Remote Sensing Image Classification Algorithm Based on Texture Feature and Extreme Learning Machine

Xiangchun Liu[1], Jing Yu[2], Wei Song[1, 3, *], Xinping Zhang[1], Lizhi Zhao[1] and Antai Wang[4]

Abstract: With the development of satellite technology, the satellite imagery of the earth's surface and the whole surface makes it possible to survey surface resources and master the dynamic changes of the earth with high efficiency and low consumption. As an important tool for satellite remote sensing image processing, remote sensing image classification has become a hot topic. According to the natural texture characteristics of remote sensing images, this paper combines different texture features with the Extreme Learning Machine, and proposes a new remote sensing image classification algorithm. The experimental tests are carried out through the standard test dataset SAT-4 and SAT-6. Our results show that the proposed method is a simpler and more efficient remote sensing image classification algorithm. It also achieves 99.434% recognition accuracy on SAT-4, which is 1.5% higher than the 97.95% accuracy achieved by DeepSat. At the same time, the recognition accuracy of SAT-6 reaches 99.5728%, which is 5.6% higher than DeepSat's 93.9%.

Keywords: Image classification, gray level co-occurrence matrix, extreme learning machine.

1 Introduction

With the rapid development of the satellite technique, the satellite remote sensing makes it possible to observe the Earth from a highly continuous and repetitive manner in space. It can further understand the overall view and dynamic changes of the earth in order to more accurately understand the distribution of resources. This can help people more rationally plan the use of resources, and adopt powerful technical means to protect the environment as well as control the resource exploitation [Dai, Jiang and Tang (2004)]. At

[1] Media Computing Laboratory, School of Information Engineering, Minzu University of China, Beijing, 100081, China.

[2] School of Telecommunication Engineering, Beijing Polytechnic, Beijing, 100176, China.

[3] National Language Resource Monitoring and Research Center of Minority Languages, Minzu University of China, Beijing, 100081, China.

[4] New Jersey Institute of Technology, Newark, NJ 07102, USA.

[*] Corresponding Author: Wei Song. Email: songwei@muc.edu.cn.

Received: 30 April 2020; Accepted: 03 June 2020.

present, remote sensing images have been used in resource surveying, environmental monitoring, precision agriculture, disaster assessment, target recognition and other fields [Song, Cao, Zheng et al. (2016)]. As an important part of remote sensing image processing, remote sensing image classification is one of the current research hot area, causing a large number of researcher's interest.

At present, the classification methods of remote sensing images are mainly divided into the following aspects: (1) classification based on statistical analysis; (2) classification based on artificial neural network; (3) classification based on multi-source data fusion; (4) classification based on expert knowledge and geoscience knowledge; (5) classification based on actual conditions [Li, Wang, Bi et al. (2005)]. Among them, remote sensing image classification methods based on statistical analysis could be divided into supervised classification and unsupervised classification. Supervised classification is a method which uses annotated data to train the models, while data category for unsupervised classification is unknown. The supervised classification methods commonly used in remote sensing image classification are include the following: k-means method, decision tree and Bayesian classification method, maximum likelihood estimation method [Fu (2002); Sun, Ni and Zhou (2003); Lin (1990); Mei, Peng, Qin et al. (2001)]. The used unsupervised classification methods are as follows: Bayesian learning, maximum likelihood classification, and clustering. It can be seen that satellite remote sensing image classification technology is booming. However, remote sensing images have many data categories and large ambiguities. How to solve multi-category classification and meet certain classification accuracy is a key issue in current remote sensing image research [Li, Wang, Bi et al. (2005)].

In remote sensing technology, the spatial resolution of remote sensing images is further improved. The simple use of spectral bands as classification features in the initial stage cannot meet the high spatial resolution image classification. The reason is that the spectral statistical features of high spatial resolution remote sensing images is not as stable as low-resolution images, and similar objects exhibit large spectral heterogeneity. Also, the spectra of different features overlap each other. The increase of the spatial resolution makes the spatial traits of the features more obvious, and this can effectively distinguish the one which has the similar spectral characteristics. Thus, texture features, as a kind of spatial features, are applied to remote sensing image classification by researchers. The local consistency index obtained by the co-occurrence matrix texture extraction method is used to reduce the vegetation mixture in IKONOS remote sensing images. The texture features can also serve as multi-source data to participate in remote sensing classification of high spatial resolution images. The texture features extracted by the gray level co-occurrence matrix are used to study the forest structure parameters of IKONOS remote sensing images [Bai, Liu, Qiao et al. (2010)]. It can be seen that the gray level co-occurrence matrix, as a description method of texture features, has very superior performance in the representation of spatial features of remote sensing images, and is a texture feature with very high classification contribution.

The rapid improvement of neural networks' performance, deep learning has gradually entered people's field of vision. In the past few years, it has demonstrated excellent data representation capabilities and generalization capabilities. In recent years, the more common depth model is the deep belief network proposed by Hinton et al. [Hinton, Osindero and Teh (2006)] in 2006. Subsequently, the success of convolutional neural networks [LeCun, Bottou, Bengio et al. (1998)] on the classic target recognition datasets MNIST, CIFAR [LeCun, Cortes and Burges (1998)] proved that it is superior to the deep belief network. In 2015, Li et al. [Li and Taylor (2015)] proposed a label nature learning method based on convolutional neural networks, which proved its effectiveness in ice-water classification in satellite images.

Although neural networks have tiptop generalization capabilities, there are still a number of issues. During training, the number of hidden layers, the number of nodes per layer, the learning rate, the weight initialization and the number of iterations directly affect the recognition performance of the neural network. In the past few decades, kernel-based SVMs have been widely used in remote sensing image classification (Huang et al. [Huang, Davis and Townshend (2002)], Foody et al. [Foody and Mathur (2004)], Melgani et al. [Melgani and Bruzzone (2004)], Pal et al. [Pal and Mather (2004)], Lu et al. [Lu and Weng (2007)], Mountrakis et al. [Mountrakis, Im and Ogole (2011)]). In 2013, Mahesh pal et al. [Pal, Maxwell and Warner (2013)] proposed a kernel-based over-limit learning machine for remote sensing image classification, and proved that it is superior to kernel-based SVM in classification accuracy and computational efficiency. In fact, as early as 2009 [Pal (2009)], he proposed that the classification of features based on the extreme learning machine is better than the back-propagation algorithm. In 2016, Song et al. [Song, Cao, Zheng et al. (2016)] proposed that the combination of random subspace and nuclear extreme learning machine can improve the classification of hyperspectral remote sensing images, and proved that the total accuracy of classification is higher than that of random forest method. It can be seen that the extreme learning machine has great application value in remote sensing image classification.

Recently, Basu et al. [Basu, Ganguly, Mukhopadhyay et al. (2015)] proposed a new learning framework, DeepSat, for satellite image classification. He used the features of satellite image feature resolution as the input of the deep learning network, and used the deep confidence network training results. The feedforward backpropagation neural network is initialized. Experiments show that this new learning framework is superior to the best three types of object recognition algorithms in the SAT-4 and SAT-6 datasets. They are deep confidence networks and stack denoising automatic encoder. The traditional deep learning method is optimal in object recognition, face recognition, and handwritten digit recognition, but it is not effective in satellite image classification. And the reason is mainly the inter-class and the differences within the class are too large, the number of annotation data is too small relative to the entire dataset, and the spatial context information is lost during the learning training. In response to these problems, we propose to introduce the features of gray-scale co-occurrence matrix in addition to the key features that are effective in the research of remote sensing images, so that the obtained image features have more vivid spatial context, texture and other information. Furthermore, in view of the relatively large complexity and time complexity of the existing deep learning space, we propose to use the extreme learning machine for data classification. The extreme learning machine has attracted more and more attention from researchers in recent years because of its advantages of random input parameters, short training time, and convenient multi-classification. Through the introduction of these algorithms, we have obtained an effective remote sensing image classification algorithm with the number of feature extractions reduced by nearly half, and the classification training model is simpler. The classification accuracy is significantly improved on the SAT-4 and SAT-6 datasets.

2 Algorithm basic framework

In order to solve the problem of weakening spatial information and training in remote sensing image classification, we propose a new image classification method. First, extract the original image into a feature combination, and then input it into the extreme learning machine for training and learning to achieve multi-label classification. Therefore, the basic procedure consists of feature extraction and classification training.

2.1 Feature extraction

The original image belongs to the RGB color space, which is an uneven color space that does not conform to human visual perception characteristics. HIS was proposed by American colorist Hamunseu in 1915. It reflects the way in which human visual systems perceive color, and perceives colors with three basic features: hue ***H***, saturation ***S***, and brightness ***I.*** The establishment of the HIS model is based on two important facts: one is that the I component is independent of the color information of the image, and the other is that the H and S components are closely related to the way people feel the color. These characteristics make the HIS model ideal for color feature detection and analysis. Therefore, this paper chooses to convert the original image color space into the HIS color space for preprocessing. The formula for converting RGB to HIS color space is as follows:

$$H=\begin{cases}\theta, & \mathrm{G} \geq \mathrm{B} \\ 2\pi\text{-}\theta, & \mathrm{G}<\mathrm{B}\end{cases} \qquad \theta=\cos^{-1}\left[\frac{(R-B)+(R-G)}{2\sqrt{(R-G)^{2}+(R-B)(G-B)}}\right] \tag{1}$$

$$S=1-\frac{3\min(R,G,B)}{R+G+B} \tag{2}$$

$$I=\frac{R+B+G}{3} \tag{3}$$

where R, G, and B represent pixel values in the red, green and blue color channels, respectively.

We calculate the three basic feature quantities of the space and the mean and variance of the NIR channel as part of the feature representation. These features have been proved to have good representation ability in the previous satellite image classification work [Clausi (2002); Haralick and Shanmugam (1973)].

Because there are two types of grassland and forest in the datasets SAT-4 and SAT-6, we use the Enhanced Vegetation Index (EVI) with a strong vegetation resolution, and the normalized difference vegetation index (Normalized). The Difference Vegetation Index (NDVI) and the Atmospherically Resistant Vegetation Index (ARVI) feature are used to process the HIS color space obtained above. Their calculation methods are as follows:

$$EVI = G \times \frac{NIR - Red}{NIR + c_{red} \times Red - c_{blue} \times Blue + L} \tag{4}$$

Where the coefficient G, c_{red}, c_{blue}, the values of L are 2.5, 6, 7.5 and 1 respectively.

$$NDVI = \frac{NIR - Red}{NIR + Red} \tag{5}$$

$$NRVI = \frac{NIR - (2 \times Red - Blue)}{NIR + (2 \times Red - Blue)} \tag{6}$$

In view of the improved spatial resolution of the dataset, the intra-class and inter-class differences become more obvious. The above features are insufficient for the spatial variation of the image. We also introduce a gray-scale co-occurrence matrix (GSCM) to describe the spatial variation of the image in the HIS space. We quantize the three different feature quantities in the HIS color space and the NIR channel respectively. Bin (*H*), Bin (*S*), Bin (*I*), and Bin (NIR) represent the quantized numbers of each channel.

Take the H channel as an example. $f(x,y)$ is the value on the channel, and there is $f(x,y) = \mathrm{w}$, $\mathrm{w} \in [0,1,...,Bin(\mathrm{H})-1]$ assuming that the two pixels on the channel image are $p_1(x_1, y_1)$, $p_2(x_2, y_2)$, $f(p1)=w$, $f(p2)=\hat{w}$. If the pixel pair (p_1, p_2), the distance between d, the probability of simultaneous occurrence is Pr Symbiotic matrix $\mathrm{CM}_{\mathrm{d},\theta}$ define as:

$$\mathrm{C}_{d,\theta}(p_1, p_2) = \mathrm{Pr}\left\{ f(p_1) = \mathrm{w} \wedge f(p_2) = \hat{\mathrm{w}} \middle\| p_1 - p_2 \right| = d \} \tag{7}$$

among them θ generally take four directions of 0°, 45°, 90°, 135°. On the basis of the symbiotic matrix, Haralick et al. [Haralick and Shanmugam (1973)] defines 14 statistics such as energy, contrast, entropy, uniformity and correlation to describe the texture features of the image.

2.2 ELM classification

The Extreme Learning Machine (ELM) is an algorithm proposed by Huang et al. [Huang, Zhu and Siew (2004); Huang and Zhu (2006); Sun, Du, Nie et al. (2019)] to solve the single hidden layer feed-forward neural network, which can be applied to regression problems and classification problems. In the extreme learning machine, only the output weight of the hidden layer node is required, the input weight and the offset can be randomly generated, and there is no need to modify in the training process. At the same time, there is sufficient theoretical support in the training classification, which is widely accepted by scholars in the field.

Assume $\boldsymbol{X} \square \boldsymbol{R}^{\mathrm{d}}$. For the input vector, the output function of the extreme learning machine is:

$$f_L(\boldsymbol{X}) = \sum_{i=1}^{L} \beta_i h_i(\boldsymbol{X}) = h(\boldsymbol{X})\boldsymbol{\beta} \tag{8}$$

among them, $\boldsymbol{\beta} = \left[\beta_1, \beta_2, ..., \beta_n\right]^T$ is the output weight vector of L nodes in the hidden layer, $h(\boldsymbol{X}) = \left[h_1(\boldsymbol{X}), h_2(\boldsymbol{X}), ..., h_n(\boldsymbol{X})\right]^T$ is the hidden layer output vector when the input is $\boldsymbol{X}$. $h(\boldsymbol{X})$ implement mapping of input data from d-dimensional to L-dimensional. The decision function of the two classifications corresponding to the extreme learning machine is:

$$f_L(\boldsymbol{X}) = sign(h(\boldsymbol{X})\boldsymbol{\beta}) \tag{9}$$

Unlike traditional learning algorithms, extreme learning machines require minimum training errors and minimum output weight models. The corresponding optimization problems are as follows:

$$\begin{aligned} &\min\ L_{ELM} = \frac{1}{2}\|\boldsymbol{\beta}\|^2 + C\frac{1}{2}\sum_{i=1}^{N}\xi_i^2 \\ &s.t.\quad h(\boldsymbol{X}_i)\boldsymbol{\beta} = t_i - \xi_i,\quad i = 1,...,N \end{aligned} \tag{10}$$

The dual optimization problem corresponding to Eq. (10) is:

$$L_{D_{ELM}} = \frac{1}{2}\|\boldsymbol{\beta}\|^2 + C\frac{1}{2}\sum_{i=1}^{N}\xi_i^2 - \sum_{i=1}^{N}\alpha_i(h(\boldsymbol{X}_i)\boldsymbol{\beta} - t_i + \xi_i) \tag{11}$$

Among them, each Lagrangian multiplier α_i for the ith sample, the optimization condition of the above formula KKT is:

$$\frac{\partial L_{D_{ELM}}}{\partial \boldsymbol{\beta}} = 0 \rightarrow \boldsymbol{\beta} = \sum_{i=1}^{N}\alpha_i h(\boldsymbol{X}_i)^T = \boldsymbol{H}^{\mathrm{T}}\boldsymbol{\alpha} \tag{12}$$

$$\frac{\partial L_{D_{ELM}}}{\partial \xi_i} = 0 \rightarrow \alpha_i = C\xi_i,\quad i = 1,...,N \tag{13}$$

$$\frac{\partial L_{D_{ELM}}}{\partial \alpha_i} = 0 \rightarrow h(\boldsymbol{X}_i)\boldsymbol{\beta} - t_i + \xi_i = 0,\quad i = 1,...,N \tag{14}$$

where, $\boldsymbol{\alpha} = \left[\alpha_1, ..., \alpha_N\right]^{\mathrm{T}}$. Bring Eq. (12) and Eq. (13) into Eq. (14) to get:

$$\beta = \boldsymbol{H}^{\mathrm{T}}\left(\frac{\boldsymbol{I}}{C} + \boldsymbol{HH}^{\mathrm{T}}\right)^{-1}\boldsymbol{T} \tag{15}$$

among them, $\boldsymbol{I}$ as a unit matrix, $\boldsymbol{T} = \left[t_1, ..., t_N\right]^{\mathrm{T}}$. From Eq. (12) and Eq. (15):

$$\beta = \boldsymbol{H}^{\mathrm{T}}\square\,\frac{\mathrm{I}}{\mathrm{C}} + \boldsymbol{HH}^{\mathrm{T}}\square^{-1}\boldsymbol{T} \tag{16}$$

At this point, the limit learning machine output function can be expressed as follows:

$$f_L(\boldsymbol{X}) = h(\boldsymbol{X})\boldsymbol{\beta} = h(\boldsymbol{X})\boldsymbol{H}^{\mathrm{T}}\left(\frac{\boldsymbol{I}}{C} + \boldsymbol{HH}^{\mathrm{T}}\right)^{-1}\boldsymbol{T} \tag{17}$$

h(X) is treated as an unknown feature map, defined as a kernel matrix:

$$\boldsymbol{\Omega}_{KELM} = h(\boldsymbol{X}) \cdot h(\boldsymbol{X}^{'}) = K(\boldsymbol{X}, \boldsymbol{X}^{'}) \tag{18}$$

Then the output function can be expressed as:

$$f_L(\boldsymbol{X}) = \begin{bmatrix} K(\boldsymbol{X}, \boldsymbol{X}_1) \\ \vdots \\ K(\boldsymbol{X}, \boldsymbol{X}_N) \end{bmatrix}^{\mathrm{T}} \left(\frac{\boldsymbol{I}}{C} + \boldsymbol{\Omega}_{KELM} \right)^{-1} \boldsymbol{T} \tag{19}$$

The hidden layer node output vector in the kernel extreme learning machine is regarded as some unknown feature map, and the kernel function is used to calculate the inner product of the map feature. Therefore, only the given kernel function, the number of hidden layer nodes no longer needs to be specified.

Compared with convolutional neural networks, the extreme learning machine saves the initialization training of network input weights and offsets, saves the adjustment of the number of hidden layer nodes, and is a more efficient and concise multi-classification learning framework. Better classification accuracy was achieved on the SAT-4 and SAT-6 data sets.

3 Experimental system and measurement results

3.1 Test data set

SAT-4 contains 500,000 images, involving a total of 4 land cover categories, namely wasteland, forest, grassland and other types. These images are all 28×28 image blocks separated from the entire satellite tile. There is no intersection between each other. We randomly used 400,000 images as the training data set, and the remaining 100,000 images as the test data set.

SAT-6 has a total of 405,000 images belonging to six different land cover categories, including: wasteland, forests, grasslands, roads, buildings and water bodies. These images are 28×28 image blocks segmented from the naip image, with 324,000 images randomly selected as training sets and 81,000 images used as test data sets.

3.2 Experimental parameters

When extracting features from remote sensing images, we select the three main characteristic components of the image in the HSI color space and the mean and variance of the NIR channel features as part of the feature cluster, respectively, for a total of 2×4 features. In addition, EVI, NDVI, and NRVI with strong vegetation resolving power are also added to the feature cluster. In order to have stronger spatial information representation ability, we simultaneously calculate the HSI color space and the gray level co-occurrence matrix on the NIR channel, and use nine statistics including energy, contrast, entropy, uniformity and correlation to represent its texture features. Therefore, we have selected image feature clusters totaling 2×4+3+9×4=47.

We use the elm model as a single hidden layer to train the network and test the classifications performance. In view of the structural characteristics of the elm model itself, we randomly set the input weight and offset, and the activation function uses a hyperbolic tangent function.

3.3 Experimental results

We compare our classification results on the data sets SAT-4 and SAT-6 with the state-of-the-art methods which based on the deep learning algorithms. The comparison results are shown in Tab. 1 below.

Table 1: Comparison of classification accuracy rates corresponding to different classification methods

Classification Method	SAT-4 ACC/%	SAT-6 ACC/%
DBN	81.780	76.470
CNN	86.827	79.063
SDAE	79.978	78.430
DeepSat	97.946	93.916
Proposed Method	**99.434**	**99.573**

4 Data analysis and discussion

It can be easily seen from the comparison of the experimental results in Tab. 1. The proposed classification method has the current optimal classification accuracy rate, compared with the SAT-4 and SAT-6 data of the DeepSat classification framework proposed by Basu et al. [Basu, Ganguly, Mukhopadhyay et al. (2015)]. The accuracy rate on the set has also increased by 1.5% and 5.6% respectively. This is mainly due to two aspects. On the one hand, the features we have adopted are the feature components that have been proved to have strong resolving power in the previous classification of remote sensing images, and the performance is proved by the characteristic scoring method of Basu et al. The gray level co-occurrence matrix of image texture features plays a very important role in the separation criteria of different classes. The feature separation ability score calculation method is as shown in Eq. (20).

$$D_s = \frac{\overline{\|\delta_{mean}\|}}{\overline{\delta_\sigma}} \tag{20}$$

where, $\overline{\|\delta_{mean}\|}$ refers to the average of the distances of different features, $\overline{\delta_\sigma}$ refers to the mean of the standard deviations of different classes of conditional distributions. The resolution scores of the different features are obtained by calculating the maximum value of the objective function in the feature space. In addition, we also score the EMS, ARVI, and NDVI of the three channels and NIR channels on the HSI color space in the forefront of the HSI color space as part of the feature representation, which makes our features achieve very strong resolving power and the high spatial resolution of the SAT-4 and SAT-6 data sets, the spatial relationship of the co-occurrence matrix introduces a significant improvement in the recognition of high spatial resolution satellite images. It can be seen that we use 47 features with major contribution rate as feature descriptions of remote sensing images by feature contribution scoring. Compared with the feature set of Saikat Basu et al. which network has a number of features up to 150 significantly, this effectively reduces the computational and vector dimensions. Conducive to the late training classification. On the other hand, compared to the deep learning networks used by previous researchers including DBN, CNN, SDAE and DeepSat classification framework, the ELM model we introduced has a simple network structure with high accuracy and fast processing, which could use random input weight and input offset ELM successfully avoided the deep learning initialization matrix and paranoid selection, parameter tuning, layer selection and the node selection for each node. The single hidden layer network structure obtained the learning classification effect better than the above deep network model.

5 Conclusion

In this paper, experiments on the high spatial resolution datasets SAT-4 and SAT-6 show that the proposed method is superior to the existing method in the accuracy of remote sensing image classification. It improved the classification accuracy by 1.5% on SAT-4, and it improved by 5.6% on SAT-6. Compared with the existing learning methods, the proposed method has the following two contributions: (1) reducing the number and dimension of image extraction features, reducing the difficulty of classification learning; (2) reducing the hidden layer of the learning network. The number of layers avoids the parameter optimization adjustment and reduces the complexity of learning the network structure. These advantages make the proposed method more simple and efficient in practical applications, which is beneficial to the research of real-time analysis of remote sensing images and provides a new idea for researchers in related fields. After that, we will continue to observe the effect of the proposed method on other datasets, improving the generalization ability and robustness of the method, tend to discovering image features with better representation ability, and further promoting the development of remote sensing image analysis.

Funding Statement: This work was supported in part by national science foundation project of P.R.China under Grant No.61701554 and State Language Commission Key Project (ZDl135-39), First class courses (Digital Image Processing: KC2066), MUC 111 Project, Ministry of Education Collaborative Education Project (201901056009; 201901160059; 201901238038).

Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

References

Bai, M.; Liu, H. P.; Qiao, Y.; Wang, X. D. (2010): Research progress of high resolution remote sensing image classification method in LUCC. *Remote Sensing for Land and Resources*, vol. 22, no. 1, pp. 19-23.

Basu, S.; Ganguly, S.; Mukhopadhyay, S.; DiBiano, R.; Karki, M. et al. (2015): DeepSat: a learning framework for satellite imagery. *Proceedings of the 23rd SIGSPATIAL International Conference on Advances in Geographic Information Systems*, vol. 2015, no. 37, pp. 1-10.

Clausi, D. A. (2002): An analysis of co-occurrence texture statistics as a function of grey level quantization. *Canadian Journal of Remote Sensing*, vol. 28, no. 1, pp. 45-62.

Dai, C.; Jiang, X.; Tang, L. (2004): Remote sensing image application process and analysis. *Tsinghua University Press*, Beijing.

Foody, G. M.; Mathur, A. (2004): A relative evaluation of multiclass image classification by support vector machines. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 42, no. 6, pp. 1335-1343.

Fu, S. X. (2002): Remote sensing thematic analysis and geoscience map. *Science Press*.

Haralick, R. M.; Shanmugam, K. (1973): Textural features for image classification. *IEEE Transactions on Systems, Man, and Cybernetics*, vol. 1973, no. 6, pp. 610-621.

Hinton, G. E.; Osindero, S.; Teh, Y. W. (2006): A fast learning algorithm for deep belief nets. *Neural Computation*, vol. 18, no. 7, pp. 1527-1554.

Huang, C.; Davis, L. S.; Townshend, J. R. G. (2002): An assessment of support vector machines for land cover classification. *International Journal of Remote Sensing*, vol. 23, no. 4, pp. 725-749.

Huang, G. B.; Zhu, Q. Y.; Siew, C. K. (2004): Extreme learning machine: a new learning scheme of feedforward neural networks. *IEEE International Joint Conference on Neural Networks*, vol. 2004, no. 2, pp. 985-990.

Huang, G. B.; Zhu, Q. Y. (2006): Extreme learning machine: theory and applications. *Neurocomputing*, vol. 70, no. 1, pp. 489-501.

LeCun, Y.; Bottou, L.; Bengio, Y.; Haffner, P. (1998): Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, vol. 86, no. 11, pp. 2278-2324.

LeCun, Y.; Cortes, C.; Burges, C. J. C. (1998): The mnist database of handwritten digits. http://yann.lecun.com/exdb/mnist/.

Li, F.; Taylor, G. (2015): Alter-CNN: an approach to learning from label proportions with application to ice-water classification. *Neural Information Processing Systems Workshops on Learning and Privacy with Incomplete Data and Weak Supervision.*

Li, S. H.; Wang, J. L.; Bi, Y.; Chen, Y.; Zhu, M. Y. et al. (2005): Review of remote sensing image classification methods. *Remote Sensing of Land and Resources*, vol. 17, no. 2, pp. 1-6.

Lin, P. (1990): *Agricultural Remote Sensing*. Beijing Agricultural University Press, Beijing.

Lu, D.; Weng, Q. (2007): A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*, vol. 28, no. 5, pp. 823-870.

Mei, A. X.; Peng, W. L.; Qin, Q. M.; Liu, H. P. (2001): *Introduction to Remote Sensing*. Higher Education Press, Beijing.

Melgani, F.; Bruzzone, L. (2004): Classification of hyperspectral remote sensing images with support vector machines. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 42, no. 8, pp. 1778-1790.

Mountrakis, G.; Im, J.; Ogole, C. (2011): Support vector machines in remote sensing: A review. *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 66, no. 3, pp.

247-259.

Pal, M.; Mather, P. M. (2004): Assessment of the effectiveness of support vector machines for hyperspectral data. *Future Generation Computer Systems*, vol. 20, no. 7, pp. 1215-1225.

Pal, M. (2009): Extreme learning machine based land cover classification. *International Journal of Remote Sensing*, vol. 30, no. 14, pp. 3835-3841.

Pal, M.; Maxwell, A. E.; Warner, T. A. (2013): Kernel-based extreme learning machine for remote-sensing image classification. *Remote Sensing Letters*, vol. 4, no. 9, pp. 853-862.

Soh, L. K.; Tsatsoulis, C. (1999): Texture analysis of SAR sea ice imagery using gray level co-occurrence matrices. *IEEE Transactions on Geoscience and Remote Sensing*, vol. 37, no. 2, pp. 780-795.

Song, X. F.; Cao, Z. W.; Zheng, F. B.; Jiao, L. C. (2016): Hyperspectral remote sensing image classification based on random subspace kernel extreme learning machine integration. *Journal of Computer Science*, vol.43, no. 3, pp. 301-304.

Sun, J. B.; Ni, L.; Zhou, J. (2003): *Principles and Applications of Remote Sensing*. Wuhan University Press, Wuhan.

Sun, W.; Du, H.; Nie, S.; He, X. (2019): Traffic sign recognition method integrating multi-layer features and kernel extreme learning machine classifier. *Computers, Materials & Continua*, vol. 60, no. 1, pp.147-161.