OLI IMAGE BASED ON MACHINE LEARNING CLASSIFICATION[1]

Abhinav Kansal
Bal Bharati School, Pitampura

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ABSTRACT

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

Keywords- *classification; machine learning; support vector machine; neural network; decision tree; OLI images*

I.INTRODUCTION

Support Vector Machine is a strategy dependent on order limits, the fundamental guideline is that: if the preparation information is circulated in two-dimensional plane focuses arrangement calculation will be prepared to discover limits between these focuses, if the preparation information is disseminated in n-measurement grouping calculation will be prepared to discover super-plane to characterize these points. SVM has favorable circumstances in understanding little example, nonlinear and high dimensional characterization issues [3].

Fake neural system is an application like the structure of the mind data preparing. Neural system is a processing model, and there are bunches of hubs and associations between hubs. Every hub speaks to a particular yield work called initiation work. Every association between two hubs speaks to a flag through the association for estimation of weight, which is proportionate to the memory of counterfeit neural systems. Yield of the system varies from the associations, loads and initiation capacities. Neural system has attributes of example free and versatile. The procedure is a discovery, clients don't have to comprehend the inner procedure, and neural system can get grouping rules from the high- dimensional element space [4]. It is a successful example acknowledgment and characterization apparatus. Up until this point, an assortment of neural systems are utilized for remote detecting picture order, in which there are numerous achievement cases. Back proliferation neural system (BPNN) is a multi-layer one, and it is generally utilized in learning innovations. It has solid steadiness, adaptation to internal failure and great heartiness [S]. General structure of BPNN has input layer, shrouded layer and yield layer. In the learning procedure, data is entered from the info layer right off the bat, and it is gone through shrouded layer to the yield layer after the exchange procedure. The status of each layer neurons influences just the following layer of neurons state. Mistake is determined in the yield layer and exchanged back

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Choice tree (DT) arrangement utilizes inquiries to get the judge and grouping techniques. In contrast to neural systems and SVM, choice tree classifiers don't have the idea of separation among vectors, and they are considered as non-metric AI strategies. There are a few points of interest about DT: the statement of choice tree is straightforward; the order has a fast and DT gives from the earlier master information to a specialist framework. By and by, when the issue is generally basic or with few preparing tests, the master learning is viable.

II. EXPERIMENTAL DATA

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.

Figure 1. The OLI image of Experiment area.

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

III. METHODS OF STUDY

A. Selecting Samples and Exporting Features: First, we imported the picture 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 in each. category through manual interpretation. 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.

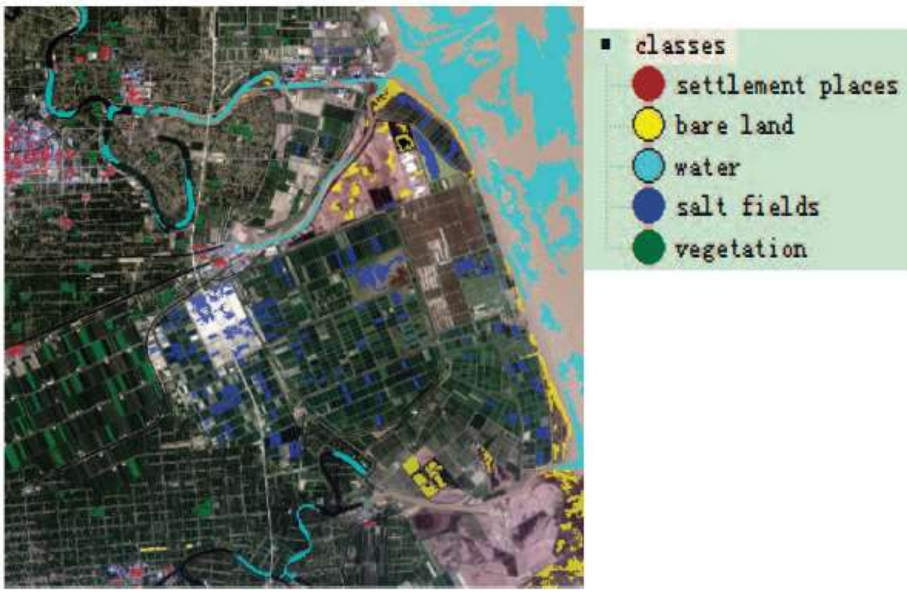

Figure 2. Sample distribution

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	$\sigma_i = \sqrt{\frac{\sum_{j=1}^{K} (X_j - \overline{X})^2}{M}}$
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	$NDWI_j = \frac{X_{Gj} - X_{NIRj}}{X_{Gj} + X_{NIRj}}$

B. Experimental Process

1) SVM classification:

There are 3keyaspects 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.

2) BPNN classification:

We used a three-layer structure to test BPNN classification, which contains input layer, unknown layer and output layer

IV. 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.

TABLE Ill. ACCURACY OF SVM CLASSIFICATlON (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 alongside the expansion of the esteem y, the preparation tests step by step expanded arrangement precision. The order of tests for free testing, when the slack variable y estimation of 0.5, SVM classifier to accomplish the most elevated characterization exactness 85.55%, demonstrating that the bigger y estimation of SVM classifier brought about by over-fitting. Second, we fixed slack variable y estimation of 0.5 to test punishment coefficient C impact on the arrangement. The exactness of preparing and testing tests were appeared Table

IV.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 esteem expands, arrangement exactness of test tests is progressively improved. At the point when C esteem increments from 100 to 300, grouping precision of test tests shifts pretty much nothing. Whenever C=300, we get a best arrangement result. Third, we tried diverse piece capacities for SVM arrangement. We chose four sorts of piece capacities: RBF portion work, polynomial part work, sigmoid bit work and direct bit capacity. Diverse portion elements of SVM classifier on the exploratory zone are appeared Table V. The outcomes demonstrate that the RBF part and polynomial bit work are better.

TABLE V ACCURACY OF SVM CLASSIFICATlON (DIFFERENT KERNELS)

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%

B. BPNN Classification Experiment and Analysis

We used different numbers of hidden nodes to test BPNN classifier

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%

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%

C. Comparison and Analysis

1) Quantitative Comparison:

• SVM characterization exactness of the preparation tests is the most astounding, and grouping precision of test .

• RBF portion with y =0.5, C=400 can influence the SVM to get the most elevated precision.

• BPNN characterization precision of preparing test is the most minimal. What's more, BPNN characterization precision of testing test is additionally the most minimal. Sixty to seventy percent exactness can't meet characterization necessities.

2) Visual investigation of Classification:

SVM characterization result is appeared as Figure 3. About all the water objects are arranged accurately, salt fields and uncovered land are ordered effectively. Misclassifications show up between vegetation articles and settlement places objects. Some vegetation objects are delegated settlement places objects.

Figure 3. SYM classification result and misclassifications.

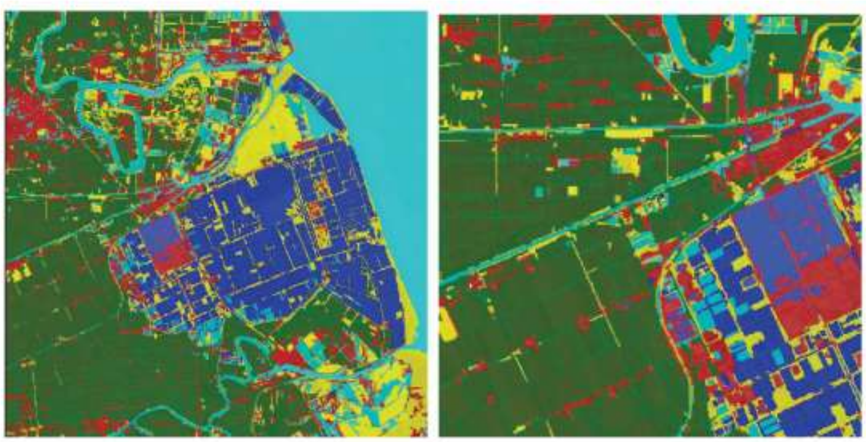

Figure 4. BPNN classification result and misclassifications.

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

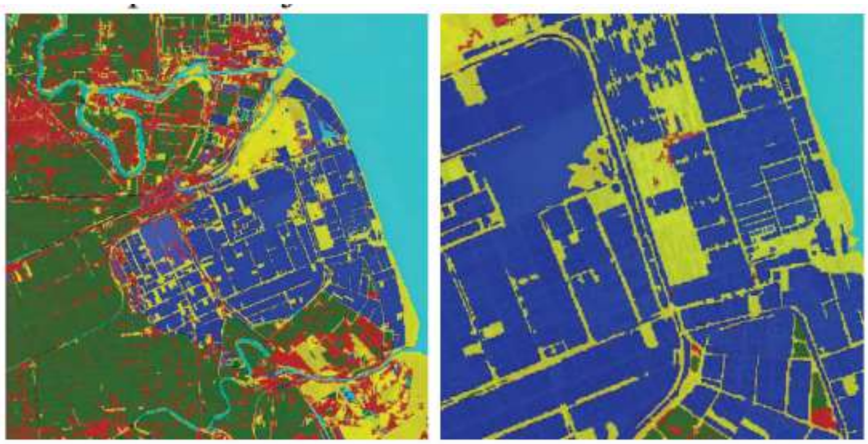

Figure 5. CART classification result and misclassifications.

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 different classifiers features importance is not same.

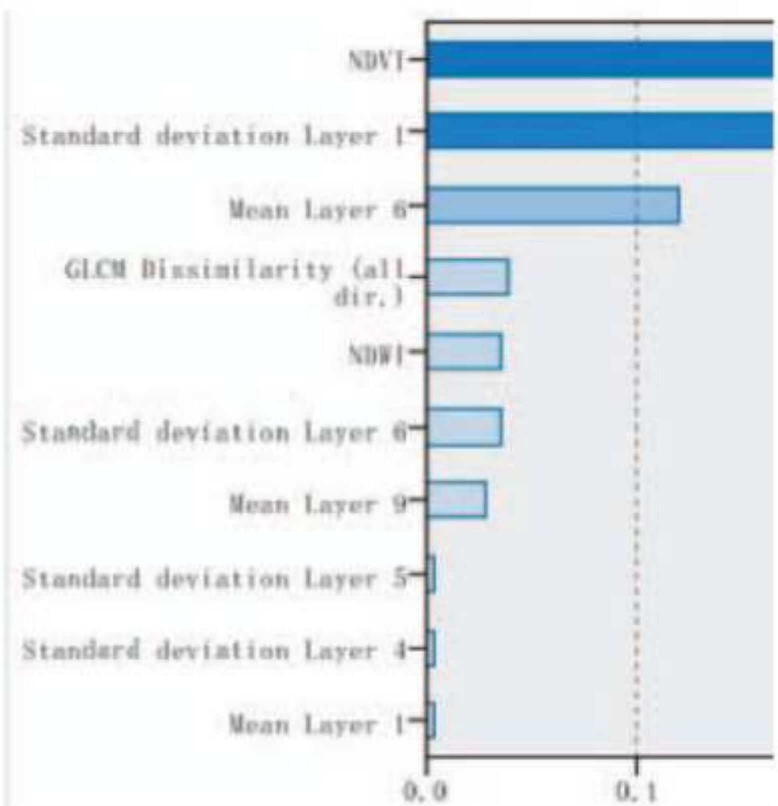

Figure 6. Feature importance of SVM classification

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.

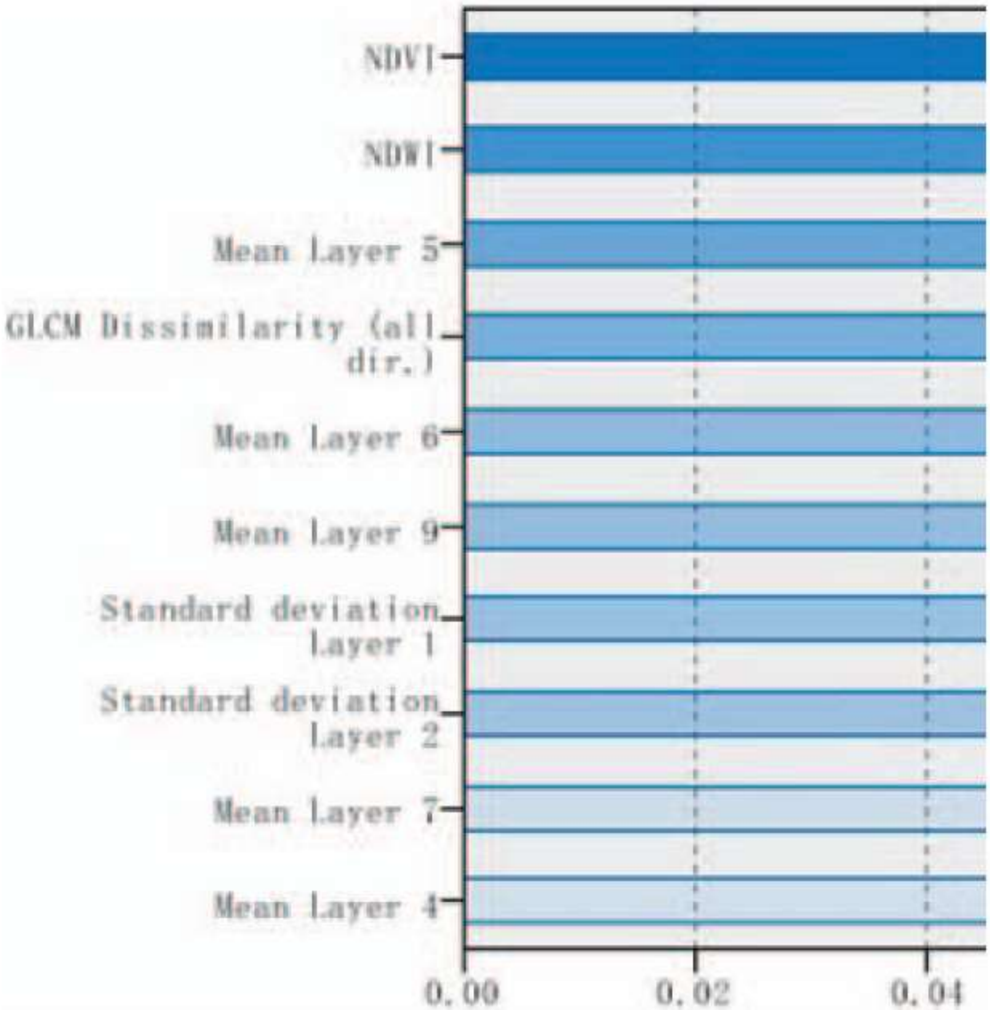

Figure 7. Feature importance of BPNN classification.

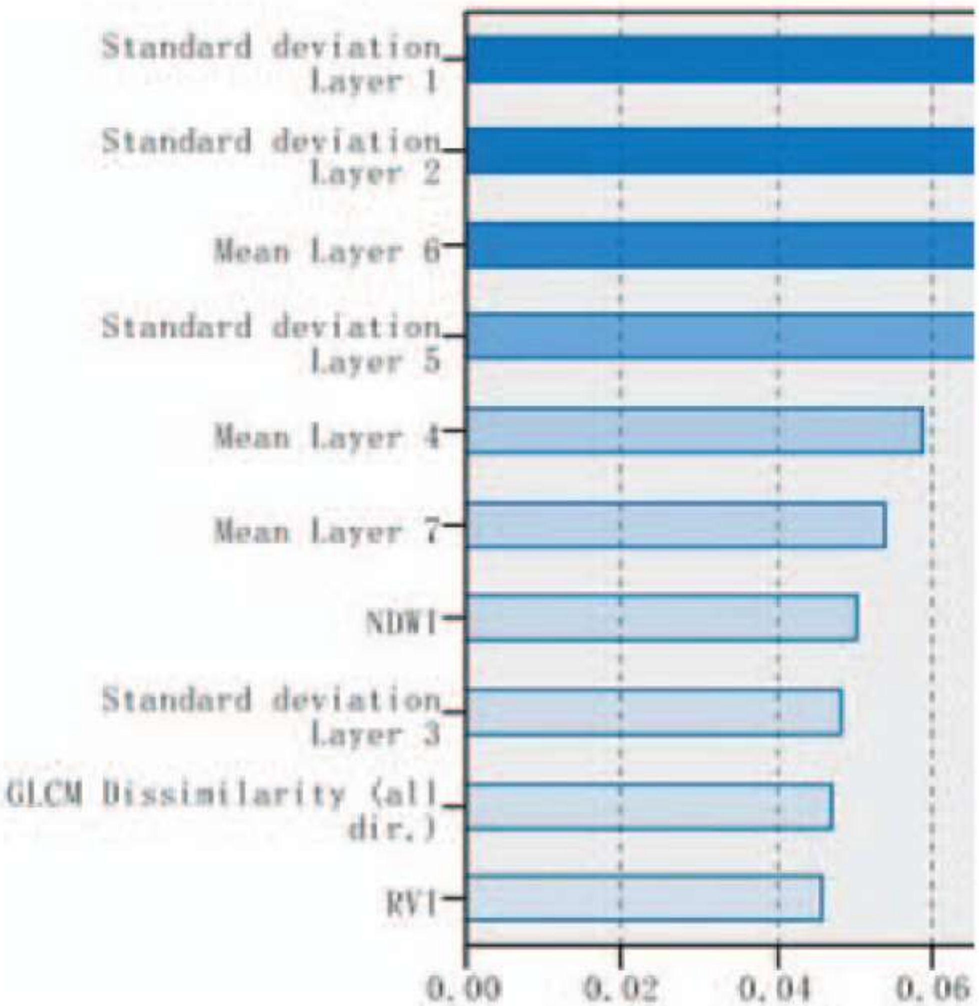

Figure 8. Feature importance of CART classification

V. CONCLUSION

A territory of OLI picture was characterized to the accompanying five classes: water, salt fields, exposed land, vegetation and settlement places. 200 models and 22-dimensional features were associated for planning and testing. With three sorts of AI estimations, the results exhibited that: SVM course of action accuracy of the arrangement tests comes to 91 % and it is the best result, SVM portrayal 1476 precision of the testing tests accomplishes 85.55% and it is in like manner the best result with testing tests. Despite the fact that visual examination of grouping, we find that: misclassifications show up between vegetation items and settlement places objects with SVM classifier, some vegetation objects are named settlement places objects with BPNN classifier, some salt fields objects, uncovered land articles and settlement places objects are arranged to wrong classifications.

In spite of the fact that Feature Importance examination, we locate that: distinctive classifiers utilize diverse highlights for preparing and order, we should utilize an assortment of highlights to improve grouping results.

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