using airborne multispectral scanners. *Phytopathology*. **91**(3), 316–323(2001).
20. Oerke, E-C., Leucker, M., & Steiner, U. Sensory assessment of *Cercospora beticola* sporulation for phenotyping the partial disease resistance of sugar beet genotypes. *Plant Methods*. **15**, 133(2019).
21. Zhang, G. S. et al. Assessment of rice leaf blast severity using hyperspectral imaging during late vegetative growth. *Australas Plant Path*. <https://doi.org/10.1007/s13313-020-00736-2>(2020).
22. Yeh, Y-H. F. et al. A comparison of machine learning methods on hyperspectral plant disease assessments. *IFAC Proceedings Volumes*. **46**(4), 361–365(2013).
23. Ahmadi, P., Muharam, F. M., Ahmad, K., Mansor, S., & Seman, I. A. Early detection of ganoderma basal stem rot of oil palms using artificial neural network spectral analysis. *Plant Dis*. <http://dx.doi.org/10.1094/PDIS-12-16-1699-RE>(2017).
24. Coops, N. et al. Assessment of *Dothistroma* needle blight of *Pinus radiata* using airborne hyperspectral imagery. *Phytopathology*. **93**, 1524–1532(2003).
25. Skoneczny, H. et al. Fire blight disease detection for apple trees: hyperspectral analysis of healthy, infected and dry leaves. *Remote Sens*. **12**, 2101(2020).
26. Bergsträsser, S. et al. HyperART: non-invasive quantification of leaf traits using hyperspectral absorption-reflectance-transmittance imaging. *Plant Methods*. **11**, 1(2015).
27. Pan, G. J., Song, C. Y., & Wang, G. L. Study on the Fluidity Factors of Blast of Early Japonica Rice in Cold Region. (China Agriculture Press, 2014).
28. Steinkamp, M. P., Martin, S. S., Hoefert, L. L., & Ruppel, E. G. Ultrastructure of lesions produced by *Cercospora beticola* in leaves of *Betavulgaris*. *Physiol Plant Pathol*. **15**, 13–26(1979).
29. Leucker, M., Mahlein, A-K., Steiner, U., & Oerke, E-C. Improvement of lesion phenotyping in *Cercospora beticola*-sugar beet interaction by hyperspectral imaging. *Phytopathology*. **106**, 177–184(2016).
30. Zhang, N., Wang, Y. T., & Zhang, X. L. Extraction of tree crowns damaged by *Dendrolimus tabulaeformis* Tsai et Liu via spectral–spatial classification using UAV–based hyperspectral images. *Plant Methods*. **16**, 135(2020).
31. Sokolova, M., & Lapalme, G. A systematic analysis of performance measures for classification tasks. *Inform Process Manag*. **45**, 427–437(2009).
32. Chang, C. C., & Lin, C. J. LIBSVM: a library for support vector machines. *Acm TIST*. **2**(27), 1–27(2011).
33. Bohnenkamp, D., Behmann, J., & Mahlein, A-K. In-field detection of yellow rust in wheat on the ground canopy and UAV scale. *Remote Sens*. **11**, 2495(2019).
34. Zang, Z. Y., Wang, J., Cui, H. L., & Yan, S. H. Terahertz spectral imaging based quantitative determination of spatial distribution of plant leaf constituents. *Plant Methods*. **15**, 106(2019).

35. Cao, X. F., Ren, H. R., Li, X. Z., Yu, K. Q., & Su, B. F. Discrimination of winter jujube's maturity using hyperspectral technique combined with characteristic wavelength and spectral indices. *Spectrosc Spect Anal.* **38**(7), 2175–2182(2018).
36. General Administration of Quality Supervision, Inspection and Quarantine of the People's Republic of China. Rules of investigation and forecast of the rice blast [*Pyricularia oryzae* (Cavara)]. (2009).
37. Cortes, C., & Vapnik, V. Support-vector networks. *Mach Learn.* **20**, 273–297(1995).
38. Hsu, C. W., Chang, C. C., & Lin, C. J. A practical guide to support vector classification. <https://www.csie.ntu.edu.tw/~cjlin/papers/guide/guide.pdf>(2016).

Figures

Figure 1

Spectral reflectance of leaves with different forms of lesions at different growth stages. **(a)** the chronic form; **(b)** the brown spot form; **(c)** the white spot form

Figure 2

Average spectral reflectance and STD of leaves with different disease degree. **(a)** average spectral reflectance at jointing stage; **(b)** average spectral reflectance at booting stage; **(c)** average spectral reflectance at heading stage; **(d)** average STD at jointing stage; **(e)** average STD at booting stage; **(f)** average STD at heading stage

Figure 3

Difference spectra of diseased and healthy leaves at different stages. **(a)** jointing stage; **(b)** booting stage; **(c)** heading stage