

# Performance Evaluation of Maximum-Likelihood Algorithm after Applying PCA on LISS 3 Image using Python Platform

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**Abstract**—This paper presents a system for multispectral image processing of LISS3 image using python programming language. The system starts with preprocessing technique i.e. by applying PCA on LISS3 image. PCA reduces image dimensionality by processing new, uncorrelated bands consisting of the principal components (PCs) of the given bands. Thus, this method transforms the original data set into a new dataset, which captures essential information. Further classification is done through maximum-likelihood algorithm. It is tested and evaluated on selected area i.e. region of interest. Accuracy is evaluated by confusion matrix and kappa statistics. Satellite imagery tool using python shows better result in terms of overall accuracy and kappa coefficient than ENVI tool's for maximum-likelihood algorithm.

**Keywords**— Kappa Coefficient, Maximum-likelihood, Multispectral image, Overall Accuracy, PCA, Python, Satellite imagery tool

## I. Introduction

Remote sensing has become a vital tool in wide areas. The classification of multi-spectral images has been a productive application that's used for classification of land cover maps [1], urban growth [2], forest change [3], monitoring change in ecosystem condition [4], monitoring assessing deforestation and burned forest areas [5], agricultural expansion [6], mapping [7], real time fire detection [8], estimating tornado damage areas [9], estimating water quality characteristics of lakes [10], geological mapping, estimating crop acreage and production, monitoring of environmental pollution, monitoring and mapping mangrove ecosystems. According to functional requirement of the system platform the whole system is designed.

System is designed in python programming language as python is object oriented language. Python offers an assortment of open-source code libraries that can significantly improve advancement. NumPy (Numerical Python) and SciPy (Scientific Python) give an arrangement of methods for working with raster information appropriate for picture investigation. GDAL (Geospatial Data Abstraction Library) offers access to more than 120 picture information groups, including PDS, ISIS2/3, FITS, ENVI, Jpeg2000, Png and Tiff. Matplotlib libraries give standard and cartographic data representation contraptions. Taken together, these libraries incorporate into a profoundly viable handling suite for scientific data compression, classification, and analysis [11].

In this paper, analysis of LISS3 image is presented. The Linear Imaging Self Scanning Sensor (LISS 3) is a multi-spectral device operating in four spectral bands, three in the visible and near infrared, as in the case of IRS-1C/1D. The new feature in LISS 3 device is the SWIR band (1.55 to 1.7

microns), which provides information with a spatial resolution of 23.5 m not like in IRS-1C/1D (where the spatial resolution is 70.5 m) [12].

The Data products are classified as Standard and have a system level accuracy. LISS 3 Standard Products comprise Path/Row primarily based products, Shift along Track product, Quadrant products and Georeferenced products. Path/Row Based products are unit generated based on the referencing scheme of every sensor. Shift Along Track applies to those products covering a user's area of interest that falls in between two successive scenes of a similar path, then the direction. LISS 3 full scene is divided into four nominal and eight derived quadrants. LISS 3 photographic quadrant products are unit generated on 1:125,000 scale. Georeferenced products are true north oriented products.

Standard Path/Row Based products cover a region of 141 x 141 km and are defined by 3 Bands. Path/Row Based mostly products comprise Raw, Radio-metrically corrected and Geo referenced levels of corrections. Quadrant products cover a region of 70 x 70 km and are characterized by 3 or 4 Bands. Quadrant products consisting of Standard and Geo referenced levels of corrections [13].

The LISS 3 image data is correlated from one band to the other. The extent of a given picture element on one band can to some level be predicted from the level of that same pixel in another band. Principal component analysis could be a pre-processing transformation that generates new images from the uncorrelated values of different images. Principal component

analysis operates on all bands at single time. Thus, it eliminates the issue of choosing appropriate bands related with the band rationing operation. Principal components describe the data with efficiency than the original band reflectance values. The first principal component accounts for a maximum portion of the variance within the data set. Resulting principal components account for successively smaller portions of the remaining variance [14].

The goals of PCA are unit to (a) extract the most important information from the data table, (b) reduces the size of the data-set by keeping thenecessary information only, (c) alter the description of the data-set, (d) to investigate the structure of the observations and therefore the variables with n bands [15]. Multispectral Transformation of Image Data by Principal Component transformation uses image data statistics to define a rotation of the original image in such a way that the new axes are orthogonal to each other and point in the direction of decreasing order of variance [16]. The transformed components are totally not correlated and are more interpretable than original image. Computationally, this can be done by 1. calculating of correlation matrix using input image data sets. 2. Calculation of eigen values and eigenvectors. 3. Calculation of principal components [17].

Principal components analysis constructs linear combinations of multispectral pixel intensities which are mutually uncorrelated and which have maximum variance. It is given as input to supervised classification. In supervised classification Samples of known identity are used to classify pixels of unknown identity. For the known samples multivariate statistical parameters are calculated. Every pixel is evaluated and assigned to the class which it most closely resembles digitally. Supervised classification is done through maximum-likelihood algorithm. The maximum likelihood algorithm is based on the probability that a pixel belongs to a particular class.

This technique is supervised based on the availability of reference end-members that are spectrally pure reflectance readings of different materials. Since these end-member-based approaches are nonparametric, there is no need to collect a large number of training samples for every category. However, as supervised techniques, they need a priori knowledge of the ground reference information in the type of a complete set of end-members. End-members are usually derived either from extensive in situ and lab work using a spectroradiometer or from a hyper-spectral image if spectrally pure pixels of the materials can be identified on the image. However, in situ data collection to obtain ground reference information in advance is not always possible prior to image classification. Therefore, when no or very less a priori ground reference information is available, unsupervised approaches appear to be an attractive alternative to the existing end-member-based methods. However, most standard unsupervised image classifiers, such as the k-means method, were designed to analyze multispectral imagery and may be inadequate for hyper-spectral data analysis for two main reasons. First, these techniques are computationally intensive, as result of all pixels in the image must be compared with all clusters through multiple iterations in order to assign them to the nearest cluster. Second, they have a tendency to suffer from

performance degradation with increased spectral dimensionality of the hyper-spectral images [18].

In the next section we present the Dataset. In section 3 we present methodology. Section 4 presents system design and implementation. section 5 present result and discussion and Section 6 presents conclusion.

## II. Data set

The digital remote sensing data IRS-P6- LISS III having spatial resolution 28.5m, 23.5m and 5m were processed and geo referenced using Ground Control Points (GCP) from survey of India map. LISS 3 Image having dimension 1153\*1153. It contains 4 bands, 3 RGB and one IR band.

The following Dataset are used for display, analysis and classification:

**Table 1:Aurangabad\_LISS\_III\_Oct\_2008**

Datatype	Multispectral radiometric high resolution
Instrument	LISS-III
Resolution	23.5m
Satellites	IRS-P6
Dimensions	1153*1153*4
File Type	TIFF
Sensor Type	LISS
Projection	Geographic Lat/lon

**Table 2:Ahmadnagar\_LISS\_III\_Dec\_2012**

Datatype	Multispectral radiometric high resolution
Instrument	LISS-III
Resolution	23.5m
Satellites	IRS-P6
Dimensions	1153*1153*4
File Type	TIFF
Sensor Type	LISSs
Projection	Geographic Lat/lon

**Table 3:E43N09**

Datatype	Multispectral radiometric high resolution
Instrument	LISS-III
Resolution	24m

Satellites	IRS-P6
Dimensions	1153*1153*4
File Type	TIFF
Sensor Type	LISS
Projection	Geographic Lat/lon

- Sort the eigenvectors by decreasing eigenvalues and choose eigenvectors with the largest eigenvalues to form a dimensional matrix.
- Use this eigenvector matrix to transform the samples onto the new subspace.

Above PCA algorithm is implemented in python in which covariance matrix is calculated by using following formula:

$$cov_{ij} = \frac{\sum_{k=1}^N (z_{ik} - \mu_i)(z_{jk} - \mu_j)}{N-1} \quad (1)$$

### III. Methodology

System is designed in a following way:

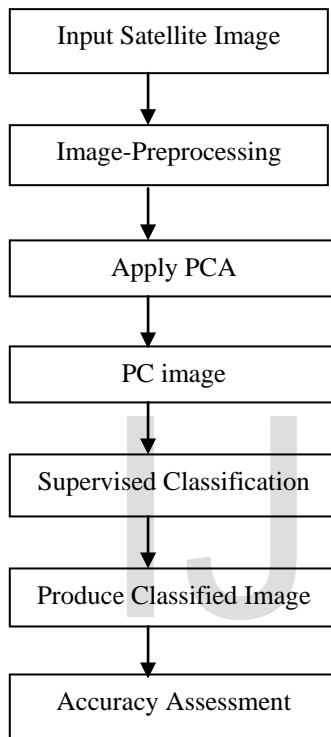


Figure 1: Flow diagram of System

To implement system we use Python IDLE platform. To do it various libraries GDAL, matplotlib, numpy, PIL, auxil, mlp are used. For classification algorithm such as k-means for unsupervised clustering and maximum-likelihood for supervised clustering are implemented.

Algorithms are described as follows:

#### 3.1 Principal component analysis

PCA algorithm is implemented in a following way:

- Take the whole image dataset.
- Compute the dimensional mean vector.
- Compute the covariance matrix of the whole image data set
- Compute eigenvectors and corresponding eigenvalues.

Where,

Z- value of cell

I,j – layer of the stack

$\mu$  – mean of layer

N- is number of cell

k- denote number of cell

After estimating covariance matrix, eigen values and eigen vector are calculated using numpy.linalg.eigh() function.

Let A be a linear transformation represented by a matrix A.

$$Ax = \lambda x \quad (2)$$

for some scalar lambda, then lambda is called the eigenvalue of A with corresponding (right) eigenvector x.

ith eigenvalue lambda, then the corresponding eigenvectors satisfy

$$A - \lambda I = 0 \quad (3)$$

The order of eigenvalues and eigenvectors is undefined, so the eigenvalues and eigenvectors are sorted into decreasing order. Then the principal components are calculated by projecting the original image bands along the eigenvectors and the resulting data matrix is rearranged in BIP format. Finally, the principal components are stored to disk, correcting the geo-referencing information in case a spatial subset of the input image was chosen with a new origin x0, y0.

#### 3.2 Maximum-likelihood Algorithm

The entire objective of maximum-likelihood classification is to automatically classify all pixels in an image into land cover classes or themes. In this algorithm the task can often be seen as of modeling probability distributions. On the basis of representative data for K land cover classes presumed to be present in a scene, a posterior probability for class k conditional on observation are “learned” or approximated. This is usually called the training phase of the classification procedure. Then these probabilities are used to classify all of the pixels in the image, a step referred to as the generalization phase.

The choice of training data is arguably the most difficult and critical part of this classification process. The standard procedure is to select areas within a scene which are representative of each class of interest. In the Classic environment, the areas are entered as regions of interest (ROIs), from which the training observations are selected. Some fraction of the representative data may be retained for later accuracy assessment. These comprise the so-called test data and are withheld from the training phase in order not to bias the subsequent evaluation. We will refer to the set of labeled training data as training pairs or training examples.

Having estimated the parameters from the training data, the generalization phase consists simply of applying the rule to all of the pixels in the image. Because of the small number of parameters to be estimated, maximum likelihood classification is extremely fast. Its weakness lies in the restrictiveness of the assumption that all observations are drawn from multivariate normal probability distributions.

Algorithm for maximum-likelihood classification:

1. The number of land cover types within the study area is determined.
2. The training pixels for each of the desired classes are chosen using land cover information for the study area.
3. The training pixels are then used to estimate the mean vector and covariance matrix of each class.
4. Finally, every pixel in the image is classified into one of the desired landcover types or labeled as unknown.

In ML classification, each class is enclosed in a region in multispectral space where its discriminant function is larger than that of all other classes. These class regions are separated by decision boundaries [19].

The maximum likelihood decision rule assumes that the histograms of the bands of data have normal distributions. It 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. If the user has a priori knowledge that the probability is not equal for all classes, the weight factors can be employed to improve the classification.

#### IV. System Design And Implementation

System is designed in a way to display LISS 3 image and perform PCA algorithm on LISS 3 image. According to functional requirement of the system platform the whole system is divided into open image, compute statistics and perform PCA and maximum-likelihood algorithm.

The layout of the system as follows

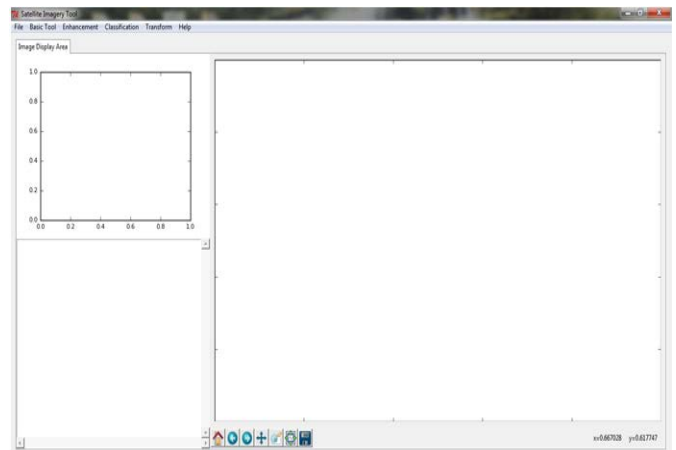


Figure 2: Layout of the system

Above figure shows the layout of the system. It contains menu bar as file, basic tool, enhancement, classification, transform and help menu. File menu also has submenus as open image and exit. Basic tool have submenu statistic. Enhancement has submenus Linear, Linear255, Linear2pc, Histogram equalization. Classification has submenus Supervised and unsupervised. Transform have submenu PCA. But in this paper we are introducing only PCA algorithm.

For displaying image we have to select open image tab in file menu. After selecting image we can select either gray scale image or RGB image. After selecting load button we have to display image in canvas. By clicking on the image we can show the z-profile which is at the top of the left side of the layout. Z-profile is a graph of No of band verses data value of selected pixel of the image.

#### V. Result and Discussion

In this paper, we used LISS 3 image of Aurangabad city, Ahmednagar city and E43N09.

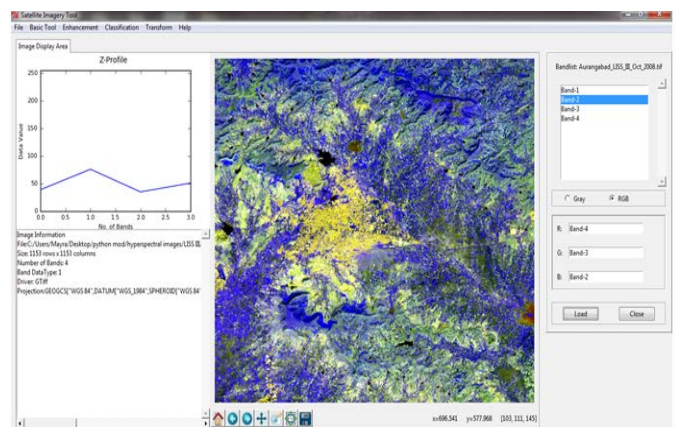


Figure 3 LISS 3 image of Aurangabad City

Above figure displays the LISS 3 image of Aurangabad city. Information about the image is shown below the Z-profile which contains size of the image, number of bands and projection. Band correlation of the LISS 3 image is shown in following table:

**Table 4: Co-relation of the LISS 3 Image of Aurangabad city**

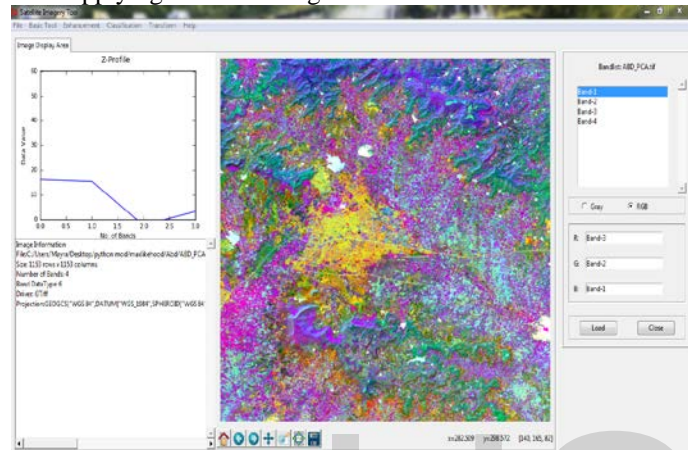
	Band-1	Band-2	Band-3	Band-4
Band-1	1.000001	0.395452	0.717185	0.649483
Band-2	0.395452	1.000001	-0.0603556	0.039494
Band-3	0.717185	-0.0603556	1.000001	0.944259
Band-4	0.649483	0.039494	0.944259	1.000001

PC -3	0.000000	0.000000	1.000001	0.000000
PC -4	0.000000	0.000000	0.000000	1.000001

Above table 2 and 3 show the Comparison for PCA algorithm using Satellite Imagery Tool and ENVI tool on LISS 3 image of Aurangabad City.

Now, supervised classification using maximum-likelihood algorithm is applied. Hence, result obtained as follows:

After applying PCA the image is as follows:



**Figure 4: After applying PCA on LISS 3 image of Aurangabad city**

Band correlation of LISS 3 image after applying PCA is shown in following table.

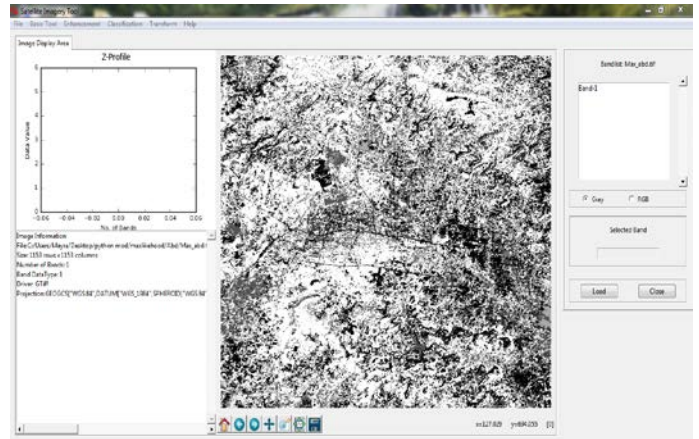
**Table 5: Co-relation of the Image after applying PCA Using Satellite Imagery Tool**

	PC-1	PC-2	PC-3	PC-4
PC-1	1.000001	0.000000	0.000000	0.000000
PC-2	0.000000	1.000001	0.000000	0.000000
PC-3	0.000000	0.000000	1.000001	0.000000
PC-4	0.000000	0.000000	0.000000	1.000001

Following table shows Co-relation of the Image after applying PCA algorithm Using ENVI software.

**Table 6: Co-relation of the Image after applying PCA Using ENVI**

	PC -1	PC -2	PC -3	PC -4
PC-1	1.000001	0.000000	0.000000	0.000000
PC -2	0.000000	1.000001	0.000000	0.000000



**Figure 5: After maximum-likelihood algorithm on LISS 3 image of Aurangabad city**

One of the foremost common means that of expressing classification accuracy is that the preparation of classification error matrix generally known as confusion or a contingency table. This matrix stems from classifying the sampled training set pixels and listing the best-known land varieties used for training (columns) versus the Pixels truly classified into every land class by the classifier.

Overall Accuracy = (109/111) 98.198%  
Kappa Coefficient = 0.9632

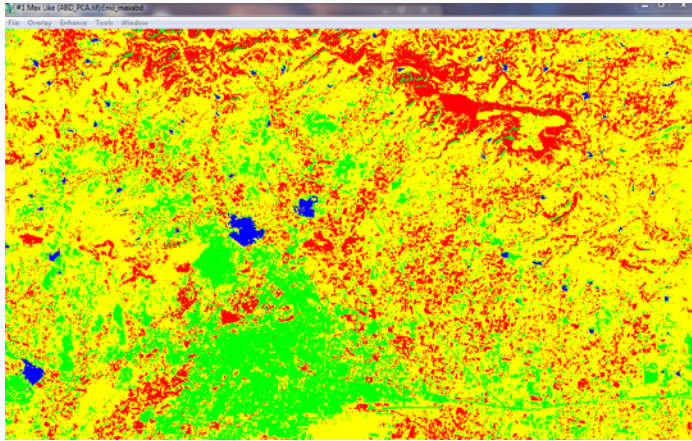
**Table 7 : Confusion matrix**

Class	R1	R2	R3	R4	Total
R1	28	0	0	0	28
R2	0	37	0	0	37
R3	0	0	22	0	22
R4	0	2	0	22	24
Total	28	39	22	22	111

The matrix is in the upper left 5 × 5 block in the table. Row 7 contains the ratios  $c_{ii}/c_{i*}$ ,  $i = 1 \dots 7$ , which are referred to as the producer accuracies. Column 7 contains the user accuracies  $c_{ii}/c_{i*}$ ,  $i = 1 \dots 5$ . The producer accuracy is the probability that an observation with label  $i$  will be classified as

such. The user accuracy is the probability that the true class of an observation is  $i$  given that the classifier has labeled it as  $i$ . The rate of correct classification, is of course one minus the misclassification rate.

In Envi After applying maximum-likelihood algorithm we get classified image as:



**Figure 6: After maximum-likelihood algorithm on LISS 3 image of Aurangabad city in ENVI**

Confusion matrix of above image in ENVI

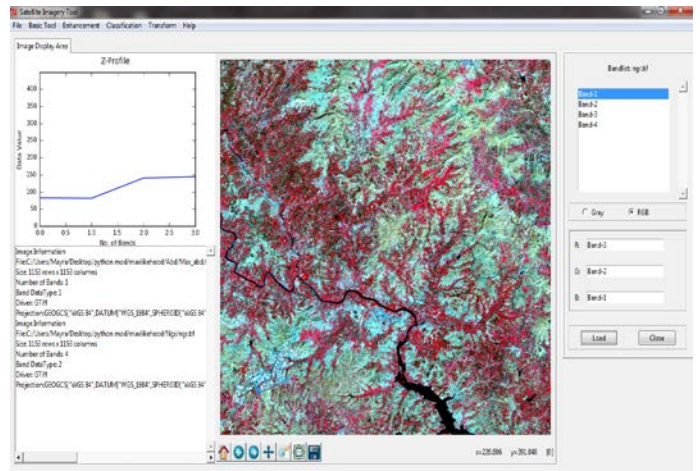
Overall Accuracy =  $(343/352)$  97.4431%

Kappa Coefficient = 0.9468

**Table 8 : Confusion matrix**

Class	R1	R2	R3	R4	Total
R1	80	0	1	0	81
R2	0	99	0	1	100
R3	0	0	80	0	80
R4	5	2	0	84	91
Total	85	101	81	85	352

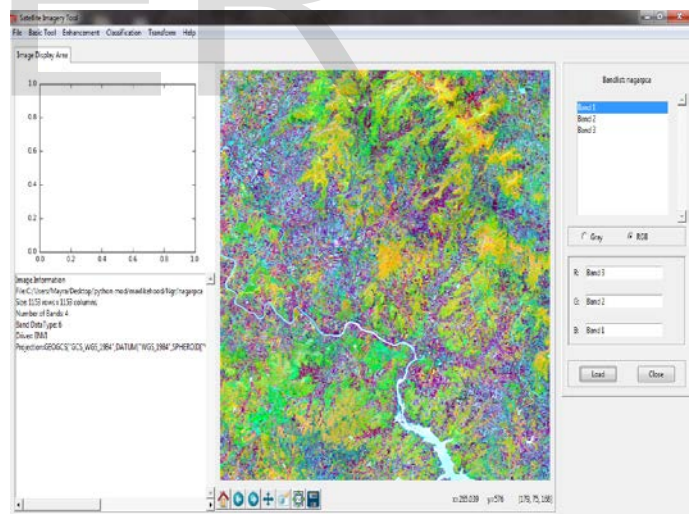
Similarly, PCA and maximum-likelihood algorithm is applied on LISS 3 image of Ahmednagar city. Hence, result obtained as follows:



**Figure 7:LISS 3 image of Ahmednagar city**

**Table 9: Co-relation of the LISS 3 Image of Ahmednagar city**

	Band-1	Band-2	Band-3	Band-4
Band-1	1.000001	0.920653	0.286000	0.770380
Band-2	0.920653	1.000001	0.137825	0.848406
Band-3	0.286000	0.137825	1.000001	0.398297
Band-4	0.770380	0.848406	0.398297	1.000001



**Figure 8: After applying PCA on LISS 3 image of Ahmednagar city**

Band correlation of LISS 3 image after applying PCA is shown in following table.

**Table 10: Co-relation of the Image after applying PCA Using Satellite Imagery Tool**

	PC-1	PC-2	PC-3	PC-4

<b>PC-1</b>	1.000001	0.000000	0.000000	0.000000
<b>PC-2</b>	0.000000	1.000001	0.000000	0.000000
<b>PC-3</b>	0.000000	0.000000	1.000001	0.000000
<b>PC-4</b>	0.000000	0.000000	0.000000	1.000001

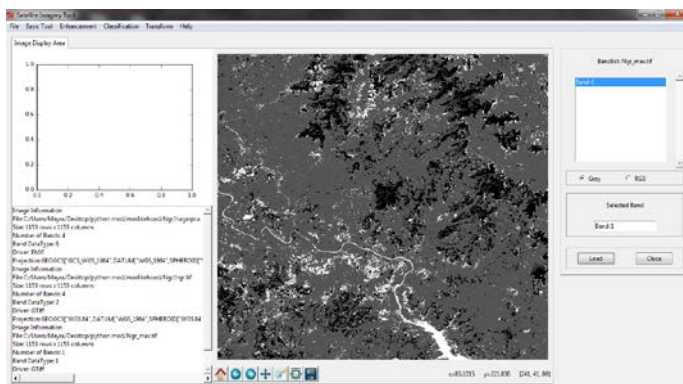
Following table shows Co-relation of the Image after applying PCA algorithm Using ENVI software.

**Table 11: Co-relation of the Image after applying PCA Using ENVI**

	<b>PC -1</b>	<b>PC -2</b>	<b>PC -3</b>	<b>PC -4</b>
<b>PC-1</b>	1.000001	0.000000	0.000000	0.000000
<b>PC -2</b>	0.000000	1.000001	0.000000	0.000000
<b>PC -3</b>	0.000000	0.000000	1.000001	0.000000
<b>PC -4</b>	0.000000	0.000000	0.000000	1.000001

Above table 7 and 8 show the Comparison for PCA algorithm using Satellite Imagery Tool and ENVI tool on LISS 3 image of Ahmednagar City.

Now, supervised classification using maximum-likelihood algorithm is applied. Hence, result obtained as follows:



**Figure 9: After maximum-likelihood algorithm on LISS 3 image of Ahmednagar city**

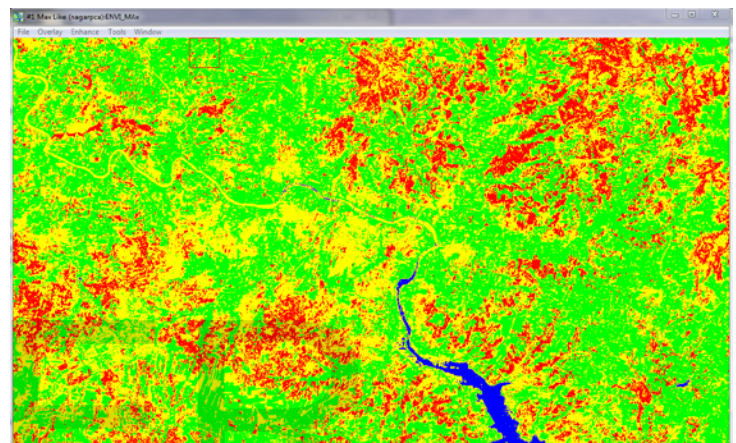
Confusion matrix after applying maximum-likelihood algorithm is as follows:

Overall Accuracy = (89/118) 93.22%  
Kappa Coefficient = 0.908686

**Table 12 : Confusion matrix**

Class	R1	R2	R3	R4	Total
R1	23	0	0	5	28
R2	0	22	0	0	22
R3	0	0	35	0	35
R4	2	1	0	30	33
Total	25	23	35	35	118

In Envi After applying maximum-likelihood algorithm we get classified image as:



**Figure 10: After maximum-likelihood algorithm on LISS 3 image of Ahmednagar city in ENVI**

Confusion matrix in Envi of above image in ENVI

Overall Accuracy = (322/353) 91.2181%  
Kappa Coefficient = 0.8821

**Table 13 : Confusion matrix**

Class	R1	R2	R3	R4	Total
R1	71	0	0	19	90
R2	1	66	0	3	70
R3	0	0	99	0	99
R4	8	0	0	86	94
Total	80	66	99	108	353

Similarly, PCA and maximum-likelihood algorithm is applied on LISS 3 image of E43N09. Hence, result obtained as follows:

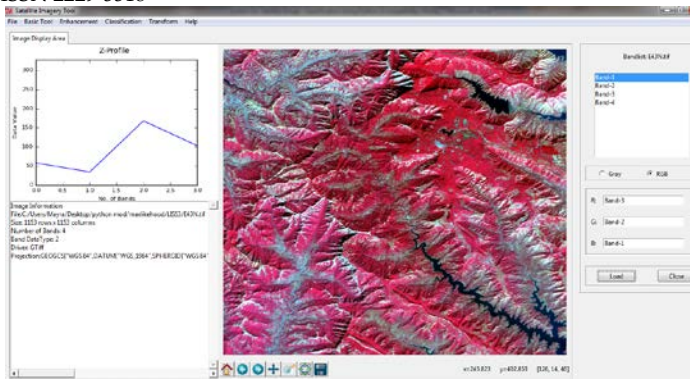


Figure 11: LISS 3 image of E43N09

Table 14: Co-relation of the LISS 3 Image of E43N09

	Band-1	Band-2	Band-3	Band-4
Band-1	1.000001	0.928866	0.492720	0.906727
Band-2	0.928866	1.000001	0.303000	0.920138
Band-3	0.492720	0.303000	1.000001	0.520075
Band-4	0.906727	0.920138	0.520075	1.000001

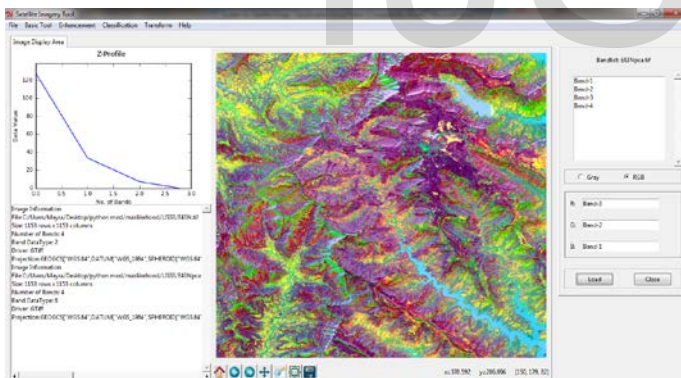


Figure 12: After applying PCA on LISS 3 image of E43N09

Table 15: Co-relation of the Image after applying PCA Using Satellite Imagery Tool

	PC-1	PC-2	PC-3	PC-4
PC-1	1.000001	0.000000	0.000000	0.000000
PC-2	0.000000	1.000001	0.000000	0.000000
PC-3	0.000000	0.000000	1.000001	0.000000

PC-4	0.000000	0.000000	0.000000	1.000001
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Following table shows Co-relation of the Image after applying PCA algorithm Using ENVI software.

Table 16: Co-relation of the Image after applying PCA Using ENVI

	PC -1	PC -2	PC -3	PC -4
PC-1	1.000001	0.000000	0.000000	0.000000
PC -2	0.000000	1.000001	0.000000	0.000000
PC -3	0.000000	0.000000	1.000001	0.000000
PC -4	0.000000	0.000000	0.000000	1.000001

Above table 12 and 13 show the Comparison for PCA algorithm using Satellite Imagery Tool and ENVI tool on LISS 3 image of E43N09.

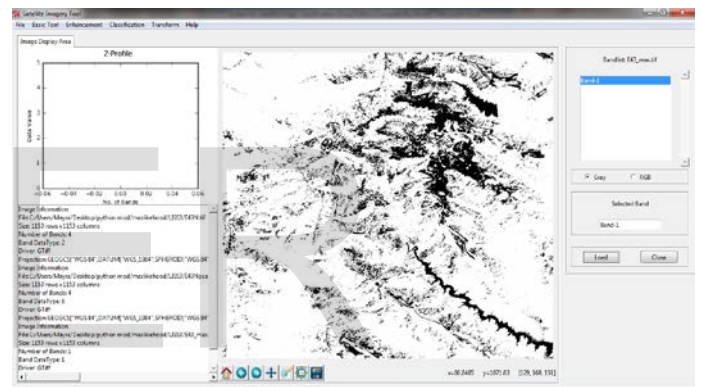


Figure 13: After maximum-likelihood algorithm on LISS 3 image of E43N09

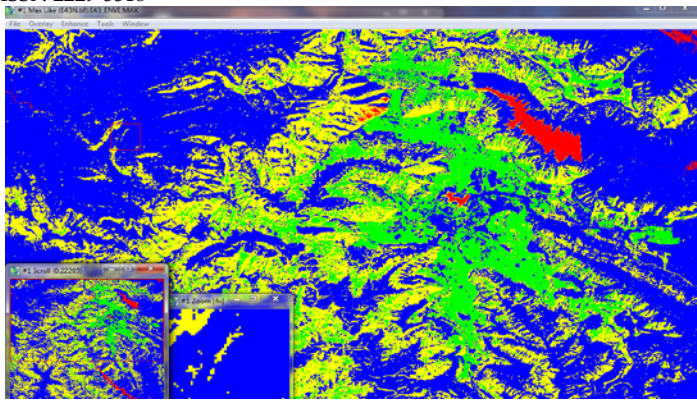
Confusion matrix after applying maximum-likelihood algorithm is as follows:

Overall Accuracy = (137/141) 97.163%  
 Kappa Coefficient = 0.94056

Table 17 : Confusion matrix

Class	R1	R2	R3	R4	Total
R1	26	0	0	0	26
R2	0	49	2	0	51
R3	0	1	46	0	47
R4	1	0	0	16	17
Total	27	50	48	16	141





**Figure 14: After maximum-likelihood algorithm on LISS 3 image of E43N09 in ENVI**

Confusion matrix of above image in ENVI:

Overall Accuracy = (439/452) 97.12%

Kappa Coefficient = 0.9253

**Table 18 : Confusion matrix**

Class	R1	R2	R3	R4	Total
R1	94	0	6	0	100
R2	0	155	0	0	155
R3	0	5	130	0	135
R4	2	0	0	60	62
Total	96	160	136	60	452

**Table 19: Sumarrization of results of maximum-likelihood algorithm**

Image	Satellite imagery		ENVI Tool	
	Overall Accuracy	Kappa Value	Overall Accuray	Kappa Value
Aurangabad	98.198%	0.9632	97.443%	0.9468
Ahmednagar	93.221%	0.9086	91.218%	0.8821
E43N09	97.163%	0.94056	97.12%	0.9253

Above table shows comparison between Satellite imager tool using python and ENVI tool on maximum-likelihood algorithm. In which satellite imagery tool shows better result

in terms of overall accuracy and kappa coefficient than ENVI tool's for maximum-likelihood algorithm.

Maximum-likelihood algorithm is having time complexity  $O(n)$  where  $n$  is the number of training example. And Its space complexity is  $O(d)$  where  $d$  is the processors.

## VI. Conclusion and Future Scope

In this way, image processing platform has been designed, which basically realizes reading image data, processing, compression and visualization on image. The System will help users get useful information with image data. Meanwhile, algorithm such as maximum-likelihood makes a good effect on image data's classification.

PCA algorithm is implemented in python. As Python is faster in numerical computing. Python provides less execution time and function to handle multispectral image data. A detail analysis of Maximum-likelihood classification on LISS 3 image has been carried out. Maximum-likelihood classifies the classes that exist in the multispectral image. Maximum-likelihood classifies pixels based on known properties of each cover type. The classification process showed that the classification result from manipulating PCA image is better in terms of accuracy than the classification made on the original images. Table 19 shows the better result in in terms of overall accuracy and kappa coefficient than ENVI tool's for maximum-likelihood algorithm.

In future the similar research can be done on different type of images such as AVIRIS, LandsatTM. The final result may vary depending on the type of image.

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