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RESEARCH ARTICLE

NIR-VGGNet19: A Novel Deep Convolutional Neural Network for Pinus NIR Spectra Classification

ZIHAO WAN[1], HONG YANG[1], MINGYU GAO[2], JIPAN XU[1], HONGBO MU[1], DAWEI QI[1], AND SHUXIA HAN[1]

[1]College of Science, Northeast Forestry University, Harbin 150040, China
[2]School of Mechatronics Engineering, Harbin Institute of Technology, Harbin 150001, China

Corresponding authors: Hongbo Mu (mhb506@nefu.edu.cn), Dawei Qi (qidw9806@nefu.edu.cn), and Shuxia Han (han_shx@163.com)

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ABSTRACT Wood is an indispensable non-renewable resource and plays an important role in our life. So, it is a necessity to apply accurate classification techniques. In this paper, a novel model of deep one-dimensional convolutional neural network NIR-VGGNet19 is proposed to classify seven pius wood by combining near-infrared spectroscopy. NIR-VGGNet19 uses a deep convolutional neural network to automatically extract features, eliminate noise, and solve the problem of spectral overlapping peaks; initially eliminates random noise by adding 1×7 convolutional kernels; then uses an attention mechanism to extract more accurate features. According to the results, when NIR-VGGNet19 was tested against other methods, NIR-VGGNet19 had the highest classification accuracy, achieving 98.41% on the test set. In contrast, the accuracy of LeNet, AlexNet, VGGNet-19, ResNet-34, back propagation neural network, and support vector machine were 70.95%, 92.54%, 93.02%, 96.67%, 76.19%, and 71.26%, respectively. Thus, it suggests that the NIR-VGGNet19 can improve the accuracy of classifying wood of the homogeneous genus.

INDEX TERMS Wood classification, near infrared spectroscopy, VGGNet-19, SE module, anti-noise.

I. INTRODUCTION

The physical and chemical properties of wood are varied depending on the species [1],and its applications and values are also diverse. Nowadays, the shortage of wood resources has prompted the research on how to exploit it more efficiently, therefore, it is particularly relevant to apply more accurate techniques to classify wood in various areas. For example, during the trade of precious wood, the fraudulent practice of using substandard wood can be avoided by applying classification identification technology. In the pharmaceutical industry, classification identification technology is needed to determine the medicinal value of each wood. In the construction industry, wood classification technology can be applied to determine the possible applications of each wood [1]. With the development of computer technology, the traditional artificial wood classification method has been gradually replaced by the image classification method based on deep learning, but when classifying wood blocks, in order to obtain clear wood grain and other features, high requirements are put forward for the equipment used to obtain the images as well as the environment, such as the need for high-resolution camera equipment and dark boxes and other environments. Therefore, in this paper, the near-infrared spectrum of wood is used as the classification object, while the deep learning method can well handle the problem of large amount of information in the near-infrared spectrum. From the above, it is concluded that the method of combining NIR spectra with deep learning has great application prospects in the field of wood classification.

The Near Infrared Spectroscopy (NIR), as a non-destructive detection technique, presents the advantages of

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being rapid and non-destructive, [2] and is widely used in the fields of species classification and content prediction. Wang et al. [3] studied the infrared spectra of ten precious wood species with a total of 30 samples, and established a wood NIR spectral cluster analysis model, a Bayesian discriminant model, and a support vector machine model after downscaling the spectral data using principal component analysis (PCA), and the results showed that the accuracy of these three models for wood classification was 83.33%, 86.67%, and 85%, respectively. In the same year, Wang et al. [4] investigated the NIR spectral data of 296 samples of five tree species and established a back propagation (BP) neural network after dimensionality reduction of the data using PCA, and the results showed that the recognition accuracy could reach 100% for tree species with different attributes and more than 85% for the classification of tree species with the same attributes. Nisgoski et al. [5] conducted the classification identification of Brazilian tree species using near-infrared spectroscopy, and the experimental results showed that the recognition accuracy of the neural network model was 100% in the spectral range of 4000-10000 cm^{-1}. Qi et al. [6] used the portable NIR spectrometer to gather the NIR spectra of five kinds of red jujube, by applying a fuzzy improved linear discriminant analysis (FiLDA), the accuracy can reach 94.4%. As the NIR spectra contain a large amount of information, the spectral bands are wide and easily overlapped, thus pre-processing is required to extract the desired features via principal component analysis (PCA), partial least squares (PLS), and other methods. However, this operation is not only time-consuming and labor-intensive, but also subject to human mistakes.

The convolutional neural network [7] (CNN), as one of the typical deep learning network models, provides strong feature extraction capability, making it broadly available for NIR feature extraction analysis. In particular, after AlexNet [8] won the ImageNet recognition competition in 2012, various high-precision convolutional neural network models have emerged, such as VGGNet [9], GoogLeNet [10], ResNet [11], DenseNet [12], etc. The convolutional neural network can automatically extract features from the data, which not only avoids human errors and improve accuracy, in addition to reducing the difficulty for feature extraction, so the use of NIR in combination with convolutional neural network has been a popular trend today. For example, Jia et al. [13] predicted the water quality with over 99% prediction accuracy using an 8-layer convolutional neural network for the analysis of near-infrared spectra. Tang and Chen [14] combined the NIR spectrum with a convolutional neural network to predict the PH of soil and achieved 90% prediction accuracy. Xia et al. [15] employed a one-dimensional convolutional neural network to classify plastics with an accuracy of up to 100%. In 2022, Li et al. [16] used a 1D-CNN to extract the feature in the NIR spectrum, and then predicted the sugar content estimation of Huangshan Maofeng tea successfully. Qi et al. [17] constructed a nine-layer 1D-CNN to predict the origin of Taiping Houkui tea, and the accuracy was 97.93%, which prove that the 1D-CNN can increase the accuracy of the prediction.

There are two main specific applications of convolutional neural networks: one is to directly input the spectrum into the convolutional neural network and use the powerful feature extraction ability of the convolutional neural network for feature extraction. For example, Singh and Tarandeep [18] successfully predicted the protein content in wheat using a CNN model for feature extraction of raw spectra and indicated that this model performed better on raw spectra than on pre-processed spectra; the other is to perform preliminary pre-processing of the spectrum and then use the convolutional neural network for feature extraction. For example, Du et al. [19] used S-G smoothing to preprocess the spectral data, after which a 1D-CNN network model was built to successfully identify foreign fibers in the cotton layer. Although the application of convolutional neural networks to NIR spectroscopy for feature extraction has been extensively applied, and good results have been achieved. However, in the field of wood classification, the combination of NIR and CNN is less common, and the network model used is shallow and weak in the feature extraction, which results in insufficient accuracy when classifying multiple homogeneous wood species.

To solve the above problems, this paper proposes a new one-dimensional deep convolutional neural network (NIR-VGGNet19) to classify seven homogeneous wood species. NIR-VGGNet19 is trained with Adam optimizer [20], Relu activation function [21] and cross-entropy loss function [22]. In order to enhance the feature extraction ability, SE module [23] is added to the network. A convolutional block with a convolutional kernel of 1×7 was added to the network in order to mitigate the noise [24]. Then, Dropout [25] layer and Batch Normalization (BN) [26] layer was added to the network to increase the generalization ability of the network model. To examine the performance of NIR-VGGNet19, this paper first conducted training as well as testing on the dataset using NIR-VGGNet19. Then, the NIR-VGGNet19 network is tested against two traditional machine learning methods to verify the superiority of using the convolutional neural network model as a feature extractor. Next, NIR-VGGNet19 is compared with three classical convolutional neural networks. At the end, an ablation experiment is added to verify the rationality of the NIR-VGGNet19 network structure.

The rest of this paper is organized as follows. Section II describes the structure of the model used in this paper and the related theoretical knowledge, as well as a brief description of the comparison methods mentioned in this paper. Section III presents the experimental results, the results of the comparison experiments and the ablation experiments. Finally, Section IV presents our conclusions.

II. MATERIALS AND METHODS

A. DATASET

The research data, obtained from the Chinese Academy of Forestry Sciences, included the near-infrared spectra of seven Pinus species, each category has 300 near-infrared spectral

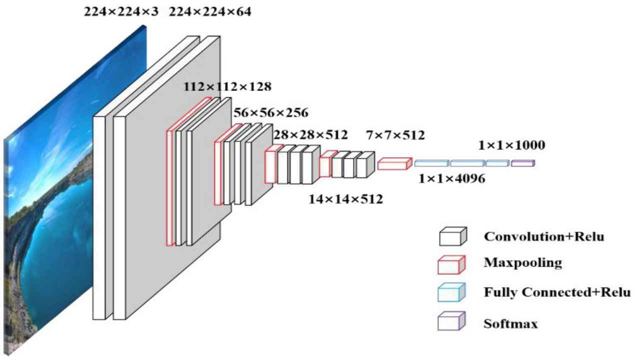


FIGURE 1. VGGNet-19.

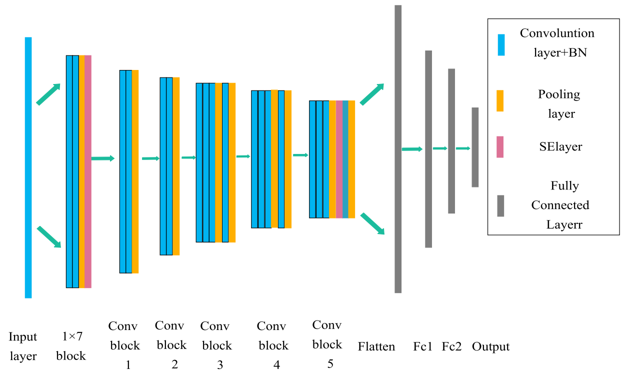


FIGURE 2. The network structure of NIR-VGGNet19.

TABLE 1. The number of training and test sets.

Class	Training set	Test set	Total
Himalayan pine	197	103	300
Pinus yunnanensis	215	85	300
Pinus armandi	212	88	300
pinus khasys	213	87	300
Pinus sylvestris	212	88	300
Pinus tabulaeformis	214	86	300
Pinus koraiensis	207	93	300

data, a total of 2100 data, and each NIR data contained 125 characteristic wavelengths. During training, the ratio of dividing the training set to the testing set is 7:3. The detailed information is shown in Table 1.

B. VGGNet-19

VGGNet is an improved version of AlexNet. VGGNet uses two consecutive 3 × 3 convolutional kernels instead of 5 × 5 convolutional kernels in AlexNet, and three consecutive 3 × 3 convolutional kernels instead of 7 × 7 convolutional kernels. The main purpose of this is to increase the depth of the network while ensuring the same perceptual field, and to improve the network to some extent. VGGNet-19 contains 19 hidden layers, which are 16 convolutional layers with 3 × 3 convolutional kernels and 3 fully connected layers, and its network structure is shown in Figure 1.

From Figure 1, we can find that the input data is a two-dimensional picture of 224 × 224×3, so VGGNet-19 uses a two-dimensional convolutional neural network. Since this paper uses one-dimensional near-infrared spectral data, we need to change the two-dimensional convolutional layer to a one-dimensional convolutional layer and improve the original VGGNet-19 network for the characteristics of the spectral data.

C. A MODIFIED METHOD BASED ON VGGNET-19

1) NIR-VGGNet19

Since the experimental data in this paper are spectral data, some modifications were made to the VGGNet-19 network, and the NIR-VGGNet19 used in this paper was proposed. NIR-VGGNet19 uses VGGNet19 as the backbone network, adds a convolutional block with a 1 × 7 convolutional kernel as the noise reduction module at the front of VGGNet19, adds the SE module to the network to obtain more accurate features.

In order to adapt to the one-dimensional spectral data set, the traditional 2D-CNN is replaced by 1D-CNN [27] in this paper. In order to extract the weak peaks and overlapping peaks in the spectrum and obtain more accurate features, this paper decides to use a convolutional neural network with deeper layers as the feature extractor. Since VGGNet uses a 3 × 3 convolutional kernel instead of the previous 5 × 5 convolutional kernel, VGGNet have deeper layers, it achieves better results compared to networks such as LeNet and AlexNet [9]. Compared with the ResNet network, VGGNet simply increases the depth of the model and the structure is more concise. Meanwhile, the ResNet network is more suitable for building ultra-deep network structures, and the difference between VGGNet and ResNet is not very obvious in the case of medium depth, so VGGNet19 is used as the backbone network in this paper. Considering that the spectrum contains a large amount of useless data such as noise, the input spectrum is first filtered using a convolution layer with 1 × 7 convolution kernels. The interference of noise is reduced by expanding the perceptual field to obtain a larger overall feature. Meanwhile, After several experiments, it is found that the feature extraction ability of the network can be significantly enhanced by appropriately adding the maximum pooling layer and the SE module, and the classification accuracy of the network is significantly improved.

The structure of the proposed NIR-VGGNet19 is shown in Figure 2, and the detailed parameters of the NIR-VGGNet19 network are given in Table 2. In the classification using the NIR-VGGNet19 network, the spectral data of the seven woods are first input to the network. Then, the input data are noise-reduced by convolutional blocks with 1 × 7 convolutional kernels, after which the backbone network (VGGNet19) is used to identify fine features such as weak peaks and overlapping peaks, while the SE module is added to the backbone network to optimize these features. Finally,

TABLE 2. Network parameters of NIR-VGGNet19.

Layer	Output size	Convolution kernel/stride
1×7 block+BN	64×1×121	[1×7] ×2 / 1
Maxpool	64×1×58	[1×2] / 2
SE-Moudel	64×1×58	
Conv1_x +BN	64×1×58	[1×3] ×2 / 1
Maxpool	64×1×29	[1×2] / 2
Conv2_x +BN	128×1×29	[1×3] ×2 / 1
Maxpool	128×1×14	[1×2] / 2
Conv3_x +BN	256×1×14	[1×3] ×3 / 1
Maxpool	256×1×7	[1×2] / 2
Conv3_4 +BN	256×1×7	[1×3] / 1
Maxpool	256×1×3	[1×2] / 2
Conv4_x+BN	512×1×3	[1×3] ×3 / 1
Maxpool	512×1×1	[1×2] / 2
Conv4_4+BN	512×1×1	[1×3] / 1
Conv5_x+BN	512×1×1	[1×3] ×3 / 1
Maxpool	512×1×1	[1×2] / 2
SE-Moudel	512×1×1	
Conv5-4+BN	512×1×1	[1×3] / 1
Fc-x	4096	
Dropout		*P*=0.5
softmax	7	

the softmax [28] function is used to output the probability of each category, and the maximum value of the probability is taken as the final result to complete the classification of the seven wood spectral data.

2) CONVOLUTIONAL NEURAL NETWORK

Convolutional neural networks are used for feature extraction, and when applied to the field of spectroscopy, convolutional neural networks can extract the peak and trough features of a spectrum. Convolutional neural networks can also form filtering and derivative convolution kernels through learning of input data, which serve to suppress noise and identify overlapping peaks [29]. Convolutional neural networks mainly include convolutional layers, pooling layers, activation functions, etc. Each convolutional layer in this paper is followed by a relu activation function, which can be represented by Equation 1.

$$x_i^k = f(\sum_{c=0}^{len} W_i^l(c) * x^{k-1}(c) + b_b^l) \tag{1}$$

x_i^k is the output of channel i of the k^{th} layer of the convolutional kernel;f is the activation function;len is the length of the convolutional kernel;x^{k-1} is the output of the previous convolutional layer;b_b^l is the bias;W_i^l is the weight matrix.

The convolutional layer after adding the SE module can be represented by Equation 2, where s_i^k represents the weight matrix generated by the SE module, and u_i^k represents the optimized features.

$$u_i^k = s_i^k \times x_i^k \tag{2}$$

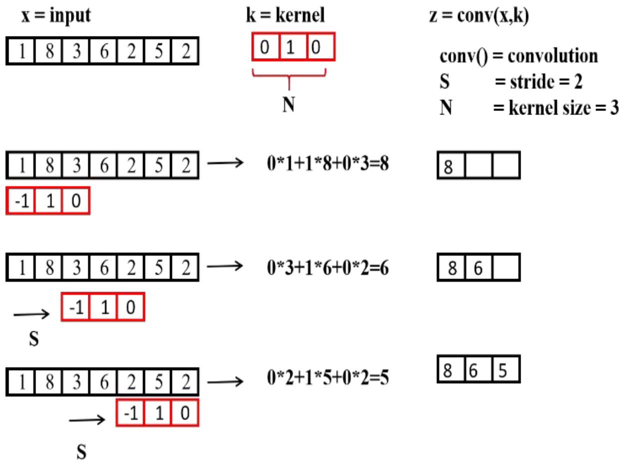


FIGURE 3. CNN.

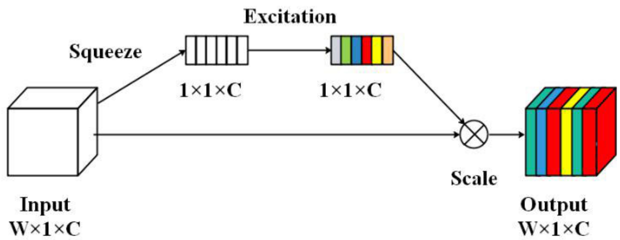


FIGURE 4. The SE model.

When the neural network is trained, the weight matrix and bias are continuously adjusted until the prediction category matches the output category, at which point the parameters within the convolutional neural network reach an optimal state. The convolution operation is shown in Figure 3. When performing the convolution operation, the weight matrix and the input information are multiplied and added separately, and since the input information is a one-dimensional spectrum, the convolution kernel will only move in one direction for the convolution operation. When the convolutional kernel is relatively small, such as when it is set to 3, the receptive field of the convolutional kernel is smaller at this time, and the convolutional neural network can recognize fine features, such as weak and overlapping peaks, but the computation is relatively large at this time, and the hardware requirements are higher. When a larger convolution kernel is selected, the perceptual field is larger and more information can be received in one operation, avoiding local noise interference as feature peaks, thus adjusting the weight matrix of the convolution kernel more precisely and giving less weight to interference features. Therefore, the convolution layer of large convolution kernel can play the role of filtering noise and greatly save training time, but it is also easy to misjudge weak peaks and overlapping peaks.

3) SE MODEL

The SE module is a plug-and-play attention module that can find the relationship between feature channels and assigns different weight coefficients to different channels, ultimately

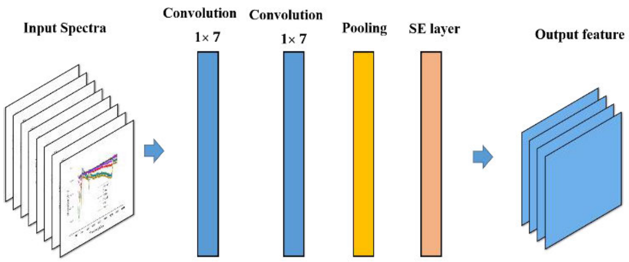


FIGURE 5. 1 × 7 convolutional block.

improving the performance of the network significantly. The structure of SE module as shown in Figure 4. It is mainly consist of three operations. The first is Squeeze, which compresses the feature map into a 1×1×C vector through a global average pooling layer; the second step is the excitation, which performs nonlinear transformation on the squeeze results through two fully connected layers to obtain the attention score of each channel; finally, the Scale is performed. The scale operation multiplies the 1 × 1×C vectors obtained from the excitation as weights with the input features, thus giving different weights to the channels to obtain a more accurate feature map [23] after processing.

4) 1 × 7 CONVOLUTIONAL BLOCK

The convolution kernel achieves the local perception of the input data by weighting and summing a certain local block of the input, and then completes the task of feature extraction, so the size setting of the convolution kernel is critical. In order to suppress the noise in the spectrum, a convolutional block with a 1 × 7 convolutional kernel is added to the forefront of the VGGNet-19 network in this paper. This convolutional block contains two convolutional layers, a pooling layer and an SE module, thus the features after 1 × 7 convolution block can be expressed by Equation 2. Its structure is shown in Figure 5. Two convolutional layers with 1 × 7 convolutional kernels are used to suppress the noise in the spectra for initial pre-processing of the spectra, after which the pooling layer is used to reduce the parameters while retaining the main features to improve the generalization ability of the model, and finally the SE model is added to process the obtained features using the attention mechanism for subsequent fine feature extraction. 1 × 7 convolutional block can increase the perceptual field, obtain more global features [30], suppress the high frequency noise in the data, and serve to speed up the training speed.

D. METHODS FOR COMPARISON

1) EVALUATION INDICATORS

In order to evaluate the performance of NIR-VGG19, this paper uses precision (P), recall (R), f1-score ($F1$) and accuracy ($Accuacy$) as evaluation indicators. All evaluation indicators are defined as follows:

$$P = TP/(TP + FP) \tag{3}$$

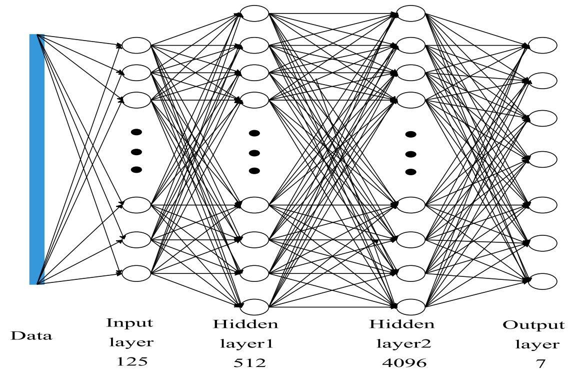


FIGURE 6. The structure of BP neural network.

$$R = TP/(TP + FN) \tag{4}$$

$$F1 = (2 \times P \times R)/(P + R) \tag{5}$$

$$Accuacy = (TP + TN)/(TP + TN + FP + FN) \tag{6}$$

In the formula: ***TP*** means the prediction is true, the actual is true, and the prediction is correct; ***FP*** means that the prediction is true, the actual is false, and the prediction is wrong; ***FN*** means that the prediction is false, the actual is true, and the prediction is wrong; ***TN*** means that the prediction is false, the actual is false, and the prediction is correct.

2) BP NEURAL NETWORK

The BP neural network [31] used in this paper includes an input layer, 2 hidden layers, and an output layer. For a better comparison with NIR-VGGNet19, the neurons in the hidden layer are 512 and 4096, respectively, the input layer is 125, corresponding to 125 features, and the output layer is 7 to output 7 categories, the structure is shown in Figure 6.

3) SVM

The SVM uses the hinge loss function to calculate the empirical risk and adds a regularization term to the solution system to optimize the structural risk. It is a sparse and robust classifier. The SVM can perform nonlinear classification through kernel methods, and is one of the common kernel learning methods. However, the SVM algorithm was originally designed for binary classification problems, when dealing with multi-class classification problems, it is necessary to construct a suitable multi-class classifier.

4) DEEP LEARNING METHODS

Since the NIR-VGGNet19 proposed in this paper belongs to a deep learning-based classification method, NIR-VGGNet19 is tested against LeNet, AlexNet, and ResNet-34 in this paper. Since this paper uses VGGNet-19 as the backbone network, the comparison test between NIR-VGGNet19 and VGGNet-19 is arranged in the ablation experiment chapter in this paper.

LeNet has 7 layers, including 3 convolutional layers, 2 pooling layers and 2 fully connected layers, where all convolutional kernels are 5 × 5 with a step size of 1 and

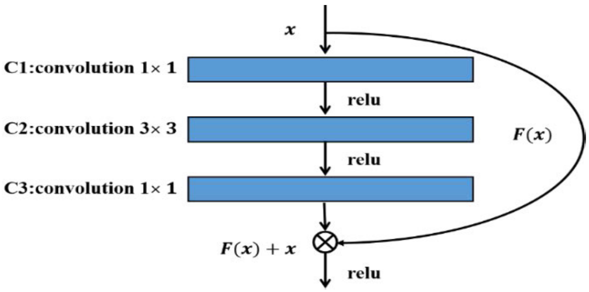
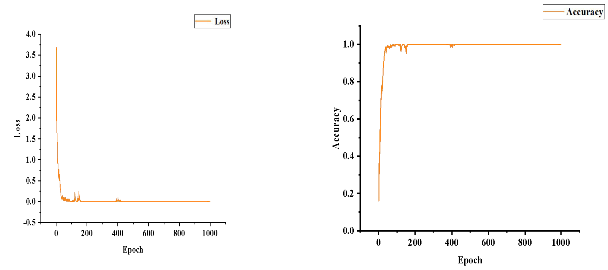


FIGURE 7. Residual structure.



(a) Loss (b) Accuracy

FIGURE 8. The loss curve and accuracy curve of training set.

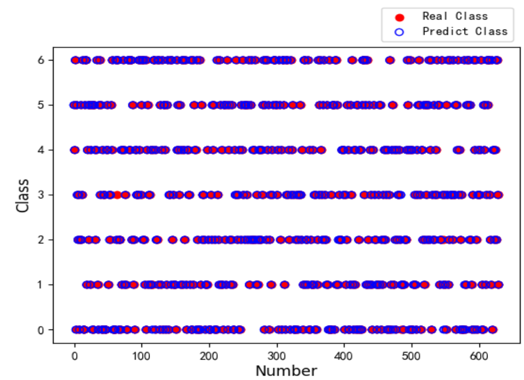


FIGURE 9. The predicted in test datasets.

TABLE 3. Experimental environment.

Hardware Environment		Software Environment	
Memory	16.00GB	System	Windows10
CPU	Inter Core i5-7300HQ/2.50GHz/4 core	Environment configuration	Pytorch-gpu 1.1.0 + Python 3.6.9 + cuda 10.1+ cudnn 7.6.5
GPU	NVIDIA GeForce GTX 1050 Ti(4G)		

global average pooling is used uniformly. AlexNet has 8 layers, including 5 convolutional layers and 3 fully connected layers, the first convolutional kernel is 11 × 11, the second convolutional kernel is 5 × 5, and the third, fourth and fifth convolutional kernels are 3× 3. ResNet-34 has 34 layers, starting with a convolutional layer with 7 × 7 convolutional kernels, followed by a 3 × 3 maximum pooling layer, then a series of residual structures with 3 × 3 convolutional kernels, and finally an average pooling layer and a fully-connected layer. The residual structure is shown in Figure 7.

The residual structure consists of three convolutional layers, two convolutional layers with 1 × 1 convolutional kernels are used to reduce the number of parameters, and a convolutional layer with 3 × 3 convolutional kernels is used to extract features. In Figure 7, x represents the input features of the previous layer, and the features F(x) are obtained after the processing of the convolutional layers, and finally x is summed with F(x) as the final features passed to the next layer. The residual structure can be used to pass the features from the previous layer to the next layer, thus avoiding the loss of information.

III. RESULTS AND DISCUSSION

A. EXPERIMENTAL ENVIRONMENT

NIR-VGGNet19 is trained on a GPU (GTX1050TI 4G), and the experimental environment is shown in Table 3. The model was trained for 1000 epoch, the batch size is 1100, the learning rate is 1×10^{-3}.

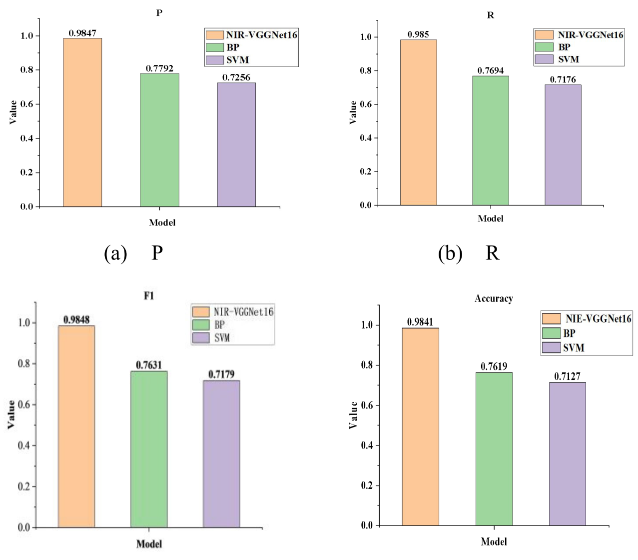
B. EXPERIMENTAL RESULTS

Figure 8 shows the variation of loss function and accuracy in the training set. The loss function drops to the lowest value of 0 when the iteration reaches 100 times, and the accuracy reaches 100%. The loss function decreases to 0 and tends to be stable, indicating that the model can converge and the training effect is good. The accuracy of 100% on the training set indicates that the model has a good fitting ability in the training set data.

Figure 9 shows the prediction effect of the trained model on the test set, the red dots represent the true category, the blue hollow circles represent the predicted category, the x-axis represents the number of predicted samples, and the y-axis uses 0-6 to represent the 7 categories. It is found from Figure 9 that the blue hollow circles basically overlap with the red dots, indicating that the prediction accuracy is high. Through the result of testing 630 samples, it can be found that the prediction accuracy is as high as 98.41%, which is 23% higher than BP Neural Network in classifying the wood with the same genus [32] and 11.74% higher than SVM in classifying 10 precious wood, [3] indicating that the model has good prediction ability and can accurately achieve wood classification.

C. COMPARED WITH TRADITIONAL TAXONOMY

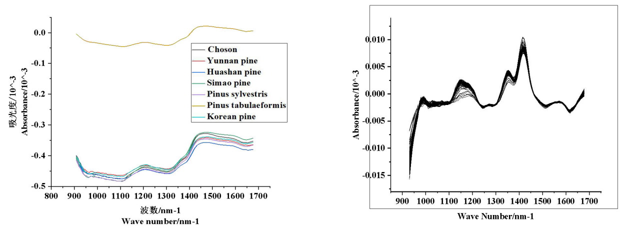
In this section, NIR-VGGNet19 is compared with two traditional machine learning methods to verify the superiority of using convolutional neural network models as feature extractors. First, the initial spectra are classified using three methods, NIR-VGGNet19, BP and SVM, respectively, and their accuracy is compared separately. Then, the spectra



(a) P (b) R

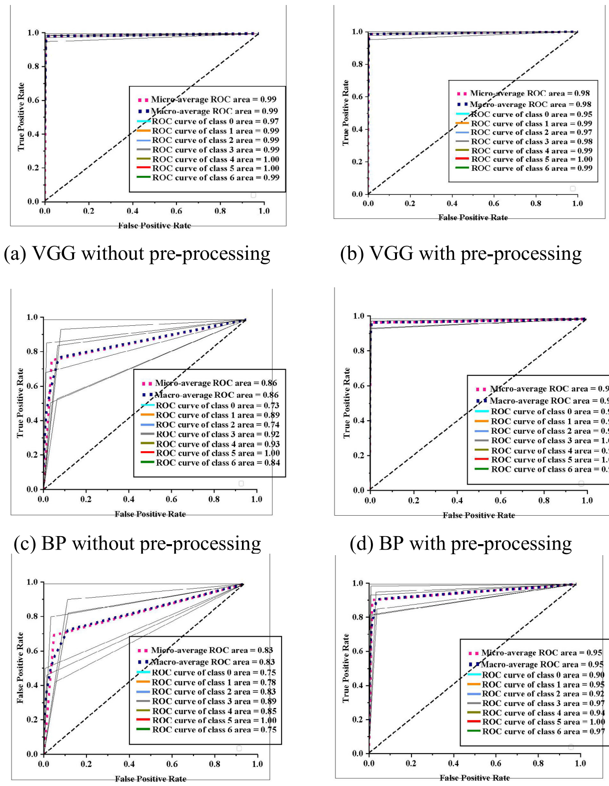
(c) F1 (d) Accuracy

FIGURE 10. Comprehensive rating index.



(a) Initial Spectrum (b) Pre-processed Spectrum

FIGURE 11. Spectrum.



(a) VGG without pre-processing (b) VGG with pre-processing

(c) BP without pre-processing (d) BP with pre-processing

(e) SVM without pre-processing (f) SVM with pre-processing

FIGURE 12. ROC curves.

are subjected to first-order derivation and S-G smoothing, and the processed spectra are classified by BP neural network and SVM classifier. After that, the obtained results are compared with those obtained from the previous step of NIR-VGGNet19. This is used to demonstrate the superiority of using convolutional neural network as a feature extractor compared to other feature extraction methods.

When using SVM for classification, we experimented with one versus rest [33] method and one versus one [34] method to build a multi-classification SVM [35] classifier, and the results showed that the accuracy was 69.84% when using one versus rest method, but 71.27% when using one versus one method, therefore, this paper finally used one versus one method to build a multi-classification SVM classifier.

1) INITIAL SPECTRUM TEST

Table 4 shows the comparison results of NIR-VGGNet19, BP neural network and SVM in terms of precision (P), recall (R), F1-score (F1) and accuracy (Acc). The results show that NIR-VGGNet19 has the best four evaluation indicators for seven kinds of wood identification, followed by BP neural network, and SVM has the worst performance.

The comprehensive indicators of the three models are shown in Figure 10. The results show that the values of P, R, F1 and Accuracy of NIR-VGGNet19 are the highest, so the performance of NIR-VGGNet19 is the best, all reaching more than 98%, while both BP neural network and SVM have a big gap with NIR-VGGNet19.

2) PRE-PROCESSED SPECTRA TEST

Because the spectrum contains a lot of useless information, the BP neural network and the SVM cannot classify tree species well. In order to evaluate the feature extraction ability of NIR-VGGNet19, first-order derivation and S-G smoothing are performed on the spectral data. The initial and pre-processing spectrogram are shown in Figure 11.

In this paper, we examine whether pre-processing the spectrum can improve the classification accuracy by plotting the ROC curve, as shown in Figure 12, where the ROC curves for each type of wood and the average ROC curves obtained using two different methods are given separately. The axes y represent the true rate and the axes x represent the false rate, when the curve is closer to the upper left corner indicates the higher classification accuracy. In the Figure 12, without preprocessing the spectrum, the average AUC value of the ROC curve obtained using the NIR-VGGNet19 model was 0.99, but after preprocessing the spectrum, the AUC dropped to 0.98, indicating that preprocessing has a negative impact on the NIR-VGGNet19 model. This is because the convolutional

TABLE 4. Network evaluation index.

Category	Model	*P*	*R*	*F1*	*Acc*
Himalayan pine	NIR-VGGNet19	97.03%	95.15%	96.08%	95.15%
	BP	61.11%	53.40%	56.99%	53.40%
	SVM	60.00%	58.25%	59.11%	58.25%
Pinus yunnanens-is	NIR-VGGNet19	98.82%	98.82%	98.82%	98.82%
	BP	65.45%	84.71%	73.85%	84.71%
	SVM	78.12%	58.82%	67.11%	58.82%
Pinus armandi	NIR-VGGNet19	96.63%	97.73%	97.18%	97.73%
	BP	71.42%	51.14%	59.60%	51.14%
	SVM	57.52%	73.86%	64.68%	73.86%
pinus khasys	NIR-VGGNet19	100%	98.85%	99.42%	98.85%
	BP	90.36%	86.21%	88.24%	86.21%
	SVM	84.34%	80.46%	82.35%	80.46%
Pinus Sylvestris	NIR-VGGNet19	100%	100%	100%	100%
	BP	64.34%	94.32%	76.50%	94.32%
	SVM	69.47%	75.00%	72.13%	75.00%
Pinus Tabulaefor mis	NIR-VGGNet19	100%	100%	100%	100%
	BP	100%	100%	100%	100%
	SVM	100%	100%	100%	100%
Pinus koraiensis	NIR-VGGNet19	96.84%	98.92%	97.87%	98.92%
	BP	92.75%	68.82%	79.01%	68.82%
	SVM	58.43%	55.91%	57.14%	55.91%

neural network itself can remove the noise and identify the overlapping peaks well. The pre-processing method of S-G convolutional smoothing and first-order derivation can suppress the noise and identify the overlapping peaks, but it also reduces the signal-to-noise ratio of the spectrum and loses a large amount of useful information, thus leading to a decrease in the classification accuracy. The average AUC value is around 0.8 when the initial spectrum is classified using BP neural network and SVM model, but after processing the spectrum, the average AUC value reaches above 0.9.

TABLE 5. Test set accuracy.

Model	Accuracy
NIR-VGGNet19	**98.41%**
BP	97.77%
SVM	91.43%

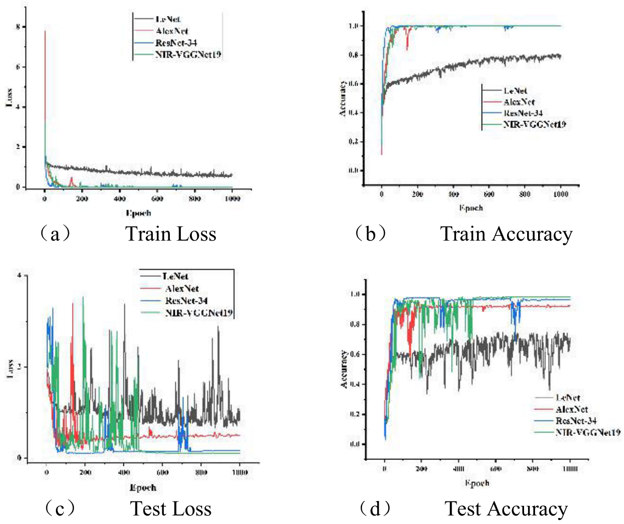


FIGURE 13. Loss function and accuracy variation curve.

This shows that the classification accuracy of the BP neural network and SVM model has been greatly improved after pre-processing the data.

In order to further test the classification ability of NIR-VGGNet19, this paper use BP neural network and SVM classifier to classify the pre-processed spectra, respectively, and compare with the obtained results in the test set with NIR-VGGNet19 in the initial spectra. The results are shown in Table 5.

It can be concluded from the table 5 that NIR-VGGNet19 has the highest classification accuracy than BP neural network and SVM model when classifying the pre-processing NIR spectra. Although the classification accuracy of the BP neural network and SVM model was greatly improved after data pre-processing.

Based on the above results, it can be concluded that using NIR-VGGNet19 as a feature extractor is superior compared to other spectral processing methods.

D. COMPARISON WITH DEEP-LEARNING METHODS

In this section, NIR-VGGNet19 is tested against three classical neural network models, LeNet, AlexNet and ResNet-34, and the loss function and accuracy change curves of the above four models are compared in the training set and test set, respectively, as shown in Figure 12.

LeNet has 7 layers, AlexNet has 8 layers, ResNet-34 has 34 layers, and NIR-VGGNet19 has 21 layers due to the addition of the noise reduction module.

From Figure 13(a) and 13(b), it can be found that when training in the training set, LeNet cannot fully fit the training set data due to the shallow depth of the model with only 7 layers, so the final accuracy reaches only 79.86%, while AlexNet, ResNet-34 and NIR-VGGNet19 all reach 100% accuracy. It can also be found that the convergence speed of ResNet-34 is the fastest among these three, followed by NIR-VGGNet19, and AlexNet is the slowest, but the stability of NIR-VGGNet19 is the best. The results when tested on the test set are shown in Figure 13(c) and Figure 13(d), and combined with Figure 14, it can be found that when tested on the test set, the accuracy of the LeNet network model is only 70.95% because it does not adequately fit the training set, while the accuracy of AlexNet, ResNet-34 and NIR-VGGNet19 are 92.54%, 96.67% and 98.41%, all above 90%, with NIR-VGGNet19 having the highest accuracy.

The above experimental results show that when comparing NIR-VGGNet19 with several common convolutional neural network models, NIR-VGGNet19 achieves the best results, with both convergence speed and stability when training on the training set and the highest accuracy when testing on the test set. From LeNet, AlexNet and ResNet-34, it can be found that the accuracy rate increases with the increase of model depth, which is in accordance with the general rule, but the model depth of NIR-VGGNet19 is shallower than that of ResNet-34, but the accuracy rate is 1.74% higher, which proves the superiority of NIR-VGGNet19.

E. ABLATION EXPERIMENT

In this section, this paper first shows that the SE module can be installed in any part of the network, and the classification accuracy of the network can be improved by changing the installation position; Afterwards, it is verified that adding a convolution block with a convolution kernel of 1×7 can not only enhance the feature extraction capability of the network, but also enhance the anti-interference ability of the network; Finally, the improved NIR-VGGNet19 network is compared with the original VGGNet19, which proves that the network applied in this paper can achieve better results.

1) SE MODULES

In this section, the impact of SE module installation location on network performance is explored. The installation position of the SE module is divided into four conditions, condition1: Add SE module before each convolutional layer; Condition2: Add SE module after the convolutional layer with the convolution kernel of 1×7; condition3: Add SE module before the last convolutional layer; Condition4: Add the SE module after the convolution block with the convolution kernel of 1×7 and before the last convolution layer. The prediction results obtained in the test set for the above four cases are shown in Table 6.

Table 6 shows that by adding the SE module, the classification accuracy of the network model increases from 93.65% to more than 97%, indicating that the performance of the network can be improved by adding the SE module. By changing the position of the SE module, it can be found that the classification accuracy of the network is the higher when the SE module is added after the 1×7 convolutional block and before the last convolutional layer, so this paper combines the condition2 with condition3, adding the SE module to the position of condition 4, and the final accuracy rate reaches 98.41%.

TABLE 6. Accuracy of Moving SE Module.

Method	Accuracy
No SE	93.65%
condition 1	97.14%
condition 2	97.93%
condition 3	97.46%
condition 4	**98.41%**

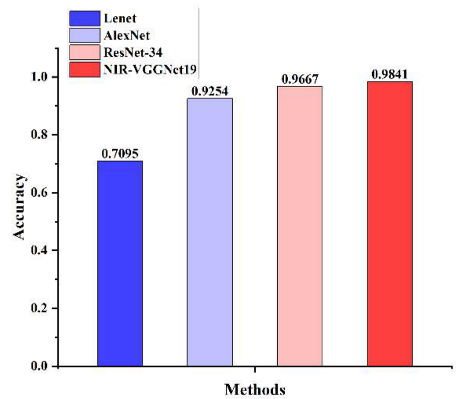


FIGURE 14. Test Set Accuracy Comparison.

TABLE 7. Accuracy of 1 × 7 convolution block.

With or without 1×7 convolution block	Accurary
With	**98.41%**
Without	97.77%

2) 1 × 7 CONVOLUTIONAL BLOCK

In this section, this paper tests whether the 1×7 convolution block can improve the classification performance of the network by comparing the classification accuracy of the network model with or without the 1×7 convolution block. The test results are shown in Table 7; At the same time, the changes of loss function during training are analyzed, so as to analyze the stability of the network model after adding 1×7 convolution blocks. The results are shown in Figure 14.

It can be found from Table 7 that after adding 1×7 convolution blocks, because the network model has a deeper depth and the 1×7 convolution kernel can well suppress high-frequency noise, the classification accuracy of the network is higher; At the same time, it can be found from Figure 15 that although the depth of the network increases after adding the 1×7 convolution block, the convergence speed of the network model during training is faster and the fluctuation

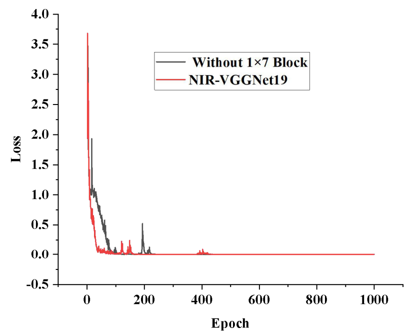


FIGURE 15. Loss curve of 1 × 7 Convolutional Block.

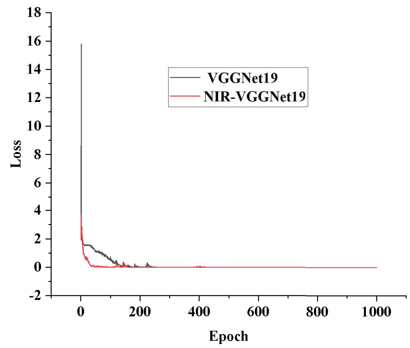


FIGURE 16. Loss curve comparison.

TABLE 8. Test set accuracy.

Model	P	R	F1	Accuracy
NIR-VGGNet19	**98.47%**	**98.50%**	**98.48%**	**98.41%**
VGGNet19	93.07%	93.24%	93.08%	93.02%

TABLE 9. Confusion matrix.

Model	Actual Category	Prediction Category Class 0	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Total
NIR-VGGNet19	Class 0	98	1	2	0	0	0	2	103
	Class 1	1	84	0	0	1	0	0	85
	Class 2	2	0	86	0	0	0	0	88
	Class 3	0	0	0	86	0	0	1	87
	Class 4	0	0	0	0	88	0	0	88
	Class 5	0	0	0	0	0	86	0	86
	Class 6	0	0	1	0	0	0	92	93
VGGNet19	Class 0	86	10	2	3	1	0	1	103
	Class 1	2	78	1	3	1	0	0	85
	Class 2	3	0	78	1	4	0	2	88
	Class 3	1	3	1	82	0	0	0	87
	Class 4	0	0	0	2	86	0	0	88
	Class 5	0	0	0	0	0	86	0	86
	Class 6	1	0	1	0	1	0	90	93

is smaller. This is because the input spectral information is processed by the 1 × 7 convolution block to eliminate the noise in advance, so the model converges more stably and faster in the subsequent feature extraction. Therefore, the network structure after adding the 1 × 7 convolution block is more reasonable and the stability is better.

3) VGGNet19 COMPARISON TEST

Compared with the original VGGNet19 network, the NIR-VGGNet19 network used in this paper adds 1 × 7 convolution block, SE module, and three max pooling layers. To examine the performance of the improved NIR-VGGNet19 network, in this section, the NIR-VGGNet19 network is compared with the VGGNet19 network in detail. The feature extraction ability, convergence speed and stability of the model are evaluated by analyzing the changes of the loss function during the training process, and the generalization ability and prediction effect of the model are analyzed by analyzing the test classification accuracy and confusion matrix.

Figure 16 shows the changes in the loss function when using the NIR-VGGNet19 and VGGNet19 networks respectively for training. Table 8 and Table 9 (using 0-7 to replace the seven types of wood) show the confusion matrix of the accuracy and prediction results of the two models in the test set to evaluate the generalization ability of the two models.

As can be seen from Figure 16, although the NIR-VGGNet19 network increases the depth of the network, the convergence speed is still faster than the VGGNet19 network, and the stability is also higher. In conclusion, the performance of NIR-VGGNet19 in the training set is better than VGGNet19.

It can be found from Table 9 that the generalization ability of the NIR-VGGNet19 network is better, and the prediction accuracy on the test set is much higher than that of the VGGNet19 network; From the confusion matrix, the number of prediction errors of VGGNet-19 is higher than that of NIR-VGGNet-19, especially in classes 1, 2, 3, and 4, but the difference is smaller in classes 5, 6, and 7. However, the overall accuracy of NIR-VGGNet19 is significantly higher than that of VGGNet-19, indicating that the classification performance of NIR-VGGNet19 is superior.

In summary, the NIR-VGGNet19 network has faster convergence speed and higher stability during training, and has higher classification accuracy during testing on the test set, indicating that the model has better generalization ability. This shows that the improvement of the model is successful.

IV. CONCLUSION

As mentioned above, this paper proposes a novel convolutional neural network model, NIR-VGGNet19, to classify NIR spectral data of seven genus wood species, and the accuracy can reach 98.41% on the test set. NIR-VGGNet19 uses VGGNet19 as the backbone network for feature extraction, which omits the process of manual feature extraction and can quickly and accurately identify tree species with the same attributes. It avoids human errors compared to traditional machine learning methods. When VGGNet19 was tested against BP and SVM, respectively, the accuracy of NIR-VGGNet19 was 22.22% higher than BP neural network and 27.14% higher than SVM when no preprocessing was performed on the spectral data. After preprocessing the spectral data, the accuracy of NIR-VGGNet19 is 0.64% higher than that of BP neural network and 6.98% higher than that of SVM. The above results demonstrate the superiority of NIR-VGGNet19 as a feature extractor. To suppress noise, NIR-VGGNet19 adds 1×7 convolutional blocks to the front of the network, and the accuracy is improved by 0.64% after the addition. To extract finer features, the SE module is added to the network in this paper, which improves the accuracy of the network by 4.76%. Finally, the accuracy of NIR-VGGNet19 is improved by 5.39% over the original network (VGGNet19). NIR-VGGNet19 also achieves optimal results when tested against other common convolutional neural network models. The accuracy of NIR-VGGNet19 improved 27.46% over LeNet, 5.87% over AlexNet, and 1.74% over ResNet-34.

NIR-VGGNet19 uses near-infrared spectra as the research object, and can obtain information of various types of woods quickly and accurately. The use of deep convolutional neural network as a means of spectral analysis enhances the feature extraction ability of the model and solves the characteristics of large amount of spectral information and difficult analysis, which is important for the classification of woods of the same genus. However, reviewing the above, there are some limitations in this study. The most important one is that the existing wood spectral dataset is small and lacks a large dataset like ImageNet, which limits the development of applying convolutional neural networks to NIR spectral analysis, so it would be a good development direction to continuously enrich the dataset or adopt migration learning methods. Besides, combining NIR spectra with wood pictures for feature extraction is also a further research direction in the future.

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ZIHAO WAN was born in Shandong, Dongying, China, in 1998. He is currently pursuing the academic master's degree with Northeast Forestry University. His research interests include image processing, spectral analysis, machine learning, and artificial intelligence.

HONG YANG received the B.E. degree in electronic information engineering from the Chengdu University of Information and Technology, Chengdu, China, in 2020. He is currently pursuing the M.E. degree in optical engineering with the College of Science, Northeast Forestry University, Harbin, China.

His research interests include image processing, pattern recognition, machine vision, and visual servo.

MINGYU GAO was born in Heilongjiang, China. He received the master's degree in engineering from Northeast Forestry University. He is currently pursuing the Ph.D. degree in engineering with the Harbin Institute of Technology. He has published four articles as the first author, including three in the field of science.

JIPAN XU was born in Henan, China, in 1997. He is currently pursuing the academic master's degree with Northeast Forestry University. His research interests include image processing, spectral analysis, machine learning, and artificial intelligence.

HONGBO MU was born in Tongliao, Inner Mongolia, China. He received the Ph.D. degree. He is a Master's Student Supervisor at Northeast Forestry University. He is currently the Head of the Department of Physics, College of Science. His research interests include photoelectric detection and digital image information processing of biomass materials, artificial neural network recognition, wood modification, and protection and functionalization design. He is a member of the CPC and the Discipline Inspection Committee of the College of Science. He was a member of the Working Committee of Agriculture and Forestry, from 2018 to 2022, and the Special Committee of Physics Education Reform and Research, from 2018 to 2022, both affiliated with the Steering Committee of University Physics Course Teaching in Higher Education, Ministry of Education.

DAWEI QI received the B.Sc. degree in radio from the Department of Radio, Peking University, in 1982, the M.Eng. degree in signal processing from the Department of Electronic Engineering, Harbin Shipbuilding Engineering Institute, in 1988, the Ph.D. degree in mechatronics from the School of Mechanical and Electrical Engineering, Northeast Forestry University, in 2003, and the Ph.D. degree in control science and engineering from Harbin Engineering University, in 2005.

He served as the Dean, a Professor, and a Doctoral Supervisor with the College of Science, Northeast Forestry University, from 2012 to 2019, where he is currently a Postdoctoral Fellow, a Professor, and a Doctoral Supervisor with the Department of Physics. He has published more than 110 academic papers, including more than 30 SCI- and EI-indexed papers. He has presided over more than 11 scientific research projects, including five national projects. His research interests include nondestructive detection of biomass material defects, digital image processing, pattern recognition, and 3-D reconstruction. He was a member of the Steering Committee of University Physics Curriculum, Ministry of Education; the Director of the Agriculture, Forestry and Water Working Committee of the Steering Committee of University Physics Curriculum, Ministry of Education; a member of the Heilongjiang Provincial Committee, Chinese People's Political Consultative Conference; and the leader of the discipline of biophysics. He is the Vice Director of the Heilongjiang Physical Society and the Harbin Physical Society. He is an Editorial Board Member of *Journal of Northeast Forestry University* and the *Journal of Forest Engineering*.

SHUXIA HAN received the B.Sc. degree in physics and the M.Eng. degree in solid-state physics and microelectronics from Heilongjiang University, in 1987 and 2000, respectively, and the Ph.D. degree from the Department of Physics, College of Science, Northeast Forestry University, in 2010.

From 1987 to 2001, she was a Senior Engineer with the Materials Research Institute, Turbine Corporation. She is currently an Associate Professor and a Supervisor of the master's degree in optical engineering with the College of Science. She has published more than 20 papers, including four EI-indexed papers. Her research interests include biological image information processing and recognition, and wood nondestructive testing and image processing.