MACHINE LEARNING AND OPERATIONAL LAND IMAGER (OLI): EXPLORING THE EMPLOYABILITY OF 3 MACHINE LEARNING CALCULATIONS IN THE EFFICACIOUS USE OF SUPPORT VECTOR MACHINE (SVM) & BACK PROPAGATION NEURAL NETWORK (BPNN) IN REMOTE DETECTING PICTURES

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ABSTRACT

Grouping for remote detecting pictures needs to fabricate manages through machine learning. OLI pictures are helpful multispectral pictures put into utilization in 2013. Three sorts of machine learning calculations were considered for characterizing an OLI picture in this paper. Tests and 22 highlighted places being used to test the three sorts of machine learning calculations. The outcomes are appeared as quantitative examination, visual investigation and highlight significance correlation. The outcomes are as per the following: In this three machine learning calculations, utilizing SVM can get the best outcomes, BPNN make the most exceedingly awful outcomes and distinctive classifiers utilize diverse highlights for preparing and order.

EXPERIMENTAL DATA PREPARED ON

The research area is located in She Yang of Jiangsu Province. The area is located in the seaside and the beach is muddy. As *Fig. 1* shows, close to the beach area are salt fields, there are less geographic Feature types. The region is divided into the following five categories: water, salt fields, bareland, and settlement

Figure 1. The OLI image of Experiment area.

The experimental data for the region is the OLI(Operational Land Imager, operators of land-based imager)multispectral images in April 14, 2013 and the spatial resolution is 30 meters. Landsat8 was launched successfully in 2013, and OLI is main payload of Landsat8.The sensor parameters are shown in Table I.

TABLE I. OLl SENSOR PARAMETERS

Band	Band Type	Spectrum (μ/m)	Resolution
Band1	Deep Blue	0.433-0.453	30m
Band2	Blue-Green	0.450-0.515	30m
Band3	Green	0.525-0.600	30m
Band4	Red	0.630-0.680	30m
Band5	Near IR	0.845-0.885	30m
Band6	SWIR-1	1.560-1.660	30m
Band7	SWIR-2	2.100-2.300	30m
Band8	Pan	0.500-0.680	15m
Band9	Cirrus	1.360-1.390	30m

METHODS OF STUDY

A. Selecting Samples and Exporting Features First, we imported the image into eCognition8.7 and divided it as homogeneous image objects. After many experiments, segmentation parameters were decided as follows: segmentation scale size is 75, the shape factor is0.1, and compactness factor is 0.5.Second, we selected 40 image objects as samples inech . Category through manual interpretation. Sample distribution was shown in Figure 2. We exported their features as experimental data. We chose 22 features as follows: Mean Layer 1-7, Mean Layer 9, Standard deviation Layer 1-7, Standard deviation Layer 9, GLCM Homogeneity (all dir.), GLCM Dissimilarity (all dir.), Area, Length and Width, NDVI, and NDWI. The definitions of features are shown in table II. The symbols have the following meanings: i represents the band number, j represents number of pixels in the object, M represents the total number of pixels in the object, N represents the total number of grayscales, P represents the frequency of grayscales. Third, selecting samples at random, half of them as training samples, the other half as testing samples.

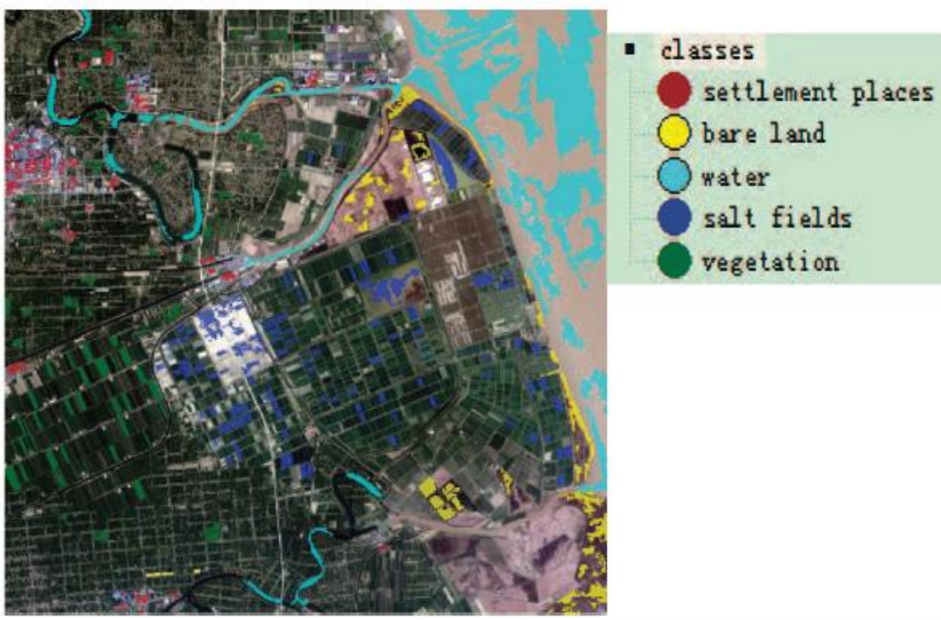

Figure 2. Sample distribution

TABLE II. DEFINITIONS OF SELECTED FEATURES

Feature		Definition
Spectrum Features	Mean Layer	$\overline{X_i} = \frac{\sum_{j=1}^{M} X_{ij}}{M}$
	Standard deviation	$\sigma_i = \sqrt{\frac{\sum_{j=1}^{M} (X_j - \overline{X})^2}{M}}$
Texture Features	GLCM Homogeneity (all dir.)	$HOM = \sum_{i,j=0}^{N-1} \frac{P(i,j \mid d,\theta)}{1+(\lvert i-j \rvert)}$
	GLCM Dissimilarity (all dir.)	$DIS = \sum_{i,j=0}^{N-1} \lvert i-j \rvert \cdot P(i,j \mid d,\theta)$
Geometry Features	Area	number of pixels in the object
	Length/Width	ratio of Object length and Object width
Custom Features	NDVI	$NDVI_j = \frac{X_{NIRj} - X_{Rj}}{X_{NIRj} + X_{Rj}}$
	NDWI	$NDWI_j = \frac{X_{Gj} - X_{NIRj}}{X_{Gj} + X_{NIRj}}$

Experimental Process

1) SVM classification :

There are three main factors Impact SVM learning and classification: the kernel, the value of slack variables and penalty coefficient C. We used different kernels, different slack variables and different penalty parameters to test the capabilities of SVM classifier. And the best classification result would be taken as SVM classification result.

2) BPNN classification:

We used a three-layer structure to test BPNN classification, which contains input layer, hidden layer and output layer. Three-layer structure model is mainly affected by the number of nodes in the hidden layer. We trained different BPNN classifier by setting different number of nodes in the hidden layer and look for the best classifier for the five categories. And the best classification result would be taken as BPNN classification result.

3) CART classification:

CART algorithm uses the GINI index to select a tree and the growth of the tree is a binary tree. We set the number of layers below the root node to control the size of the tree. We set different number of layers to generate different sizes CART. And the best classification result would be taken as CART classification result.

4) Comparison :

We put the 3 best results together to find the best algorithm for classification.

EXPERIMENT AND ANALYSIS

A. S VM Classification Experiment and Analysis First, we selected the most commonly used kernel RBF kernel to train the SVM classifier. We fixed penalty coefficient C value of 10 to test slack variable y effect on the classification. The accuracy of training and testing samples are shown in Table III.

TABLE Ill. ACCURACY OF SVM CLASSIFICATION (RBF,C=IO)

γ	Accuracy of Classification	
	Training Samples	Testing Samples
0.1	79.50%	83.60%
0.3	82.53%	85.26%
0.5	86.65%	**85.55%**
0.7	89.05%	85.27%
0.9	**91.00%**	84.90%

From Table III, we can find that along with the increase of the value y, the training samples gradually increased classification accuracy. The classification of samples for independent testing, when the slack variable y value of 0.5, SVM classifier to achieve the highest classification accuracy 85.55%, indicating that the larger y value of SVM classifier caused by over-fitting. Second, we fixed slack variable y value of 0.5 to test penalty coefficient C effect on the classification. The accuracy of training and testing samples were shown in Table IV.

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TABLE IV. ACCURACY OF SVM Classification (RBF, r=O.5)

C	Accuracy of Classification	
	Training Samples	Testing Samples
10	86.60%	85.00%
100	90.60%	87.10%
200	92.23%	87.13%
300	93.00%	**87.27%**
400	**93.48%**	84.11%

From Table IV, we can find that When C value increases, classification accuracy of test samples is gradually improved. When C value increases from 100 to300, classification accuracy of test samples varies little. When C=300, we get a best classification result. Third, we tested different kernel functions for SVM classification. We selected four types of kernel functions: RBF kernel function, polynomial kernel function, sigmoid kernel function and linear kernel function. Different kernel functions of SVM classifier on the experimental area are shown in Table V. The results show that the RBF kernel and polynomial kernel function are better.

TABLE V ACCURACY OF SVM CLASSIFICA TlON(DIFFERENTKERNELS)

Kernel Function	Accuracy of Classification	
	Training Samples	Testing Samples
RBF	**93.00%**	**87.27%**
Polynomial	91.13%	87.10%
Sigmoid	78.50%	67.12%
Linear	83.27%	74.17%

BPNN Classification Experiment and Analysis

We used different numbers of hidden nodes to test BPNN classifier. The accuracy was shown in Table VI. As can be seen from the results, the number of hidden layer nodes affects the BP neural network classifier greatly. For the classification of training samples, with the hidden nodes increases, the training sample classification accuracy gradually increases. For the classification of testing samples, with the hidden nodes increases, the classification accuracy increases a little, and then declines. When the number of nodes in the hidden layer was set to 3, we got the best classification accuracy of 73.15%.

TABLE VI. ACCURACY OF BPNN CLASSIFICATION

Number of Nodes	Accuracy of Classification	
	Training Samples	Testing Samples
2	67.90%	65.00%
3	75.13%	**73.15%**
4	80.50%	73.00%
5	81.03%	73.00%
6	80.26%	70.37%
7	82.21%	70.15%
8	81.09%	69.75%
9	82.07%	69.55%
10	82.55%	69.50%
20	**82.57%**	63.77%

CART Classification Experiment and Analysis

CART can use pre- prunning and post-prunning ways to control the growth of a tree and prevent a tree grow too "lush" to avoid over-fitting problems. We use pre- prunning way to test CART classification in this paper. We set the maximum depth of the tree to control the tree. If the layer of the decision tree has reached the maximum tree depth, then stop growing. (The maximum tree depth here represents the largest tree layers not including the root node.)The results are shown in Table VII. As can be seen from the table, for the training samples, when maximum tree depth grows from 3-7 the classification accuracy gradually increased. When the depth grows from 7-10 the classification accuracy doesn't change. But for the testing samples, when maximum tree depth grows, the classification accuracy increases a little, and then declines. When the maximum tree depth grows to 5, the accuracy reaches 80.10%, and then it declines. When the depth is more than 7, the accuracy doesn't change any more.

TABLE VII. ACCURACY OF CART CLASSIFICATION

Maximum Tree Depth	Accuracy of Classification	
	Training Samples	Testing Samples
3	76.90%	65.00%
4	79.33%	73.15%
5	81.15%	**80.10%**
6	81.23%	73.00%
7	**85.20%**	70.37%
8	**85.20%**	70.37%
9	**85.20%**	70.37%
10	**85.20%**	70.37%

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Comparison and Analysis

1) Quantitative Comparision:

From the tables above, we can find that:

• The training sample classification accuracy is always higher than the classification accuracy of test samples.

• SVM classification accuracy of the training samples is the highest, and classification accuracy of test samples is also the highest.

• RBF kernel with y =0.5, C=400 can make the SVM get the highest accuracy.

• BPNN classification accuracy of training sample is the lowest. And BPNN classification accuracy of testing sample is also the lowest. Sixty to seventy percent accuracy can't meet classification requirements.

• CART classification of the training samples shows that prunning trees can improve the efficiency of classification. CART classification of the testing samples shows that pruning trees not only can improve the efficiency of classification, but also improve the classification accuracy and avoid over-fitting.

2) Visual analysis of Classification:

SVM classification result is shown as Figure 3. Nearly all the water objects are classified correctly, salt fields and bare land are classified correctly. Misclassifications appear between vegetation objects and settlement places objects. Some vegetation objects are classified as settlement places objects.

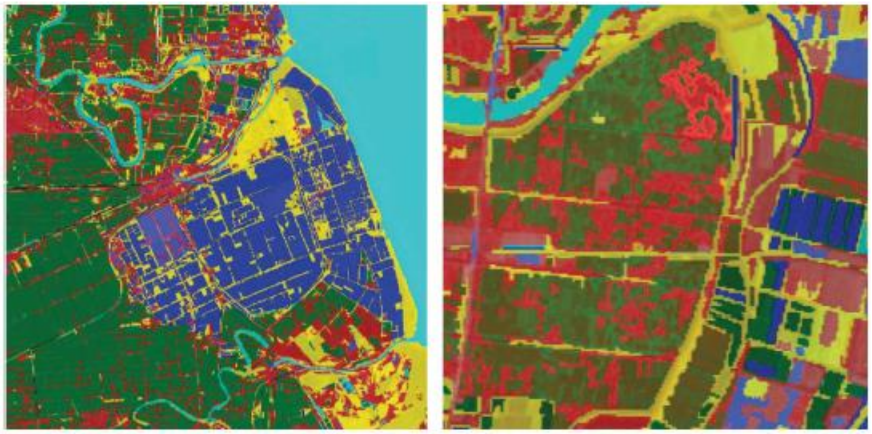

Figure 3. SYM classification result and misclassifications.

BPNN classification result is shown as Figure 4. There are a few misclassifications in the picture. Some slim dividing lines of vegetation objects are classified to water. Some vegetation objects are classified as settlement places objects.

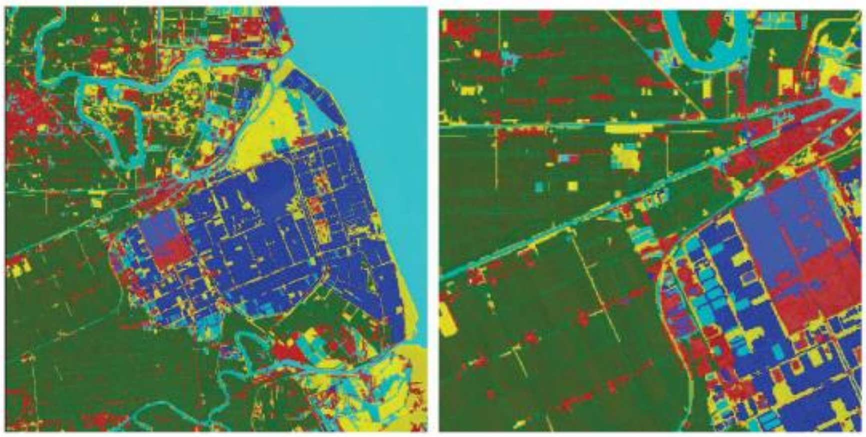

Figure 4. BPNN classification result and misclassifications.

CART classification result is shown as Figure 5. Water objects are classified correctly. Some salt fields objects are classified to bare land objects, vegetation objects and settlement places objects.

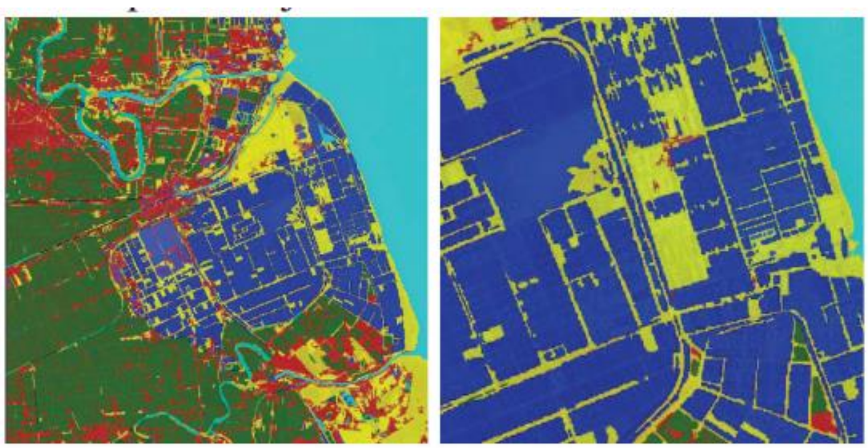

Figure 5. CART classification result and misclassifications.

3) Feature Importance:

We put 22 features to carry out the experiment. Because so many features we chose, we only show the most important 10 features in the figures. From the figures below, we can find in dif-

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ferent classifiers features importance is not same. In figure 6 we can find that the importance of these features is

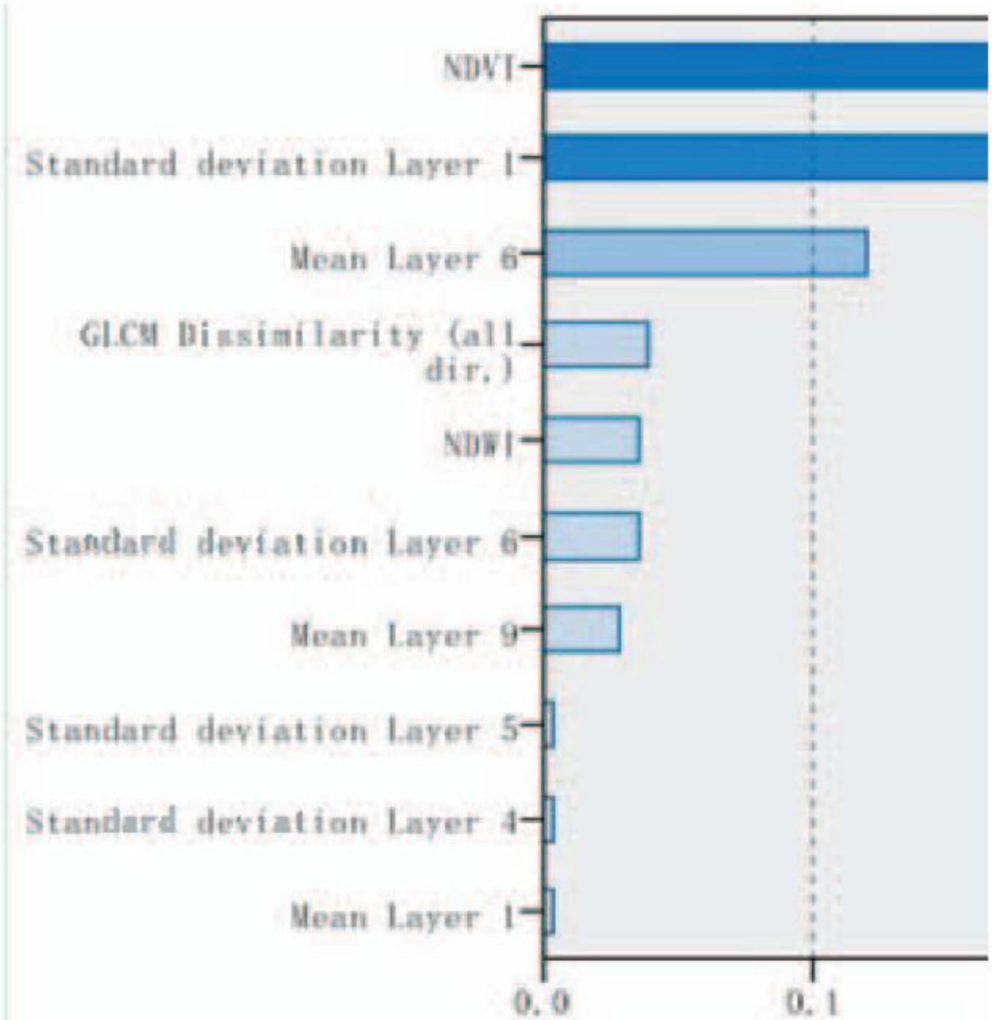

Figure 6. Feature importance of SVM classification

In figure 7 we can find that the importance of these features is average too. The most important 3 are NOVI,NDWI and Mean Layer 5.

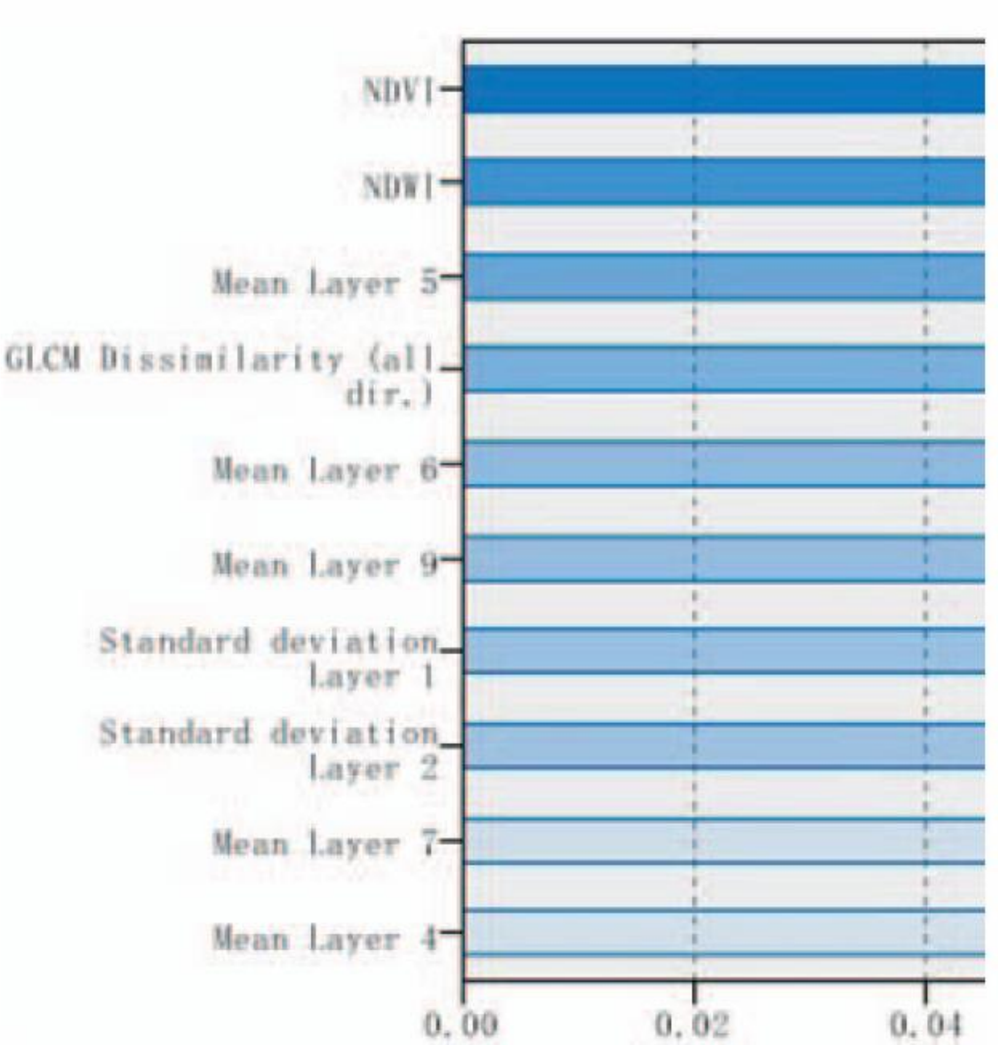

Figure 7. Feature importance of BPNN classification.

In figure 8 we can find that the most important 3 are NDWI, Standard deviation Layer land Mean Layer 6 and the other features not important in the CART classifier

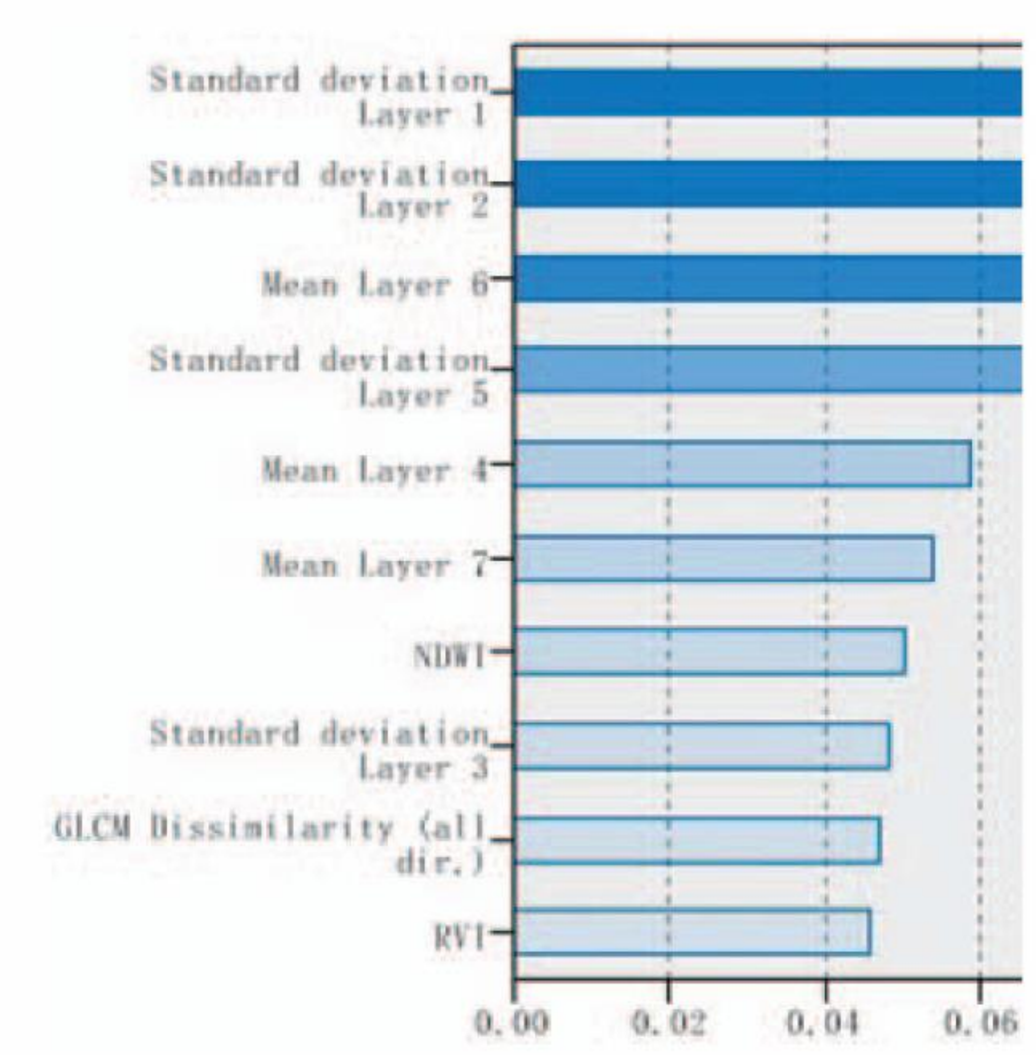

Figure 8. Feature importance of CART classification

CONCLUSION

Three kinds of machine learning algorithms were studied for classifying remote sensing images in this paper. An area of OLI image was classified to the following five categories: water, salt fields, bare land, vegetation and settlement places. 200 samples and 22-dimensionalfeatures were applied for training and testing. With three kinds of machine learning algorithms, the results showed that: SVM classification accuracy of the training samples reaches 91 % and it is the best result, SVM classification1476accuracy of the testing samples reaches 85.55% and it is also the best result with testing samples. Though visual analysis of classification, we find that: misclassifications appear between vegetation objects and settlement places objects with SVM classifier, some vegetation objects are classified as settlement places objects with BPNN classifier, some salt fields objects, bare land objects and settlement places objects are classified to wrong categories.

Though Feature Importance analysis, we find that: different classifiers use different features for training and classification, we should use a variety of features to make better classification results.