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EXPLORING THE MULTI-LAYER PERCEPTRON (MLP) BASE MACHINE LEARNING CLASSIFICATION FOR OPTIMISED BIOLOGICAL SYSTEM ADMINISTRATION.

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ABSTRACT

Waterbody distinguishing is basic to environmental change, water assets, biological system administration, and hydrological cycle. Multi-layer perceptron (MLP) is a famous and exemplary technique under a profound learning structure to identify target and group pictures. Hence, this examination receives this technique to recognize the water assortment of Landsat. To think about the exhibition of grouping, the most extreme probability and water list are utilized for each investigation region. The grouping results are assessed from precision lists and nearby correlation. The assessment result shows that a multi-layer perceptron (MLP) can accomplish preferable execution over the other two strategies. In addition, the slim water additionally can be obviously recognized by the multi-layer perceptron. The proposed technique has the application potential in mapping worldwide scale surface water with multi-source medium-high goals satellite information.

I.INTRODUCTION

Support Vector Machine(SVM) was proposed by Vapnik in 1992 and extended to the treatment of non-linear data later .SVM is a method based on classification boundaries, the basic principle is that: if the training data is distributed in two-dimensional plane points classification algorithm will be trained to find boundaries between these points, if the training data is distributed in n-dimension classification algorithm will be trained to find super-plane to classify these points.SVM has advantages in solving small sample, nonlinear and high dimensional classification problems.

The article arranged strategy, as a rule, be utilized for high goals remote picture, which requires colossal time in picture division. The AI is to choose huge preparing tests and recognize surface water utilizing diverse insightful calculations, including most extreme probability, bolster vector machine, neural system, profound learning, limitation vitality minimization. These strategies are programmed and productive with less manual work. Ongoing advancement in profound learning has indicated the promising answer for the objective discovery and picture arrangement over the different picture handling fields. In spite of the convolutional neural systems under the profound learning, engineering has been generally used to distinguish the objective in remote detecting pictures by utilizing marked preparing sample ,not many examinations have announced the utilization of profound figuring out how to remote detecting information everywhere scale. Along these lines, this investigation plans to investigate the capability of the multi-layer perceptron dependent on profound learning structure for distinguishing water body in Landsat OLI pictures

II. EXPERIMENT

The experiment has been done in She Yang of Jiangsu Province. The territory is situated in the ocean side and the seashore is sloppy. As Fig. 1 shows, near the seashore zone are salt fields. The district is isolated into the accompanying five classifications: water, salt fields, uncovered land, and settlement.

Figure 1. Experiment area of OLI image

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.

TABLE I. OLI 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

A. Choosing Samples and Exporting Features First, we brought the image into ecognition and partitioned it as homogeneous picture objects. After numerous analyses, division parameters were chosen as follows: division scale size is 75, the shape factor is 0.1, and the minimization factor is 0.5. Second, we chose 40 picture questions as tests in each. classification through manual understanding. Test circulation was displayed in Fig 2. We sent out their highlights as trial information. We picked 22 highlights 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 images have the accompanying implications: I speak to the band number, j speaks to measure of pixels in the item, M speaks to the amount of pixels in the article, N speaks to the complete number of grayscales, P speaks to the recurrence of grayscales. Third, choosing tests aimlessly, half of them as preparing tests, the other half as testing tests.

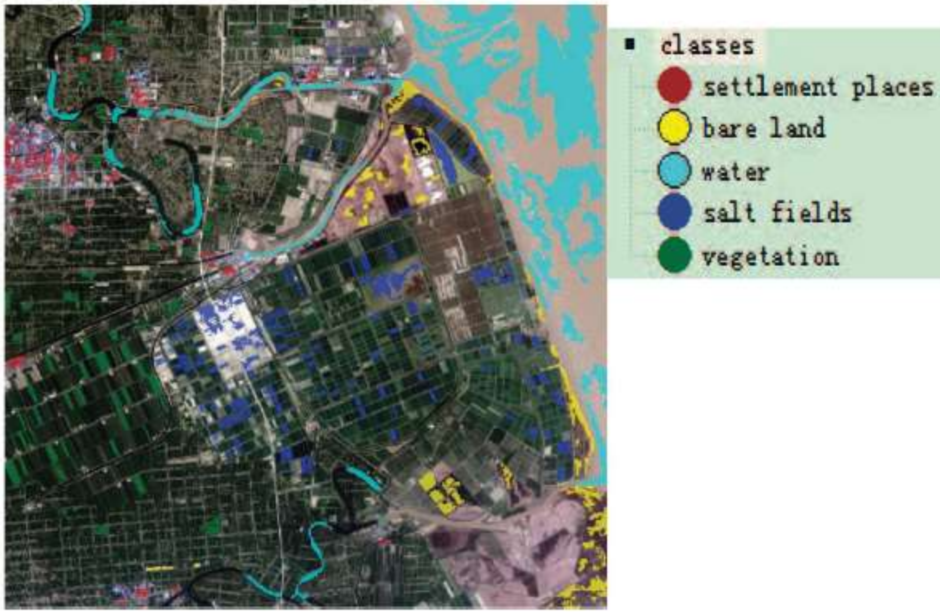

Figure 2. Sample distribution

TABLE II. SELECTED FEATURES DEFINITIONS

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.)	$HOM = \sum_{i,j=0}^{N-1} \frac{P(i,j\|d,\theta)}{1+(\|i-j\|)}$
	GLCM Dissimilarity (all dir.)	$DIS = \sum_{i,j=0}^{N-1} \|i-j\| \cdot P(i,j\|d,\theta)$
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 3 key aspects 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 utilized a three-layer structure to test the BPNN arrangement, which contains an input layer, an obscure layer, and a yield layer. The three-layer structure model is for the most part influenced by the measure of lumps in the concealed layer.

IV. ANALYSIS

We have selected kernel RBF to train SVM model, for that we fixed penalty coefficient C value of 10 to test slack variable i.e. y. The accuracy of are given below

TABLE Ill. SVM CLASSIFICATlON ACCURACY

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 nearby the development of the value y, the arrangement tests a tiny bit at a time extended portrayal accuracy. The precision of getting ready and testing tests were showed up in Table IV.

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TABLE IV. SVM Classification ACCURACY (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 to 300, 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 SVM CLASSIFICATlON ACCURACY (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 analysis

Different number of hidden node has been used to analyses BPNN classifier. The accuracy was shown in Table VI. We got 73.15% of classification accuracy after setting hidden layers' nodes to 3

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TABLE VI. BPNN CLASSIFICATION ACCURACY

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. CART CLASSIFICATION ACCURACY

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%

D. Comparision and Analysis

1) Quantitative Comparison:

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 pruning 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:

The SVM characterization result appears as Figure 3. Practically all the water objects are masterminded precisely, salt fields and revealed land are requested adequately. Misclassifications appear between vegetation articles and settlement places objects. Some vegetation objects are designated settlement places objects.

Figure 3. Result and misclassifications of SYM classification

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

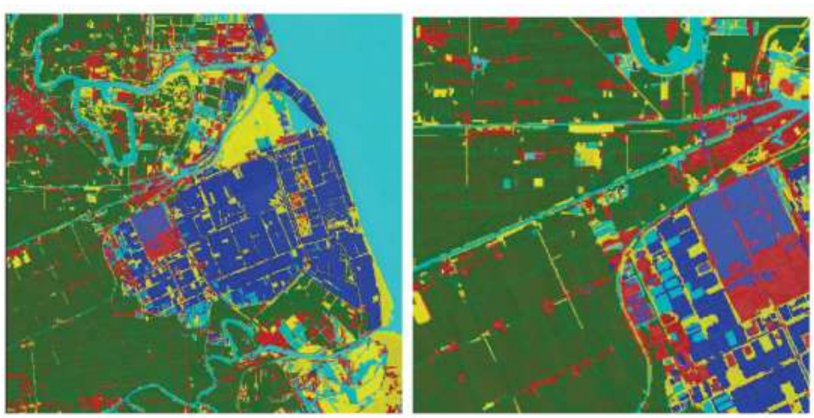

Figure 4. Result and misclassifications of BPNN classification

CART arrangement result appears as Figure 5. Water objects are ordered effectively. Some fields like salts fields, land, vegetation's articles and settlement are arranged in such a way

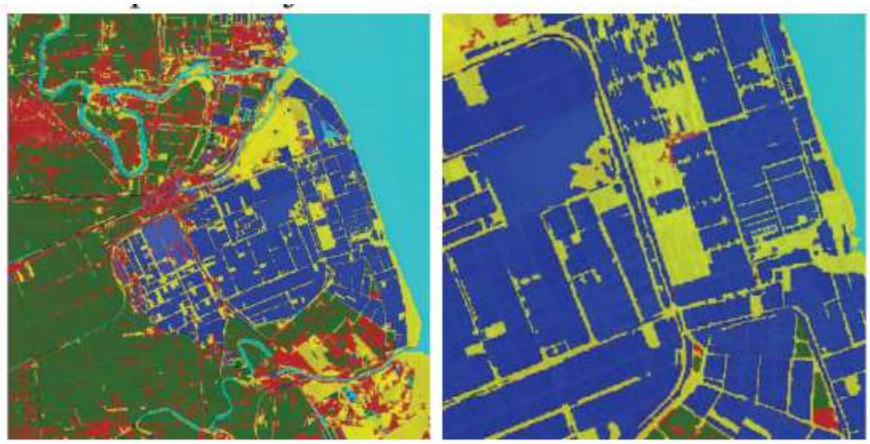

Figure 5. Result and misclassifications of CART classification

3) Feature Importance:

We put 22 highlights to complete the investigation. Since such a significant number of highlights we picked, we just show the most significant 10 highlights in the figures. From the figures beneath, we can discover in various classifiers that highlights significance isn't the same. In figure 6 we can find that the significance of these highlights is

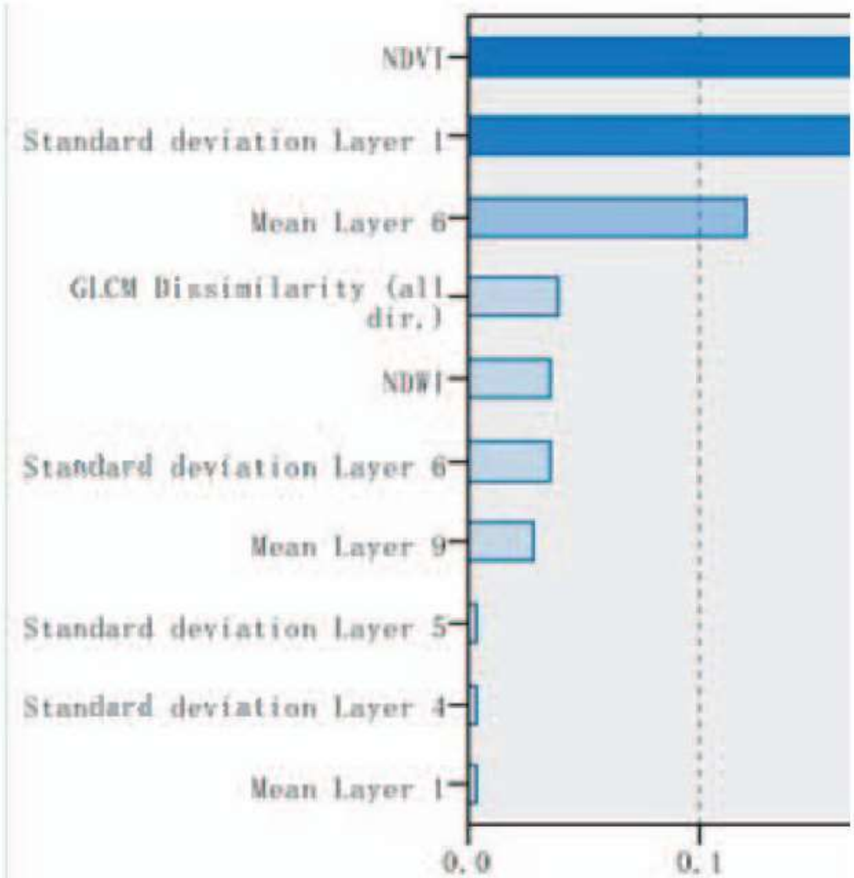

Figure 6. SVM classification Feature importance

In figure 7 we can find that the significance of these highlights is normal as well. The most significant 3 are NOVI, NDWI and Mean Layer 5.

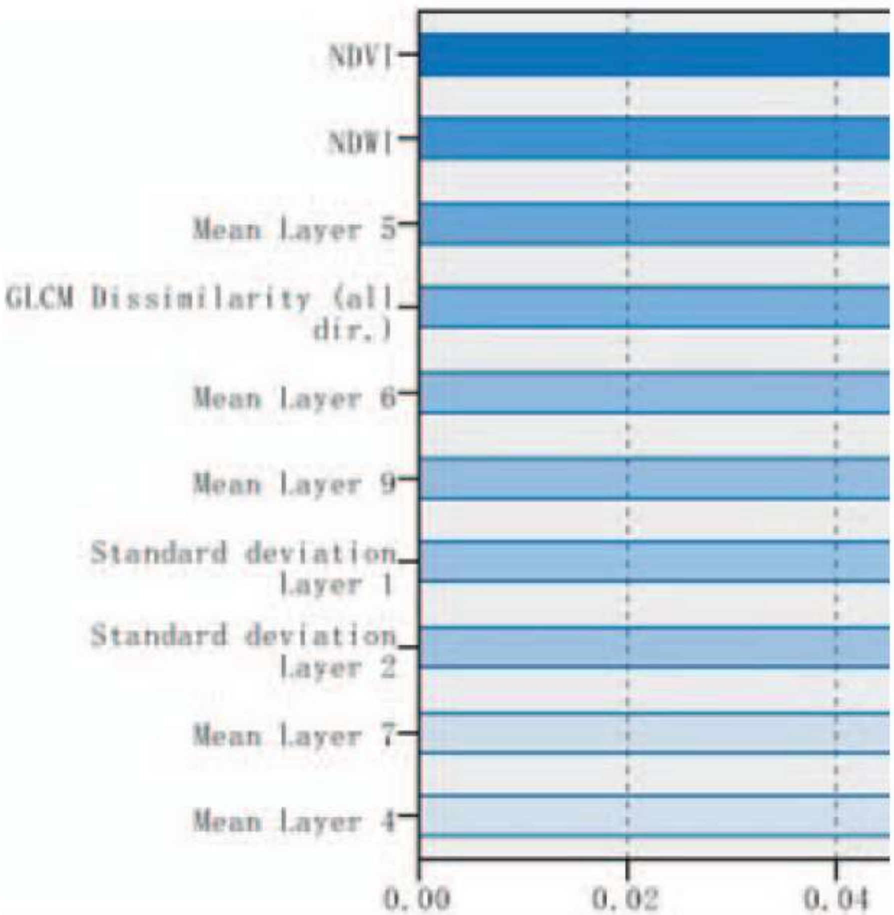

Figure 7. BPNN classification Feature importance

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

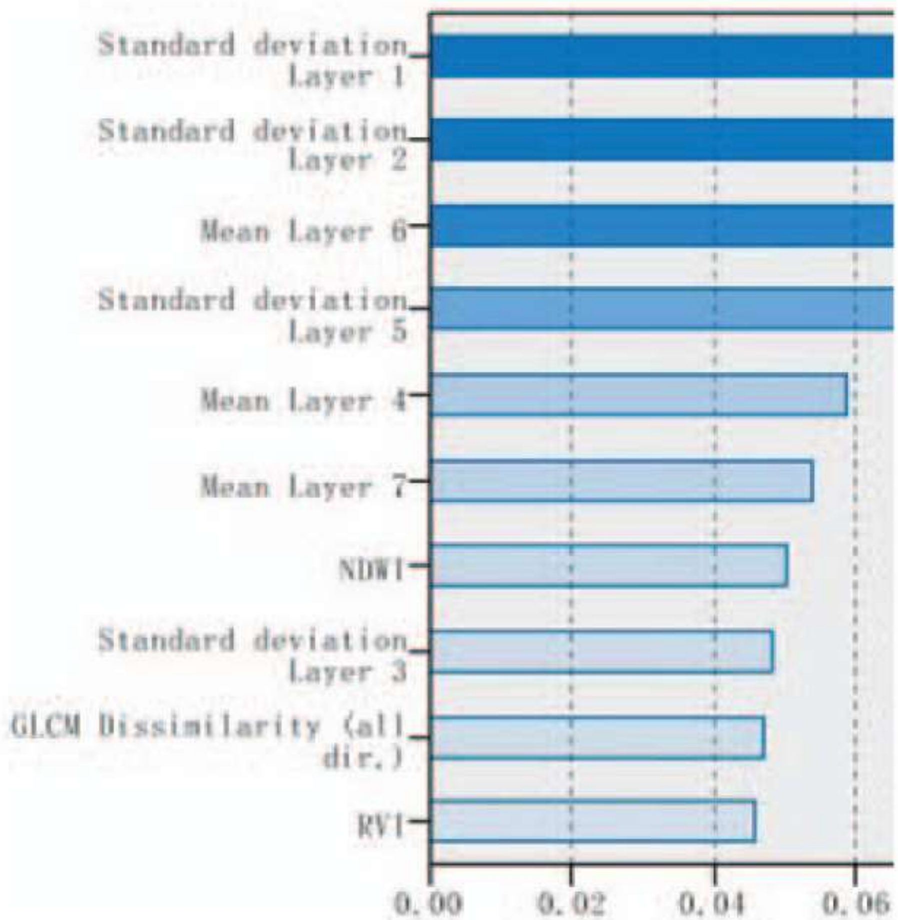

Figure 8. CART classification Feature importance

V. CONCLUSION

The examination embraces a multi-layer perceptron to decide the water collection of the Landsat 8 picture. Contrasting and ML and WI strategy, this technique is increasingly all-inclusive to extricate water bodies at various districts. Exactness files and nearby visual examination show that a multi-layer perceptron has higher order accuracy and preferred execution over that of WI and ML. In addition, meager water, including little lake and dainty waterway, likewise can be recognized by the multi-layer perceptron. This end shows that a multilayer perceptron can be actualized in mapping huge scope surface water later on.