AN ENSEMBLE CLASSIFICATION ALGORITHM FOR HYPERSPECTRAL IMAGES

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ABSTRACT

Hyperspectral image analysis has been used for many purposes in environmental monitoring, remote sensing, vegetation research and also for land cover classification. A hyperspectral image consists of many layers in which each layer represents a specific wavelength. The layers stack on top of one another making a cube-like image for entire spectrum. This work aims to classify the hyperspectral images and to produce a thematic map accurately. Spatial information of hyperspectral images is collected by applying morphological profile and local binary pattern. Support vector machine is an efficient classification algorithm for classifying the hyperspectral images. Genetic algorithm is used to obtain the best feature subjected for classification. Selected features are classified for obtaining the classes and to produce a thematic map. Experiment is carried out with AVIRIS Indian Pines and ROSIS Pavia University. Proposed method produces accuracy as 93% for Indian Pines and 92% for Pavia University.

KEYWORDS

Morphological Profile, Local Binary Pattern, Hyperspectral Image, Genetic Algorithm, Support Vector Machine

1. INTRODUCTION

Hyperspectral remote sensing is defined as the technique of obtaining information about earth's surface or objects through the analysis of data collected by hyperspectral sensors. Land cover classification is used for identifying different types of earth's surface. Hyperspectral imaging is a spectral imaging technique and also related to multispectral imaging. Hyperspectral deals with imaging narrow spectral bands over a continuous spectral range while multispectral imaging deals with several images at discrete narrow bands.

Classifying the types of heterogeneous classes present in the hyperspectral image is one of the research issues in remote sensing [1].Classifying the pixels in the hyperspectral image and identifying their relevant class belongings depends on the feature extraction and classifier selection process. A feature is a property that differentiates one class from other and the process of transforming the input data into the set of features is called feature extraction.

Multiple classifier approach for spectral-spatial classification of hyperspectral images is proposed. A method based on mathematical morphology for pre-processing of hyperspectral data

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is used. Opening and closing morphological transforms are used in order to isolate bright (opening) and dark (closing) structures in images [2].

The large dimensionality of the hyperspectral image makes it harder for classification. A lot of redundancy in the data to be removed [3]. Complexity lies in the nature of high dimensional hyperspectral data and the consequent ground truth demand for supervised classification [4]. This aspect known as Hughes phenomenon implies that the required number of labelled training samples for supervised classification increases as a function of dimensionality. In remote sensing, the number of training samples available is limited and this limitation becomes relevant in case of high number of features. This problem is identified by a model that is less sensitive to Hughes phenomenon provided it should reduce the redundancy of the dataset available.

Several unsupervised and supervised algorithms have been developed for classification of multispectral images. However, these algorithms fail to deliver high accuracies for classifying hyperspectral images. The feature selection and extraction for SVM are also explained [5].SVM gives good results in the linear domain classification. But hyperspectral domain is a non-linear one. Non-linear domain can be converted into linear domain by using kernel trick.

Kernel methods provides a machine learning paradigm for building nonlinear methods from linear ones [6], [7]. Kernel methods intrinsically cope with nonlinearities in a very flexible way and are effective when dealing with low numbers of high-dimensional samples. Many types of kernels like linear, polynomial, radial basis function (RBF), sigmoid etc., are available. Selection of proper kernels gives proper results. The usage of SVM classifier for hyperspectral images is shown [8]. The Support Vector Machine with kernel trick has been successfully used in hyperspectral image classification [9].

For combining classification methods features such as pixel wise, extended morphological profile and feature extraction using genetic algorithm is used. Spectral and spatial information of hyperspectral data is needed for accurate classification. Basic morphological operations are applied to obtain morphological profiles. Principal component analysis is applied to hyperspectral images as a feature extraction technique [10]. To form extended morphological profile, principal component analysis and morphological profile is combined.

Local binary pattern is an effective operator for texture classification where the centre pixel is consider as a threshold for neighbourhood pixels. Local binary pattern is experimentally evaluated for land-use and land cover classification. Texture characterization approach performs well when combined with gray-level variance [11].

2. PROPOSED METHODOLOGY

2.1. Morphological Processing

Morphological processing is a non-linear operation related to the shape or morphology of features in an image. Mathematical morphology is a tool for extracting image components that are useful in the representation of region shape. The basic operators of morphology are dilation, erosion, opening and closing. When morphology is used, the fundamental operators are applied to a hyperspectral image with a set of particular shape known as structuring element.

The work of erosion operator in a hyperspectral data is, it provides an output where the structuring element fits the object in an image and the work of dilation is, it gives an output image where the structuring element hits the object in an image.

Opening smoothes the contour of an object and eliminate thin protrusions to isolate bright structures in an image while closing tends to smooth sections of contours and eliminating small holes, filling gaps in the contours to obtain dark structures in images. Basic morphological operation is applied to obtain morphological profile. Principal component analysis is applied to hyperspectral data. Extended morphological profile is obtained by combining principal component analysis and morphological profile.

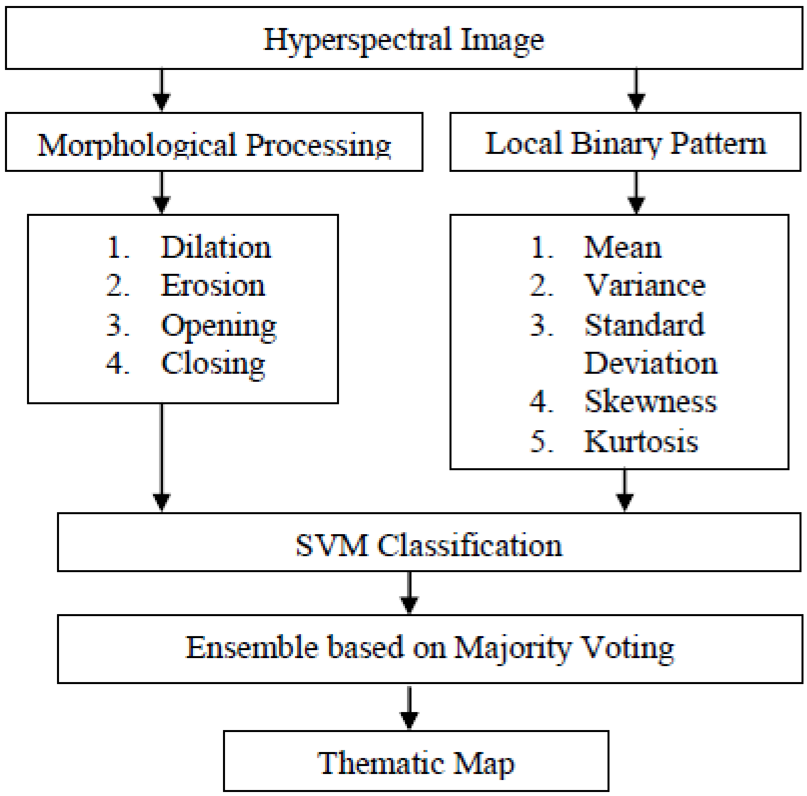


Figure 1. Proposed Methodology

2.2. Local Binary Pattern

Local Binary Pattern is an effective texture operator which labels the pixels by thresholding the neighbourhood of each pixel and obtained result is a binary number. An important property of local binary pattern is it has robustness to monotonic gray level changes due to illumination variations.

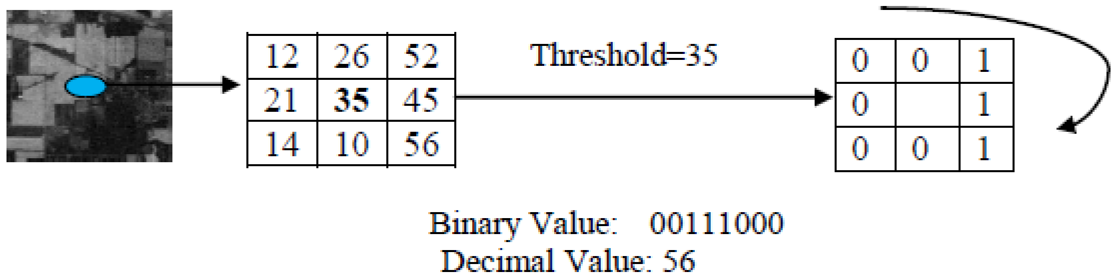


Figure 2. Concept of Local Binary Pattern

The concept of local binary pattern is follows. Consider a 3×3 matrix from hyperspectral data. From the matrix, centre pixel value is assigned as threshold for surrounding pixels. If surrounding pixel value is greater than threshold, the pixel value is set as 1 otherwise 0. From the surrounding pixel values obtain a binary value along clock-wise and replace the centre pixel value with decimal value obtained from binary value. Processed hyperspectral data is applied to statistical and co-occurrence features. Statistical features such as mean, variance, standard deviation and gray level co-occurrence features such as skewness, kurtosis is calculated. The formula for statistical features is shown in Table I.

Table 1. Formula for Statistical Features

Feature	Formula	Significance
Mean	$\mu_{ij} = \left(\sum_{1\le i\le M}\sum_{1\le j\le N} X_{ij}\right)/MN$	Measures average intensity
Variance	$\sigma_{ij} = \left(\sum_{1\le i\le M}\sum_{1\le j\le N} (x_{ij}-\mu_{ij})^2\right)^{0.5}/MN$	Measures contrast in image
Standard Deviation	$\sigma_{ij}^2 = \left(\sum_{1\le i\le M}\sum_{1\le j\le N} (x_{ij}-\mu_{ij})^2\right)/MN$	Measures higher contrast in image
Skewness	$skew(x_{ij}) = \left(\sum_{1\le i\le M}\sum_{1\le j\le N} (x_{ij}-\mu_{ij})^3\right)/\sigma_{ij}^3$	Finds pixel distribution skewed to left or right
Kurtosis	$kurt(x_{ij}) = \left(\sum_{1\le i\le M}\sum_{1\le j\le N} (x_{ij}-\mu_{ij})^4\right)/\sigma_{ij}4$	Measures distribution is tall or short compared to normal distribution

2.3 Support Vector Machine

Support Vector Machine is based on class separation through margins in which samples are mapped using kernel function to a higher feature space to achieve linear seperability of data. Popular kernels are Polynomial, Linear and Radial Basis Function. The ability of separation with nonlinear distributions is analyzed according to problem domain. Samples of two classes can be linearly separable by hyperplane in high feature space. SVM training consists of finding optimal hyperplane where distance between each can be maximized. Samples in margins are used to build classification decision boundary. From training samples, consider a set of n points as

$$D = \{(x_i, y_i) \mid x_i \in R^p, y_i \in \{-1,1\}\}_{i=1}^{n} \quad (1)$$

Where y_i is 1 or -1 for x_i class and x_i is p-dimensional vector.

Select two hyperplanes to separate hyperspectral data and distance between two plane is maximum. The hyperplane should satisfy the condition as w.x-b=0. The equation for hyperplane for separating the margins is w.x-b=1 or w.x-b= -1.Consider the constraint for margin to prevent data falling from one to another.$w.x_i-b \geq 1$ for 1st class and $w.x_i-b \leq -1$for 2nd class. The distance between two hyperplane is $\frac{2}{\|w\|}$ and $\|w\|$ is minimum.

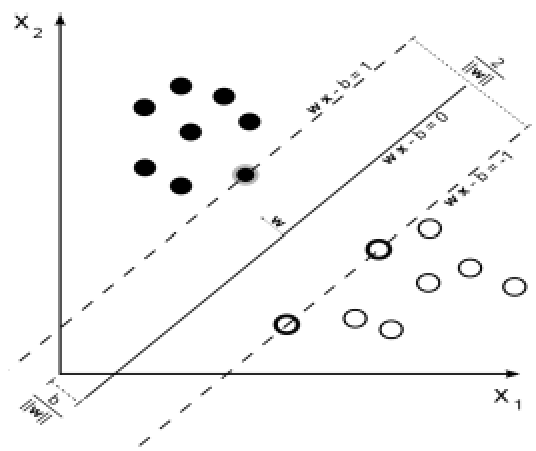


Figure 4. Hyperplane separation

2.4. Ensemble Classification

Ensemble classification method uses multiple classifiers to classify data by majority voting method. The output of classifiers is represented by soft labels with membership values of various classes. Decision profile is built from soft labels for supporting larger classes. From these, classifiers with different accuracy are obtained. Majority voting method is used for getting greater accuracy level in classifiers. This method is performed using genetic algorithm.

The process of genetic algorithm is selection, crossover and mutation. At first initial population is selected with randomly selected individuals from morphological profile and local binary pattern. Calculate the fitness of each chromosome in the population. Each chromosome encodes a binary string. Each bit in the string will shows the characteristics of the solution and a value corresponding to the fitness function. Value of fitness is assigned to each solution depending on how close to solve the problem.

3. Experimental Design

The Experiments were carried on two datasets such as, Indian Pines and Pavia University taken by AVIRIS(Airborne Visible/Infrared Imaging Spectrometer) and ROSIS(Reflective Optics System Imaging Spectrometer) sensor.

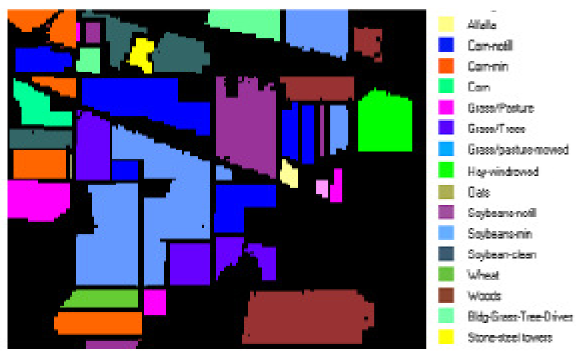
i. The Indian Pines Dataset is an agricultural area recorded over Northwestern Indiana, with145 x 145 pixels and a spatial resolution of 20m per pixel having 220 channels.

ii. The Pavia University dataset is an urban area recorded over the University of Pavia, Italy. The image is composed of 610×340 pixels with spatial resolution of 1.3m/pixel and a spectral range of 0.43µm to 0.86µm having 103 bands.

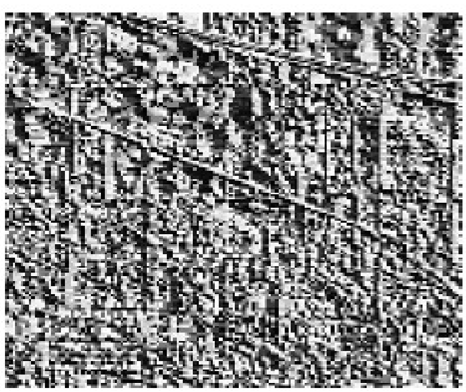
At first dilation, erosion, opening and closing operations are performed. Statistical features and co-occurance are calculated by using the formulas. By using majority voting using genetic algorithm best feature is identified for classification. As the size of training data is important in remote sensing images, experiments were carried out by different training sizes for evaluation. 30% training samples were used for final phase of testing.

4. RESULTS AND DISCUSSION

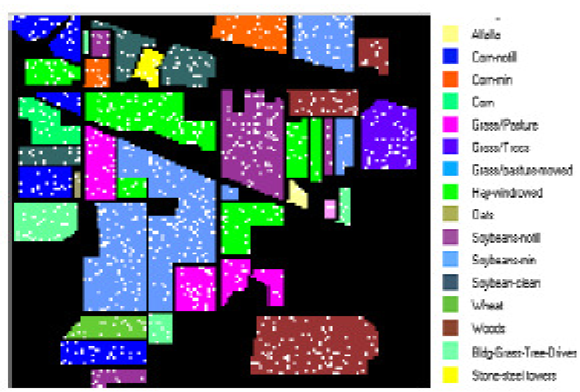
(a) ROSIS Indian Pines



(b) Ground Truth

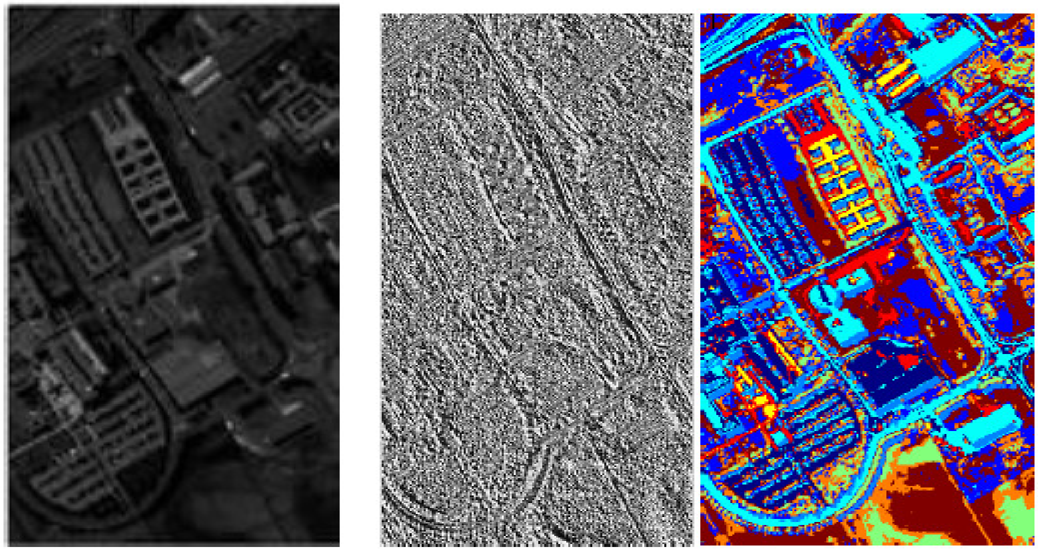


(c)Local Binary Pattern



(d) Classification map

Figure 5. Results for AVIRIS Indian Pines dataset



(a) (b) (c)

(b) Figure 6. (a) ROSIS Pavia University (b) Local Binary Pattern (c) Classification Map

From table 2, classes like grasspasture and grasstress have good accuracy level compared to other classes. Accuracy table for ROSIS Pavia university is shown in table 3. From table 4 classes like baresoil and gravel have better accuracy compared with other classes. From 5 baresoil and bitumen have good accuracy level compared to other classes. After obtaining the feature values, best feature is selected and selected feature is classified using support vector machine to obtain the classification map

Table 2. Accuracy table for Various classes in AVIRIS Indian Pines Dataset using SVM(%)

Class Name	Dilation	Erosion	Opening	Closing	Mean	Variance	Standard Deviation	Kurtosis	Skewness
Alfalfa	70.98	71.56	69.23	69.71	71.78	60.92	62.54	75.96	64.65
Cornnot	92.76	93.97	84.12	91.94	92.43	80.98	86.96	84.12	97.85
Cornmin	80.72	82.68	75.56	79.53	83.74	70.56	73.65	75.16	72.98
Corn	91.86	93.54	90.47	89.52	93.66	82.99	92.19	86.91	83.65
Grasspasture	96.52	97.15	91.75	95.29	97.08	90.18	94.25	95.12	92.75
Grasstrees	98.59	98.63	97.23	90.74	97.64	98.43	98.96	96.15	97.74
Grasspasture	62.70	65.79	54.12	53.14	66.53	55.98	58.74	75.82	55.78
Hay	86.59	89.34	84.92	85.41	87.42	76.25	75.79	78.95	88.92
Oats	79.91	82.18	81.73	82.59	81.53	61.82	82.96	70.41	90.85
Soybeannot	50.94	59.87	54.97	52.40	57.76	70.63	55.95	40.76	58.74
Soymint	71.99	82.97	75.64	76.35	83.92	81.58	87.95	78.68	87.52
Soyclean	69.42	74.48	70.09	75.12	76.54	59.60	65.74	69.87	66.74
Wheat	72.84	78.56	76.52	82.18	79.12	66.86	69.33	71.49	81.74
Woods	79.25	84.63	82.41	85.15	83.19	82.91	86.77	72.96	77.89
Trees	76.81	80.84	67.88	69.34	81.29	73.54	77.56	88.93	72.18
Steel	66.72	71.96	56.38	68.75	73.85	52.52	76.32	82.68	88.90
Overall Accuracy(%)	**78.03**	**81.75**	**75.81**	**77.94**	**77.03**	**72.85**	**77.85**	**77.74**	**79.93**

Table 3. Accuracy table for ROSIS Pavia university using SVM(%)

Class Name	Dilat ion	Erosion	Opening	Closing	Mean	Variance	Standard Deviation	Kurtosis	Skewness
Asphlat	75.23	76.03	75.85	78.25	81.24	76.52	77.58	62.89	61.30
Meadow	89.56	90.25	89.93	87.23	89.56	83.45	85.27	88.98	85.96
Gravel	59.30	61.56	62.58	65.45	75.85	67.20	69.75	52.74	49.36
Trees	65.69	67.85	68.96	6345	75.87	78.58	79.85	54.03	58.32
Sheets	82.95	83.69	82.89	87.85	93.54	88.96	89.74	80.25	82.63
Bare soil	91.58	85.09	87.41	82.47	86.43	87.23	89.57	91.02	91.78
Bitumen	87.96	89.54	90.74	86.56	89.21	87.41	84.12	85.64	84.10
Bricks	78.54	80.23	81.45	79.85	82.78	82.45	81.23	62.17	68.33
Shadow	50.96	55.89	60.74	60.85	76.20	65.52	74.92	45.95	66.54
Overall Accuracy(%)	**75.75**	**76.68**	**77.83**	**76.88**	**83.40**	**79.48**	**81.33**	**69.29**	**72.03**

Table 4. Accuracy table for ROSIS Indian pines using Ensemble Classification (%)

Class Name	Dilation	Erosion	Opening	Closing	Mean	Variance	Standard Deviation	Kurtosis	Skewness
Alfalfa	94.78	89.74	85.72	89.68	82.62	83.54	87.58	85.54	89.74
Cornnot	93.75	97.86	97.88	87.82	97.8	97.78	97.68	91.74	92.46
Cornmin	94.10	94.16	84.18	94.08	94.06	94.12	84.14	78.23	80.25
Corn	96.26	86.28	96.32	93.36	96.38	96.85	86.42	82.41	90.78
Grasspasture	92.12	99.01	99.03	99.11	99.05	99.08	85.09	96.34	91.78
Grasstrees	99.95	99.92	99.94	99.42	99.25	99.65	85.74	98.54	92.82
Grasspasture	98.23	98.36	88.68	88.45	98.52	98.54	92.68	82.74	83.89
Hay	96.51	86.58	96.5	86.53	96.75	86.69	85.71	92.71	96.78
Oats	89.94	89.98	85.78	82.85	87.41	86.98	83.57	78.71	85.49
Soybeannot	95.63	74.63	85.53	92.74	95.87	94.38	92.54	89.78	92.74
Soymint	89.69	89.75	87.58	87.96	84.32	87.96	87.92	92.56	93.78
Soyclean	87.29	84.53	84.89	87.65	96.84	95.6	93.68	78.63	96.14
Wheat	89.08	85.07	83.10	82.18	89.87	97.92	96.51	89.74	97.56
Woods	94.31	94.85	84.72	94.88	92.71	82.34	93.87	93.84	92.18
Trees	88.37	97.41	97.56	97.78	97.99	86.58	96.59	96.78	78.85
Steel	81.61	85.59	99.64	84.87	91.71	78.52	98.10	87.12	89.92
Overall Accuracy(%)	**92.60**	**90.85**	**91.06**	**90.58**	**93.82**	**91.65**	**90.48**	**88.46**	**90.32**

Table 5. Accuracy table for ROSIS Pavia University Using Ensemble Classification (%)

Class Name	Dilation	Erosion	Opening	Closing	Mean	Variance	Standard Deviation	Kurtosis	Skewness
Asphlat	86.96	89.63	90.54	90.01	91.85	91.05	92.47	86.56	82.11
Meadows	68.65	96.35	97.10	94.59	97.54	95.78	94.50	94.68	93.52
Gravel	86.41	88.98	89.78	89.66	85.78	92.02	83.78	75.40	72.96
Trees	87.30	90.58	91.56	91.58	93.99	93.07	90.51	89.45	82.15
Sheets	9.69	95.75	97.58	96.89	97.45	98.07	97.85	96.65	90.19
Bare soil	95.98	96.87	95.03	97.89	92.12	90	95.30	96.09	97.63
Bitumen	92.74	97.63	92.13	92.78	85.74	84.65	89.76	98.78	94.58
Bricks	87.51	91.78	91.78	87.45	90.52	89.25	86.78	86.05	88.74
Shadow	79.69	80.30	84.12	79.32	87.68	80.54	84.48	85.65	65.30
Overall Accuracy (%)	**89.21**	**89.45**	**92.06**	**91.13**	**91.40**	**90.68**	**90.60**	**89.92**	**85.24**

5. CONCLUSION

Hyperspectral sensors collects images in large number of spectral channels. Detailed spectral signature for every spatial location gives more information about an image provides differentiate between materials and objects. Morhological profile and local binary pattern techniques given high classification accuracies for hyperspectral data. In this work, a new method for classificaction of hyperspectral images is used. Basic operations in morphological processing is performed and statistical features is also done for obtaining of features. Genetic algorithm is used for selecting best features among different features. Support vector machine is used for classifying the various types of classes present in the dataset.Proposed method produces accuracy as 93% for Indian pines and 92% for Pavia University.

REFERENCES

[1] Shwetank, Jain Kamal & BhatiaK.J, (2010) "Review of Crop Identification and Classification using Hyperspectral Image Processing System", International Journal of computer Science and Communication, vol.1, no.1,pp.253-258,2002

[2] J.Benediksson, J.Palmason and J.R.Sveinsson, and J. Chanusssot, (2005) "Classification of hyperspectral data from urban areas based on extended morphological profile."IEEETrans.Geosci.Remotesens., vol .43, no.3, pp480-491,

[3] F.Melgani and L.Bruzzone, (2004) "Classification of hyperspectral remote sensing images with support vector machines" IEEE Transactions on Geoscience and Remote Sens., vol.42, no.8,pp 1778-1790,

[4] Y.Tarbalka, M.Fauvel, J.Channusot, and J.Benediktsson, (2010) "SVM and MRF based method for accurate classification of hyperspectral images," IEEE Geo science Remote sensing Lett., vol.3 no.7, pp.736-740,

[5] G. Breim, J. Benediksson and J.Sveinsson, (2002) " Multiple classifiers applied to multisource remote sensing data" IEEE Geo science Remote sensing vol. 40, no. 10,pp.2291-2299,

[6] B.Scholkopf, A.Smola, (2002) "Learning with Kernels-Support Vector Machines, Regularization, Optimization and Beyond" MIT press series,

[7] G.Camps-Valls,J.L.Rojo-Alvarez and M.Martinez-Romon,(2007) "Kernel Methods in Bioengineering, Signal and Image Processing", Idea Group Publishing, Hershey, PA,

[8] Farid Melgani, Lorenzo Bruzzone, (2004) "Classification of Hyperspectral Remote Sensing Images with Support Vector Machines" IEEE Trans. Geoscience Remote Sensing, vol.42,no.8,pp.1778-1790,
[9] G.Camps-valls, L.Bruzzone, (2005) "Kernel based methods for hyperspectral image classification," IEEE Transactions on Geoscience Remote Sens.vol.43,no.6,pp.1351-1362,
[10] Andrey Bicalho Santos, Arnaldo de Albuquerque araujo, David Menotti, (2013) "IEEE Journal of selected topics in applied earth observations and remote sensing" vol.6, No.3,
[11] M. Muscia , R. Q. Feitosaa, , M. L. F. Vellosob, T. Novackc, G. A. O. P. Costa, (2012) "Texture Characterization in Remote Sensing Imagery using Binary Coding Techniques. Proceedings of the 4th GEOBIA, - Rio de Janeiro - Brazil. p.437

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