A Spatial and Spectral Feature Based Approach for Classification of Crops Using Techniques Based on GLCM and SVM

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Abstract This paper highlights the study regarding the classification of crop types using the techniques based on Gray Level Co-occurrence Matrix (GLCM) and support vector machine (SVM). The dataset used was from IRS-LISS IV sensor with 5.8 m spatial resolution having three spectral bands of date 4-October 2014 for our chosen location at 20°07′13.5″N 75°23′05.3″E. Classification of all three bands followed by classification of GLCM measures (of all three bands) was accomplished by using Support Vector Machine classifier with Radial Basis Function. The accuracy of classification obtained from GLCM was 90.29% with the Kappa coefficient

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0.88 whereas the corresponding values obtained from three band classification were 86.04% and 0.83, indicating the superiority of the GLCM-based approach.

Keywords GLCM · SVM · Crop classification · IRS-LISS IV data
Spatial feature

1 Introduction

Spatial features play an important role in crop-type discrimination. Generally, plantation of crops varies as per their types; it can be done either in a single row, multiple rows, or can be in straight line for suitability and to increase the crop yield. These types of spatial arrangement provide fine spatial details while we use remote sensing data for classification; however, it needs images with high spatial resolution. In classification based on spatial information, spatial image elements are collectively used with spectral characteristics for making the classification decision. Spatial elements generally used are texture, contexture geometry, etc. [1]. Remote sensing has great potential in identifying the crops grown in agricultural land. Availability of commercial imagery with high resolution such as IKONOS-2, Worldview 2, Geoeye-2, QuickBird-2, etc., with less than 4 m spatial resolution has made it simple to classify smaller objects from complicated environment. However, there may have been several restrictions while using only the spatial information because of the diverse nature of landscapes and the spectral dissimilarity within each class [2, 3]. In this work, we have examined the use of Gray level co-occurrence Matrix (GLCM) with support vector machine for classification of crop types using IRS LISS IV data and compared their corresponding results.

1.1 Study Area

Study area selected for this work covers mostly crops which is portion of Kachori, Pimpalgaon, Pal, Walan, and Wanegaon Villages in Aurangabad District of Maharashtra State in India. These villages are located at 20°07′13.5″N 75°23′05.3″E and about 35 km in the direction of North from Aurangabad city, 5 km from Phulambri and 350 km from State capital of Maharashtra, and it is surrounded by Khultabad and Kanand Taluka towards west, and Sillod Taluka towards East [4]. The study area is given in the form of the standard false color composite in Fig. 1.

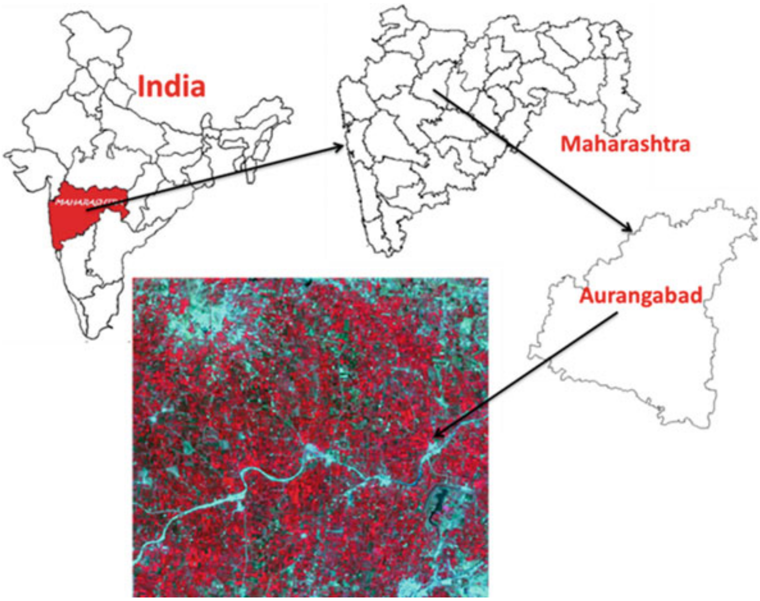

Fig. 1 Study area demonstrated in FCC of LISS-IV data

Table 1 IRS-LISS IV data multispectral bands

Band	Spectral range (µm)	Spatial resolution (m)
B2	0,52–0,59	5.8
B3	0,62–0,68	5.8
B4	0,77–0,86	5.8

1.2 Data Used

IRS-LISS IV Data having 5.8 meter spatial resolutions at nadir, The LISS-IV is a high-resolution multispectral sensor operates in three (B2, B3, and B4) bands. LISS-IV can be functioned in either of the two modes. It has a swath of 23 km in the multispectral mode for three bands, while in panchromatic mode, the full swath of 70 km can be covered in any one single band, and this can be chosen by ground command [5]. This camera can be slanted in the across track direction and can be revisited after 5 days to the same area. Data used in this work is of 4-October 2014 (Kharif season) received from National Remote Sensing Centre (NRSC, ISRO) India. Table 1 illustrates the wavelengths of all three bands of LISS-IV data in Multispectral mode. The acquired data Projected on 43rd North zone of UTM (Universal Transverse Mercator) and WGS-84 datum (World Geodetic System). Ground truth data were collected by MyGPS coordinate Android Application using Global Positional System (GPS) enabled smartphone.

2 Method Used

To do the analysis of remote sensing data, several steps are needed to be followed, and the method adopted to carry out this work is discussed below:

2.1 Preprocessing

Data received from the NRSC were geometrically and radiometrically corrected, in preprocessing firstly all three bands are layer stacked and created a spatial subset of size 1825 × 1646 after this Gray Level Co-occurrence Matrix is computed.

2.2 GLCM

To do the statistical texture analysis, texture features are computed from the statistical dissemination of observed groupings of DN values at quantified locations relative to each other in the image. According to the number of intensity points or pixels in each grouping, statistics can be categorized into first order, second order, and higher order statistics. The Gray Level Co-occurrence Matrix (GLCM) method is used to extract second order statistical texture features [6–10]. Eight texture measures as given in Table 2 were computed with processing window of 3×3 co-occurrence shift X = 1 and Y = 1. Resultant image for each band of LISS-IV data is given in Fig. 2, whereas equation for each of these measures is given in Table 2.

2.3 Classification

As per the visual Image interpretation and ground truth data, 249 pixels have been trained for seven Classes namely Cotton, Maize, Sugarcane, Settlement (Built-up area), Rock area, and Waterbody from a subset of the image. To perform classification, two approaches has been followed initially Support Vector Machine classifier with RBF kernel have been applied on the original three bands of the Image and in a second approach similar training pixels were selected from all the eight GLCM measures of all three bands and SVM has been applied with RBF to these layers.

The SVM is the most often used important technique for supervised classification [11] and generates good results from noisy and complex data. SVM classifiers, characterized by self-adaptability with rapid learning speed and limited requirements of training sample size, have confirmed a fairly reliable methodology in the smart processing of remote sensing data [12, 13]. SVM divides the classes with decision borderline which maximizes the margin between them. This decision boundary is

Table 2 GLCM Measures with their Mathematical formulation

Eq. No	Measures	Equation
1	Mean	$Mean = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} i * p(i, j)$
2	Variance	$Variance = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} (i - u)^2 \, p(i, j)$
3	Homogeneity	$Homogeneity = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} \frac{1}{1+(i-j)^2} \, p(i, j)$
4	Contrast	$Contrast = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} P(i, j)(i - j)^2$
5	Dissimilarity	$Dissimilarity = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} P(i, j)\lvert i - j\rvert$
6	Entropy	$Entropy = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} P(i, j) \log(p(i, j))$
7	Second moment	$SecondMoment = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} \{P(i - j)\}^2$
8	Correlation	$Correlation = \sum_{i=1}^{Ng} \sum_{j=1}^{Ng} \frac{(i,j)p(i,j)-\mu_x\mu_y}{\sigma_x\sigma_y}$

Ng = No. of Distinct gray levels in the image
P(i, j) = probability of each pixel value

called as hyper plane and the nearby data points are referred as support vectors which are critical components of training sets. There are several options to use different kernels for SVM namely those kernels are linear, Polynomial, Sigmoid and Radial Basis Function (RBF) out of that RBF kernel type gives a better result than others. Function for SVM is given in Eq. (1).

$$f(x) = \sum_i \alpha_i \, K(x_i, x) + b \tag{1}$$

where α_i is the Lagrange Multiplier, $K(x_i,x)$ means the Kernel function, and in this work, it is the Radial Basis function given in Eq. (2);

$$K\left(x, x'\right) = \exp\left(-\gamma \left\| x - x' \right\|^2\right) \tag{2}$$

where γ is the gamma term which is the floating point value and greater than or equal to 0.01, and we have considered the gamma value 0.042. RBF kernel maps samples into a higher dimensional space nonlinearly; it can deal with the circumstance when the relation between class labels and attributes is nonlinear [11, 14, 15]. Classification layers generated are given Fig. 3. Finally, accuracy assessment was made by using confusion matrix wherein commission error, omission error followed by Producer Accuracy (PA), and Users Accuracy (UA) were computed for all classes, and overall accuracy along with Kappa coefficient was also computed for both classification layers.

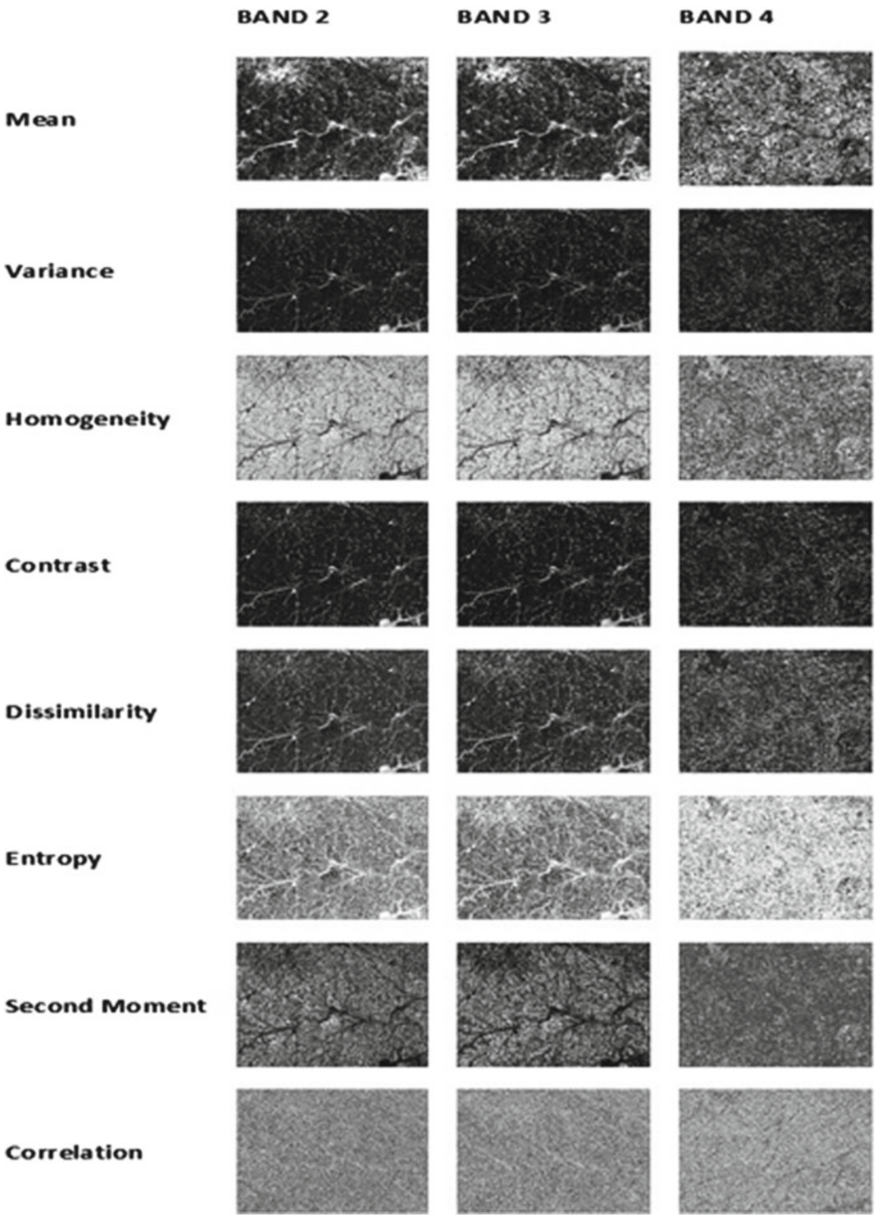

Fig. 2 Eight GLCM measures of three bands of LISS-IV data

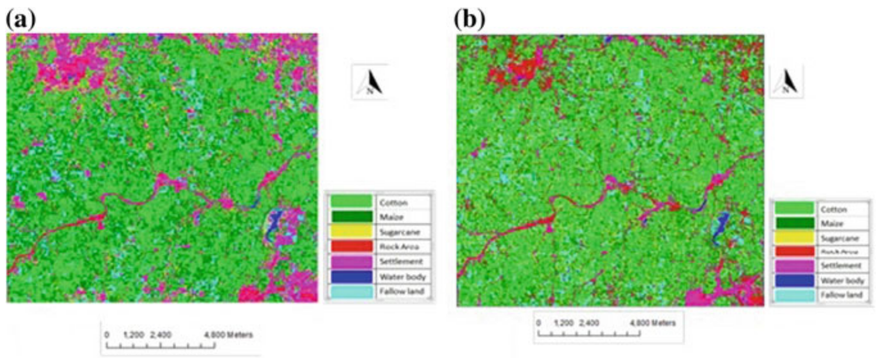

Fig. 3 Classified layers: **a** all three bands. **b** GLCM measures

2.4 Result and Discussion

Result analysis has been performed by using error matrix generated of 659 testing pixels and computed Producer Accuracy and Users Accuracy (UA). UA is defined as the ratio of the main diagonal cell value to the sum of the same row. As an alternative, it can also be derived from the commission error using the following equation:

$$\text{Users Accuracy} = 100 - \text{commission error}(\%) \tag{3}$$

Producer Accuracy is the ratio of the main diagonal cell of a column to the sum of the same column. It can also be obtained by subtracting omission errors from 100.

$$\text{Producers accuracy} = 100 - \text{omission error}(\%) \tag{4}$$

Results obtained from confusion matrix clearly state that classification of all GLCM stacked layers gives better results than ordinary three bands. Table 3 demonstrates the PA and UA for all seven classes for both approaches

Table 3 Producers and users accuracy obtained for each class

Class	Three bands		GLCM	
	PA (%)	UA (%)	PA (%)	UA (%)
Cotton	75.00	68.97	87.50	78.65
Maize	87.50	70.00	77.08	80.43
Sugar cane	34.48	76.92	60.34	71.43
Rock area	90.29	89.42	93.20	97.96
Settlement	90.00	90.76	98.33	91.47
Water body	100.00	100.00	100.00	100.00
Fallow land	100.00	99.24	100.00	100.00

The overall accuracy obtained for three bands is 86.04% with Kappa Coefficient of 0.83 whereas for GLCM, it was 90.29% and Kappa Coefficient 0.88. As compared to Fallow land, Waterbody, settlement, and rock area the PA and OA are less for all three classes of crops because of the similarity in reflectance behavior and complicated spatial arrangements of crops. As far as the literature concern, comparison of results with the results obtained by others is a very difficult task for RS data classification, because of variation in datasets, study area, sample, or ground truth data. Researchers had used first- and second-order GLCM measures for texture feature extraction, and applied SVM for classification to classify soil, vegetation, and water body and got good accuracy [16]. Zhang et al. had used two methods in his first method and mean of the texture values in several directions was used as texture features of the image whereas in the second approach, texture feature extraction based on the direct measure and GLCM fusion algorithm, and SVM with Gaussian radial basis function are used for classification. They performed these experiments on GeoFen-2, QuickBird, and GeoEye-1 sensor data, which are having high spatial resolution and they got superior results [17]. These discussed works have been applied to data with less than 3 m spatial resolution, which is very high wherein we have used data with 5.8 m spatial resolution and got reasonably good accuracy.

3 Conclusion

In this work, the classification has been performed on all three bands as well as the 8 GLCM measures of those three bands. As per the confusion matrix average Producer's and User's accuracy for all seven classes is higher; while applying SVM with RBF on GLCM measures, than applying it on three bands of LISS-IV data. Results state that GLCM, while used with support vector machine, gives better results for crop type classification. Accuracy can be enhanced by using remote sensing data with high spatial resolution.

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