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PERFORMANCE EVALUATION OF SVM KERNELS ON MULTISPECTRAL LISS III DATA FOR OBJECT CLASSIFICATION

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Abstract- Object based classification plays an important role in every field. Support vector machine is the popular algorithm for object based classification. Support vector machine classifies the data points using straight line. Some datasets are impossible to separate by straight line. To cope with this problem kernel function is used. The central idea of kernel function is to project points up in a higher dimensional space hoping that separability of data would improve. There are various kernels in the LIBSVM package. In this paper, Support Vector Machine (SVM) is evaluated as classifier with four different kernels namely linear kernel, polynomial kernel, radial basis function kernel and sigmoid kernel. Several datasets are being experimented to find out the performance of various kernels of SVM .By changing the value of 'C' and γ varying results are observed. Among these RBF kernel with a value of C = 1000 and gamma=0.75 got an excellent accuracy of 99.1509%.The SVM-RBF kernel gave an edge over the other kernels with an accuracy of 99.1509% while linear at 98.9623%, polynomial at 98.6792% and Sigmoid at 98.5849%.

Index terms: SVM, LibSVM, Kernels, Object based classification, Transformed Divergence.

I. INTRODUCTION

Image Classification is an important step in the utilization of remote sensing data. Image classification can be defined as processing technique that applies quantitative methods to the pixels in the image to convert the digital values into feature classes or categories (Mahendra HN.et.al., 2015) [1].The categorized data thus obtained may then be employed to create thematic maps of the land cover present in an image. Classification includes determining an appropriate classification system, selecting training samples, image pre-processing, extracting features, selecting fitting classification approaches, post-classification processing and accuracy assessment. Numerous classification methodologies are available to classify the remotely sensed data and to generate a land cover map.[2] Many of these classical approaches are based on object identification and pattern recognition techniques like Maximum Likelihood classier (MLC), k-nearest neighborhood, minimum distance to mean, parallelepiped classifiers etc. Each of this classifier is based on a unique principle and assumption. The objective of this study was to evaluate various kernels of Support Vector Machine for effectiveness and prospects for object based image classification.. However Dixonet.al, 2008, noted that the accuracy improvement after using ANN is generally marginal and also the training time required is higher when compared to the Support Vector machines. SVM is a classification technique based on kernel methods that has been proved very effective in solving complex classification problems in many different application domains.[3]

L Bruzzone [4], has addressed the problem of the classification of RS images by SVMs. The authors propose a theoretical discussion and experimental analysis aimed at understanding and assessing the potentialities of SVM classifiers in hyper dimensional feature spaces. Then, they assess the effectiveness of SVMs with respect to conventional feature reduction based approaches. C.Huang et al [5-7] has explained the theory of SVM and provides an experimental evaluation of its accuracy, stability, and training speed in deriving land cover classifications from satellite images.

SVM classifier is used to perform supervised classification on RS image to identify the class associated with each pixel. It is derived from statistical learning theory [8-10]. It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyperplane, and the data points closest to the hyperplane are called support vectors. The support vectors are the critical elements of the training set. Gómez- Chova et.al. [11] Recently, more attention has been played to discriminative approaches, the Laplacian SVM (LapSVM), which deforms the kernel matrix of SVM with the relations found by building the graph Laplacian. Gianinetto et.al [12] demonstrated the capabilities of OBIA in multi-scale thematic classification using pan-sharpened RS imagery. The overall accuracy of 85% is achieved with a kappa value of 0.84.

The present study aims at analyzing the performance of four different SVM kernels [13] in classification of LISS III multispectral data. The four different kernels of SVM classifier namely linear, polynomial, radial basis function (RBF), and sigmoid are considered for the test. The mathematical representation of each kernel is listed below:

Linear $K(x_i,x_j) = x_i^T x_j$

Polynomial $K(x_i,x_j) = (g x_i^T x_j + r)^d, g > 0$

RBF $K(x_i,x_j) = \exp(-g\|x_i - x_j\|^2), g > 0$

Sigmoid $K(x_i,x_j) = \tanh(g x_i^T x_j + r)$

where: g is the gamma term in the kernel function for all kernel types except linear, d is the polynomial degree term in the kernel function for the polynomial kernel, r is the bias term in the kernel function for the polynomial and sigmoid kernels, g, d, and r are user-controlled parameters, as their correct definition significantly increases the accuracy of the SVM solution.

Deilmai *et al*. [14] verified the comparison of two classification methods (MLC and SVM) to extract land use and land cover in Johor Malaysia. An evaluation of accuracy of the classified images shows that the overall kappa and overall accuracy for SVMis 0.86 and 91.67% respectively. Abbas et al [15] described land use classification using a SVM and MLC in Qazvin, Iran, by TM images of Landsat 5. The evaluation results with the SVM an overall accuracy of 86.67 % and a kappa is 0.82 has a higher accuracy than the MLC algorithm in land use mapping.
Zylshal et al [16] verified the classification of vegetation and non vegetation of RS image. The overall accuracy for the vegetation and non vegetation classes using SVM and ANN are achieved

86% and 82% respectively. Yekkehkhany et al [17]. The proposed SVM with different kernels. RBF kernel yielded higher overall accuracy and kappa coefficient with 82.28 % and 0.79 respectively. Okwuashi et al [18] verified the different kernels and the polynomial kernel furnished the best accuracy with degree = 3 and C= 100, the kappa value is 0.8671

Izquierdo-Verdiguier et al., [19] addressed a novel semi supervised kernel partial least squares (KPLS) algorithm for nonlinear feature extraction to handle both land-cover classification and biophysical parameter retrieval issues. The method depends on fusion by the two kernel functions like the standard RBF kernel based on labeled information and a kernel directly learned by clustering the data many times and at different scales across the data manifold. In this approach the average gains in the root-mean-square error of +5% and reductions in bias estimates of +3% are received for biophysical parameter retrieval compared to standard PCA feature extraction.

Rupali et al. [20] explained a crop classification using SVM on LISS-III imagery. Many kernel functions are employed and compared in this study for mapping the input space with including linear, sigmoid, and polynomial and Radial Basis Function (RBF). Comparative analysis clearly explored that higher overall classification accuracy of 94.82% was observed in the kernel based SVM compared with that of traditional pixel-based classification is 69.64% using maximum likelihood classifier (MLC).

Vikas Sharma et al., [21] described the performance of SVM using Linear, Polynomial, Radial Basis Function (RBF) and Sigmoid. Overall accuracy (OA), Kappa Index Analysis (KIA), Receiver Operating Characteristic (ROC) and Precision (P) have been considered for evaluation of accuracy of SVM kernels.For investigation QuickBird sensor data and Landsat (ETM+) RS data are utilized.SVM with polynomial kernel got more accuracy than other kernels on both the images. Alim Samat *et al* [22] proposed SVM and state-of-the-art DA algorithms, including information-theoretical learning of discriminative cluster for domain adaptation (ITLDC), joint distribution adaptation (JDA), and joint transfer matching (JTM), are also considered. In addition to that, unsupervised linear and nonlinear subspace feature transfer techniques including PCA, randomized nonlinear principal component analysis (rPCA), factor analysis (FA) and non-negative matrix factorization (NNMF) are investigated and compared.

Samat et al., [23] proposed a design protocol to generate a more significant candidate sample set for active learning, set goal to reduce the unlabeled sample search complexity, and increase the performance of classification and accuracy. For comparison and validation purposes, six state-of-the-art AL methods were tested on real hyperspectral images with different resolution both with and without the proposed sample design protocol. Aiye Shi et al [24] proposed the algorithm with the combination of information and class separability as a new evaluation criterion for hyperspectral imagery. Moreover, the correlation between bands is used as a constraint condition. The differential evolution algorithm is adopted during the search of optimal band combination. The experimental results show that the band combination is better than the based on the information, weighted information and class separability.

Prasad et al [25] addressed the accuracy and reliability of SVM classifier for classifying multispectral RS image of Hyderabad area (INDIA) and also compare its performance with ANN classifier. Here Fuzzy Incorporated Hierarchical clustering has been proposed for clustering the multispectral satellite images into LULC sectors. Results illustrated the overall accuracies of SVM is 93.159% and ANN is 89.925% and the respective kappa values are 0.893 and 0.843. Benqin Song.et. al [26] developed a novel method for one-class classification (OCC) using a kernel sparse representation model for RS image . The proposed OCC method is evaluated and compared with several existing OCC methods in three different case studies.
Remaining sections give the details about the study area, methodology follows with experimental results and the conclusion.

II. STUDY AREA

The study area is apart of Visakhapatnam city of Visakhapatnam district, Andhra Pradesh, India. The study area falls in the latitude of 83°11’E to 83°18’E and longitude of 17°40’N to 17°45’N. The area contains many diversified features like sea water, three different vegetation types, fallow lands, barren areas, coal polluted water etc. The total area is 114.97 Square Kilometers.

The study area map is shown in fig 1. The LISS III satellite data of Resource sat 2 was used for the study. Linear Imaging Self Scanner III was launched by Indian Space Research Organization (ISRO) in the year April 20, 2011. It has a spatial resolution of 23.5m, spectral resolution of three bands ranging between 0.5 – 0.7µm

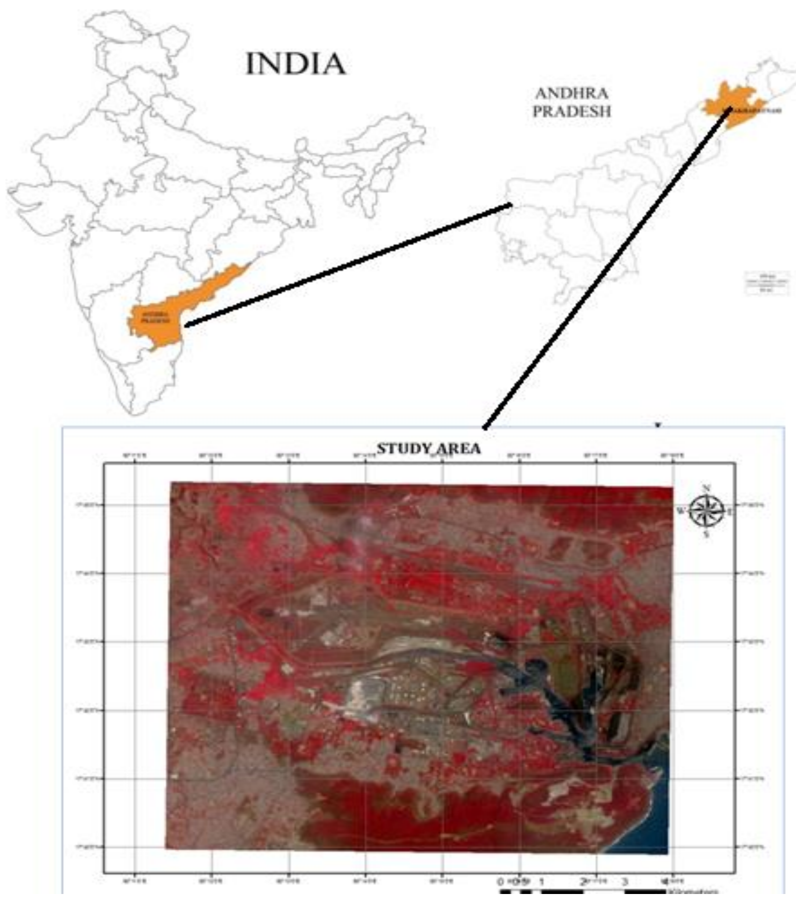

Figure 1 Study area of false color Vizag city

III. METHODOLOGY

The methodology involves five important steps. Radiometric and geometric corrections, Training sample selection, classification using various kernels, accuracy assessment and comparative analysis.

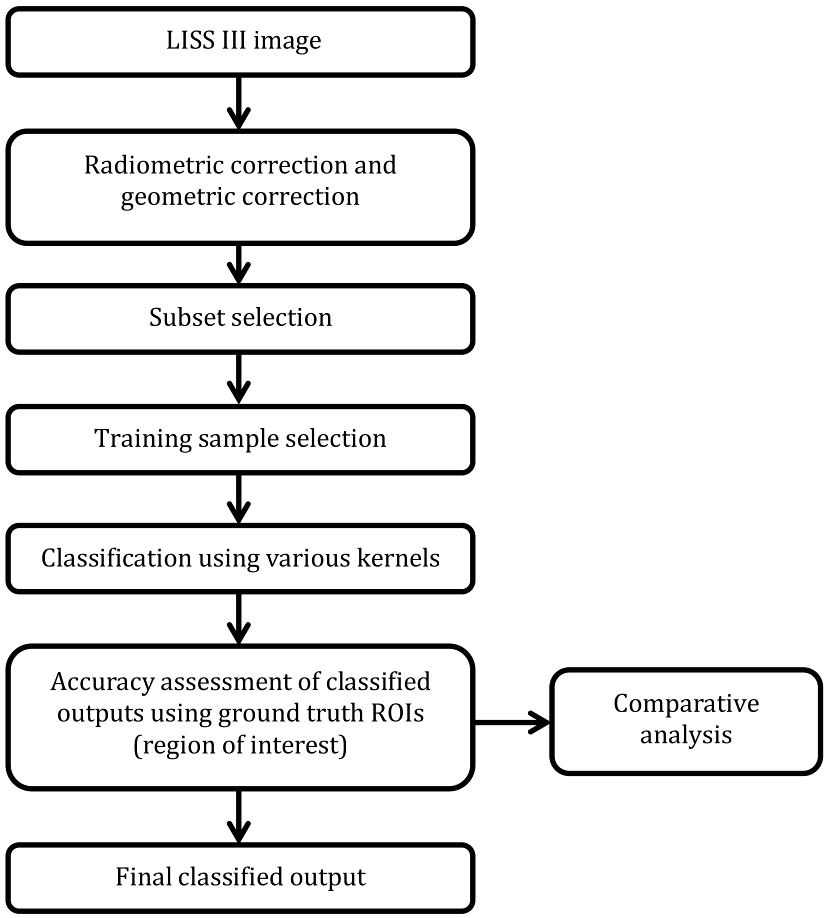

Figure 2.Methodology flow chart

The LISS III Resource sat data is initially checked for radiometric and geometric errors. A subset of the radio metrically corrected data is then considered for further processing. Training samples are collected from the data and are used for classification. Four different kernels of SVM are considered which are to be tested using different parameters. The pyramid levels and the classification probability threshold are kept zero for all the tests performed.

In the linear kernel, the penalty parameter is fine tuned. In the polynomial kernel, various combinations of gamma value from 0.25 to 1.0 and the polynomial levels from 1 to 4 are tested. In the sigmoid and radial basis kernel, four different gamma values of 0.25, 0.50, 0.75 and 1.0

are tested and the respective results are compared. Ground truth ROIs are collected from the image based on the Google earth historical images and field visits. The classified images are tested for accuracy with the ground truth ROIs and the percentages of each class and the overall accuracy are examined.

IV. EXPERIMENTAL RESULTS

The ROIs selected were checked for seperability using Transformed divergence (TD) method – which is one of the well-known and most reliable methods for calculating the ROI seperability. The results of TD are given in table 1. After obtaining a satisfactory seperability between the ROIs, the classification was carried out using the considered four kernels of SVM.

Table 1. Transformed Divergence seperability values for the considered ROIs.

Fallow land 1	Tin roofs/ ships	1.81898975
Vegetation	Vegetation 3	1.99344988
Barren area	Fallow land 1	1.99677355
old concrete surface	Fallow land 1	1.99957074
old concrete surface	Tin roofs/ ships	1.99996818
Fallow land 1	Fallow land 2	1.99999075
Built up	Fallow land 2	1.99999626
Fallow land 2	Tin roofs/ ships	1.99999853
Barren area	Fallow land 2	1.99999883
Built up	Tin roofs/ ships	1.99999907
Vegetation	Vegetation1	1.99999961
Vegetation1	Vegetation 3	1.99999977
Built up	Barren area	1.99999999
All other combinations		2

a. SVM – Linear Kernel

The Linear kernel was tested by varying penalty parameter of 100, 500 and 1000 .The results for each of these combinations are tested and finally at C=1000 got good results. The classified output RS image for linear kernel at C=1000 is shown in figure 3 and accuracy analysis of all the objects are calculated.

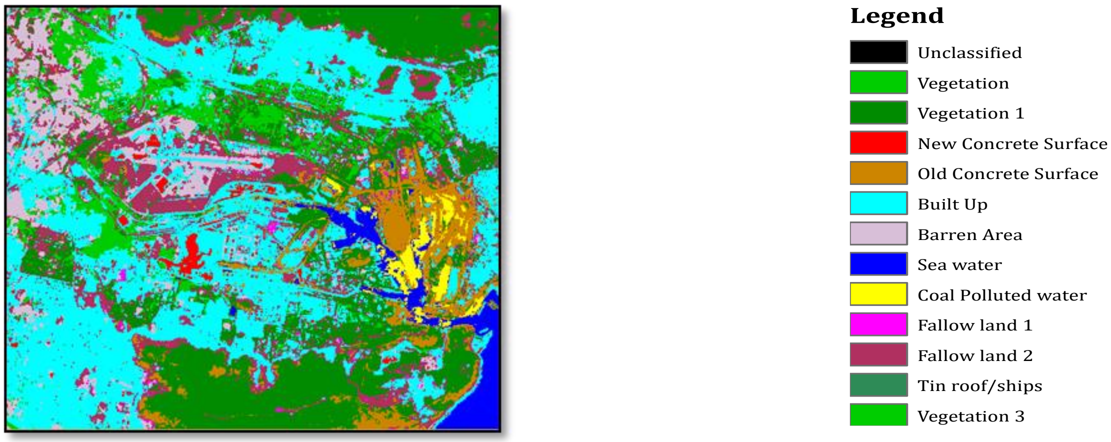

Figure 3. Classified output of Linear kernel with Penalty Parameter(C) of 1000

b. SVM – Polynomial Kernel

The polynomial kernel was applied by taking a constant gamma (γ) value of 0.25 and changing the polynomial degree (D) from 1 to 4. Consequently the 'γ' value is changed to 0.50, 0.75 and 1.00 and polynomial 'D' changing from 1 to 4. The result of each of these combinations is tested and finally at D is 3 and γ = 0.75 got good results. The classified output RS image for polynomial kernel at D=3 & γ=0.75 is shown in figure 4 and accuracy analysis of all the objects are calculated.

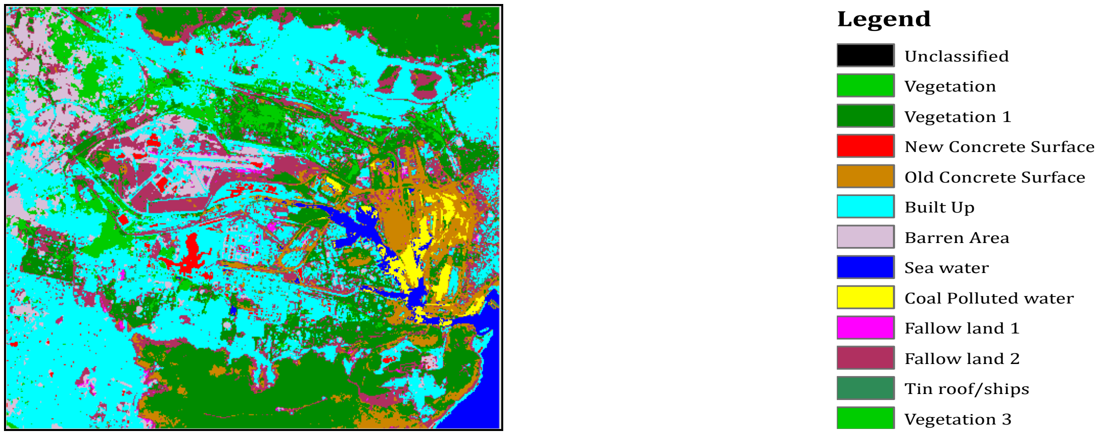

Figure 4. Classified output of polynomial kernel with D is 3,γ = 0.75.

c. Radial basis Kernel:

The radial basis kernel was tested by varying 'C' of 100,500,1000 and changing the γ value of 0.25, 0.50, 0.75 and 1.00. The results of each of these combinations are tested and finally at C=1000 & γ = 0.75 got good results. The classified output RS image for RBF kernel at C=1000 & γ=0.75 is shown in figure 5 and accuracy analysis of all the objects are also shown in figure 6.

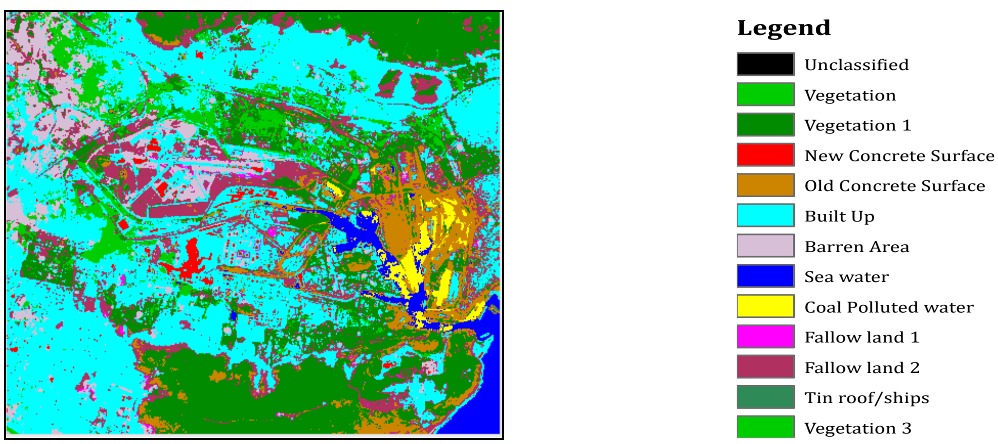

Figure 5 Classified output of radial basis kernel with C=1000,γ = 0.75.

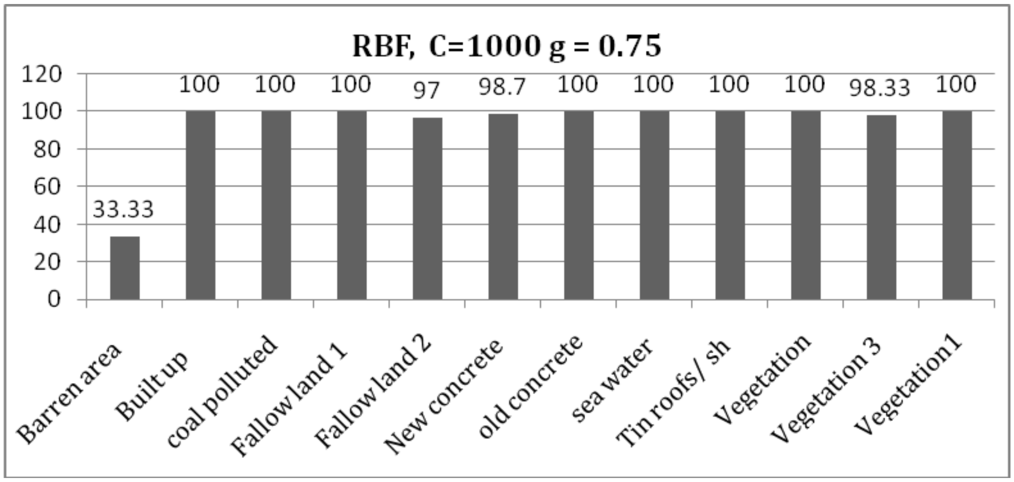

Figure 6. Accuracies of each class (in %) with γ = 0.75, c= 1000

d. Sigmoid Kernel

The sigmoid kernel was tested by keeping a constant penalty parameter of 1000 and changing the γ value of 0.25, 0.50, 0.75 and 1.00. The results of each of these combinations are tested and got good results at γ=0.75. The classified output RS image for sigmoid kernel at C=1000 & γ=0.75 is shown in figure 7 and accuracy analysis of all the objects are calculated.

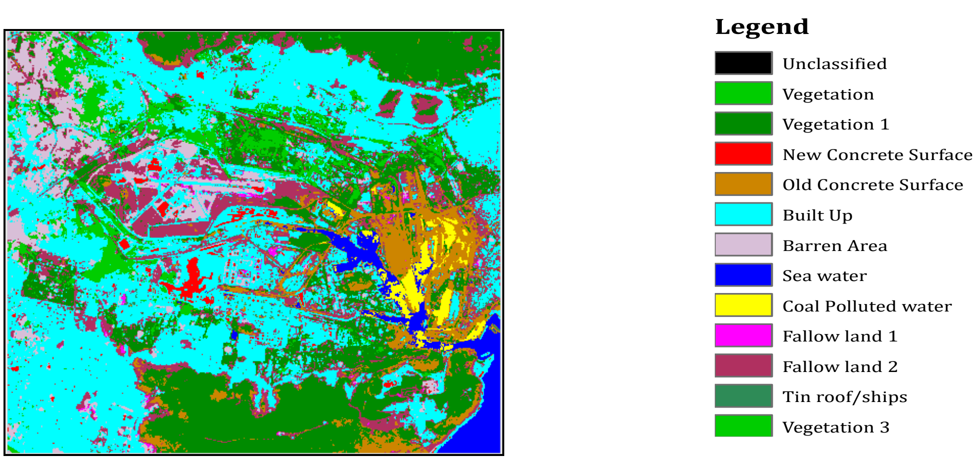

Figure 7. Classified output of Sigmoid kernel with g = 0.75.

It can be observed from the results that, RBF kernel gave accuracies up to 99% for the considered LISS III image. It was observed from the classification results that a C value of 1000 and a γ value 0.75 worked well for all the kernels for the considered image. In table 2 overall accuracy comparison was made between the linear, polynomial, radial basis and sigmoid kernels for different 'C' and a γ values. It was observed that Radial basis kernel gave an edge over the other kernels with an accuracy of 99.1509 % while linear at 98.9623 %, polynomial at 98.6792 % and Sigmoid at 98.5849 %.

Among the linear kernels, a 'C' value of 1000 gave good results for the considered image. In the polynomial kernels, polynomial 3 gave good results with a 'γ' value of 0.25, 0.50 and 0.75. Whereas, for 'γ'= 1.0, polynomial 2 achieved good results. But Overall observation of the polynomial kernel results showed that, a polynomial D is 3 with a 'γ' value of 0.25 gave very high accuracy. It was observed that in the SVM RBF kernels, a changing C value gave varying accuracies. Among the RBF kernels 'C' of 1000 and γ =0.75 gave an excellent accuracy of 99.1509%.Sigmoid kernel gave good results with a 'γ' value of 0.75 and a bias value of 1.00. However the results of classification from sigmoid kernel in the other C and γ value combinations have shown significant confusion between the fallow land 1 and fallow land 2 classes. The accuracy of four kernels is listed in table 2.

Table 2. Classification of overall accuracy & kappa for all the kernels

Accuracy / **Kernel**	**Overall Accuracy**	**Kappa Coefficient**
Linear C=1000	98.9623%	0.9879
Poly3, γ=0.75	98.6792%	0.9846
RBF, γ =0.75	99.1509%	0.9901
Sig, γ = 0.75	98.5849%	0.8899

The final classified RS image with accuracy of 99.1509% using SVM_RBF kernel with a C of 1000 and γ =0.75 is shown in figure 8.

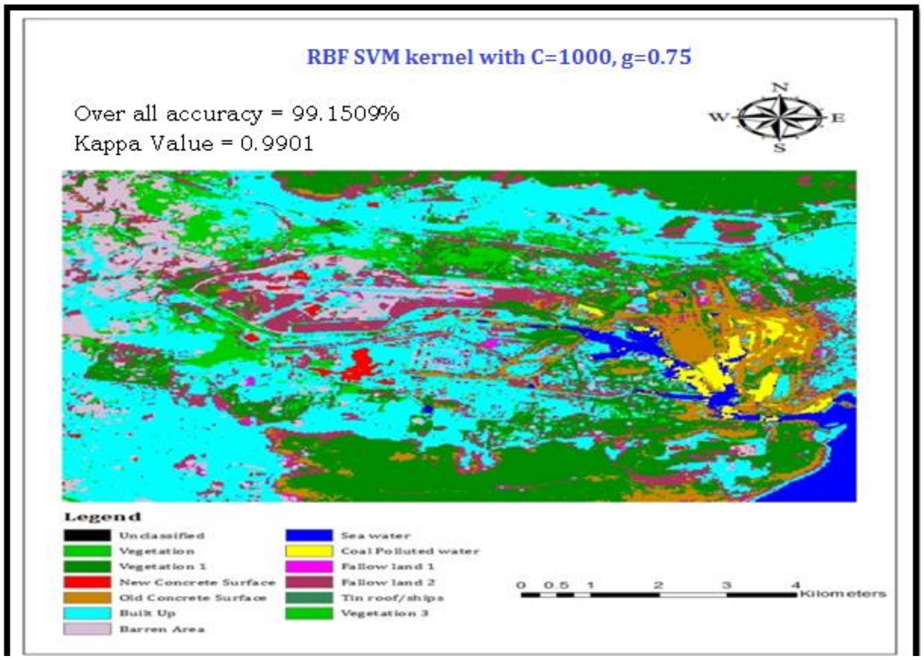

Figure 8. Best classified output of RS image with SVM_RBF. Kernel.

V. CONCLUSIONS

The proposed research work presents a comparison study on the performance of SVM algorithm using different SVM's kernels for object based classification of multi-spectral remote sensing Liss-III RS Image. For classification, different SVMs classifiers based on several well-known kernel functions (i.e. Linear, RBF, polynomial and Sigmoid) are applied to LISS-III 23.5m RS Images. However, the selection of the type of kernel is not an easy task even if the choice of these parameters has a significant effect on the performance of this algorithm. The result shows that the accuracy of RBF-based SVM classifier for various Objects are relatively better than other three kernel functions. In this regard, RBF obtains 1 % better Overall Accuracy (OA) compared with Sigmoid and 3rd degree polynomial kernels. Different degree of the polynomial kernel and different width of the RBF kernel were evaluated. It was observed that in the SVM RBF kernel, changing a value of 'C' gave varying accuracies. Among these RBF kernel with a value of C = 1000 and gamma=0.75 got an excellent accuracy of 99.1509%.The SVM-RBF kernel gave an edge over the other kernels with an accuracy of 99.1509% while linear at 98.9623%, polynomial at 98.6792% and Sigmoid at 98.5849%.

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