Remote Sensing Science
Volume 6, 2018, PP. 9-17

Prediction Model of Nitrogen Content in Apple Leaves based on Ground Imaging Spectroscopy

Baichao LI [1], Xicun ZHU [1,2*], Ruiyang YU [1], Xiaoyan GUO [1], Shujing CAO [1] , Huansan ZHAO [1]

1. College of Resources and Environment, Shandong Agricultural University, Tai'an 271018, China.
2. Key Laboratory of Agricultural Ecology and Environment, Shandong Agricultural University, Tai'an 271018, China.

Abstract

A prediction model of apple leaf nitrogen content based on ground imaging spectroscopy was established to rapidly and nondestructively detect nitrogen content in apple leaves. SOC710VP hyperspectral imager was used to obtain the imaging spectral information of apple leaves, and the average spectral curve of interest region was extracted. The study is to analyze the characteristics of imaging spectral curves of apple leaves with different nitrogen content. On the basis of the SG smoothing and first derivative pretreatment of the spectral curve, the maximum sensitive band with nitrogen content is screened and the spectral parameters are constructed. Three modeling methods of BP, SVM and RF were used to establish the prediction model of nitrogen content in apple leaves. The results showed that in the visible range, the nitrogen content of apple leaves was negatively correlated with the reflectance of the spectral curve, and was most obvious in the green range. The R^2 of BP, SVM and RF of apple leaf nitrogen content prediction model were 0.7283, 0.8128, 0.9086, RMSE were 0.9359, 0.7365, 0.5368, the R^2 of test model were 0.6260, 0.7294, 0.6512, RMSE were 0.9460, 0.7350, 0.9024.Comparing the prediction results of the three models, the optimal prediction model is SVM model, which can well predict the nitrogen content of apple leaves.

Keywords: Apple Leaves; SVM; Ground Imaging Spectroscopy

1 INTRODUCTION

Nitrogen is an important element in the process of growth and development of apple. The number of leaf nitrogen content of fruit trees can directly reflect the apple tree growth conditions, so the rapid and nondestructive detection of leaf nitrogen content on fruit growth monitoring and yield prediction has important significance. The traditional method of measuring vegetation nitrogen is mainly in field sampling and laboratory determination. Although the measurement accuracy is accurate, it needs to spend a lot of manpower and material resources, and the timeliness is poor, it is difficult to meet the actual needs. Spectral imaging technology has gradually emerged in recent years, because of its high spectral resolution, multi band and mapping one and other characteristics, can do quantitative analysis on vegetation composition and structure of vegetation in remote sensing application shows a strong advantage.

Some achievements have been made in the study of vegetation nitrogen by imaging spectroscopy. *Inoue* et al. Used the 400-900nm range of visible near infrared hyperspectral images, established a multiple regression model, predicted the nitrogen content of rice leaves, and coefficient of determination R^2reached 0.72. *Stroppiana* and other hyperspectral images of paddy rice canopy were collected and the vegetation index was established by hyperspectral data. When studying the correlation between vegetation index and nitrogen content, a new normalized spectral vegetation index is proposed, which makes the correlation between spectral data and nitrogen content higher[1]. *Goel* by setting up different levels of nitrogen gradient, hyperspectral image of maize is obtained by using airborne hyperspectral imager. The results of the study show that in the visible and near infrared (409-947nm) of the 72 bands, the 498nm and 671nm band spectral reflectance can reflect the vegetation nitrogen level, the detection of hyperspectral technology based on the realization of Corn Nitrogen content[2]. *Vigneau*, etc., discussed the feasibility of nondestructive testing of nitrogen content in Wheat Leaves by using ground objects to move hyperspectral imaging equipment. By establishing PLS regression model between leaf spectral information and nitrogen content, it is indicated that hyperspectral imaging technology has potential application in non-destructive detection of plant nitrogen. It provides a new method for further monitoring and monitoring nitrogen distribution.[3] *Elfatih M. Abdcl-Rahman* et al. Proposed a random forest regression algorithm based on hyperspectral data to predict nitrogen content in sugarcane leaves. *Dongyan Zhang* et al. used pixel by pixel averaging method to enhance spectral characteristics. According to reflectance differences, it was proved that the extracted hyperspectral reflectance could reflect the nutrient differences of different leaf positions. *Jinmeng Li* and other researchers have studied the prediction model of nitrogen content in Citrus Leaves under different pretreatment conditions by using imaging spectroscopy. It is proved that the artificial neural network model of back propagation is more suitable for the prediction of nitrogen content in citrus leaves[4]. *Jun Sun* and other lettuce as the research object, based on hyperspectral image spectral information and texture information, it is proved that combining texture information can effectively predict vegetation nitrogen and improve the performance of the model[5]. *Xiaolei Zhang* use continuous projection algorithm to extract characteristic wavelengths and set up a partial least square method model. By calculating the predicted value of nitrogen content corresponding to each pixel in the hyperspectral image under characteristic wavelengths, the leaf distribution map of nitrogen concentration of rape was established according to the spatial location of pixels, and the feasibility of visualization of nitrogen content in rape leaves was illustrated[6]. *Keqiang Yu* using pepper as the research object, based on hyperspectral imaging technology, screening characteristic band uses the random forest algorithm, established partial least squares regression model for nitrogen content of pepper leaves the distribution map visualization. And the visual distribution of SPAD is used to test it to prove the accuracy of the result[7]. *Shuwen Wang* using hyperspectral imaging technology in cold region under different nitrogen levels of corn canopy spectral study using vegetation index, establish different models under different nitrogen levels, the effective estimation of nitrogen content in maize[8].

Most studies used one or two modeling methods to predict the nitrogen content of vegetation, but there was no discussion on the comparison of nitrogen content with different models. At the same time, the use of ground spectral imaging technology in the prediction of nitrogen content in apple leaves is relatively less. In this study, hyperspectral imaging technology was applied to SG curve smoothing and first derivative preprocessing of spectral curves. Back Propagation model(BP), Support Vector Machines(SVM) and Random Forest model(RF) were applied to establish apple leaf nitrogen prediction model. By comparing the results of the three modeling methods, the most suitable nitrogen prediction model for apple leaves was selected to provide a theoretical basis for the rational prediction of the content of nitrogen in apple.

2 MATERIALS AND METHODS

2.1 Sample Collection

Stop during the apple growing period of autumn (September 18, 2016) samples were collected. According to the distribution of samples of orchard of Mengyin county land use planning, selected 113 trees good growth status of apple trees as the sampling object, collecting 3 pieces of fully mature, non-destructive, no pests and diseases of healthy leaves as a sample in each apple tree the central branch of tree nutrition. Quickly put into the bag, sealed, numbered, placed in the bag, and then put into the black bag with ice bag, back to the laboratory.

2.2 Materials and Methods

1) Ground Imaging Spectrometry

The hyperspectral imaging system used in this experiment consists was SOC710VP portable hyperspectral imager (Figure 1), hard ash board and computer. The SOC710VP portable hyperspectral imager has a wavelength range of 400-1000 nm and a spectral resolution of 4.68nm, with a total of 128 bands. In the measurement, the lens aperture is set at 5.6, the field view angle of the spectrometer is 25 degrees, and the sample is placed vertically in the center of SOC hard gray board. The hyperspectral image information of each sample is collected by imaging spectrometer (Figure 2). Initial image correction using SRAnal710 software of SOC710VP portable hyperspectral imager.

FIG.1 SOC710VP PORTABLE HYPERSPECTRAL IMAGER

FIG.2 COLLECTION OF IMAGE INFORMATION

2) Determination of Nitrogen Content

Nitrogen content in leaves was determined by Kjeldahl method (GB 7173-87). The test sample will be in 30 minutes to 105 ℃ after fixing, maintained at 70-80 ℃ after drying, crushing and mixing with concentrated sulfuric acid at high temperature - cook, which organic compounds containing nitrogen into ammonia nitrogen, then titrated with standard acid solution according to the consumption standard for liquid nitrogen content.

3) Extraction of Spectral Curve

For each leaf hyperspectral image samples, on the right side of each leaf main vein (avoid vein), rectangular pixel area from 50 long 50 pixels as a region of interest (region of, interesting, ROI). The spectral data of ROI were extracted by ENVI, and the average spectrum of the extracted three slices of apple leaf light spectrum was used as the original sample spectrum.

3 RESULTS AND ANALYSIS

3.1 Spectral Imaging Characteristics of Apple Leaves with Different Nitrogen Content

Figure 3 is the spectral curve of all samples. The graph of apple leaves shows the same trend at different nitrogen levels by fig. 3. The spectral curves between 400-490nm and 560-700nm are low, and there is no large fluctuation, and the trend is low reflectivity, and there is no big fluctuation, the trend is slow. There is an upward trend between 460-550nm and a downward trend between 550-560nm, and a peak at 550nm. There is a great difference in nitrogen content between apple leaves and 460-560nm. A sharp upward trend between 700-750nm and marked red edge characteristics. The overall trend of spectral curves between 750-1000nm is relatively slow, but the noise is larger. The difference of leaf reflectance of different nitrogen content is easy to be obvious.The cause of the spectral curves of apple leaves was analyzed. In the range of visible light, the chlorophyll content of leaves had a great influence on the spectral curve. The spectral reflectance of leaves is low between 400-490nm and 560-700nm due to the strong absorption of chlorophyll. The chlorophyll green reflection between 460-560nm is strong, so there is a wave peak. Chlorophyll has little effect on the leaf reflectivity after 700nm.

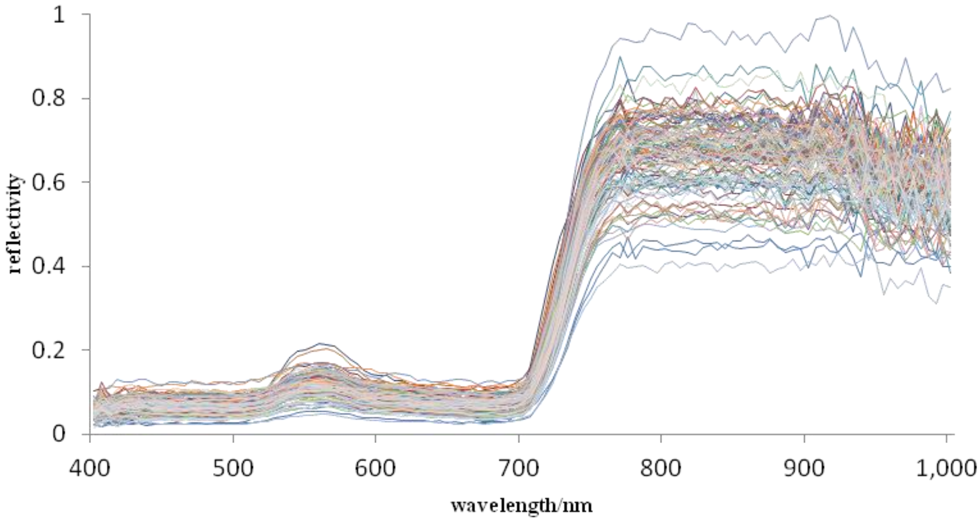

Fig.3 the spectral curves of apple leaves

The spectral curves of 5 samples with different nitrogen contents were selected, as shown in Fig. 4. In the visible range, the reflectance was negatively correlated with the nitrogen content, and the lower the nitrogen content, the higher the reflectance. In addition, the leaf spectral curve of the lower nitrogen content was smaller in the green peak, and the higher the nitrogen content, the greater the peak value. With the decrease of nitrogen content, the position of green peak changes to the short wave,

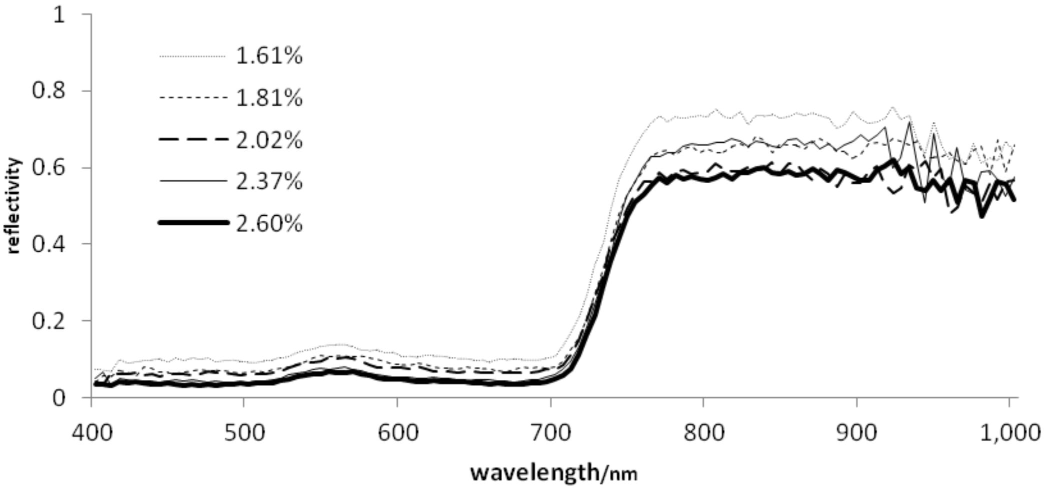

Fig. 4 Spectral curves of different nitrogen level apple leaves

3.2 Screening of Sensitive Bands

In addition to the nitrogen content of the leaves, the spectra of the samples are also affected by the physical characteristics of the background and surface texture of the leaves, resulting in noise. Therefore, it is necessary to preprocess the original spectrum to eliminate the influence of noise. In this study, S-G differentiation (Savitsky-Golay smoothing and) and first derivative transformation are used to eliminate the noise of spectral curves. The correlation coefficient between the original spectral curve and the nitrogen content after SG smoothing and first derivative is shown in fig. 5.

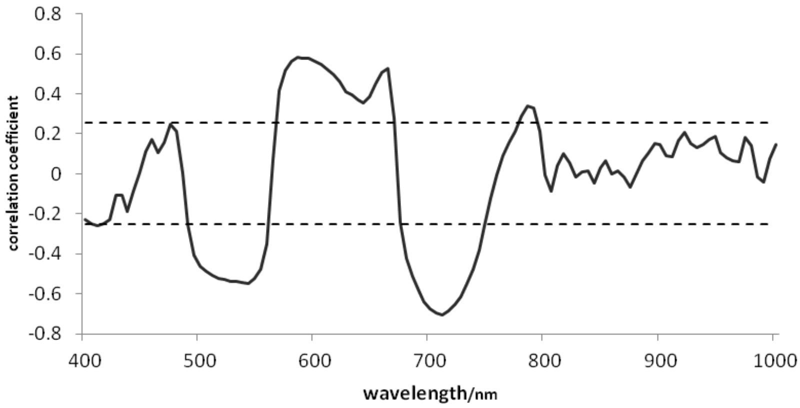

Fig.5 Correlation analysis of spectral curves and nitrogen content after pretreatment

As shown in Fig. 5, after the pretreatment, the spectral curves in 485-550nm and 665-740nm band had extremely significant negative correlation (P<0.01). The 560-660nm band has very significant positive correlation (P<0.01). In addition to some discrete points into extremely significant correlation, 475-550nm and 660-725nm, 560-655nm band are the sensitive band of the nitrogen content of apple. According to the sensitive band determined, this study selected 525.28nm (peak), 571.53 nm (peak), 623.35 nm (Valley), 649.43 nm (peak), 691.40 nm (peak) and 776.23 nm (peak) wavelength of the 6 highest correlation coefficient as the sensitive wavelength.

Of all the 113 samples, 83 (75%) samples were used as training samples, and the remaining 30 (25%) samples were used to verify the reliability of the model.

3.3 Establishment and Test of Apple Leaf Nitrogen Content Model Based on BP, SVM and RF

1) BP MODEL

BP model is based on the theoretical basis of neural mathematical model, is a system of neural structure and brain cells to mimic the human brain's way of working, multi-layer BP neural network is a one-way transmission of feed forward neural networks. BP neural network is composed of input layer, hidden layer and output layer. Set the input layer of 6 units, respectively, $R_{525.28}$, $R_{571.53}$, $R_{623.35}$, $R_{649.43}$, $R_{691.40}$, $R_{776.236}$ bands, output layer leaf nitrogen content of 1 nodes, after repeated training to determine the hidden layer nodes is estimated to be 6, the establishment of the topological structure of 6-6-1BP neural network structure, with a sample of 83 training model extraction. And comparing the test result with the actual value. Fig. 6 (a) is the training result, which is modeled by BP neural network. The coefficient of determination is R^2=0.7283 and the root mean square error is RMSE=0.9359.

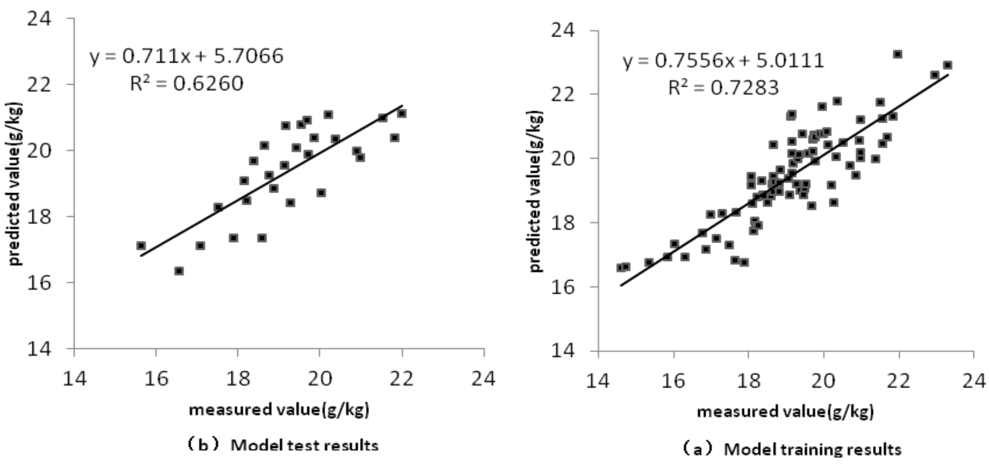

FIG.6 FITTING EFFECT OF MEASURED VALUE OF NITROGEN AND BP NEURAL NETWORK MODEL

Fig. 6 (b) is the reliability test of the BP neural network modeling results by using 30 samples, the test result is R^2=0.6260, the root mean square error is RMSE=0.9460.

2) SVM Model

Support vector machine (SVM) is a machine learning theory for small sample training and classification. Based on the principle of structural risk minimization, it can solve practical problems such as nonlinear, small sample and so on, and the generalization ability is excellent. After systematic analysis and repeated tests, the SVM regression type is set asε-SVM and the kernel function type is Gauss kernel function. The accuracy of setting the allowed termination iteration is 0.001. The regression model of 83 training samples was fitted, and the training results and actual values were compared.

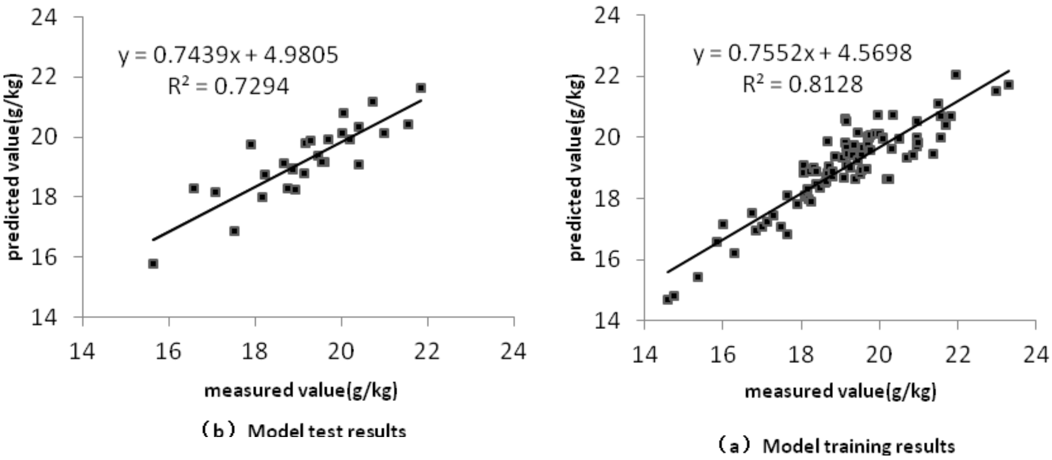

FIG.7 FITTING EFFECT MAP OF THE MEASURED VALUE OF NITROGEN AND THE PREDICTED VALUE OF SVM

Fig. 7 (a) is a nitrogen content estimation model established by SVM. The coefficient of determination of the fitting equation is 0.8128, root mean square error is 0.7365, and the fitting accuracy is high.

Fig. 7 (b) uses 30 samples to test the reliability of the SVM results. The test result is that R^2=0.7294, the root mean square error is 0.7350. The nitrogen prediction result is better.

3) RF Model

RF is a classification algorithm containing multiple decision trees . Random forests are randomised in the use of variables (columns) and the use of data (rows). Many classification trees are generated and the results of the classification trees are summarized. Through systematic analysis and repeated tests, the final parameter Ntress=300 was selected, and the proportion of random forest training samples was 50%, and the parameters Mtry=4. The regression model of 83 training samples was fitted, and the training results and actual values were compared.

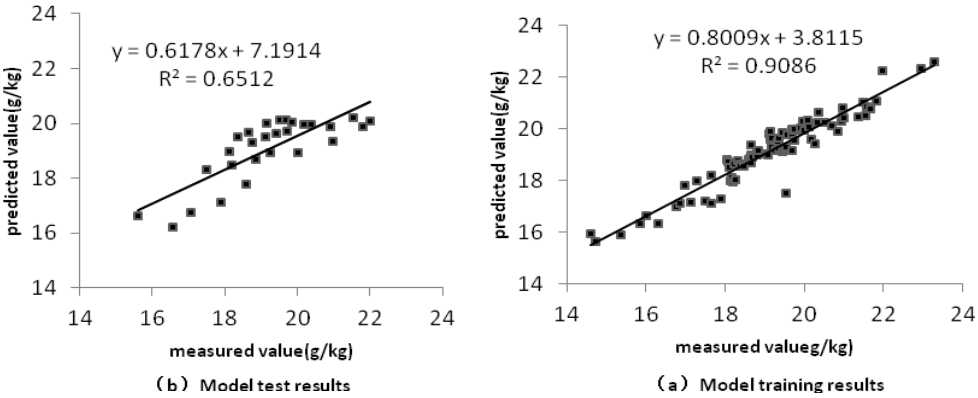

FIG.8 FITTING EFFECT DIAGRAM OF MEASURED VALUE OF NITROGEN AND PREDICTION VALUE OF RANDOM FOREST MODEL

Fig. 8 (a) is the result of RF. The determination coefficient of the fitting equation reaches 0.9086, and the root mean square error is 0.5368.

Fig. 8 (b) reliability test for RF results using test samples The determination coefficient of the fitting equation is 0.6512, and the root mean square error is 0.9024. The test results are more feasible.

3.4 Comparison of the Results of Three Models

The nitrogen content model of apple leaves was established by three different methods, BP, SVM and RF. The results were shown in table 1.

TABLE 1 TRAINING AND TESTING RESULTS OF THREE MODELS

Model class	R_c^2	RMSEC	R_p^2	RMSEP
BP	0.7283	0.9359	0.6260	0.9460
SVM	0.8128	0.7365	0.7294	0.7350
RF	0.9086	0.5368	0.6512	0.9024

From table 1, we can see that the three models have good prediction effect. Compared with three different models, the BP neural network is superior to the other two models in modeling results and prediction results compared with SVM and RF. Moreover, the root mean square error of modeling results and prediction results is greater than the other two models. It shows that in the three prediction models, the prediction effect of BP neural network is poorer than that of support vector regression and RF. Comparison of SVM and RF. In the modeling results, the decision coefficient of the stochastic forest model is higher than the SVM, and the root mean square error of the model is smaller than the SVM. The results show that the training results are better by using the RF. However, the prediction results of models are different. The decision coefficient of SVM regression is higher than that of RF. Meanwhile, the root mean square error of SVM prediction is less than that of random forest models. It shows that the model established by SVM regression has good prediction effect. Compared with the RF, SVM has better stability in training and testing, and the decision coefficients of the two processes have reached a high level, and the root mean square error has been controlled within a reasonable range. However, the modeling and prediction results of stochastic forest models have a large coefficient of difference, which indicates that the model is unstable, and the prediction results are not as good as SVM. Compared with SVM, it is not suitable for establishing nitrogen prediction models.

In the comparison of the three models, the SVM is better than the other two models whether in prediction or in the stability of the model. Therefore, the model established by SVM is the optimal model.

4 CONCLUSION

The hyperspectral curves of apple leaves with different nitrogen contents were different. In the visible range, the reflectance was negatively correlated with the content of chlorophyll, and the lower the nitrogen content, the higher the reflectance was. Reflection peaks formed at 550nm.

The BP, SVM and RF hyperspectral prediction models were established. The prediction effect of the three models is comprehensively compared. The SVM prediction results determine the coefficient of 0.7294 and the root mean square error of 0.7350. The prediction effect and error of the model is better than that of BP and RF. The SVM is considered as the best model to predict the nitrogen content of apple leaves. It is feasible to predict the nitrogen content of apple leaves by hyperspectral imaging technology, which provides a certain theoretical basis for the management of information nutrient in apple.

ACKNOWLEDGMENTS

This paper was supported by the National Natural Science Foundation of China (41671346), Funds of Shandong “Double Tops” Program（SYL2017XTTD02）.

REFERENCES

[1] Stroppiana D Boschetti M,Brivio P, et al. Plant nitrogen concentration in paddy rice from field canopy hyperspectral radiometry[J].Field Crops Research，2009，111(1/2): 119 一 129.

[2] Goel, Prasher S.O., Landry J.A., et al. Potential of air borne sensing to detect nitrogen deficiency and weed infestation in Electronics in Agriculture, 2003, 38: 99-124.

[3] Vigneau N., Ecarnot M., Rabatel G.,et al. Potential of field hyperspectral imaging as a nondestructive method to assess leaf nitrogen content in Wheat. Field Crops Research,2011，122: 25-31.

[4] Jinmeng LI, Xujun YE, Qiaonan WANG, et al. Development of prediction models for determining N content in citrus leaves based on hyperspectral imaging technology [J]. Spectroscopy and Spectral Analysis, 2014, 34(1): 212-216.

[5] Xiaolei ZHANG, Fei LIU, Pengcheng NIE, et al. Rapid detection of nitrogen content and distribution in oilseed rape leaves based on hyperspectral imaging[J]. Spectroscopy and Spectral Analysis, 2014, 34(9): 2513-2518.

[6] Keqiang YU, Yanru ZHAO, Xiaoli LI, et al. Application of hyperspectral imaging for visualization of nitrogen content in pepper leaf with different positions[J]. Spectroscopy and Spectral Analysis, 2015, 35(3): 746-750.

[7] Shuwen WANG, Shan ZHAO, Changli ZHANG,et. Forecasting model for nitrogen content of maize canopy during seedling stage in cold region based on imaging spectral technique [J]. Transactions of the Chinese Society of Agricultural Engineering, 2016, 32(13): 149-154.

[8] Jun SUN, Xiaming JIN, Hanping MAO, et al. Detection of nitrogen content in lettuce leaves based on spectroscopy and texture using hyperspectral imaging technology[J]. Transactions of the Chinese Society of Agricultural Engineering, 2014, 30(10): 175-181.

[9] Jun SUN, Xiaming JIN, Hanping MAO, et al. Discrimination of Lettuce Leaves’Nitrogen Status Based on Hyperspectral Imaging Technology and ELM[J]. Transactions of the Chinese Society of Agricultural Machinery, 2014, 45(7): 277-282.

[10] Yande Liu, Xiaogang JIANG,Yanhua Zhou, et al. Quantitative analysis of chlorophyll, water and nitrogen for navel orange leaf based on imaging technology Hyperspectral[J]. Journal of Chinese Agricultural Mechanization, 2016, 37(3): 218-224.

[11] Xicun ZHU, Yuanmao JIANG, Gengxing ZHAO, et al. Hyperspectral estimation of kalium content in apple florescence canopy based on fuzzy recognition[J]. Spectroscopy and Spectral Analysis,2013, 33(4): 1023-1027.

[12] Longguo WU, Jianguo HE, Guishan LIU, et al. Non-destructive determination of moisture in jujubes based on near-infrared hyperspectral imagine technique[J]. Journal of Optoelectronics Laser, 2014,25(1): 135-140.

[13] Ronghua JI, Lihua ZHENG, Xiaolei DENG, et al. Forecasting Chlorophyll Content and Moisture of Apple Leaves in Different Tree Growth Period Based on Spectral Reflectance[J]. Transactions of the Chinese Society of Agricultural Machinery, 2014,45(8): 274-280.

[14] Qinhong LIAO, Dongyan ZHANG, Jihua WANG, et al. Assessment of chlorophyll content using a new vegetation index based on multi-angular hyperspectral image data[J]. Spectroscopy and Spectral Analysis, 2014, 34(6): 1599-1604.

[15] Yanru ZHAO, Keqiang YU, Xiaoli LI, et al. Study on SPAD visualization of pumpkin leaves based on hyperspectral imaging technology[J]. Spectroscopy and Spectral Analysis, 2014, 34(5): 1378-1382.

[16] Xibin DING, Fei LIU, Chu ZHANG, et al. Prediction of SPAD value in oilseed rape leaves using hyperspectral imaging technique[J]. Spectroscopy and Spectral Analysis, 2015, 35(2): 486-491.

[17] Jianmin TANG, Qinhong LIAO, Yiqing LIU, et al. Estimating leaf area index of crops based on hyperspectral compact airborne spectrographic imager(CASI) data [J]. Spectroscopy and Spectral Analysis, 2015, 35(5): 1351-1356.

[18] Yipeng YANG, Qiao WANG, Qing XIAO, et al. Quantitative remote sensing inversion methods of chlorophyll-a concentration in Taihu lake based on TM data[J]. Geograpy and Geo-Information Science, 2006, 22(2): 5-8.

[19] Shuangping HUANG, Tiansheng HONG, Xuejun YUE, et al.Multiple regression analysis of citrus leaf nitrogen content using hyperspectral technology[J]. Transactions of the Chinese Society of Agricultural Engineering, 2013, 29(5): 132-138.

[20] Shuangping HUANG, Tiansheng HONG, Xuejun YUE, et al. Hyperspectral estimation model of total phosphorus content for citrus leaves[J]. Transactions of the Chinese Society of Agricultural Machinery, 2013, 44(4): 195, 202-207.

[21] Liwen WANG, Yaxing WEI, et al. Progress in inversion of vegetation nitrogen concentration by hyperspectral remote sensing[J]. Spectroscopy and Spectral Analysis, 2013, 33(10): 2823-2827.

[22] Tian XIA, Wenbin WU, Qingbo ZHOU, et al. Comparison of two inversion methods for winter wheat leaf area index based on hyperspectral remote sensing[J]. Transactions of the Chinese Society of Agricultural Engineering, 2013, 29(3): 139-147.

[23] Keqiang YU, Yanru ZHAO, Xiaoli LI, et al. Application of hyperspectral imaging for visualization of nitrogen content in pepper leaf with different positions[J]. Spectroscopy and Spectral Analysis, 2015, 35(3): 746-750.

AUTHORS

Baichao Li, he is working on his Master degree in Agricultural Information major at Shandong Agricultural University. His research interest is agricultural information.

Xicun ZHU，He is an associate professor in College of Resources and Environment Shandong Agricultural University. His research interests include the applications of agricultural remote sensing and information technology

Ruiyang YU.he is working on his Master degree in Cartography and Geographic Information E ngineering major at Shandong Agricultural University. His research interest is hyperspectral remote sensing.

Xiaoyan GUO.she is working on her Master degree in Land Resource Management major at Shandong Agricultural University. Her research interest is hyperspectral remote sensing.

Shujing CAO.she is working on her Master degree in Land Resource Management major at Shandong Agricultural University. Her research interest is agricultural remote sensing.

Huansan ZHAO.he is working on her Master degree in Land Resource Management major at Shandong Agricultural University. His research interest is hyperspectral remote sensing.