PERFORMANCE EVALUATION OF SUPPORT VECTOR MACHINE AND MAXIMUM LIKELIHOOD CLASSIFIER FOR MULTIPLE CROP CLASSIFICATION

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Abstract

This experiment is design and developed based on Support Vector Machine (SVM) for crop classification using LISS-III imagery dataset. 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). This paper illustrated the results using dataset of Aurangabad district with classification of four types of crops including cotton, maize, sugarcane and Bajara. Comparative analysis clearly explored that higher overall classification accuracy (94.82%) was observed in the kernel based SVM compared with that of traditional pixel-based classification (69.64%) using maximum likelihood classifier (MLC). From the experimental results we observe that the overall performance of the system is achieved 94.82% using SVM with kernel functions including linear kernel, Radial Basis Function, Sigmoid and Polynomial with degree 3 compared with other degree and penalty parameter. The author recommended that the SVM with kernel functions including linear kernel is the best choice for multiple crop classification.

Introduction

Remote sensing has shown great achievement in identifying the crops growth in agricultural land discrimination. It plays an important role in crop classification, crop growth monitoring and crop health assessment. The rapidly growing number of earth observation satellites provides a much better coverage in space, time and the electromagnetic spectrum than in the past decades. Remotely sensed satellite image analysis is a challenging task considering the volume of data with combination of channels in which the image is acquired. Single crop classifications were performed using various techniques and accurately classified crops like wheat, Alfalfa. After classifying single crops there were need and challenge of classification of multiple crops. The use of remote sensing is needed, since the monitoring of agriculture concerns special problems, which are not common to other economic sec tors. Agricultural production heavily depends on seasonal patterns related to the life cycle of crops Carfagna and Gallego, et al. provides a first exhaustive description of different possibilities of the use of remote sensing for agricultural statistics [1]. In particular, remote sensing techniques may represent a suitable tool for particular problems in agricultural survey like reliability of data, incomplete sample frame and sample size, methods of unit's selection, measurement of area, non-sampling errors, gap in geographical coverage and non-availability of statistics at disaggregated level is explained [1].

Numerous classification algorithms have been developed since acquisition of LISS-III image. Maximum likelihood classifier (MLC), a parametric classifier, is one of the most widely used classifiers. The support vector machine (SVM) represents a group of theoretically superior non-parametric machine learning algorithms. There is no assumption made on the distribution of underlying data. The SVM employs optimization algorithms to locate the optimal boundaries between classes and can be successfully applied to the problems of image classification with large input dimensionality [2]. SVMs are particularly appealing in the remote sensing field due to their ability to generalize well even with limited training samples, a common limitation for remote sensing applications (Remotely sensed images provide a synopsis of the area under investigation and are useful for the construction of the spatial reference frame. Furthermore, classified satellite images can be used as auxiliary variables to improve the precision of ground survey estimates, generally with a regression or a calibration estimator.

The number of different classes that can be determined is normally relatively small using this type of methods. The statistically based methods, on the other hand, will normally provide a larger number of classes, but the classifiers will then normally be specifically adjusted to the data set at hand, and it is difficult to adopt the classifier to other environmental conditions [3].

Related Work

Salient work in the fields of various crop classification techniques is presented here for last 12 year. In the study of Multispectral classification, (Bischof, H.W. Schneider 1992) uses LANDSAT Images using Neural Network was carried out. In this work, they classified Landsat TM data on pixel-by-pixel basis using a three layer back propagation neural network [4]. Moreover, a method based on the neural networks for post classification smoothing was also presented and shown to be superior to conventional filters. Authors compared their results with the Gaussian maximum Likelihood Classifier and have reported the performance of neural network better than the maximum likelihood classifier. Classification accuracy by the neural network was 91.0% which was better than the weighted majority filter whose accuracy was 89.1% [5].

(R. Garcia et al. 2003) work on fusion of Multispectral & panchromatic images using wavelet transform approach. They used SPOT XI & SPOT P2 degraded to 40m & 20m resolution and classified Apple tree, Cherry tree, Almond, Pine and Ripe Corn classification. Author achieved accuracy using Principal Component Analysis (PCA) is 78.76% and using Hue-Saturation-Intensity 77.73% [6]. (Fabio Del Frate, et al. 2003) classified crops using C-band SAR Data with ERA-ORA &AIR SAR by adding various polarizations. The data collected by the AirSAR are at three frequencies, P- (0.45 GHz), L- (1.3 GHz), and C- (5.3 GHz) band and fully polarimetric. Author separates Maize, Potato, Wheat, Grass and Berley crops with overall accuracy 91.1% [7]. (Farid Melgani, et al. 2004) were classified Soybean, Grass and crops using Indiana's Indian Pines, AVIRIS sensor taken in 1992 with 220 bands using Support Vector Machine(SVM), K-Nearest Neighbour(KNN), Raial Basis Functions(RBF) with hyper spectral images datasets. Overall accuracy for SVM is 94.38%, KNN is 85.60% and RBF is 88.89% [8].

(Jill Heaton et al. 2006) was classified various crops like Grass, Agriculture and Saltsedar using Airborne Hyper SpecTIR imagery with 178 bands. They worked on supervised techniques like Spectral Angle Mapper (SAM), Maximum Likelihood (ML) and Support Vector Machine (SVM). They got highest overall accuracy in SVM 98.8% [9].

(Kiri Wagstaff et al. 2006) were classified crops corn, grapes, and cotton using Support Vector Machine with overall accuracy 82%. Author was collected datasets using Multi-angle Imaging Spectro radiometer instrument (G. Camps-Valls et al. 2006) were work on HyMap 128 bands imagery. Support Vector Machine was applied for classification of crops using hyper spectral data and SVM recognition rate 99.74% for corn type classification [10].

(Boxiaxin Hu. and Anne Smith 2007) was classified vegetation using CHRIS hyper spectral data with 4 bands. They classified various types of crops including potato, spring wheat, grass, alfalfa. The overall accuracy using supervised classification was 88%. (Boxiaxin Hu, et al. 2007) uses CHRIS 4 Bands hyper spectral & multi-angular remote sensing data using supervised classification with overall accuracy 88% [11]. (Rabindra K. Panigrahy, et al. 2009) worked on AWIFS dataset using SWIR band for crop discrimination and classification. They were applied Supervised Maximum Likelihood classification technique for the discrimination of different Rabi season crops (rabi rice, groundnut and vegetables) and other vegetation with overall accuracy 77.72% [12]. (Qiong An et al.2009) have used adaptive feature selection model In his work for rice crop with MODIS data the extracted spectral characteristics are analyzed using statistical method and dynamic changes of temporal series of indices including NDVI, EVI, and MSAVI are studied and by taking account of computational complexity & time effectiveness of calculation the Adaptive Feature selection model (AFSM) is studied. They got 94 % accuracy which was larger than general classification by 3% [13]. (Jiali Shang et.al. 2010) have worked on Multi-temporal RADARSAT-2 and TerraSAR-X SAR data for crop mapping in Canada & they found that when multi-frequency SAR (X- and C-band) are combined, classification accuracies above 85% are achieved prior to the end of season. Crops can be identified with accuracies between 86% (western Canada) and 91.4% (eastern Canada) [14].

(Cankut Ormeci, et al. 2010) classified discriminate crops using SPOT 5 and Multispectral images by applying unsupervised classification with accuracy 84.33%, Supervised Classification with accuracy 83.45% and Object based classification with accuracy 87.50% [15]. (Jiong You, Zhiyuan Pei & Donglian Wang, 2013) classified crops by using multiple techniques. They used multispectral SPOT 5 four band images for experiment. They classified three types of crops including single cropping rice, late rice & cotton of south china region. They used three classification algorithms namely Maximum Likelihood Classifier (MLC), Classification based on Probability Calibration Algorithm (CPCA), Maximum Likelihood Classification with Kernel Density Estimation (MLCKDE). The resultant accuracy using MLC was 80.84%, MLCKDE was 79.09% and CPCA was 87.80% [16]. (J. Senthilnath, S.N. Omkar & Nitin Karnwal 2013) worked on crop stage classification using AVIRIS Indian Pines Image with 220 spectral bands of Utter Pradesh Region of India. They classified crop types Alfalfa, corn, wheat, oats, grass trees. They employed various classification techniques including Principal Component Analysis with sub techniques like PCA-ISODATA, PCA-AIS, PCA-HAIS, and PCA-NHAIS. The accuracy of PCA-ISODATA was 71.8%, PCA-

AIS were 80.9%, PCA-HAIS was 89.1% & PCA-NHAIS was 87.8% [17].

(Mark W. Liuet al. 2014) proposed high resolution combined with low resolution. In this study they used LANDSAT & MODIS images with six bands. They classified corn, cotton, rice & soybeans with overall accuracy 62.9%[18]. (C. Jeganathan, Nitish Kumar Sinha, et al. 2014) worked on identification of seasonal cropping pattern and uses dataset Resourcesat-2 has 24 days repetivity and LISS III data have a spatial resolution of 23.5-m at four spectral bands: Green (0.52 µm–0.59 µm), Red (0.62 µm–0.68 µm), NIR (0.77 µm–0.86 µm) and SWIR (1.55 µm–1.70 µm). Author were classified rice, maize, sugarcane and Mango were identified with 96%, 95% and 91% accuracy using seasonal stacks of planting, developing and harvesting stages[19].

After doing literature we conclude that supervised techniques gives better results rather than unsupervised techniques. We find that authors used different datasets with various band combination and it effect on varying overall accuracy.

Methodology

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 [19]. In fact, remote sensed images provide spatial coverage of a field, and can be used as a proxy to measure crop and soil attributes [04].

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 [20].

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. Supervised classification is complex than unsupervised classification. It has various methods like Support Vector Machine, Maximum Likelihood, Neural Net, etc. Unsupervised Classification is a clustering technique in which pixel are grouped into certain categories in terms of the similarity in their spectral values. In this analysis all pixels in the input data are categorized into one of the groups specified by the analyst. Before classification Clusters must be made using K-Means & ISODATA.

A. 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.

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,

$$f(x) = \text{sign}((w, x) + b)$$

Equation (1)

Which finds the optimum separating hyper plane as presented in Figure 1

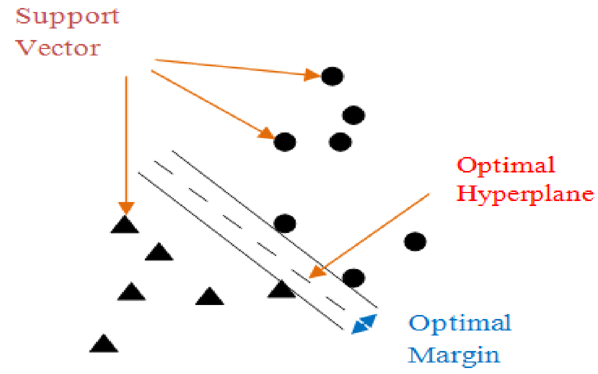

Figure 1. SVM classifier in linear case

Where, ω is normal to the hyper plane, and |b| is the perpendicular distance from hyper plane to ‖ω‖ 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:

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

Equation (2)

Where, αi is the Lagrange multiplier.

2. Nonlinear case: If the case is nonlinear as the Figure 2. 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.

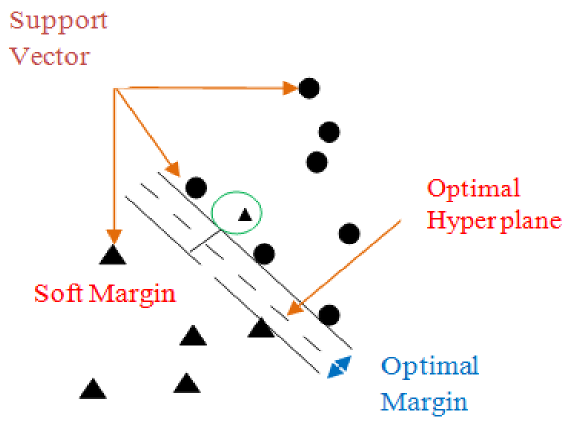

Figure 2. SVM classifier in Non linear case

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:

$$K(x,xi) = (\emptyset(x),\emptyset(xi))$$

Equation (3)

Then the new functions to classify the data are:

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

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. *S*igmoid kernel:

$$K(x,xi) = \tanh(gxTxi + r)$$

Equation (8)

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 $\frac{k\ (k-1)}{2}$ hyper plane which separate each pair of classes. In the two cases the final label is that mainly chosen [21]. 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) have recently gained prominence in the field of machine learning and pattern classification [21]. 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.

B. Maximum Likelihood Classifier

The maximum likelihood decision rule is based on the probability that a pixel belongs to a particular class. The basic equation assumes that these probabilities are equal for all classes, and that the input bands have normal distributions. Maximum likelihood classification assumes that the statistics for each class in each band are normally distributed and calculates the probability that a given pixel belongs to a specific class. Unless you select a probability threshold, all pixels are classified. Each pixel is assigned to the class that has the highest probability (that is, the maximum likelihood). If the highest probability is smaller than a threshold you specify, the pixel remains unclassified. The maximum likelihood Equation (9) is as follows:

$$ML = gi(x) - |n\ {}^{*}p(wi) - \frac{1}{2}|n * |\sum_i| - \frac{1}{2}(x-mi)^t \sum_1 -1(x-mi)$$

Equation (9)

Where, i denotes class, x is the n-dimensional data (where n is the number of bands), p (w_i) is probability that class w_i occurs in the image and is assumed the same for all classes, |Si| is determinant of the covariance matrix of the data in class w_i, Si-1 is its inverse matrix and mi is mean vector [22].

Experiment

A. Study Area

An area of Aurangabad district, India, was chosen as the study area. 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 shown in Figure 3. 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.

Figure 3: Study Area of Aurangabad District

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.

B. Performance Measures

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 [23]. To classify and evaluate performance based on individual, average & overall classification accuracy for a given dataset, here we have used supervised technique including MLC and SVM. Initially, the data set is used to arrive at the classification matrix which is of size n*n, where n is the number of classes available in datasets. The performance measures considered are: user's accuracy (n_i), producer's accuracy (n_a), overall accuracy (n_o) and Kappa coefficient (k). These are defined as

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

$$n_a=\frac{1}{no}\sum_{i=1}^{no} ni \qquad no=\frac{1}{N}\sum_{i=1}^{no} qii$$

Equation (10)

Where, q_{ij} is the classification matrix shows how many samples belonging to class i and classified into class j. For accurate classification matrix is diagonal. q_{ii} is the total number of correctly classified samples, n_c is the number of samples for the class c_i and n is the number of samples in the data sets. Here, numbers of samples are 58 created using Rectangle for accuracy assessment. The kappa coefficient is statistical measure of integrator used for grouping of qualitative class. It is considered as more robust for analyzing classification matrix [24]. The kappa coefficient can be used for scales with more than 2 categories. In particular to assess examiner agreement for categorical outcomes has grown almost exponentially and widely used statistics for measuring the degree of reliability for raters.

$$K=\frac{ObserverdAccuracy-\varepsilon}{1-\varepsilon} \qquad \text{Equation (11)}$$

Kappa coefficient is calculated using multiplication of classification pixel and actual pixels.

Result and Interpretation

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. Ground control point (GCP) extraction is an essential step in automatic registration of remote sensing images. However the lack of quantitative and objective methods for analyzing the GCP quality becomes the bottleneck that prevents the broad development of automatic image registration [25]. Total 58 training clusters (twelve sample clusters for each class) were collected in developing stage of all crops. 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 4.

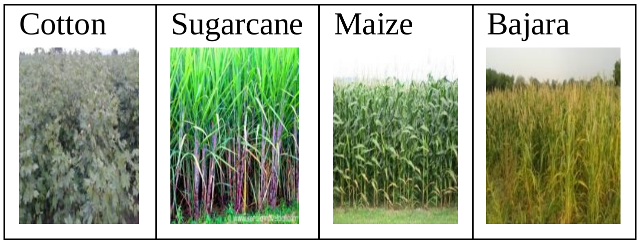

Figure 4: Pictures of different representative fields at Aurangabad for classification purposes like cotton, Maize, Sugarcane and Bajara.

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. 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.

Figure 5 describes the false color composite image of study area and Figures 6 illustrates the four types of crops classified image.

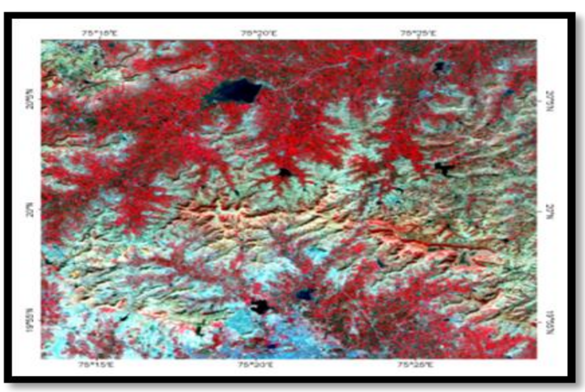

Figure 5: LISS-III False Color Image (4 Bands)

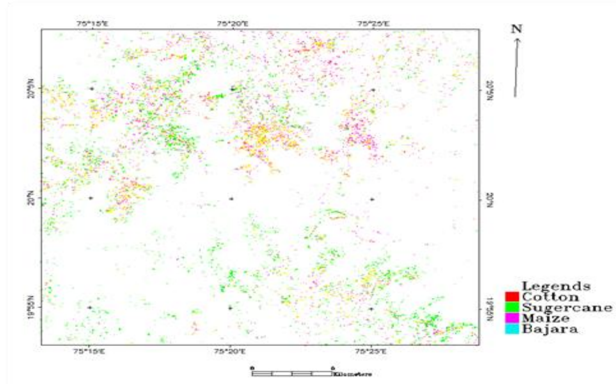

Figure 6: Crop Classification Using SVM with highest OA

Results of different studies that focused on crop area identification with remotely sensed data. In our study, we have considered LISS-III Multispectral Image with 4 bands (G, R, NIR and SWIR) of Aurangabad District. The training samples and test samples were selected directly from the image based on the field data and training samples are used for supervised classification. The accuracy of the classified images was assessed using producer's accuracy, user's accuracy, commission, omission, overall accuracy and kappa coefficient. When Kappa coefficients measures are based on range, $K > 0.80$ and onwards then it indicates that good accuracy of results, when it is $0.40 < K > 0.80$ indicates middle accuracy and finally $K < 0.40$ it shows less accuracy [25]. .Here, result proves Kappa coefficient value 0.8998 and it means after performing SVM with linear kernel techniques it gives good accuracy for classification.

Following Table shows effect of penalty parameter on changing OA and kappa coefficient. We have done a comparison between the simplest linear kernel and other more complicated ones. The one which is in the middle is related to 3^{rd} degree Polynomial kernels which are more advanced than the linear one. It uses the non-linear equations for transition inputs to feature space. As a result, it is more time consuming and complicated than the previous kernel but release more reliable results with higher accuracies. Since the more degree the polynomials are, the more complicated and time taking the process we have extended degree but the 3 rd. degree gives a better performance with regard to complication, time taking, number of training data which is needed and the accuracy. RBF kernel is the most popular kernel among other researches; the more usage is due to the RBF kernel's relevance to the nature of LISS-III data which is in Gaussian contribution. It is obvious that a Gaussian kernel will be more related to such these data. So the higher performance of algorithm is the result of using this kernel. The results of this study indicate that ROI derived from original spectral bands of LISS -III imagery could be used for crop classification and show satisfactory results. We have applied various types of supervised techniques like ML classifier with Overall Accuracy 69.64% compared with types of kernel functions. Classification results of the analysis and image classifications can be seen at Table [1-4] with kappa coefficient values.

Table 1. Linear Kernel Function

PP	OA (%)	Kappa
50	91.37	0.8371
100	94.82	0.8998
150	91.37	0.8286
200	94.82	0.8998
250	91.37	0.8371
300	91.37	0.8371

Table 2. Polynomial Kernel Function

PP	Degree	OA (%)	Kappa
100	1	89.65	0.8069
	2	91.37	0.8371
	3	94.82	0.8998
	4	91.37	0.8286

Table 3. RBF Kernel Function

PP	OA (%)	Kappa
50	89.65	0.8069
100	91.37	0.8371
150	91.37	0.8371
200	94.82	0.8998
250	91.37	0.8286
300	91.37	0.8236

Table 4. Sigmoid Kernel Function

PP	OA (%)	Kappa
50	89.65	0.8069
100	89.65	0.8069
150	89.65	0.8069
200	89.65	0.8069
250	89.65	0.8069
300	89.65	0.8069

Table 5. Maximum Likelihood Classifier

Scale Factor	OA (%)	Kappa
255	69.64	0.6131

SVM (Sigmoid kernel), SVM (Polynomial kernel), SVM (RBF kernel and SVM (Linear kernel) gives highest overall accuracy 94.82%. Supervised classification is usually appropriate when we want to identify relatively few classes, when we have selected training sites that can be verified with ground truth data, or identify distinct, homogeneous regions that represent each class. . In the experiments, the results obtained using Support vector machine classifier using penalty parameter approach.

Conclusion

This paper presented a comparative study on the performance of supervised techniques specifically SVM kernels for classification of four band LISS-III data in agricultural region. Comparative analysis clearly explored that substantially higher overall classification accuracy (94.82%) was observed with SVM kernel, compared with that of traditional techniques. Literature review shows OA 88.89% using RBF. The experimental evaluation explained that the accuracies of Linear, RBF and Polynomial are better than Sigmoid and ML classifier. The result also shows penalty parameter plays important role in improving OA in all kernel functions. In polynomial Kernel function 3rd order provides better overall accuracy. It is an ongoing effort for the remote sensing community to continue to develop methods for producing improvement in crop mapping. The preliminary results shows multispectral data with identification of 4 types of crops like Cotton, Sugarcane, Maize and Bajara using SVM classifier with the overall accuracy is 94.82% compared with supervised techniques including MLC, we got 69.64% result.

For the future works, we will plan to use different kinds of temporal dataset. Also, it is expected that a future work would be to develop a new kernel function accounting for increasing performance.

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