RESEARCH ARTICLE OPEN ACCESS

Multiple Crop Classification Using Various Support Vector Machine Kernel Functions

Rupali R. Surase*, Karbhari V. Kale**
*(Department of Computer Science & IT, DR. B.A.M.U. Aurangabad, INDIA)
** (Department of Computer Science & IT, DR. B.A.M.U. Aurangabad, INDIA)

ABSTRACT
This study was carried out with techniques of Remote Sensing (RS) based crop discrimination and area estimation with single date approach. Several 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). The present study highlights the advantages of Remote Sensing (RS) and Geographic Information System (GIS) techniques for analyzing the land use/land cover mapping for Aurangabad region of Maharashtra, India. Single date, cloud free IRS-Resourcesat-1 LISS-III data was used for further classification on training set for supervised classification. ENVI 4.4 is used for image analysis and interpretation. The experimental tests show that system is achieved 94.82% using SVM with kernel functions including Polynomial kernel function compared with Radial Basis Function, Sigmoid and linear kernel. The Overall Accuracy (OA) to up to 5.17% in comparison to using sigmoid kernel function, and up to 3.45% in comparison to a 3rd degree polynomial kernel function and RBF with 200 as a penalty parameter.
***Keywords* -** Supervised Classification; Ground Control Points; Kernel functions; Crop Classification;

I. INTRODUCTION

Discrimination of crops from other land cover classes and crop classifications are very important activities in India for agricultural monitoring and timely forecasting of crop production. Accurately identifying crops using information derived from earth observation can contribute to improved use of resources and aids agricultural planning. In this regard, airborne as well as space-borne remote sensing data particularly Synthetic Aperture Radar (SAR) data has shown promising results in crop monitoring and classification with reasonably high accuracy [1].The results obtained from this new method were found to be superior to several kernel functions of a single date. In the past, remote sensing has been shown to be valuable tool in separate applications in agriculture. Remote sensing techniques have been successfully applied in classifications of arable crops and in quantification of vegetation characteristics at different spatial and temporal scales. The crop discrimination and mapping using space data is carried out either by visual or digital interpretation techniques. Visual techniques generally are based on standard FCC (False Color Composite) generated using green, red and near-IR bands assigned blue, green and red colors. The digital techniques are applied to each pixel and use full dynamic range of observations and are preferred for crop discrimination. The field size was shown to have a strong effect on classification accuracy with small fields tending to have lower accuracies even when the effect of mixed pixels was eliminated [2,3]. Medhavy et al. (1993) showed that when supervised classification is adopted, use of training strategy based on selection of isolated pixels has higher classification accuracy than selecting blocks of pixels as training set [4].

II. OBJECTIVES OF RESEARCH

Crop classification accuracy as influenced by training strategy, data transformations and spatial resolution of data. The specific objectives of the study include:

1. To study the performance of SVM kernel functions when applied to single date satellite data to delineate various crops;
2. To apply SVM with different strategies including RBF, Sigmoid, Linear and Polynomial kernels to the single date data and compare the classification performance for each strategy.

III. STUDY AREA

Aurangabad district is located in central part of Maharashtra is establish to be tactically as the gateway to the Marathwada region. It is the districts headquarter and located in central part of the state. The geographic coordinates near the center of the area are North Latitude (Degree) is 19 and 20 & East Longitude (Degree) is 74 to 76.Aurangabad District is located mainly in Godavari Basin and it's some part towards North West of Tapi River Basin. This District's general down level is towards South and East and Northwest part comes in Purna – Godavari

river basin. Different land cover types exist in this area, forming very complex landscapes.
For Present Experimental Work Data Obtained From Resourcesat-1(IRS-P6) Satellite With LISS-III Sensor. LISS-III Multispectral Image Acquired On November 2010 With Four Spectral Bands (Green, Red, Near-Infrared And Short Wave-Infrared) With 23.5 M Meter Spatial Resolution Used For Study Area. Images Were Captured With Swath Area Of 141 Km Using Data Quantization Of NIR Band With 7 Bit And SWIR Band With 10 Bit Data. All Four Bands With Their Wavelength Is B2 (0.52-0.59), B3 (0.62-0.68), B4 (0.76-0.86) And B5 (1.55-1.70) Of Green, Red, Near Infrared And Short Wave Infrared Band. According To Crop Calendar In This Region, Four Major Crops Cotton, Maize, Bajara And Sugarcane Were Grown In The Study At Developing Stage In Start Of November. The Ground Truth Data Was Acquired Based On The Imaging Date And Coverage Area. To Obtain The Geo-Location Information Of Land Features With Rectangle. GPS Acquisition Method Was Used To Record The Coordinate Information In The Form Of Latitude-Longitude, And The Position Accuracy Is Better Than 1m. The Following Figure Shows Study Area [5, 6]:

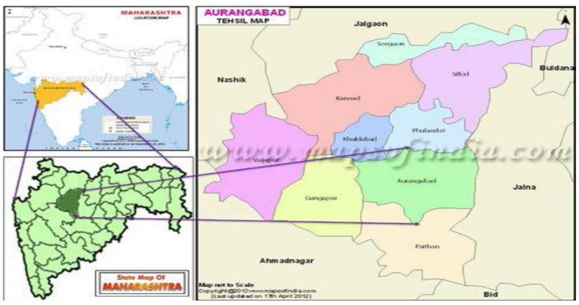

Fig 1: Study area of Aurangabad District, INDIA.

IV. MATERIAL AND METHOD

This data is received from Linear Imaging and Self Scanning Sensor (LISS) which operates in three spectral bands in NIR and one band in SWIR with 23.5 meter spatial resolution and a swath of 141 km. The IRS-Resourscesat-1 LISS-III satellite imagery has four bands i.e. Band 2 - Green, band 3 - Red, band 4 - NIR and band 5 - SWIR. Figure 2 shows the Original Satellite Image.

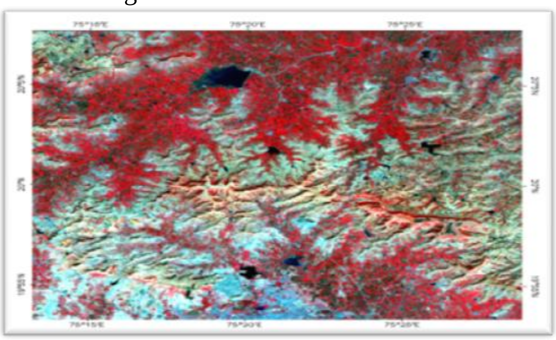

Fig 2: LISS-III Imagery Dataset

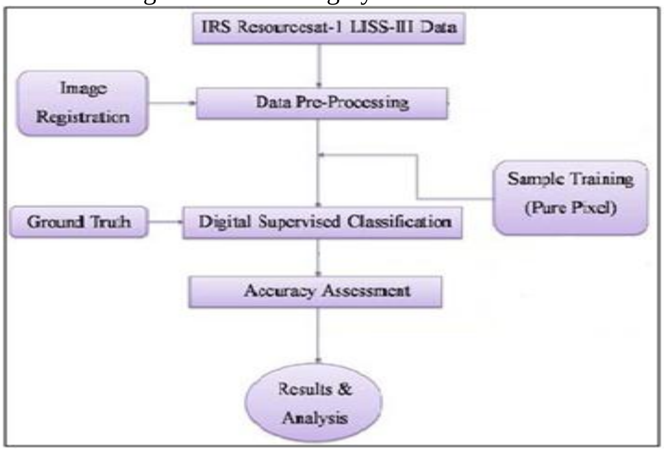

Fig 3: Proposed diagram of workflow methodology

1. *Pre-processing-*

All basic statistics were calculated for pre-processing of dataset based on four bands including min, max, mean, standard deviation, eigenvalue, eigenvector, correlation and covariance [8]. Following Table shows experimental work done using ENVI 4.4.

TABLE 1: Min, Max, Mean, Standard Deviation and Eigen value of four bands

Nov 2010	Min	Max	Mean	StdDev	Eigen Value
Band 1	0	255	85.0565	11.8261	669.9890
Band 2	0	185	57.7196	14.4003	185.5990
Band 3	0	160	82.9617	14.7289	41.1530
Band 4	0	238	79.4271	18.3704	4.90272

TABLE 2: Basic Statistics dataset with correlation, covariance and eigenvector

Nov 2010	Band 1	Band 2	Band 3	Band 4
Band 1	1.0000	0.9477	0.2847	0.7820
Band 2	0.9477	1.0000	0.2338	0.8603
Band 3	0.2847	0.2338	1.0000	0.5111
Band 4	0.7820	0.8603	0.5111	1.0000
Correlation				
Band 1	139.8571	161.4060	49.5951	169.9039
Band 2	161.4060	207.3689	49.5900	227.5946
Band 3	49.5935	49.5900	216.9430	138.3111
Band 4	169.9039	227.5946	138.3111	337.4747
Covariance				
Band 1	0.4062	0.5138	0.3109	0.6886
Band 2	-0.2534	-0.3677	0.8944	0.0200
Band 3	-0.6121	-0.2580	-0.2949	0.6868
Band 4	-0.6292	0.7308	0.1273	-0.2316
Eigenvector				

2. *Digital Supervised classification*

In this work, four classification approaches of SVM kernel methods have been used. To gain the benefits from remotely sensed data managers, consultants, and technicians have to understand and to be able to interpret the image. The remote sensing literature review presents with a number of supervised methods that have been developed to tackle the multispectral data classification problems. Remote sensing techniques are widely used in agriculture and agronomy [9]. In fact, remote sensed images provide spatial coverage of a field, and can be used as a proxy to measure crop and soil attributes [10]. However, classifying remotely sensed data into a thematic map remains a challenge because many factors, such as the complexity of the landscape in a study area, selected remotely sensed data, image-processing and classification approaches may affect the success of a classification [11]. Supervised classification requires ground cover and ROI file. Selection of quality training samples requires knowledge with properties of the different ground features in the satellite imagery.

2.1 Support Vector Machine: Support Vector Machine (SVM) is a supervised classification method derived from statistical learning theory that often yields good classification results from complex and noisy data. A brief description of SVM is made here and more details can be found.

2.1.1 Linear case: We should now consider the case of two classes' problem with N training samples. Each sample is described by a Support Vector (SV) Xi composed by the different "band" with n dimensions. The label of a sample is Yi. For a two classes case we consider the label -1 for the first class and +1 for the other. The SVM classifier consists in defining the function,

$$\mathrm{f(x)} = \mathrm{sign}((w,x) + b) \quad \text{Equation (1)}$$

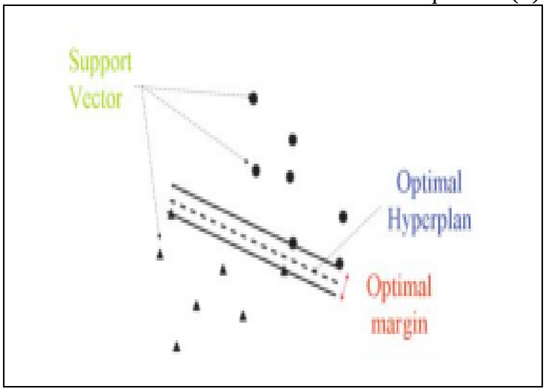

Fig 4. SVM classifier in linear case

Which finds the optimum separating hyper plane as presented in Fig 5. Where ω is normal to the hyper plane, and |b| is the perpendicular distance from hyper plane to ǁωǁ the origin. The sign of f(x) gives the label of the sample. The goal of the SVM is to maximize the margin between the optimal hyper plane and the support vector. So we search the $\min\frac{||w||}{2}$. To do this, it is easier to use the Lagrange multiplier. The problem comes to solve:

$$\mathrm{f(x)} = \mathrm{sign}\ (\textstyle\sum_{i=1}^{Ns} yi \cdot \alpha i(x \cdot xi) + b$$

Equation (2)

Where, αi is the Lagrange multiplier.

2.1.2 *Nonlinear case*:

If the case is nonlinear as the Fig 5. The first solution is to make soft margin that is particularly adapted to noised data. The second solution that is the particularity of SVM is to use a kernel.

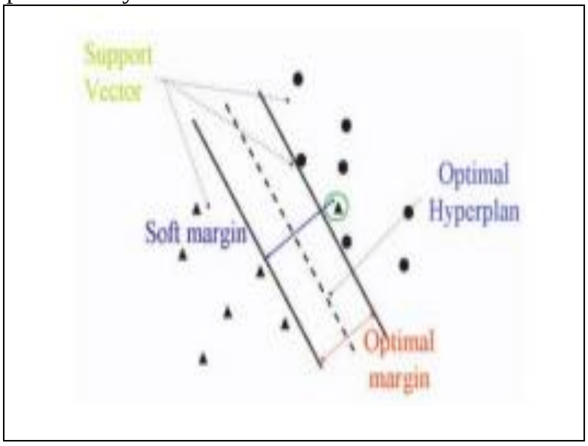

Fig 5. SVM classifier in Nonlinear case

The kernel is a function that simulates the projection of the initial data in a feature space with higher dimension Φ: Kn → H. In this new space the data are considered as linearly separable. To apply this, the dot product (x, xi) is replaced by the function:

$$K(x,xi) = (\emptyset(x), \emptyset(xi)) \quad \text{Equation (3)}$$

Then the new functions to classify the data are:

$$\mathrm{f(x)} = \mathrm{sign}\ (\textstyle\sum_{i=1}^{Ns} yi \cdot \alpha i(x \cdot xi) + b$$

Equation (4)

Four kernels are commonly used:

1. linear kernel:
$$K(x,xi) = xTxi$$
Equation (5)
2. Polynomial kernel:
$$K(x,xi) = (gxTxi + r)d, g > 0$$
Equation (6)
3. Radial Basis kernel:
$$K(x,xi) = exp\frac{|x-xi|^2}{2\sigma^2}$$
Equation (7)
4. Sigmoid kernel:
$$K(x,xi) = \tanh\ (gxTxi + r)$$
Equation (8)

2.1.3 *Multiclass case*:

The principle of SVM was described for a binary classification, but many problems have more than two-class problem. There exist different algorithms to multiclass problem as “One Against All” (OAA) and “One Against One” (OAO). If we consider a problem with K class, OAA algorithm consists in the construction of k hyper planes that separate respectively one class and the (k-1) other classes. OAO algorithm consists in the construction of $\frac{k\ (k-1)}{2}$ hyperplane which separate each pair of classes. In the two cases the final label is that mainly chosen (B. Yekkehkhany1 et al., 2014). In the case of SVMs, nonlinear classifiers were obtained by taking the dot product in kernel-generated spaces. It separates the classes with a decision surface that maximizes the margin between the classes. The surface is often called the optimal hyper plane, and the data points closest to the hyper plane are called support vectors.

The support vectors are the critical elements of the training set. SVM become a nonlinear classifier through the use of nonlinear kernels. While SVM is a binary classifier in its simplest form, it can function as a multiclass classifier by combining several binary SVM classifiers (creating a binary classifier for each possible pair of classes).Support Vector Machines (SVM) has recently gained prominence in the field of machine learning and pattern classification [12]. 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. If the Kernel Type is Polynomial, set the Degree of Kernel Polynomial to specify the degree used for the SVM classification (the d term used in the above kernel functions). The minimum value is 1 (default), and the maximum value is 6. Increasing this parameter more accurately delineates the boundary between classes. A value of 1 represents a first-degree polynomial function, which is essentially a straight line between two classes.

3. Accuracy Assessment

Accuracy assessment always requires the comparison of remote sensing results with an external source with ground truth based on samples. Overall Accuracy is calculated using ratio of Users & Producers Accuracy [13]. The performance measures considered are: user’s accuracy (n_i), producers accuracy (n_a), overall accuracy (n_o) and Kappa coefficient (k). These are defined as

$n_i=\frac{qii}{\sum_{j=1}^{no} qij}$ $n_a=$ $\frac{1}{no}\sum_{i=1}^{no} ni$

$no\frac{1}{N}\sum_{i=1}^{no} qii$ Equation (9)

Where, qij is the classification matrix shows how many samples belonging to class i and classified into class j. For accurate classification matrix is diagonal. qii is the total number of correctly classified samples, nc is the number of samples for the class ci and n is the number of samples in the data sets. The kappa coefficient is statistical measure of integrator used for grouping of qualitative class. It is considered as more robust for analyzing classification matrix [14].

The kappa coefficient can be used for scales with more than 2 categories. In particular the use of kappa statistics to assess examiner agreement for categorical outcomes has grown almost exponentially. The kappa coefficient is widely used statistics for measuring the degree of reliability for raters.

$K=\frac{ObserverdAccuracy-\mathcal{E}}{1-\mathcal{E}}$ Equation (10)

Where,

$\mathcal{E}=\frac{\sum_{i=1}^{N}(Classifiedclassitotalpixels*actualclassitotalpixels)}{(totalpixels^2)}$

Kappa coefficient is calculated using multiplication of classification pixel and actual pixels as shown in equation (5).

V. RESULT AND DISCUSSION

The results of this study show that, classification of remotely sensed imagery gives valuable information about crop discrimination. The proposed method is applied to the extracted single date approach. Based on the available reference crop map, several types of crop classes are considered and the training and test data are collected. In our study, we have collected ground truth points using My GPS Coordinate Application through mobile device of various villages which are in our database image like Tajnapur, Sherodi, Yesgoan, Phulambri, Khultabad, Nirgudi etc. with various crop fields’ latitude and longitude. When we were taking ground control points that time all four types of kharif crops identified. At the time of collection of points crops were in developing stage shown in following Figure 5.

Cotton	Sugarcane	Maize	Bajara
			

Fig 5: Pictures of different representative fields at Aurangabad for classification purposes like cotton, Maize, Sugarcane and Bajara.

At the times of taking ground truth selected crop area more than three Acre and then though center of that particular field strongest center point collected and using these points ROI was created using Rectangle shape. At time of collecting GCP accuracy of signal plays an important role for providing accurate location with accuracy of Latitude and Longitude.

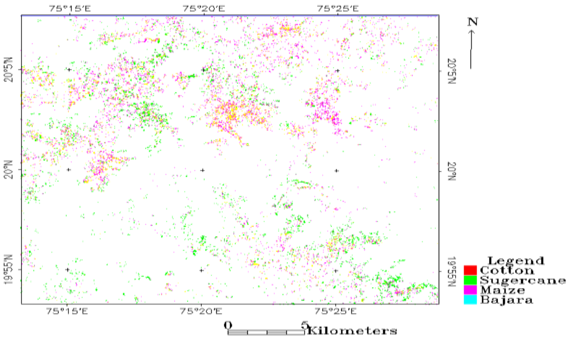

Fig 6: Multiple crop classification using Sigmoid Kernel

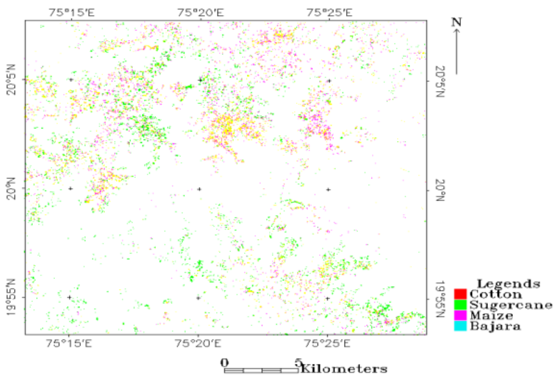

Fig 7: Multiple crop classification using Linear Kernel

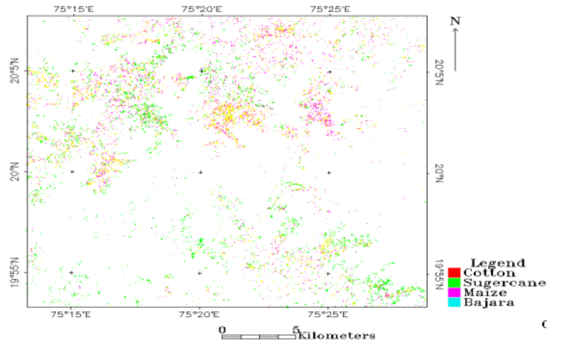

Fig8: Multiple crop classification using Radial Basis Kernel

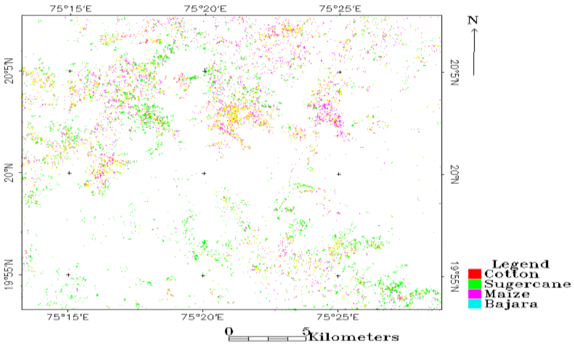

Fig 9: Multiple crop classification using Polynomial Kernel

In Fig. 6-9 crop discrimination is showed using various color pixels. The differences were given as pixel of the total testing data with confusion matrix.

TABLE 3: CONFUSION MATRIX USING SVM FUNCTIONS FOR CROP CLASSIFICATION

SVM	**Classes**	GROUND TRUTH(PIXEL)				
		Cotton	**Sugarcane**	**Maize**	**Bajara**	**Total**
SK	**Cotton**	32	3	0	0	35
	Sugarcane	0	18	0	0	18
	Maize	0	3	2	0	5
	Bajara	0	0	0	2	2
	Total	32	24	2	2	60
LK	**Cotton**	32	3	0	0	35
	Sugarcane	0	19	0	0	19
	Maize	0	2	2	0	4
	Bajara	0	0	0	2	2
	Total	32	24	2	2	60
RBF K	**Cotton**	32	3	0	0	35
	Sugarcane	0	21	0	0	21
	Maize	0	2	0	0	2
	Bajara	0	0	0	2	2
	Total	32	24	2	2	60
P K	**Cotton**	32	3	0	0	35
	Sugarcane	0	21	0	0	21
	Maize	0	2	0	0	2
	Bajara	0	0	0	2	2
	Total	32	24	2	2	60

In Table 3, we look solely at the confusion matrix for classification with high resolution images, it is clear that a large differences for each category between the classification map and the reference data compared with classifiers.

TABLE 4: ACCURACY ASSESSMENT USING SVM KERNEL FUNCTIONS (PIXEL)

SVM	Classes	PA	UA	C	O	KC	OA
SK	Cotton	32	32	3	0	0.8069	89.65 %
	Sugarcane	18	18	0	6		
	Maize	2	2	3	0		
	Bajara	2	2	0	0		
LK	Cotton	32	32	3	0	0.8371	91.37 %
	Sugarcane	0	5	0	5		
	Maize	2	0	2	0		
	Bajara	2	0	2	0		
RBFK	Cotton	32	32	3	0	0.8998	94.82 %
	Sugarcane	21	21	0	3		
	Maize	2	2	0	0		
	Bajara	2	0	2	0		
PK	Cotton	32	32	3	0	0.8998	94.82 %
	Sugarcane	21	21	0	3		
	Maize	2	2	0	0		
	Bajara	2	0	2	0		

PA=Producers Accuracy, UA=Users Accuracy
KC=Kappa Coefficient, OA=Overall Accuracy
SK=Sigmoidal Kernel, LK=Linear Kernel
C=Commission, O=Omission, PK=Polynomial Kernel, RBFK=Radial Basis Function Kernel

Table 4 above clarifies Users Accuracy, Producers Accuracy, Kappa Coefficient and Overall Accuracy with kernel functions. Experimental result shows that sigmoid kernel gives 89.65% OA with Kappa Coefficient 0.8069 with Penalty parameter 100; linear kernel shows 91.37 % OA & KC 0.8371 with Penalty parameter 150, Radial Basis Function and Polynomial function increases performance of experiment with OA 94.82% and KC increases with 0.8998. The KC 0.8998 shows good accuracy crop types discrimination. Classification results generated from SVM Kernel overestimated with four types of crops.

TABLE 5: CLASSIFIED AREA OF FOUR TYPES OF CROPS AREA IN KM2 AND IN PIXEL

CLASS	SVM Classifiers							
	SK		LK		RBK		PK	
	KM^2	Pixel	KM^2	Pixel	KM^2	Pixel	KM^2	Pixel
Cotton	12874000	32185	123740000	30935	13168800	32922	13168800	32922
Sugarcane	10456400	26141	14711200	36778	13414400	33536	13414400	33536
Maize	14300000	35750	8790400	21976	9802800	24507	9802800	24507
Bajara	1074400	2686	45700	1506	540320	10700	540320	10700

In this section we present the results obtained for crop classification problem. In our study we consider area measure in KM2 and pixels covered in LISS-III satellite image containing 4 types of crops of a region around Aurangabad, Maharashtra, INDIA.

VI. Conclusion

This study explores the framework of crop identification by remote sensing and pursues the effective crop identification method. It will be appropriate for the regions of complex agriculture landscapes that result in same crop may generate multiple centers in the discriminant space due to the impact of landform and planting pattern.

This paper presented a comparison study on the performance of different SVM's kernels for classification of single date LISS-III four band data in agricultural region. The experimental evaluations demonstrated that the accuracies of RBF and polynomial based SVM classifier for various crop types are relatively better than other two kernel functions. In other words, RBF and polynomial obtains almost 5.17 % and 3.45 % better OA compared with linear and sigmoid kernels respectively. In addition, RBF kernel shows the best results with respect to the speed of its convergence. It is obtained with regard to the time of process. Indeed, RBF and polynomial is the most frequently used kernel in optical remote sensing data. Author recommends that for RBF Kernel rather than using 100 as a standard penalty parameter 200 also increases performance.

VII. ACKNOWLEDGEMENT

The authors are thankful to Coordinator, UGC SAP (II) for providing permission to utilize the infrastructure at “Geospatial Technology Research Laboratory” in Department of Computer Science and IT, Dr. Babasaheb Ambedkar Marathwada University (M.S.) INDIA. Thanks to research supervisor for technical discussion at every stage of implementation. Author must thankful to Department of Computer Science & IT for providing LISS-III dataset for research purpose. Author must express profound gratitude to Mr. R M. Surase & Mr. S. K. Gaikwad for providing valuable time and unfailing support for collection of ground control points through the process of researching.

REFERENCES

[1] Dipanwita Haldar1, Anup Das1, Manoj Yadav, Ramesh S. Hooda2, Shiv Mohan, and Manab Chakraborty, Analysis of Temporal Polarization Phase Di®erence for Major Crops in India, Progress In Electromagnetics Research B, Vol. 57, 299, 2014.

[2] Batista, G., M. Hixson & M. E. Bauer. 1985. Landsat MSS crop classification performance as a function of scene characteristics. International Journal of Remote Sensing 6:1521-1533.

[3] Buechel, S. W., W. R. Philipson & W. D. P h ilpot. 1989. The effects of acomplex environment on crop separability with Landsat TM. Remote Sensing of Environment 27: 261-272.

[4] Medhavy, T. T., T. Sharma, R. P. Dubey, R. S. Hooda, K. E. Mothi kumar, M. Yadav, M. L. Manchanda, D. S. Ruhal, A. P. Khera & S. D. Jarwal. 1993.

[5] http://www.mapsofindia.com/maps/maharashtra/maharashtralocation.htm.

[6] http://upload.wikimedia.org/wikipedia/commons/archive/2/25/20090410163205%21MaharashtraAurangabad.png.

[7] Clarke, G.M. & Cooke, D., A Basic course in Statistics. Arnold,1998

[8] C. Jeganathan, Nitish Kumar Sinha, Harshit Rajan, Tanmoy Royet Al.,” *Extracting Seasonal Cropping Patterns Usinf Multi-Temporal Vegetation Indices From IRS LISS-III data in Muzaffarpur district of Bihar, INDIA*”, The Egyptian Journal of Remote ensing and Space Science, 2014.

[9] Bischof, H.W. Schneider and A. J. pinz. “*Multispectral classification of landsat – image using Neural Networks*”, IEEE transactions Geoscience Remote Sensing, 30(3):482-490, 1992.

[10] Richards JA, Jia X,”*Remote sensing digital image analysis*”, Springer Verlag, Berlin Heidelberg,2006.

[11] B. Yekkehkhany, A. Safari1, S. Homayouni, M. Hasanlou, ” *A Comparison Study of Different Kernel Functions for SVM-based Classification of Multi-temporal Polarimetry SAR Data*”, The International Archives of the Photogrammetry, Remote Sensing and Spatial InformationSciences, Volume XL-2/W3, 2014 The 1st ISPRS International Conference on Geospatial Information Research, 15–17 November 2014, Tehran, Iran.

[12] Landgrebe, David. "*Information extraction principles and methods for multispectral and hyperspectral image data."* Information processing for remote sensing 3-38,82 ,1999.

[13] V. N. Vapnik. The Nature of Statistical Le Learning Theory. Springer, New York, 2nd edition, 2000.