Land Cover classification in remotely sensed data based on Deep Convolutional Neural Network

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Abstract- **Land Cover classification in image processing is the task of classifying pixels whose spectral characteristics are similar and allocating them to the designated classification classes such as forests, grassland, wetlands and build-up areas. With the development of remote sensing technology and accuracy, the application of land cover images has become more widely spread. Many methods have achieved good classification results in the classification of land cover images. This paper discusses the issues and prospect by the combined effect of various methods and reviews the classification methods of remotely sensed images in statistical methods and recent machine learning methods.**

***Keywords*: Image, Classification, Support Vector Machine, Deep learning, Remote sensing.**

I. INTRODUCTION

Land Cover Image Classification is an active part of research in remote sensing field. Remote sensing images are captured by remote sensors on the aircraft. These images contain information collected from the spectral data reflected by the ground objects. Therefore, remote sensing images have the characteristics of high spectral resolution with many bands and abundant information. The methods used for processing remote sensing images include transformation [1], Dimensionality Reduction[2], Noise Reduction[3], Classification[4]. Unlike normal images, remote sensing images are rich in spectral information and this spectral information can reflect the physical structure of the object, which is helpful for image classification. Classification of images by software is to classify and identify the information of the earth's surface and its environment, so as to identify and extract the feature information. It is a specific application which uses automatic pattern recognition technology in remote sensing field. Moreover, the information collected by remote sensing sensors will be richer with detailed content with the further evolution of remote sensing imagers, the amount of information contained in land cover images is greater and the scope of application in Land Cover images is wider. The number of imaging bands in remote sensing images is wider. The number of imaging bands is higher and the ability to resolve object is stronger (i.e) higher spectral resolution compared to multispectral images.

However due to high dimensional characteristics of remote sensing images, the similarity between the mixed pixels and spectra, remote sensing image classification technology still faces series of problems and challenges that needs to be solved[5],[6]. During the acquisition of remote sensing images, the interference due to atmospheric conditions seriously affects the quality of the data and its classification accuracy. The data of remotely sensed Land Cover images have high dimensionality because the images are obtained by using spectral reflectance values collected by airborne or space borne imaging spectrometers in hundreds of bands. In practical applications, it is relatively easy to collect remote sensing image data, but it is extremely difficult to obtain image-like label information. Therefore classification of images faces lack of labelled samples that lead to hughes phenomenon [7]. In recent days, people often focused on spectral information to achieve image classification and developed many classification methods such as Random Forest (RF), Support Vector Machine (SVM)[8],K-Nearest Neighbours(KNN)[9] and Neural Networks[10]. Dimension reduction methods have also been proposed such as Principal Component Analysis (PCA)[11], Independent Component Analysis(ICA)[12], Linear Discriminant Analysis(LDA)[13] . Laplacian Eigen map (LE)[14] also known as spectral clustering. In this technique, Classification methods are based on spatial information which have not achieved good classification results. According to the concepts explained in [15,16] spatial context information plays a main role in the classification of remote sensing images and avoids homologous phenomena caused by using only spectral information. In [17,18] an Extended Morphological Profile(EMP) method has been performed to extract the spatial information of the remote sensing image. In addition, the joint sparse representation models also extracts spatial information [19,20]. Deep Learning[21] has excellent capabilities in digital image processing. In recent years, image enhancement, image classification and target detection have set off a wave of deep learning. Some models have been used in remote sensing images such as Convolutional Neural Network (CNN), Deep Belief Network(DBN)[22] and Recurrent Neural Network(RNN). Inorder to solve the problem of poor classification which results due to the lack of training samples, a new classification based on tensor model was proposed[23,24]. In [25,26] the fusion based method are used to enhance the remote sensing images for better image classification. The optimization process described in this research work finds optimal fusion parameters to improve the performance of remote sensing images. An investigation on various satellite image enhancement techniques has been performed in [27]. Classification after performing fusion based enhancement improves classification accuracy. In [28] a multi-index learning approachfor classification of high-resolution remotely sensed images over urban areas was proposed. It has been widely decided that spatial features derived from textural, structural, and object-based methods are significant information sources to complement spectral properties for accurate urban classification of high-resolution imagery. However,the spatial features are series of parameters, such as scales, directions, and statistical measures, leading to high-dimensional feature space. The high- dimensional space is almost impossible to deal with considering the huge storage and computational cost while processing high-resolution images. Remote sensing Image Classification methods are classified into Supervised classification [29-30], Unsupervised Classification [31, 32] and Semi-supervised Classification [33,34] based on usage of training samples in the remote sensing image classification process. This paper also discusses issues related to each techniques and prospects to conduct image classification. The article is organized as follows. Section II reviews the existing methods in the field of remote sensing image classification. Section III draws the conclusion of the overall discussion in brief.

II. Remote Sensing Image Classification Techniques

Recent work gives the idea about ongoing research in the field of remote sensing image processing. Mainly this paper focuses on statistical and recent machine learning methods to handle the issue of high dimensionality and training with a limited number of samples. Figure 1 shows the classification methods of Land Cover Images based on Convolutional Neural Network(CNN). This section gives a well known remote sensing image classification methods.

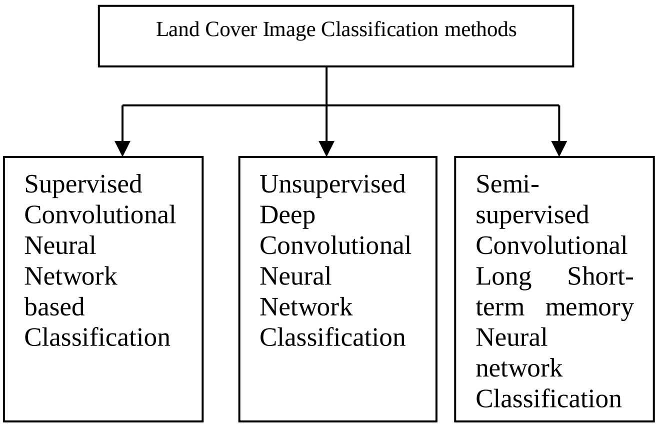

Fig 1: Classification methods of Land Cover Images based on CNN

Supervised Convolutional Neural Network based Classification

It is a commonly used method for remote sensing image classification. Many Supervised methods have been developed to tackle the remote sensing data classification problem. The basic process is to determine the discriminant criteria based on the known sample category and prior knowledge, and calculate the discriminant function. Commonly used supervised classification methods include Maximum Likelihood Classification, Support Vector Machine, Artificial Neural Network, Decision Tree Classification method. Supervised Classification algorithms can be classified into parametric and nonparametric techniques. In parametric classifiers such as Maximum Likelihood Classifier, the data is assumed to follow a statistical distribution with high dependence on assumptions related to statistical distribution. Hence these classifiers suffer from the problem of dimensionality reduction[35]. Non Parametric Classifiers such as decision tree classifiers and Neural Network Classifiers are used to classify remote sensing images. In fact, neural network classifiers, particularly back propagation algorithm have been viewed as a substitute for MLC. Though neural network approaches have certain advantages, these are slow in training phase. Recently Support Vector Machine (SVM) based on machine learning algorithms are proposed to overcome the limitations of nonparametric classifiers. The Classification methodology of SVM attempts to separate samples belonging to different classes by tracing maximum margin hyperplane in the kernel space where samples are mapped[36]. In SVM the classification surface cannot separate the two types of sample points without error but maximize the classification gap between the two types. Suppose a Hyperspectral image $Y = \{y_1, y_2, ...y_n\}$, and the spectral vector of the ith pixel of the image is represented as $y_i = \{y_{i1}, y_{i2}, ...y_{iD}\}$, D is the total number of bands and n is the total number of pixels. In addition, define $Z = (z_1 z_2 .....z_n)$ the classification mark image in the formula $Z_i \in (-1,1)$. The arithmetic process of a classic SVM classifier is $Z_i = \mathrm{sgn}\left(\sum_{j=1}^{l_n} z_i \alpha_i \left(y_j^T . y_i\right) + d\right)$. l_n is the number of a priori marks. α_i is a soft interval parameter by setting d=0, the optimal classification plane can pass the origin of the coordinate system, thereby simplifying the calculation. In practical, it is not all linearly separable, so slack variables are introduced. The numerical expression of the support vector machine after introducing the slack variable is $\max \sum_{i-1}^{n} \alpha_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} \alpha_i \alpha_j z_i z_j (y_i^T y_j)$ $0 \le \alpha_i$ <C, i=1,…n. $\sum_{i=1}^{n} \alpha_i z_i = 0$. C is a constant, which is the penalty factor or regularization parameter. For nonlinear cases, the SVM classification method can no longer meet the classification requirements and the kernel function. After introducing the concept of kernel function, the basic idea of SVM is, transform the input space to s transformation and then find the optimal linear classification surface in this new space. This nonlinear transformation is achieved by defining the appropriate inner product function. The commonly used kernel functions include linear kernel functions and Gaussian kernel functions. For deeper analysis of SVMs in remote sensing image

classification [37,39] can be referred. Results from SVM based Classification can be compared with parametric and nonparametric classifier namely Maximum Likelihood Classifier (MLC) and the back propagation neural network classifier repectively. [38] proposes differentiating and identifying vegetation types with high level of confidence using remote sensing data .As per the relevance analysis the network mainly uses the information from the sentinel-2 images acquired in summer. The analysis helps to understand the behaviour of deep learning models in agricultural applications. The MLC algorithm was provided in the multispec software [40] and the BP-NN algorithm in the MATLAB toolbox. The idea of the kernel Fisher Discriminant Analysis is to solve the well known problem of Fishers Linear Discriminant Analysis in a kernel feature space, that produces a nonlinear discriminant classifier in the input space [41]. This method forces to include all the training samples and thus the property of sparsity is lost. Minimum Distance Classifier is a supervised classification based on the distance of pixels in the feature space as a classification basis[42]. Feature points are used as the centre of category and covariance matrix is used to support the dispersion of surrounding points. The basic assumption of similarity measure is if the feature differences between two modes are below a set threshold, the two modes are said to be similar. It uses the area formed by the collection of numerous training sample points to represent various decision-making regions. There are many forms of distance calculation including Mahalanobis distance, Absolute Value distance, Euclidean distance, Che's distance and Bath's distance. The Mahalanobis distance and Barth-Parametric distance does not consider the class mean vector, but consider the distribution of each feature point around the center of the class. So it results an effective classification than other distance criteria. Maximum Likelihood Classifier (MLC) method is based on Bayesian criterion. It is a nonlinear classification method. The Statistical Feature values of training samples are calculated during classification. Due to large amount of data in remote sensing image, the covariance matrix generated will be very large and it is more difficult to calculate when using this covariance matrix. Therefore this method obtained better results with classification boundaries[43].

At present, Artificial Neural Networks is the most popular classification method. It is a widely used intelligent control, information processing and combinatorial optimization. However, it has weakness such as the need for a large amount of training data, operation speed is slow and difficulty in obtaining decision surface in the feature space. This method is commonly used in Back Propagation Neural Networks [44],Radial Basis Neural Networks[45] and Wavelet Neural Networks[46]. Among these, the back propagation neural network model(feed forward network model) is the most widely used model in neural network. It consists of an input layer, a hidden layer and an output layer. The input of a node is the input signal given from the input layer to transmission of the output layer which is the forward propagation process. Between the output signal and the desired signal, if an error occurs, then the error is transferred to the back propagation process and the weight of each layer is adjusted to the magnitude of the error of each layer. In practical, neural network method can be used but it needs human supervision to ensure its accuracy. In recent years, remote sensing image classification methods have introduced spatial information of remote sensing images. This technique is referred as Spatial-Spectral Joint features. Deep Learning method originates from artificial neural networks. Compared to other techniques, deep learning has a stronger pumping ability. It also helps to extract feature information. This method is commonly used in Convolutional Neural Network(CNN), Deep Learning[47] and Deep Belief Network(DBN)[48]. A 1D CNN network structure for pixel level land cover classification is not limited by a sparsely labelled dataset. It has achieved superior performance in accuracy using only limited number of training samples.

Unsupervised Deep Convolutional Neural Network Classification

The Unsupervised Classification method refers to the remote sensing image classification based on the spectral similarity of the data, (i.e) the clustering technique without any prior knowledge. Commonly used unsupervised classification include K-means, Iterative Self-Organizing method and Agglomerative hierarchical[49]. The idea behind K-means clustering method[50] is that the sum of the squares of the distances from all the pixels in each class to the center point of the class is the smallest. Initially, the center point is randomly selected and other pixels to be classified according to the prescribed principles to complete the initial clustering. Recalculate and modify the centre point and classify again, then iterate until the position of the clustering center points no longer changes. Find the best clustering center and stop the iteration. The major drawback of this technique is the number of selected categories cannot be changed during the calculation process. This kind of defects can help to find a better initial clustering center with auxiliary methods that improve the accuracy of classification.

The ISODATA algorithm[51] is similar to the K-means classification algorithm. There is no need to continuously adjust the cluster center during the classification process. Hence the chance of human error is reduced and the initial parameters have less input with unique spectral characteristics. A lot of image analysis and post processing is required to attain reliable classification results. The cluster categories may be classified under same spectrum. This makes the matching of cluster groups and categories difficult, because the spectral cluster groups between different images cannot maintain their continuity and are difficult to compare. In [52], a new unsupervised image classification approach was proposed by constructing hypergraph in which it is possible to model complex relationship to determine its shape and appearance features which boost the clustering performance.[56] proposes a method to explore spatial characteristics of remotely sensed images to distinguish urban settlements, water bodies, agricultural and forest areas.

Semi-supervised Convolutional Long Short-term memory Neural network Classification

Semi-supervised Classification uses both labelled and unlabelled data to train the classifier. The drawback of supervised method is that, the classification accuracy depends on the number of training data sets of label points and obtaining a large number of Hyperspectral image class labels. Although unsupervised methods are not sensitive to labelled samples, due to lack of prior knowledge, the relationship between clustering categories and real categories is uncertain [53]. Semi-supervised Classification makes up for the lack in unsupervised and supervised learning. This image classification is based on the same type of labelled and unlabelled samples on the feature space. Semi-supervised classification methods include algorithms like model generation algorithms, Semi-supervised support vector machines; Graph based Semi-supervised algorithms and self-training, collaborative training and triple training. Based on the above techniques Semi-supervised classification method is reviewed only a small number of labelled samples are required for Semi-supervised learning [54,58]. It combines both labelled and unlabelled data to improve its classification accuracy. Self training is a commonly used remote sensing image classification algorithm. A classifier is trained with labelled samples and a large number of unlabelled samples are labelled with this classifier. This type of classification is simple and convenient. However, the number of initial training samples is limited; it is difficult to train a classifier with good generalization performance with high accuracy.

Graph based semi-supervised methods handles major issues of image classification in remote sensing field. Graph construction is helpful for the purpose of representing complex relationships among the pixels. For remote sensing images, clustering is not possible to represent relationships among the images as a simple graph representation in pair-wise relation. In simple graph, single similarity function is used to represent the relation between two vertices. Different features are extracted from images and fed to single similarity function. It is overcome by representing the relationship among vertices by constructing hypergraph. Hypergraph is a generalization of a simple graph in which a set of vertices is defined as a weighted hyperedge. A complex relationship among pixels can be modelled by hyperedge construction. Due to these characteristics hyperplane is constructed in various applications such as image classification [55] and image retrievel. [57] proposes a Semi-supervised Convolutional Long-short term memory neural network for time series remote sensing images. It achieves an accurate, robust and automated land cover classification

III. Conclusion

As in recent times, Land cover images is becoming a promising technology, there is high need to focus on Landcover image classification. Several methods for Land cover Image Classification including supervised, unsupervised and semi supervised Convolutional Neural Network classification methods are discussed in this paper have a large scope in future. Hence, convolutional based methods have been shown to be more robust to large or complex feature spaces in comparision to other methods.

REFERENCES:

1.Ma. Y, Li.R, Yang.G, Sun.L and Wang.J, ‘A Research on the combination strategies of multiple features for hyperspectrel remote sensing image Classification’, Journal of Sensors, Article ID 77341973, pg.14,2018.

2.Binol.H, ‘Ensemble Learning based multiple kernel Principal Component Analysis for dimensionality reduction and Classification of Hyperspectral imagery’, Mathematical Problems in Engineering, Article ID 9632569, pg.14,2018.

3.Kwon.H, Hu.X, Theiler.J, Zare.A and Gurram.P, Algorithms for Multispectral and Hyperspectral image analysis, Journal of Electrical and Computer Engineering, Article ID 908906,pg.2,2013.

4.Ablin.R, Sulochana.C, A Survey of Hyperspectral Image Classification in remote sensing, International Journal of Advanced Research in Computer and Communication Engineering, Vol.2,Issue.8,pg.2986-3000.

5.Camps-valls.G and Bruzzone.L, Kernel-based methods for Hyperspectral image classification, IEEE Transactions on Geoscience and Remote Sensing, Vol.43, No.6,pp.1351-1362,2005.

6.Camps-valls.G, Bandos Marsheva.T.V and Zhou.D, Semisupervised Graph based Hyperspectral image classification, IEEE Transactions on Geoscience and Remote Sensing, Vol.45,no.10,pp.3044-3054,2007.

7.Hughes.G, On the mean accuracy of statistical Pattern Recognizers, IEEE Transactions on Information theory, Vol.14, no.1,pp.55-63,1968.

8.Wang.X and Feng.Y, New Method based on support vector machine in classification for Hyperspectral data, in 2008 International Symposium on computational Intelligence and Design,pp.76-80, Wuhan, China 2008.

9.Ma.L, Crawford.M, Tian.J, Local Manifold Learning-based K-Nearest Neighbor for Hyperspectral Image Classification, IEEE Transactions on Geoscience and Remote Sensing, 48(11),pp.4099-4019,2010.

10.Fu.A,Ma.X and Wang.H, Classification of Hyperspectral image based on hybrid neural networks in IGARSS 2018, IEEE International Geoscience and Remote Sensing symposium, pp.2643-2646, Valencia, Spain,2018.

11.Imani.M and Ghassemian.H, Principal Component Discriminant Analysis for feature Extraction and Classification of Hyperspectral Images in Iranian Conference on Intelligent Systems,pp.1-5,Iran 2014.

12.Wang.J and Chang C.I. , Independent Component analysis based Dimensional Reduction with applications in Hyperspectral Image analysis, IEEE Transactions on Geoscience and Remote Sensing, vol.44,no.6,pp.1586-1600,2006.

13.Du Q., Modified Fishers Linear Discriminant analysis for Hyperspectral Imagery, IEEE Transactions on Geoscience and Remote Sensing Letters, Vol.4,no.4,pp.503-507,2007.

14.Belkin.M and Niyogi.P, Laplacian Eigen maps for dimensionality reduction and data representation, Neural Computation, Vol.15,no.6, pp.1373-1396, 2003.

15.Yan.Y, Zhao Y., Xue H.F., Kou X.D. and Liu Y., Integration of spatial –spectral information for Hyperspectral image classification in 2010 second International Conference on Geoscience and Remote Sensing, pp.242-245,Qingdao, 2010.

16. Xu X., Li J., Zhang Y. and Li S., A Subpixel Spatial-Spectral feature mining for Hyperspectral Image Classification in IEEE International Geoscience and Remote Sensing Symposium, Spain ,pp.8476-8479, 2018.

17.Wang.J, Zhang G., Cao M. and Jiang N., Semi-Supervised Classification of Hyperspectral image based on spectral and extended morphological profiles in 2016 eighth workshop on Hyperspectral image and signal processing: Evolution in Remote Sensing,pp.1-4, Los Angeles,2016.

18.Zhang X, Sun Y. and Qi W., Hyperspectral Image Classification based on extended morphological attribute profiles and abundance information, ninth workshop on Hyperspectral image and signal processing: Evolution in Remote Sensing, pp.1-5, Amsterdam, Netherlands, 2018.

19. Chen Y., Nasrabadi N.M. and Tran T.D., Hyperspectral Image Classification using dictionary-based sparse representation, IEEE Transactions on Geoscience and Remote Sensing,Vol.49,no.10,pp.3973-3985,2011.
20. Fang Z., Li S., Kang X. and Benediktsson J.A., Spectral- Spatial Hyperspectral image Classification via-multiscale adaptive sparse representation, IEEE transactions on Geoscience and Remote Sensing, vol.52,no.12,pp.7738-7749,2014.
21. Voulodimos A., Deep learning for computer vision: a brief review, Computational Intelligence and Neuroscience, Article ID 7068349, pages 13,2018.
22. Guo Y., Liu Y., Oerlemans A., Lao S., Wu S. and Lew M.S., Deep Learning for visual understanding; a review, Neurocomputing, vol.187,pp.27-48,2016.
23. Makantasis K., Doulamis A.D., Doulamis N.D. and Nikitakis A., Tensor based classification models for Hyperspectral data analysis, IEEE Transactions on Geoscience and Remote Sensing, Vol.56,no.12,pp.6884-6898, 2018.
24. Makantasis K., Doulamis A., Doulamis N., Nikitakis A. and Voulodimos A., Tensor-based nonlinear classifier for high order data analysis in IEEE International Conference on Acoustics, Speech and Signal Processing, Canada, 2018.
25.Ablin.R, Sulochana.H, Improved Visualization using a fusion technique based on KNN matting of Remote Sensing Images, Journal of the Indian Society of Remote Sensing, vol.46,pg.179-187,2018.
26. Ablin.R, Sulochana.H, Iterative based Visualization-oriented fusion scheme for Hyperspectral images, Signal,Image and Video Processing, Springer, vol.12,Issue.4,pg.757-765,2018.
27.Ablin.R,Sulochana.H, Prabin.G, An investigation in satellite images based on image enhancement techniques, European Journal of Remote Sensing,vol.53(10),pp.1-9,2019.
28. Mou. L, Ghamisi. P, and Zhu. X, “Deep recurrent neural networks forhyperspectral image classification,” IEEE Trans. Geosci. Remote Sens., vol. 55, no. 7, pp. 3639–3655, Jul. 2017.
29. Jiang J., Huang L., Li H. and Xiao L., Hyperspectral Image Supervised classification via multi-view nuclear norm based 2D PCA Feature Extraction and Kernel ELM in IEEE International Geoscience and Remote Sensing Symposium, pp.1496-1499, Beijing, 2016.
30. Zhang L., Xia G.S., Liang L. and Tai X.C., Deep Learning for remote sensing image understanding, Journal of sensors, Article ID:7954154, pgs.2,2016.
31. Paoli A., Melgani F. and Pasolli E., Clustering of Hyperspectral images based on multiobjective particle swarm optimization, IEEE Transactions on Geoscience and Remote sensing, vol.47,no.12,pp.4175-4188,2009.
32.Jian.W, Unsupervised Intrusion Feature Selection based on Genetic Algorithm and FCM in Information Engineering and Applications,pp.1005-1012,Springer,2012.
33.Wang.C, Guo.Z, Wang.S, Wang.L and Ma.C, Improving Hyperspectral image classification for fine land use assessment application using semisupervised machine learning, Journal of Spectroscopy, pgs.8,Article ID: 969185, 2015.
34.Han.Y, Ren.J, Hong.Z et.al, Active learning algorithms for the classification of Hyperspectral sea Ice images, Mathematical Problems in Engineering, Article ID: 124601, pgs.10, 2015.
35. Hughes G.F., On the mean accuracy of statistical pattern recognition , IEEE Transactions on Information Theory, Vol.14, pp.55-63, 1968.
36. Vapnik V.N., Statistical Learning Theory, Newyork, John Wiley and Sons, 1998.
37. Gualtieri J.A. and Cromp R.F., Support Vector machines for Hyperspectral remote sensing classification in proceedings of the SPIE, 27th AIPR Workshop, pp.221-232, 1998.
38.Manuel Campos-Taberner, Francisco Javier Garcia-Haro, Beatriz Martinez, Emma Izquierdo-Verdiguier, Clement Atzberger, Gustau Camps-Valls & Maria Amparo Gilabert, Understanding deep learning in land use classification based on Sentinel-2 time series, Rep 10,17188,2020.
39. Melgani.F and Bruzzone.L, Classification of Hyperspectral remote sensing images with support vector machines , IEEE transactions on Geoscience and Remote Sensing, vol.42, pp.1778-1790,2004.
40.http://dynamo.ecn.purdue.edu/bieh/multispec
41.Mika.S, Kernel Fisher Discriminants, Ph.D thesis, Department of Computer Science, University of Technology, Berlin, Germany 2002.
42.Jing R, Li Chun-ping, Improved minimum distance classifier- weighted minimum distance classifier, Journal of Computer Application, vol.25,2005.pp.992-994.
43. Sun J, JianyuYang et. al., Automatic remotely sensed image classification in a grid environment based on the maximum likelihood method, Mathematical and computer modelling, vol.58,issue:3-4,pp.573-581,2013.
44.Lei Y, Fusion method of PCA and BP neural network for face recognition in International Conference on computer science and service system, pp.3256-3259, Nanjing, China 2011.
45. Sarnel H, Senol Y and Sagirilibas D, Accurate and robust image registration based on radial basis neural networks,23rd International Symposium on computer and Information science,pp.1-5, Turkey 2008.
46. Gao X, a Comparative research on wavelet neural networks in proceedings of the International Conference on Neural Information Processing, pp.1699-1703,2002.
47.Makantasis K, Karantzalos K, Doulamis.A and Doulamis.N, Deep Supervised learning for Hyperspectral data classification through convolutional neural networks in IEEE International Geoscience and Remote sensing symposium, pp.4959-4962, Italy 2015.
48. Li.T, Zhang J.P. and Zhang Y., Classification of Hyperspectral image based on deep belief networks in IEEE International Conference on Image Processing, pp.5132-5136, France 2014.
49. Duda T. and Canty M., Unsupervised Classification of satellite imagery: Choosing a good algorithm, International Journal of remote sensing, vol.23,11, pg.2193-2212.

50. Jianpeng Qi; Yanwei Yu et.al., K-Means An effective and efficient K-means clustering Algorithm, IEEE International Conferences on Big Data and Cloud Computing (BDCloud), 2016.
51. Qian Wang, Qingli Li et al**.,** An improved ISODATA algorithm for hyperspectral image classification, 7th International Congress on Image and Signal Processing, 2014.
52. Huang.Y, Liu.Q and Metaxas.D, Video object segmentation by hypergraph cut in Proceeding on IEEE conference CVPR,pp.1738-1745, 2009.
53. Cheng.Z and Xie.F, Semi-Supervised classification of Hyperspectral images based on spatial features and texture information, Bulletin of surveying and mapping, vol.51,no.12,pp.56-59,2016.
54.Yanping.T, Chao.T, Jun.Z, Yang.Z and He.X, Hyperspectral image classification combined with active learning and semisupervised graphs, Journal of Surveying and Mapping,Vol.44,no.8,pp.919-926,2015.
55.Ji.R,Gao.Y,Hong R, Liu. Q, Tao.D and Li.X, Spectral Spatial constraint Hyperspectral Image classification, IEEE Transactions on Geoscience and Remote Sensing,vol.52,no.3,pp.1811-1824,2014.
56.Ankita Chatterjee, Jayasee Saha, Jayanta Mukharjee, Subhas Aikat and Arundhati Misra, Unsupervised Land cover Classification of Hybrid and Dual-Polarized images using Deep convolutional Neural Network, IEEE Transactions on Geoscience and Remote Sensing,vol.18,no.6,pp.969-973,2021.
57.S.Jing and T.Chao, Time series land cover classification based on semi-supervised convolutional long short-term memory neural networks,1521-1528,2020.
58.Haoyan Xie and Hai Huang, Classification of Land Cover Remote Sensing images based on Pattern Recognition,Scientific Programming, Article ID 8319692,2022.