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Modified RVM based Land Cover Classification of Multispectral Satellite Images

D. Menaka* and L. Padma Suresh**

Abstract : This paper presents a multispectral image classification method based on relevance vector machines (RVMs). The existing algorithms for land mapping involve approaches based on Support vector machine (SVM). The Relevance Vector Machine (RVM) is the recently used classification scheme which produces accurate results. It is shown that the classification accuracy is best obtained using RVM-based classification, with significantly smaller relevance vector rate and therefore it performs much faster testing time compared with SVM-based classification. The work involves a Bayesian framework in attaining sparse solutions in the classification task. The various performance indices evaluate the classifier accuracy and the comparable results prove the proposed classifier works better.
Keywords : Multispectral satellite images, wavelet transform, Modified-RVM.

1. INTRODUCTION

Over the recent decades, vast extents of multispectral satellite images have become available, enabling land mapping and geographic measurements. But the recent problem is that how these images can be computerized and face challenges in the field of remote sensing [1, 2]. With increase in spatial resolution, the various land classes in an image such as vegetation, buildings, water, barren land, mountain etc., were difficult to identify. In literature, many methods regarding land cover classification exists whereas Relevance Vector Machine (RVM) classifier produces better accuracy. The RVM is modified adding more sparse vectors in determining sparse regression matrix after extracting the land features. The proposed modified RVM classifier is compared to different supervised classifiers such as KNN, SVM and Sparse SVM classifier. The proposed classifier involves more sparse nature which comprises of reduced reluctance vectors during training. The time complexity and error rate is reduced in the proposed classification scheme with improved accuracy and classification efficiency. Chen et. al [3] proposed the relevance vector machine to classify the multispectral images. Here during the training period, the pixels need more time to train the data without incorporating sparsity. This algorithm does not consider the pixels scattered between the clusters.

The remaining structure of the paper is explained as below: Section II comprises of initial processing of the input original image which includes preprocessing and feature extraction steps. The classifier algorithm with RVM sparse coding is discussed in Section III. The Section IV is devoted to experimental results and comparison analysis. Finally Section V is ended with conclusion of the work done.

* Asst.Professor, Dept. of Electronics and Instrumentation Engineering, Noorul Islam University, Kumaracoil, Thuckalay, India. *E-mail : menakaberita@gmail.com*

** Principal, Mar Baselios College of Engineering and Technology, Kollam, India. *E-mail : suresh_lps@yahoo.co.in*

2. PROPOSED WORK

In this work, the RVM based classification algorithm was applied to several remote sensing images which improve the accuracy qualitatively and quantitatively. The paper is structured as follows: Brief description on feature extraction, then focussed on the classification results compared with other classifiers.

2.1. Pre-processing

The pre analysis of the original multispectral image is done using Gaussian filter which increases the image quality. The presence of noise depends on convolution of image pixel with the 2D Gaussian function that depends on the kernel coefficients. The 2D Gaussian function is given below:

$$\mathrm{G}(x, y) = \frac{1}{2\Pi\sigma^2} e^{\frac{x^2+y^2}{\sigma^2}} \tag{1}$$

where the standard deviation of the Gaussian distribution matrix is represented by σ where the kernel coefficients depends on σ.

2.2. Wavelet Transform

This work is explored by the advantages of Wavelet Transform by incorporating it as a preprocessor before classification. The decomposed image constitutes of an approximation and three detailed information sub bands. The approximation band is decomposed and the first level decomposition is illustrated in Fig.1. The preprocessed image is decomposed into approximation, horizontal, vertical and diagonal sub bands as in Fig. 2. From the decomposed detail coefficients, Wavelet Coefficient Co-occurrence Matrices (WCCMs) features are extracted. The co-occurrence matrices are also used in determination of second-order statistical features as similar to GLCM [4-6].

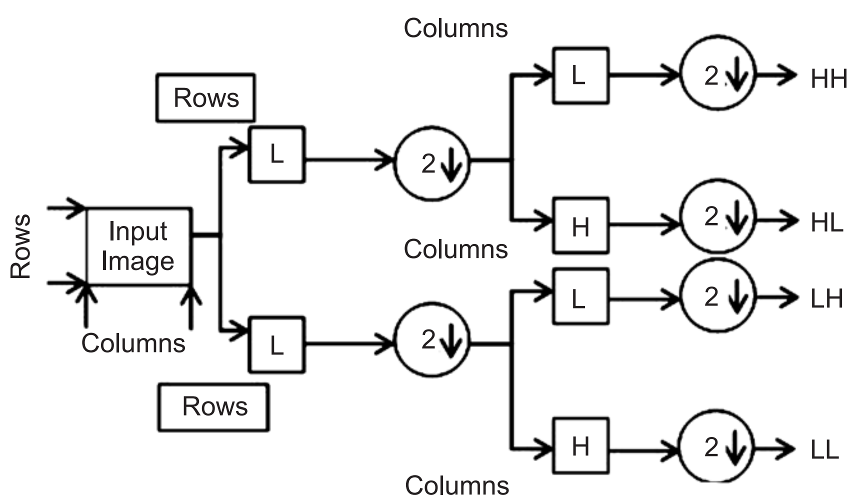


Figure 1: Decomposition in the first level of wavelet transform

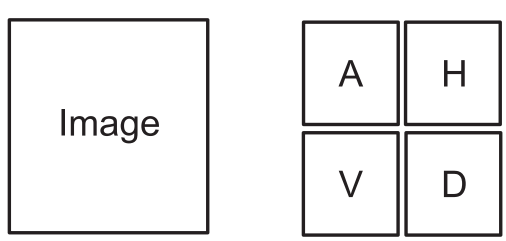


Figure 2: Representation of input image and its decomposition into sub bands

The data base comprises of the wavelet co-occurrence features such as contrast, correlation, energy, and homogeneity determined from the co-occurrence matrix C (i, j). Given an image I of size N x N, the co-occurrence matrix C is defined as,

$$\mathrm{C}(i, j) = \sum_{x=1}^{\mathrm{N}}\sum_{y=1}^{\mathrm{N}}\begin{cases}1, & \text{if } \mathrm{I}(x,y) = i \text{ and } \mathrm{I}(x+\Delta_x, y+\Delta_y) = j \\ & 0, \text{otherwise}\end{cases} \tag{2}$$

The calculated statistical features found from the co-occurrence matrices in the directions 0°, 45°, 90° and 135°, were described by Eqs. 3-6.

$$\text{Contrast} = \sum_{i,j=0}^{\mathrm{N}} (i-j)^2\, \mathrm{C}(i,j) \tag{3}$$

$$\text{Correlation} = \frac{1}{\mathrm{N}-1}\sum\left(\frac{x-\bar{x}}{\sigma_x}\right)\left(\frac{y-\bar{y}}{\sigma_y}\right) \tag{4}$$

$$\text{Energy} = \sum_{i=1}^{\mathrm{N}}\sum_{i=1}^{\mathrm{N}} \mathrm{C}(i, j)^2 \tag{5}$$

$$\text{Homogeneity} = \sum_{i,j=0}^{n} \frac{1}{(1+(i-j)^2)\, \mathrm{C}(i, j)} \tag{6}$$

The detailed procedure of the decomposition process of the discrete wavelet transform is illustrated in Figure 1 and Figure 2. The co-occurrence matrices are generated for the offsets {[0 1], [–1 1], [–1 0], [–1 –1]} representing one neighboring pixel in possible four directions [1]. Here the neighboring immediate pixels (2, 1) of the preprocessed image are exposed in P_H concurrence matrix as 3, due to 3 occurrences with pixel intensities 2 and 1 adjacent to each other. The statistical features obtained from the four matrices are used for classification by applying to the proposed classifier.

3. MODIFIED RVM CLASSIFIER

Relevance Vector Machine (RVM) is a statistical learning method proposed by Tipping (2001) constitutes a Bayesian approximation for solving nonlinear regression models and is often used for classification and pattern recognition [8]. RVMs offer excellent sparseness characteristics and robustness produces probabilistic outputs that permit the capture of uncertainty in the predictions compared with SVM [9-11].

The recent machine learning methodology based on kernel is the RVM (Relevance Vector Machine) introduced by Tipping [8-9], as a Bayesian function instead to the SVM. The sparseness is achieved by means of sparse distribution of weights in the sparse regression matrix. Let's consider the set of sample input vectors $\{x_n\}_{n=1}^{\mathrm{N}}$ where with targets $\{t_n\}_{n=1}^{\mathrm{N}}$. The targets specify the number of classes which were the real values [12,13]. The accurate prediction of target t is based on the objective function $y(x)$ defined over the regression sparse matrix,

$$y(x\,;w) = \sum_{i=1}^{\mathrm{M}} w_i \phi_i\,(\mathrm{X})\, \mathrm{W}^{\mathrm{T}}\, \varphi(\mathrm{X}) \tag{7}$$

The objective function is determined based on the weighted sum of the sparse relevance vectors where M is the size of sparse matrix provided $\varphi(\mathrm{X}) = (\phi_1(x), \phi_2(x), \ldots, \phi_{\mathrm{M}}(x))^{\mathrm{T}}$ and weight $\mathrm{W} = (w_1, w_2, \ldots, w_{\mathrm{M}})^{\mathrm{T}}$. The training of RVM used for classification is performed with relevance vectors using RVM algorithm. The sparse RVM utilizes the kernel ϕ_m specified in the below equation:

$$y(x\,;w) = \sum_{m=1}^{\mathrm{M}}\sum_{i=1}^{\mathrm{N}} \mathrm{W}_{mi}\, \phi_m\,(x-x_i) \tag{8}$$

The proper selection of the kernel function depends upon the sparseness property of the RVM at each weight.

For N set of training pairs $\{x_n, t_n\}_{n=1}^{N}$ with weights W = $(w_1, w_2, \ldots, w_N)^T$, the values $y(x)$ produces a new data with sparse data or non-zero elements [14,15]. A two class image classification is considered with training values X = $\{x_1, \ldots x_N\}$. The target specifying the number of class labels is $t = \{t_1, \ldots t_N\}$ where $t_i \in \{0,1\}$.

The likelihood function based on the Bernoulli distribution can be expressed as:

$$p\left(\frac{t}{w}\right) = \prod_{i=1}^{N} \sigma\{(y(x_i))\}^{t_i} \left[1 - \sigma\{(y(x_i))\}\right]^{1-t_i} \tag{9}$$

where w, the set of adjustable weights and $\sigma(y)$, the logistic sigmoid function applied to $y(x)$ and is given as:

$$\sigma(y(x)) = \frac{1}{1 + \exp(-y(x))} \tag{10}$$

Similarly modifying (10), multiclass classification can be obtained from the likelihood function given as:

$$p\left(\frac{t}{w}\right) = \prod_{i=1}^{N} \prod_{j=1}^{J} \sigma\left\{(y_j(x_i))\right\}^{t_{ij}} \tag{11}$$

where an iterative method is used to obtain $p\left(\frac{t}{w}\right)$. For the target '$t$' the proposed classifier produces multiple outputs $y_j(x)$ for the set of adjustable weights 'w' [16-18]. The objective function can be maximized by the equation below:

$$f(w_1, w_2, \ldots, w_N) = \sum_{i=1}^{N} \log p\left(t_i \mid w_i\right) + \sum_{i=1}^{N} \log p\left(w_i \mid \alpha_i *\right) \tag{12}$$

where α_i^* represents the maximum a posteriori (MAP) estimate of the hyperparameter α_i and $\alpha = (\alpha_1, \alpha_2, \ldots, \alpha_N)^T$.

In eq (12), the first term represents the likelihood of the class labels whereas the second term represents to the prior 'w_i'. In the solution obtained, the gradient of 'f' with respect to 'w' is determined and the training samples having non-zero coefficients 'w_i' called relevance vectors will provide the decision function [19-22].

4. RESULTS AND DISCUSSION

The proposed work is summarized and also the extensive of the work is briefly discussed here. The computations for different classifiers like KNN, MSVM [7] and Sparse SVM were compared with the proposed modified RVM classifier and were implemented in MATLAB software and the results were evaluated with various parameters.

4.1. Experimental Results

In this paper a supervised classification method is implemented. The accuracy of the proposed method is experimentally verified testing with many multispectral remote sensing images and the result is discussed. The satellite image chosen to discuss is the input SPOT satellite image of 500x500 pixels which is the coast of the Persian Gulf at Abu Dhabi (figure 3).

The Gaussian filtered image is decomposed by wavelet transform where statistical training features are obtained from the detailed sub bands and applied to the classifier. Figure 4 shows the classified output images showing various land classes like water, buildings, land and vegetation.

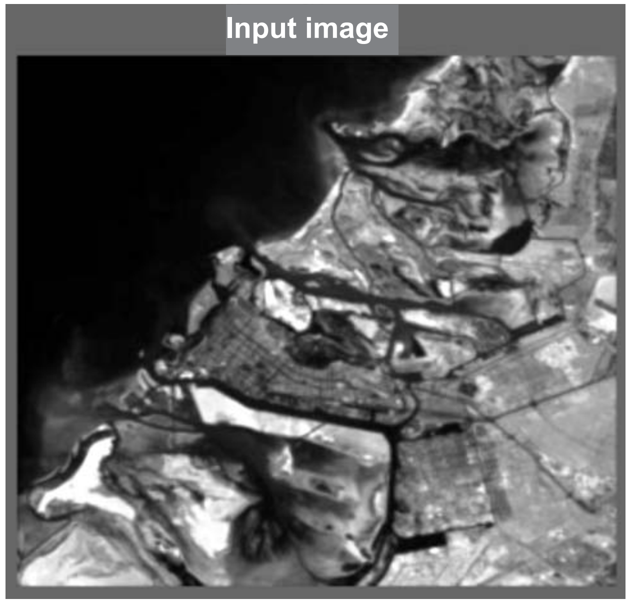


Figure 3: Input Multispectral satellite image

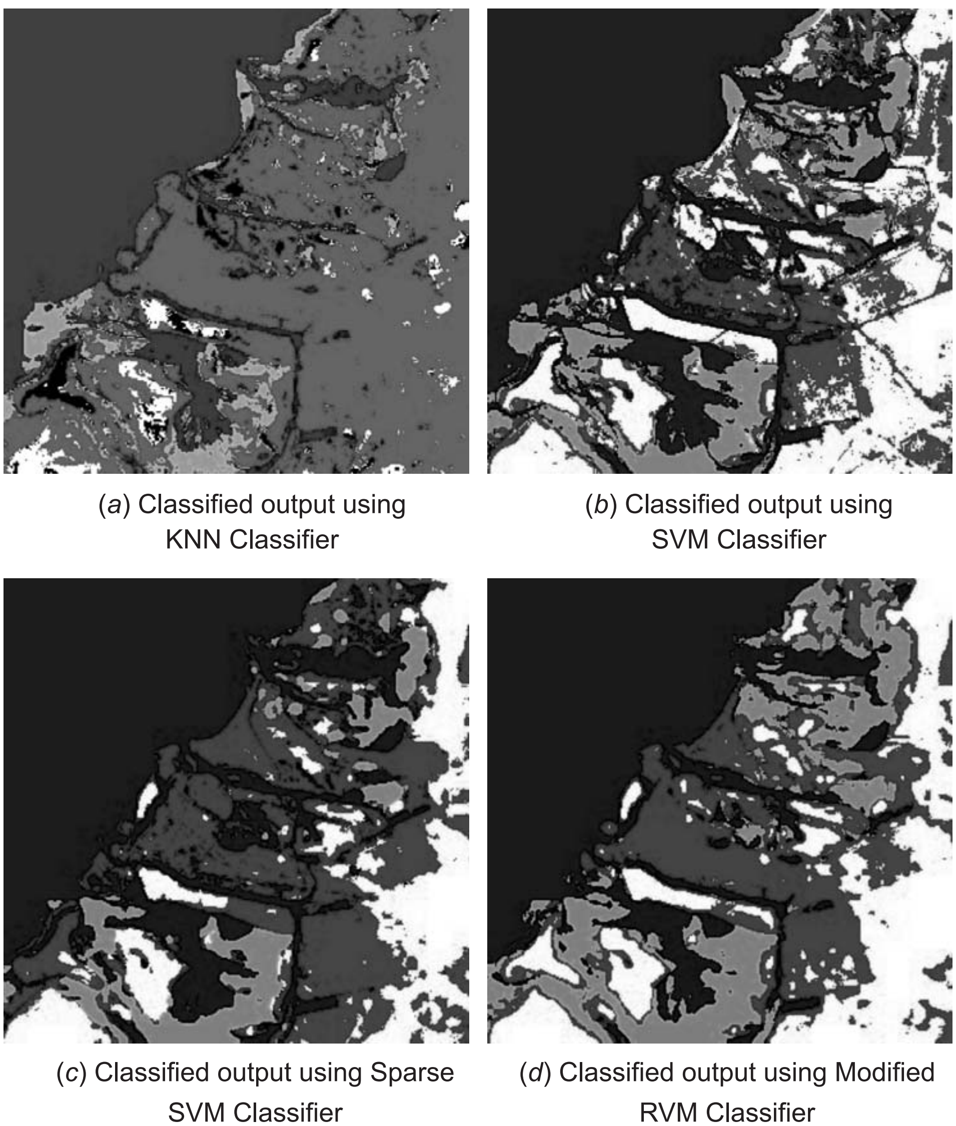
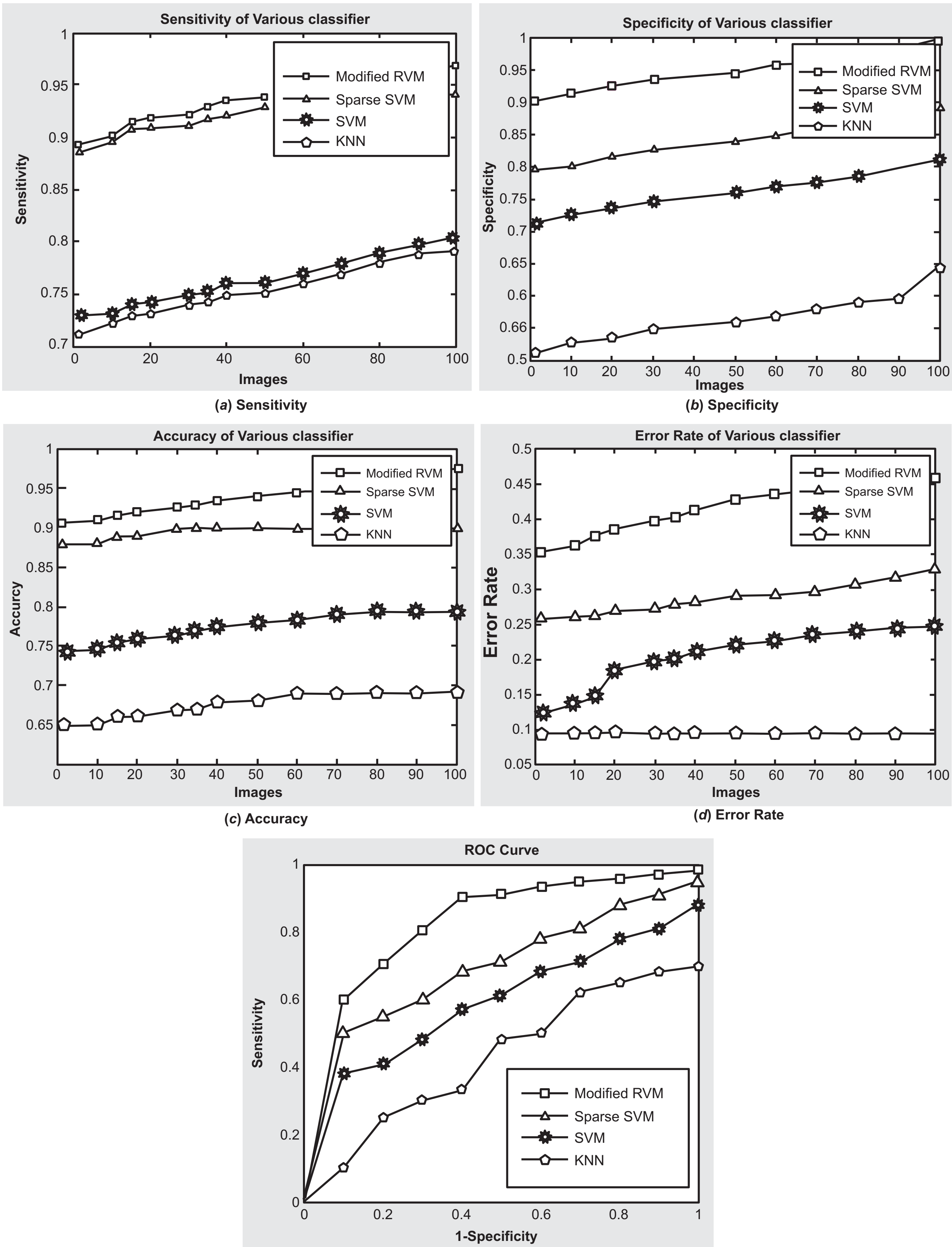


Figure 4: The classification results of different techniques for the original Coast of Persian Gulf, Abu Dhabi image (blue denotes water, red-buildings, yellow-land, green-vegetation zones)

4.2. Performance Evaluations



(*a*) Sensitivity

(*b*) Specificity

(*c*) Accuracy

(*d*) Error Rate

(*e*) ROC Curve

Figure 5: Performance Evaluation Graphs

The performance evaluation of the proposed technique compared with other classifiers is explained in this section. The performance measures such as sensitivity, specificity, accuracy and error rate were evaluated and discussed considering an average of 100 training samples. Sensitivity measures the proportional value of correctly identified land use pixels whereas specificity measures the proportional value of correctly identified land cover pixels. The performance analysis graphs (figure 5), it is inferred that the proposed classifier gives accurate land cover classified output as compared with other existing methods.

Table 1 and 2 explains the performance evaluation measures and the accuracy statistics of the proposed classifier compared with other classifiers.

Table 1

Performance Evaluation measures for different Classifiers

Classifiers	*Accuracy (%)*	*Error Rate*	*Sensitivity*	*Specificity*
Modified RVM	91.79	0.0954	0.946	0.922
Sparse SVM	86.49	0.2484	0.891	0.8319
MSVM	75.68	0.2532	0.736	0.7397
KNN	56.76	0.4486	0.721	0.5597

Table 2

Accuracy statistics of Land cover maps generated by different methods

Classifiers		*KNN*	*MSVM*	*Sparse SVM*	*Modified RVM*
Overall Accuracy		67.1094	86.3167	95.0242	97.4910
Kappa Coefficient		0.5430	0.8119	0.9305	0.9500
	Land Class				
Producer Accuracy	Building [red]	99.72	75.03	93.17	97.63
	Vegetation [green]	71.92	97.84	100	100
	Water [blue]	83.13	86.85	100	100
	Land [yellow]	9.63	94.09	89.28	93.39
User Accuracy	Building [red]	53.16	93.4	90.64	100
	Vegetation [green]	57.22	68.84	100	100
	Water [blue]	100	92.49	94.71	100
	Land [yellow]	100	82.44	99.05	97.24

The results were evaluated and compared with the ground truth pixels for each land class. As SVM is complex in terms of the number of kernel functions needed for classification [15], the RVM is preferable in real time land cover classification that require low complexity. It is however noted that the increased training time of RVM does not significantly affects the classification accuracy.

In table 2, the accuracy using the methods KNN, SVM and Sparse SVM are much lower than the results obtained using the proposed modified RVM classifier. Compared with the existing classifiers, the Kappa Coefficient of the proposed modified RVM classifier increases by 0.041, 0.143 and 0.237 respectively, whereas the overall accuracy increases by 0.093, 0.159 and 0.283 respectively. In addition, the producer accuracy and user accuracy are also noted to be improved obviously. The overall accuracy and the kappa coefficient from table 2 shows that the state of the art proposed classifier is best suited for multispectral land cover classification.

5. CONCLUSION

The modified sparse based RVM classifier for land cover classification on remote sensing images is proposed and implemented in this paper. The proposed method could successfully perform classification of remote sensing images. During the training period, the modified RVM requires a reduced number of relevance vectors with more sparse representation property. The experimental results demonstrate the effectiveness of the proposed classification scheme and ensure accurate classification for different multispectral satellite images.

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