Intelligent identification on cotton verticillium wilt based on spectral and image feature fusion

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Research Article

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Abstract

Background

Verticillium wilt is the major disease of cotton, which would cause serious yield reduction and economic losses, and the identification of cotton verticillium wilt is of great significance to cotton research. However, the traditional method is still manual, which is subjective, inefficient, and labour-intensive, and therefore, this study has proposed a novel method for cotton verticillium wilt identification based on spectral and image feature fusion. The cotton hyper-spectral images have been collected, while the regions of interest (ROI) have been extracted as samples including 499 healthy leaves and 498 diseased leaves, and the average spectral information and RGB image of each sample were obtained. In spectral feature processing, the preprocessing methods including Savitzky-Golay smoothing (SG), multiplicative scatter correction (MSC), de-trending (DT) and mean normalization (MN) algorithms have been adopted, while the feature band extraction methods have adopted principal component analysis (PCA) and successive projections algorithm (SPA). In RGB image feature processing, the EfficientNet was applied to build classification model and 16 image features have been extracted from the last convolutional layer. And then, the obtained spectral and image features were fused, while the classification model was established by support vector machine (SVM) and back propagation neural network (BPNN). Additionally, the full spectrum and feature band spectrum were used as comparison for SVM and BPNN classification respectively.

Result

The results showed that the average accuracy of EfficientNet network for cotton verticillium wilt identification was 93.00%. By full spectrum, SG-MSC-BPNN model obtained the better performance with classification accuracy of 93.78%. By feature bands, SG-MN-SPA-BPNN model obtained the better performance with classification accuracy of 93.57%. By spectral and image fused features, SG-MN-SPA-FF-BPNN model obtained the best performance with classification accuracy of 98.80%.

Conclusions

The study demonstrated that it was feasible and effective to use fused spectral and image features based on hyper-spectral imaging to improve identification accuracy of cotton verticillium wilt. The study provided theoretical basis and methods for non-destructive and accurate identification of cotton verticillium wilt.

1. Background

Cotton is native to tropical and subtropical regions and is a perennial, short-day crop, and it is a strategic material related to the national economy and people's livelihood. China is with the largest cotton
production and consumption in the world, while cotton is also the second largest crop after cereals [1].
Cotton verticillium wilt is a serious disease resulting in yield reduction and economic losses, which is
caused by fungal infection through various media such as cottonseed, diseased plant residues, soil,
fertilizer, water, and agricultural tools [2]. The infected cotton leaves would gradually turn yellow, wither
and fall off, which would lead to small cotton bolls and high boll drop rate, and finally result in a decrease
in yield and quality [3, 4]. Therefore, the identification of cotton verticillium wilt is of great significance to
cotton breeding and genetic research. However, the traditional method is generally manual, which is labor-
intensive, subjective, and even destructive [5]. In conclusion, it is necessary to develop an intelligent
detection method for cotton verticillium wilt identification.

As an emerging high-precision non-destructive testing technology, hyperspectral imaging technology is
widely used in all walks of life, and its application in the agricultural field is particularly important and
prominent [6]. Hyperspectral imaging technology is developed by combining spectral and imaging
technologies, which can simultaneously obtain spatial and spectral information of objects [7].
Hyperspectral images have the characteristics of "integration of maps", and also have the advantages of
fast, non-destructive and simple, and have become an important research field in the identification and
detection of crop diseases, the combination of machine learning and deep learning to establish
classification models can accurately identify and detect diseases. Feng et al. [8] developed a
hyperspectral imaging system for an accurate prediction of the above-ground biomass of individual rice
plants. Linear stepwise regression analysis and 5-fold cross-validation were adopted to select valid
variables and construct the model. In the tillering to elongation stage, the $R^2$ value of fresh weight (FW)
was 0.940 and dry weight (DW) was 0.935. In the booting to heading stage, the $R^2$ value of FW was 0.891
and DW was 0.783, indicating that hyperspectral imaging is superior to visible light imaging. Pan et al. [9]
combined PLS-DA, KNN, and SVM three classification models for pathogenetic process monitoring and
eye detection of pear black spot disease, and the raw data were processed by three methods: first
derivative (1st Der), MSC, mean centering (MC), while the PCA algorithm was used to extract the
characteristic bands. And it showed that the SVM model had a good effect on early detection of pear
black spot disease by hyperspectral technology. Abdulridha et al. [10] obtained hyperspectral images of
asymptomatic, early and late infected citrus leaves to classify the diseased leaves in different periods.
Pham et al. [11] built a push-broom hyperspectral system to collect hyperspectral image data, and SVM
and artificial neural networks models were used to classify surface defects of jujubes online, which can
be used for accurate surface defect detection of many other fruits. Gao et al. [12] used hyperspectral
imaging to early detect grapevine leafroll disease in a red-berried wine grape cultivar, while squares-
support vector machine was established for classification, and the results indicated that the virus-
infected grapevines could be detected during asymptomatic stages with high accuracy. Xuan et al. [13]
adopted hyperspectral imaging for early diagnosis and pathogenesis monitoring of wheat powdery
mildew, the partial least squares discriminant analysis model obtained the best performances with
classification accuracy of 91.4% in validation sets. Lu et al. [14] proposed a spectrum extraction method
based on the spots region, while SVM and extreme learning machine (ELM) were established to identify
the two similar diseases of tea white star and anthrax disease, and the results showed that the ELM
model had the best performance with classification accuracy of 95.77%. The above studies showed that hyperspectral imaging technology combined with traditional machine learning methods has achieved good results in crop disease identification and detection. However, there are few reports about cotton verticillium wilt identification, and this study would verify the feasibility and fill the gap.

In recent years, deep learning has been widely used in agriculture research [15], which has proved powerful image feature extraction ability [16]. Convolutional neural network (CNN) is the most commonly used and prominent network for image feature extraction in deep learning, which acquired general acknowledgement for diverse application areas [17]. Tetila et al. [18] constructed five deep learning methods to evaluate the classification of soybean pest images, including Inception-V3, Resnet-50, VGG-16, VGG-19 and Xception, the results indicated that deep learning architectures outperformed traditional classification model, which could help specialists and farmers for pest control management in soybean fields. Li et al. [19] proposed a novel deep learning framework for hyperspectral classification based on a fully CNN. After the deep features of hyperspectral data were enhanced, the optimized ELM was utilized for classification, which outperformed the traditional classification algorithms. Khanramaki et al. [20] presented an intelligent ensemble classifier of deep CNNs to recognize three citrus pests including citrus Leafminer, Sooty Mold, and Pulvinaria, which achieved an average accuracy of 99.04%. Shin et al. [21] used six deep learning algorithms to detect powdery mildew, persistent fungal disease in strawberries, and the results showed the average classification accuracy (CA) > 92%, while ResNet-50 gave the highest CA of 98.11% in classifying the healthy and infected leaves. Liu et al. [22] used MobileNetV2 model as the primary network to identify and classify six common citrus diseases, which could reduce the model size and keep good classification accuracy. Priyadarshini et al. [23] proposed a deep CNN-based architecture for maize leaf disease classification, which achieved an accuracy of 97.89%. Zhong et al. [24] proposed a novel method to identify apple leaf diseases based on DenseNet-121 deep convolution network, which achieved 93.71% accuracy. The above studies demonstrated that deep learning had excellent potential for the image feature extraction, which would provide a new intelligent method for the identification of cotton verticillium Wilt.

Therefore, this study proposed a novel method for intelligent identification of cotton verticillium wilt based on hyper-spectral imaging by spectral and image feature fusion (FF). Hyperspectral imaging technique was used to obtain spectral and image information, and the spectral data were processed using SG, MSC, DT and MN, then characteristic spectral band were extracted using PCA and SPA. In addition, the image features were extracted by EfficientNet network. Finally, the extracted spectral and image features were fused for SVM and BPNN classification models. This study would demonstrate a feasible and effective method for cotton verticillium wilt identification with high accuracy.

2. Result And Discussion

2.1. Spectral analysis
The spectral curve of 997 cotton leaf samples were shown as Fig. 1, in which the original spectral curve, SG-MSC spectra, SG-DT spectra, and SG-MN spectra were shown as Fig. 6a-d respectively. The average spectral curve of healthy leaves and diseased leaves were shown as Fig. 2, and the result proved that the spectral reflectance was low in the blue light band of 400 ~ 500 nm. A small reflectance peak appeared in the band around 550 nm, which is caused by the reflection of chlorophyll; a trough appeared in the red band around 680 nm, which is caused by the strong absorption of chlorophyll; the spectral band from 730 to 1000 nm was the region of high reflectivity. The spectral curves of healthy leaves and diseased leaves showed typical green leaf characteristics, which had the same change trend and high similarity, but there were also significant differences in reflectivity values, which provided data support for subsequent feature extraction and modelling.

2.2. Classification results based on spectral full-band

The original spectra were processed using SG-MSC, SG-DT and SG-MN algorithms, and then SVM classification model and BPNN classification model were established. The results were shown in Table 1, in which all models were above 90.00%. By original spectral data, the classification accuracy of the SVM and BPNN model was 94.00% and 94.40% for training set, 91.17% and 92.57% for test set, respectively. By preprocessed spectral data, the optimal classification model in the SVM model was SG-MN-SVM, and the classification accuracy was 95.99% and 92.37% for training set and test set, respectively; the optimal classification model in the BPNN model was SG-MSC-BPNN, and the classification accuracy was 94.19% and 93.78% for training set and test set, respectively. In summary, SG-MSC-BPNN was the optimal classification model among all models. Besides, the results also proved that the BPNN classification model had a better performance than the SVM. The preprocessing algorithm was able to improve the model accuracy, but the full-band was too large, so it was necessary to refine the spectral bands for classification.

Table 1

Results of classification models for healthy and diseased leaves using full spectral data.
2.3. Feature band extraction

In the study, PCA and SPA algorithm were used to extract feature bands of spectral data, in which 400 ~ 1000nm were divided into 224 bands. After the PCA was conducted, the principal component loadings coefficient method [25] was applied to select the feature bands, which was computed by the correlation coefficient between the principal component and the original band variable. When the load value is at the peak or trough position of principal component load curve, the corresponding band is the feature band [26]. The PCA results of the original spectrum showed that the explained variance of the first three principal components reached 98.97%, which could well express the original variable information. Meanwhile, the explained variance of the first three principal components of the SG-MSC spectra, SG-DT spectra, SG-MN spectra was 93.33%, 98.26%, and 95.48% respectively. The scatter plot of the first three principal components of the SG-DT spectra was showed as Fig. 3, while the blue points are the scatter points of healthy leaves, and the red points are the scatter points of diseased leaves, which proved that there was an obvious contrast between healthy leaves and diseased leaves, so it was feasible to use the spectral data after PCA for modelling and classification. The above method was also applied to process the original spectral data and the preprocessed spectral data by SG-MSC and SG-MN, while the similar results were obtained as Additional file 1: Figure S1.

Table 2

Feature bands obtained by different preprocessing methods and different feature extraction algorithms. FBEA = feature band extraction algorithm; PM = preprocessing method; SFB = number of selected feature bands.
The loading curves of the first three principal components of the SG-DT preprocessed spectra were shown as Fig. 4, in which the 16 feature bands were selected from total 224 bands by the principal component loading coefficient method. The loading curves of the first three principal components of the other three preprocessed spectra were shown in Additional file 1: Figure S2. In the same way, the 12 feature bands of the original spectra were obtained, and the 16 feature bands of the SG-MSC spectra and SG-MN spectra were obtained. The feature bands selected by the PCA algorithm were shown in Table 2, which showed that the extracted feature bands are relatively evenly distributed in each interval of the whole band, which could characterize the whole band spectral data.

As the comparison, the successive projections algorithm (SPA) was also adopted to extract the characteristic bands, and the SG-MSC results were shown in Fig. 5. The RMSEV curve (Fig. 5a) showed that the RMSEV value was in a state of decline when the number of bands was less than 13, and then tended to be stable. When the number of characteristic bands was 13, the RMSEV reached minimum value 0.2239, so 13 characteristic bands were selected, the distribution of which were shown as Fig. 5b. By using SPA, the characteristic bands for other three preprocessed spectra were shown in Additional file 1: Figure S3. In the same way, 10 characteristic bands were obtained from the original spectrum, 7 characteristic bands from SG-DT spectra, and 15 characteristic bands from SG-MN spectra. The characteristic bands selected by SPA were shown in Table 2, from the results, the characteristic bands extracted by the SPA algorithm on the SG-DT spectra were in the forward section, and the number of

<table>
<thead>
<tr>
<th>FBEA</th>
<th>PM</th>
<th>SFB</th>
<th>Selected feature bands</th>
</tr>
</thead>
<tbody>
<tr>
<td>PCA</td>
<td>Original</td>
<td>12</td>
<td>Band53, Band105, Band111, Band114, Band124, Band132, Band136, Band141, Band156, Band166, Band199, Band221</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SG-MSC</td>
<td>16</td>
<td></td>
<td>Band34, Band 56, Band101, Band104, Band116, Band120, Band132, Band135, Band142, Band156, Band171, Band173, Band203, Band211, Band213, Band220</td>
</tr>
<tr>
<td>SG-DT</td>
<td>16</td>
<td></td>
<td>Band33, Band 38, Band56, Band101, Band102, Band105, Band119, Band132, Band141, Band157, Band172, Band174, Band197, Band204, Band213, Band221</td>
</tr>
<tr>
<td>SPA</td>
<td>Original</td>
<td>10</td>
<td>Band18, Band47, Band73, Band92, Band98, Band105, Band109, Band114, Band135, Band176</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SG-MSC</td>
<td>13</td>
<td></td>
<td>Band3, Band4, Band7, Band9, Band12, Band41, Band67, Band89, Band161, Band177, Band185, Band221, Band224</td>
</tr>
<tr>
<td>SG-DT</td>
<td>7</td>
<td></td>
<td>Band2, Band9, Band12, Band30, Band57, Band102, Band118</td>
</tr>
<tr>
<td>SG-MN</td>
<td>15</td>
<td></td>
<td>Band2, Band3, Band4, Band6, Band7, Band11, Band12, Band12, Band30, Band56, Band76, Band101, Band120, Band138, Band173, Band224</td>
</tr>
</tbody>
</table>
bands was small, which would lead to low accuracy, and comprehensive features should be further extracted.

Table 3

Results of classification models for healthy and diseased leaves using feature band data.

<table>
<thead>
<tr>
<th>Feature band extraction algorithm</th>
<th>Preprocessing method</th>
<th>SVM classification accuracy (%)</th>
<th>BPNN classification accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Training set</td>
<td>Test set</td>
</tr>
<tr>
<td>PCA</td>
<td>Original data</td>
<td>91.78</td>
<td>89.16</td>
</tr>
<tr>
<td></td>
<td>SG-MSC</td>
<td>90.58</td>
<td>89.36</td>
</tr>
<tr>
<td></td>
<td>SG-DT</td>
<td>87.58</td>
<td>86.15</td>
</tr>
<tr>
<td></td>
<td>SG-MN</td>
<td>93.79</td>
<td>90.96</td>
</tr>
<tr>
<td>SPA</td>
<td>Original data</td>
<td>94.59</td>
<td>92.77</td>
</tr>
<tr>
<td></td>
<td>SG-MSC</td>
<td>92.79</td>
<td>91.57</td>
</tr>
<tr>
<td></td>
<td>SG-DT</td>
<td>88.38</td>
<td>85.74</td>
</tr>
<tr>
<td></td>
<td>SG-MN</td>
<td>95.59</td>
<td>92.57</td>
</tr>
</tbody>
</table>

2.4. Classification results based on spectral feature bands

The feature band data selected by PCA and SPA were input into the SVM and BPNN classification models, and the classification results were shown in Table 3. The classification results of the SVM model showed that the accuracy of the training set and test set of the model was 87.58%~95.59% and 85.74%~92.77% respectively for different feature bands. And the classification results of the BPNN model showed that the accuracy of the training set and test set of the model was 91.18%~94.99% and 89.96%~93.57% for different feature bands respectively. Among the established SVM models, the original-SPA feature bands had the best classification performance, while the accuracy of the training set and test set was 94.59% and 92.77%, respectively, which proved that the SVM classification model had better performance on the original spectral data rather than SG-DT spectral data. Among the established BPNN models, the SG-MN-SPA feature bands had the best results, while the accuracy of the training set and test set was 94.99% and 93.57% respectively. In conclusion, the SG-MN-SPA-BPNN model had the best classification performance in this study. However, the model was still needed to be improved, before the practical application of cotton verticillium wilt identification, so the morphological and color characteristics based on RGB image were extracted to achieve better classification results.

2.5. Image feature extraction based on deep learning
The EfficientNet-B3 network was adopted for healthy and diseased leaves RGB image classification, and the output channels of the last convolutional layer of the network was adjusted to 16 corresponding with the spectral feature bands number. Then the modified EfficientNet-B3 network was trained based on the training set, which would extract the colour and texture features of the RGB image effectively, and the classification accuracy of the test set was 93.00%. Compared with the classification based on spectral features, the classification based on the RGB image features could achieve approximate accuracy. However, there were significant differences between spectral features and image features, so it was possible to improve the classification accuracy by fusing both features. Therefore, the forward function in the EfficientNet network was used to extract the output of the pooling layer as the image feature of cotton leaf, which were 997 one-dimensional vectors with 16 elements, and the characteristic vector curve was shown in Fig. 6a.

2.6. Fusion feature modelling

The feature bands extracted in Table 2 were respectively fused with image features, and the fusion feature curve of SG-DT-PCA-FF was shown in Fig. 6c. Compared with the SG-DT-PCA feature bands (Fig. 6b), it was obvious that the fusion features had greater differentiation, and the fusion features of the other methods had similar results, which were shown in Additional file 1: Figure S4 and Additional file 1: Figure S5, indicating that the fusion features had better characterization ability. Then the fusion features were input into the SVM and BPNN classification models, and the classification results were shown in Table 4. The results showed that the classification accuracy of all models had been significantly improved. As to the SVM model, the accuracy of the training set and test set of the model was 96.59%~98.80% and 96.19%~98.19%, respectively; As to the BPNN model, the accuracy of the training set and test set of the model was 97.40%~99.20% and 96.59%~98.80%, respectively. Especially in the SG-DT-PCA-FF-SVM and SG-DT-SPA-FF-SVM models, the fusion feature significantly improved the accuracy by 10.65% and 10.45% respectively. Among the established SVM models, the SG-MN-PCA-FF-SVM model had the best classification effect, and the classification accuracy of its training set and test set was 98.20% and 98.19%, respectively. Among the established BPNN models, the SG-MN-SPA-FF-BPNN model had the best classification effect, and the classification accuracy of its training set and test set was 99.20% and 98.80%, respectively, which outperformed all the SVM models. The results demonstrated that the fusion of spectral and image features would significantly improve the classification performance, compared with spectral features or image features alone, and the classification accuracy of the optimal model had reached 98.80%, which had a very considerable classification effect.

Table 4

Results of classification models for healthy and diseased leaves using fusion feature data.
<table>
<thead>
<tr>
<th>Feature band extraction algorithm</th>
<th>Fusion method</th>
<th>SVM classification accuracy (%)</th>
<th>BPNN classification accuracy (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Training set</td>
<td>Test set</td>
</tr>
<tr>
<td>PCA</td>
<td>Original data-FF</td>
<td>97.80</td>
<td>97.00</td>
</tr>
<tr>
<td></td>
<td>SG-MSC-FF</td>
<td>98.00</td>
<td>97.59</td>
</tr>
<tr>
<td></td>
<td>SG-DT-FF</td>
<td>97.19</td>
<td>96.79</td>
</tr>
<tr>
<td></td>
<td>SG-MN-FF</td>
<td>98.20</td>
<td>98.19</td>
</tr>
<tr>
<td>SPA</td>
<td>Original data-FF</td>
<td>96.99</td>
<td>96.59</td>
</tr>
<tr>
<td></td>
<td>SG-MSC-FF</td>
<td>98.80</td>
<td>97.39</td>
</tr>
<tr>
<td></td>
<td>SG-DT-FF</td>
<td>96.59</td>
<td>96.19</td>
</tr>
<tr>
<td></td>
<td>SG-MN-FF</td>
<td>98.20</td>
<td>97.79</td>
</tr>
</tbody>
</table>

3. Conclusion

This study has demonstrated a novel method for cotton verticillium wilt identification based on spectral and image feature fusion, which obviously outperformed than the classification method solely based on spectral features or image features. In the research, the preprocessing methods including SG, MSC, DT and MN, and the feature bands extraction methods including PCA and SPA, were studied to obtain the optimal technical route of hyperspectral data analysis for cotton verticillium wilt identification. Meanwhile, the modified EfficientNet network was adopted to identify the healthy and diseased leaves, while the image features were extracted. Then, SVM and BPNN models were established based on the full spectra, characteristic bands and fusion features, respectively. Finally, the following conclusions were drawn.

1. As to the full spectral data, SG-MSC-BPNN model had the better performance with the test accuracy of 93.78%, which proved that the preprocessing method of SG and MSC could improve the model accuracy, and the BPNN model was better than SVM.
2. As to the characteristic band data, SG-MN-SPA-BPNN model obtained the best classification accuracy of 93.57% in test set. The feature band extraction algorithms could effectively reduce the data dimension, which would promote the model generalization, but decrease the test accuracy.
3. Based on the EfficientNet network, the classification accuracy of healthy and diseased leaves was 93.00%, which could extract the leaf shape and color features effectively.
4. As to the fused features, SG-MN-SPA-FF-BPNN model obtained the best performance with the test accuracy of 98.80%. Compared with spectral or image features, the fused feature could significantly improve the model accuracy, and SG-DT-PCA-SVM model was improved by 10.65% with fused features.
The study demonstrated that it was feasible and effective to use fused spectral and image features based on hyper-spectral imaging to achieve high accuracy of cotton verticillium wilt identification, which provided a novel method for cotton breeding and disease resistance research.

4. Materials And Methods

In this study, the technical route for cotton verticillium wilt classification was shown as Fig. 7. Firstly, the cotton hyperspectral images were obtained by the crop information collection platform, and then the spectral information and RGB image were extracted by ENVI software. Secondly, SVM and BPNN were used to build classification models with the preprocessed full spectra, and the feature bands extracted by PCA and SPA, respectively. Thirdly, the modified EfficientNet network was utilized to extract the image features from RGB image. Finally, the feature bands and image features were fused for the SVM and BPNN classification of cotton verticillium wilt.

4.1. Plant cultivation and pathogen inoculation

Sample preparation was conducted at National Key Laboratory of Crop Genetic Improvement at Huazhong Agricultural University, Wuhan, China in June 2021. On June 8, 2021, 180 pots of different varieties of cotton were cultivated in the cotton greenhouse with 9 rows in total, and each row had 20 pots of cotton. On June 20, 2021, the cotton was inoculated with verticillium wilt V991. On July 13, 2021, all cotton samples were scanned using the hyperspectral camera of the intelligent information collection platform, and 997 cotton leaves were extracted from 9 hyperspectral images, including 499 healthy leaves and 498 diseased leaves.

4.2. Hyperspectral image acquisition

The cotton information collection platform was shown as Fig. 8a, and its structural diagram was shown as Fig. 8b, which was mainly composed of the industrial personal computer (IPC), motion units and imaging device. The IPC was used to control the movement of the equipment and the shooting of the camera, as well as to realize the storage of the acquired images. The motion units adopted a gantry structure with three-coordinate motion, in which the maximum travel of each axis is 6100mm, 950mm, 500mm for X, Y, Z axis respectively. The imaging device included visible light camera, infrared camera, and hyperspectral imaging unit. The hyperspectral imaging unit has been utilized in the research with the spectral range 400 ~ 1000nm, the spectral resolution 5.5nm, the spatial resolution 1024 pixel. The number of spectral bands is 224, and the full-band halogen lamp was installed as light source.

4.3. Hyperspectral data acquisition and preprocessing

The acquired hyperspectral images were shown as Fig. 9a, and the images were imported into ENVI software, while the ROIs of the cotton leaf region were extracted as shown in Fig. 9b. A total of 997 ROIs were extracted as research samples, which consisted of 499 healthy leaves and 498 diseased leaves. Then the average spectral reflectance and RGB image of each ROI were extracted by ENVI software, and
997 RGB images of leaves were obtained, which was shown in Fig. 3 including healthy leaves (Fig. 9c) and diseased leaves (Fig. 9d). In order to eliminate the influence of dark current and uneven illumination, the dark and white calibration were performed for hyperspectral images based on the Eq. 1 [27].

$$I_c = \frac{I_{raw} - I_{dark}}{I_{white} - I_{dark}}$$

Where $I_c$ is the black-and-white corrected cotton hyperspectral image; $I_{raw}$ is the cotton raw spectral image; $I_{dark}$ is dark reference image, acquired by covering the lens with an opaque cap; $I_{white}$ is white reference image, took by scanning the rectangular standard polyethylene white plate.

Due to the influence of environment and hardware, the obtained spectral curve will have some interference such as noise and spectral line drift. Therefore, in order to reduce the influences, the raw hyperspectral data needs to be processed [28]. In this research, the preprocessing methods including Savitzky-Golay smoothing (SG), multiplicative scatter correction (MSC), de-trending (DT) and mean normalization (MN) have been adopted by Unscrambler X 10.4 software, and performance of different preprocessing methods would be compared.

The main configurations of the computer used for data analysis computer was as follows: operating system of Microsoft Windows 10 Enterprise Edition LTSC (64-bit), CPU of 11th Gen Intel(R) Core (TM) i7-11700K @ 3.60GHz (3600 MHz) processor, RAM of 32.00 GB (2133 MHz), and graphics card of NVIDIA GeForce RTX 3060 (12288MB).

### 4.4. Feature band extraction and model establishment based on machine learning

The full-band spectral data of each sample has 224 spectral bands, which have multi-collinearity redundant information [29]. Full-band spectral data was used for model establishment, which would increase the model complexity and decrease the generalization ability of the model, so the dimensionality reduction method was generally applied to extract characteristic bands for modeling, effectively eliminating irrelevant information and simplifying data. Principal component analysis (PCA) [30] is a commonly used dimensionality reduction method, which recombines the original variables through orthogonal linear transformation to generate new variables [31]. PCA projects the original data into new coordinate system, where the first, second et.al principal components were obtained by the ranking of data variance, to produce mutually orthogonal new variables, and new variables $X$ is decomposed as Eq. 2. With PCA processing, the main features would be extracted, and the collinearity of data variables would be eliminated [32].

$$X = t_1p_1^T + t_2p_2^T + \cdots + t_np_n^T$$
Where the vector $t$ is the score vector, and the vector $p$ is the load vector. Besides $i \neq j$, $t_i^T t_j = 0$, $p_i^T p_j = 0$.

Compared with PCA, the successive projections algorithm (SPA) [33] is also applied as follows. Select a band from the spectral data randomly, project this band to the other remaining bands, and then take the band with the largest projection into the band combination. The above steps are repeated to obtain the feature bands, in which the new selected band has the fewest linear relationship with the previous, and finally the optimal characteristic bands would be refined by model evaluation [34, 35].

Support vector machines (SVM) [36] is a nonlinear model, which can effectively avoid the dimensional disaster of the sample space, and has the advantages of high precision, fast operation speed, and strong generalization ability [37]. This method has strong advantages in qualitative analysis of a large number of high-dimensional nonlinear hyperspectral data. Hang et al. [38] employed an SVM classifier to discriminate the rice varieties by grain shape features, and the average accuracy was 79.74% by cross validation. The purpose of the SVM algorithm is to find the optimal classification hyperplane that maximizes the separation of positive and negative samples on the feature space [39]. When using SVM to establish a classification model, it is necessary to select an appropriate kernel function. There is a lot of application experience that the radial basis function RBF has a good learning ability, and the RBF kernel function as a nonlinear function can reduce the computational complexity in the training process.

Back propagation neural networks (BPNN) [40] is an excellent artificial neural network algorithm, widely used in agriculture. Wan et al. [41] proposed a method to discriminate the rice milling degree based on color characteristic and BP neural network, and the average accuracy of the method was 92.17% for 4 rice milling degrees with 5 color features. As BPNN, the number of neurons in the input layer is usually related to the number of features, while the number of output layers is defined by the number of categories, and the number of layers and neurons in the hidden layer can be customized [42]. Each neuron represents one processing of the data, the functional relationship between the output and input of each hidden layer and output layer neuron is as Eq. (3–4).

$$I_j = \sum_i W_{ij} O_i$$

$$O_j = \text{sigmod}(I_1) = \frac{1}{1 + e^{-I_1}}$$

Where $W_{ij}$ is the weight of the connection between neuron $i$ and neuron $j$; $O_j$ is the output of neuron $j$; $\text{sigmod}$ is an activation function of the neuron used to realize nonlinear transformation.
In this paper, the above algorithm was used to establish a classification model of cotton verticillium wilt, and the classification performance of the machine learning method was evaluated. The training set and the test set were divided by random method according to the ratio of 5:5, and the 997 total samples were divided into 499 training sets and 498 test sets, while the classification accuracy of the test set was used as the model evaluation index.

4.5. Deep learning network classification and feature fusion

With rapid development of deep learning algorithms in recent years [43], a growing number of applications have been reported in agriculture, which has the advantages of adaptive learning and self-feature extraction. Duan et al. [44] proposed a rice panicle segmentation algorithm called PanicleNet based on SegNet, which outperformed the existing crop ear segmentation algorithms. As to image classification, deep learning network would definitely help for the image feature extraction. Therefore, this paper adopted a deep learning network to identify the cotton verticillium wilt with RGB image. Besides the extracted image features and above feature bands were fused for further model improvement.

When improving the performance of a convolutional neural network, we usually expand the network, generally by adjusting the depth, width and input resolution of the network. For example, ResNet [45] extended ResNet-18 to ResNet-200 by increasing the number of layers. GPipe [46] achieved 84.3% accuracy on ImageNet by extending the CNN baseline 4 times, and the VGG [47] network adopted stacking convolutional blocks to deepen the number of network layers. EfficientNet [48] is a method of mixing model scales including depth, width and resolution of the convolutional network, which can be balanced and adjusted by setting certain parameter values to achieve the best performance. Besides EfficientNet-B7 [48] achieved state-of-the-art 84.4% top-1 accuracy and 97.1% top-5 accuracy on ImageNet, compared with the previous best convolutional network (GPipe, Top-1: 84.3%, Top-5: 97.0%), while the model size is 8.4 times smaller and model speed is 6.1 times faster. The EfficientNet is unlike ResNet and SENet [49], which invented the shortcut or attention mechanism, and the base structure of EfficientNet is established by structure search, and then scaled by compound scaling rules to obtain a series of excellent networks: B0 ~ B7. The convolutional neural network model scaling method was shown as Fig. 10, The baseline network (Fig. 10a) was expanded the width, depth, or input resolution as shown in Fig. 10b, Fig. 10c, Fig. 10d respectively, and Fig. 10e combined width, depth and input resolution of the network. The EfficientNet network has balanced the classification, accuracy and efficiency, so this network was used for image feature extraction.

The EfficientNet-B0 network structure diagram was shown as Fig. 11, which was divided into 9 stages (Fig. 11a). The first stage is an ordinary convolutional layer (including BN and activation function Swish) with a convolution kernel size of 3×3 and a stride of 2. Stage2 ~ Stage8 are repeating the stacking of the MBConv structure by given number. Stage9 consists of an ordinary 1×1 convolutional layer (including BN and activation function Swish), an average pooling layer and a fully connected layer. Each MBConv will be followed by the magnification factor n, and the first 1×1 convolutional layer in MBConv will expand the channels of the input feature matrix to n times, where k3×3 or k5×5 represents the size of the convolution kernel used by depthwise (DW) Conv in MBConv. EfficientNet-B1 ~ B7 is to modify the size of the feature
matrix (H×W×C) and layers on the basis of B0. Figure 11b showed that the MBConv structure is mainly composed of 1×1 ordinary convolution (dimension-raising effect, including BN and Swish), 3×3 or 5×5 DW Conv (including BN and Swish), SE module, 1×1 ordinary convolution (dimension reduction, including BN), and Dropout layer. In the study, we adopted the EfficientNet-B3 network for image classification and image feature extraction.

The EfficientNet-B3 network was built based on Pytorch1.7.1 and cuda11.0. Because cotton verticillium wilt identification was binary classification task, we modified the output channels of the last convolutional layer to extract main feature vectors. In order to balance the ratio of spectral features and image features, the output channel number of EfficientNet-B3 network was modified according to the number of feature bands. Finally, the RGB images of 997 samples were input into the modified EfficientNet-B3 network for cotton verticillium wilt classification. Based on the previous divided dataset with 499 training sets and 498 test sets, the learning rate was set to 0.01, and the training batch (batch size) was set to 32, while the number of training rounds (epoch) was set to 30. Finally, the classification accuracy of the test set was used as the evaluation index, and the model file was saved.

With the trained model, the forward function in the EfficientNet was used to extract the output of the pooling layer as image feature, which was a set of one-dimensional vectors. Then the feature bands and the image feature were fused into a set of one-dimensional feature vectors, and normalization was conducted to achieve feature fusion (FF).

**Declarations**

**Ethics declarations**

**Ethics approval and consent to participate**

All authors read and approved the manuscript.

**Consent for publication**

Consent and approval for publication was obtained from all authors.

**Competing interests**

The authors declare no competing interests.

**Author contributions**

Z.L. designed the research, performed the experiments, analyzed the data and wrote the manuscript. Z.Z., X.Z. also performed experiments. W.Y., L.Z. revised the manuscript, and C.H. supervised the project and revised the manuscript.

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References


Figures

Figure 1
Curve plots of four spectrum of 997 cotton leaf samples: (a) original spectra, (b) SG-MSC preprocessed spectra, (c) SG-DT preprocessed spectra, (d) SG-MN preprocessed spectra.

Figure 2
Average spectral curves of healthy leaves and diseased leaves.
Figure 3

Scores scatter plots of PCA of SG-DT preprocessed spectra. Blue points: scatter points of healthy leaves, Red points: scatter points of diseased leaves.

Figure 4

The first three principal component load curves of SG-DT preprocessed spectra.

Figure 5

Selection process of characteristic bands for SG-MSC preprocessed spectra using successive projections algorithm. (a) RMSE screen plot for determining the number of characteristic bands, (b) Distribution of characteristic bands marked by each red dot.
Figure 6

Three kinds of characteristic curves of SG-DT-PCA method. (a) Graph of image features, (b) Graph of characteristic bands, (c) Graph of fusion features.

Figure 7

Technical route for cotton verticillium wilt classification by fused features
Figure 8

Cotton information acquisition platform on seedbed. (a) Greenhouse application, (b) Structure diagram.

Figure 9

Hyperspectral image acquisition and ROIs extraction, (a) Hyperspectral images, (b) ROIs, (c) RGB images of healthy leaves and (d) diseased leaves.

Figure 10

Convolutional neural network model scaling method. (a) Baseline network, (b)-(d) Conventional scaling that only increases one dimension of network width, depth, or resolution, (e) Compound scaling method that uniformly scales all three dimensions with a fixed ratio.
Figure 11

EfficientNet-B0 network structure diagram. (a) Overall structure of the network, (b) MBConv structure. MBConv is mobile inverted bottleneck conv, DWConv is depthwise conv, k3x3/k5x5 is kernel size, BN is batch norm, H×W×C denotes tensor shape (height, width, depth), and ×1/2/3/4 denotes the number of repeated layers within the block.

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- AppendixA.Supplementarymaterial.docx