SEGMENTATION BASED CLUSTERING OF HYPERSPECTRAL IMAGES

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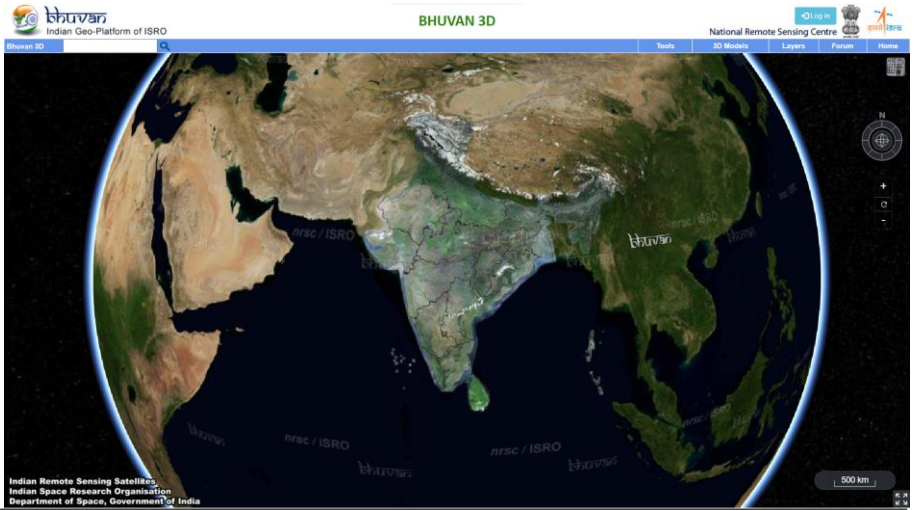
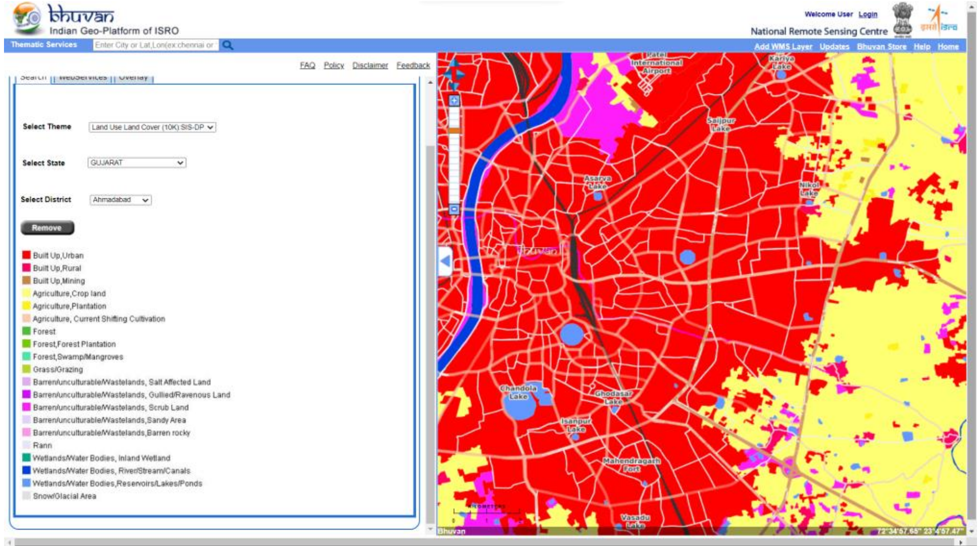
Introduction

Remote sensing refers to obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation.

- Remote sensing systems are a very important source of information for GIS, as they provide access to spatio-temporal information on surface processes on scales ranging from regional to global.
- The spatial data generally is in the form of maps, which could be showing topography, geology, soil types, forest and vegetation, land use, water resource availability etc., stored as layers in a digital form.
- Integrating many layers of data in a computer can easily generate new thematic maps.



Bhuvan, is an Indian web based utility provides a set of map based content prepared by ISRO



Land Use Land Cover data of the Ahmedabad city

Digital Image

An image is represented by its dimensions (height and width) based on the number of pixels. This pixel is a point on the image that takes on a specific shade, opacity or color. It usually represented in Grayscale, RGB. Digital Image may consists of

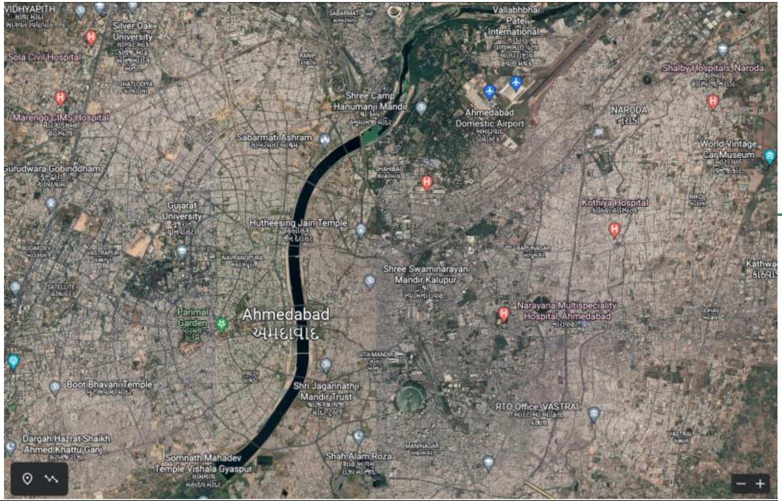
- **Spatial component** describes the quality of an image and how detailed objects are in an image. If the grid cells are smaller, this means the spatial resolution has more detail with more pixels.
- **Spectral Component** describes the amount of spectral detail in a band. High spectral resolution means its bands are more narrow.
- **Radiometric Component** corresponds to the sensitivity of a sensor, i.e. its ability to measure and to enable distinction within the same spectral band of differences in the electromagnetic energy reflected by the elementary ground surfaces.
- **Temporal Component** corresponds a series of images taken at different time to monitor the dynamic changes of the objects

Temporal data showing wildfire in 2010, 2017, and 2020.

Motivation

Information Conversion

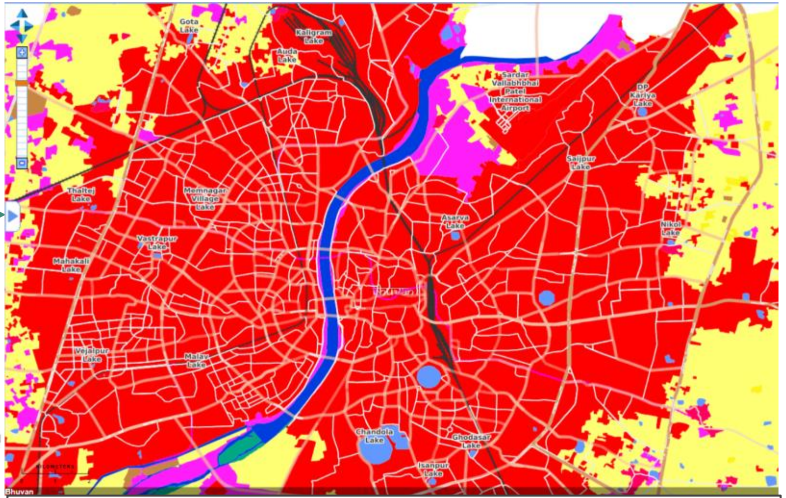
The main motivation of this work is information extraction from less interpretative image.



Unclassified image of Ahmedabad City downloaded from Google Earth

Classification

- Built Up,Urban
- Built Up,Rural
- Built Up,Mining
- Agriculture,Crop land
- Agriculture,Plantation
- Agriculture, Current Shifting Cultivation
- Forest
- Forest,Forest Plantation
- Forest,Swamp/Mangroves
- Grass/Grazing
- Barren/unculturable/Wastelands, Salt Affected Land
- Barren/unculturable/Wastelands, Gullied/Ravenous Land
- Barren/unculturable/Wastelands, Scrub Land
- Barren/unculturable/Wastelands,Sandy Area
- Barren/unculturable/Wastelands,Barren rocky
- Rann
- Wetlands/Water Bodies, Inland Wetland
- Wetlands/Water Bodies, River/Stream/Canals
- Wetlands/Water Bodies,Reservoirs/Lakes/Ponds
- Snow/Glacial Area



Classified LULC data of Ahmedabad City downloaded from Bhuvan NRSC

Need of Land Use Land Cover Data:

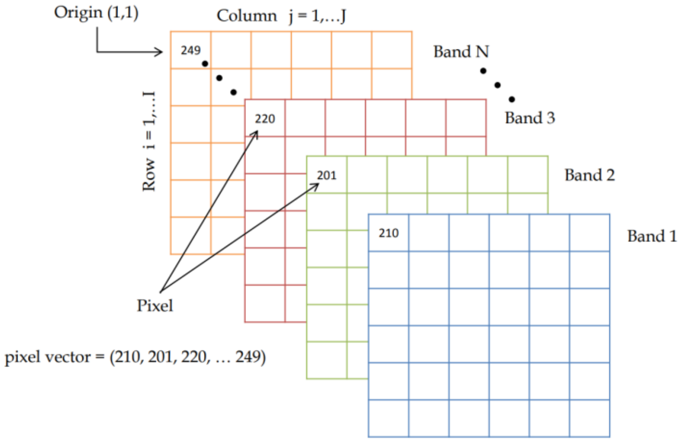
- Provides a better understanding of land utilization aspects,
- Land cover and use information may be used for planning, monitoring, and evaluation of development, industrial activity, or reclamation.

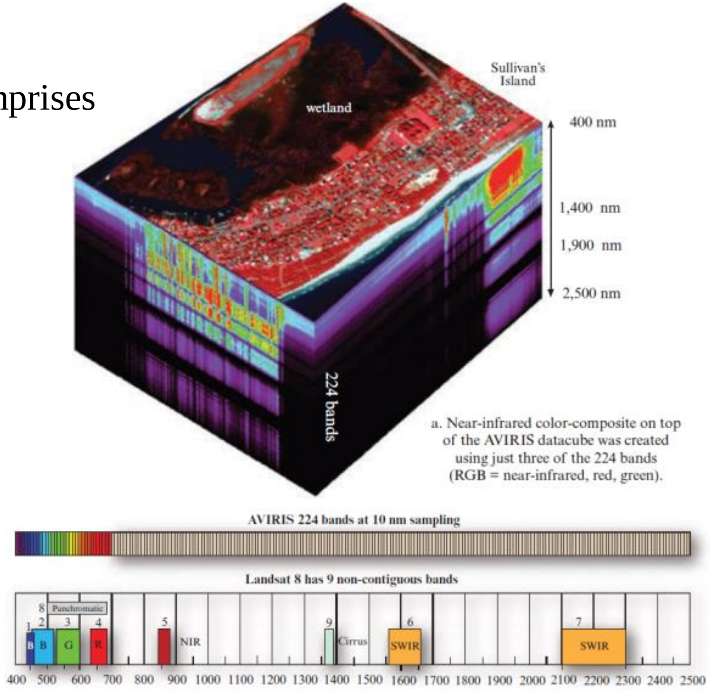
Objective

To propose a novel segmentation-based clustering methodology for classification of hyperspectral image and to improve classification accuracy of the input dataset.

Hyperspectral image is considered in the form of a matrix which comprises information in rows and columns with number of pixels and bands.

- Bands are continuous and regularly spaced.
- Higher spectral resolution, thus giving the opportunity to push further the information extraction capability





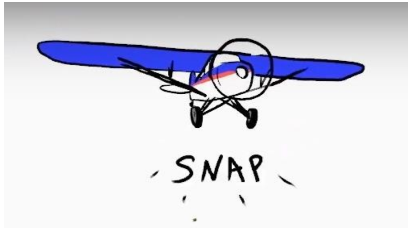
Source: Remote Sensing of the Environment – An Earth Resource Perspective, by John R. Jensen

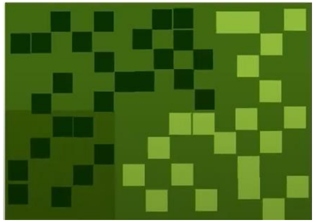
Why Hyperspectral ?

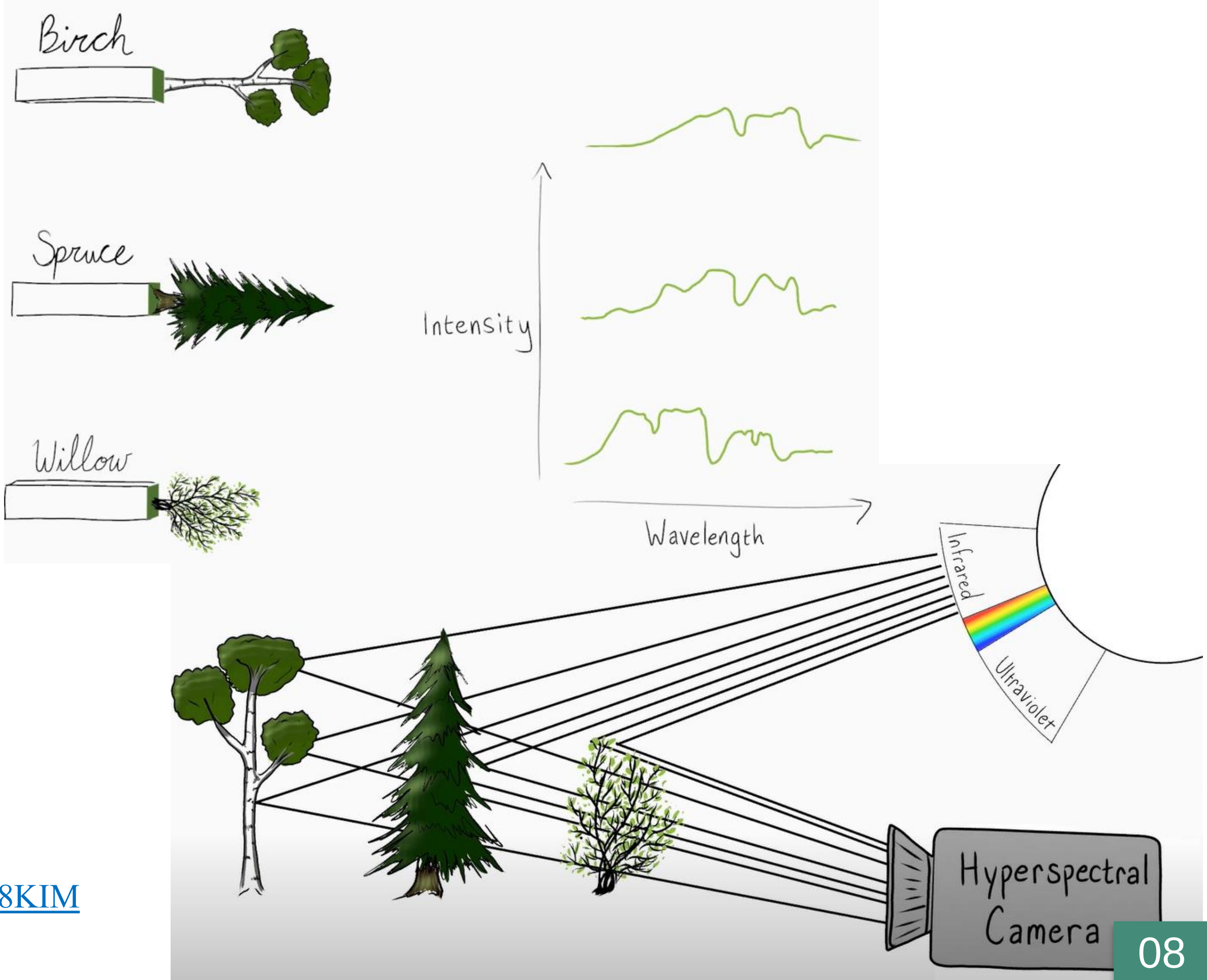
This technology has a broad range of applications across multiple fields, including:

1. **Agriculture**: HSI can be used to assess crop health and detect disease or nutrient deficiencies before they become visible to the naked eye. This can help farmers optimize fertilizer application and reduce crop loss.
2. **Environmental monitoring**: HSI can help detect pollution, track changes in land use, and monitor natural disasters such as wildfires, floods, and hurricanes.
3. **Medical imaging**: HSI can be used to diagnose and monitor skin conditions such as melanoma, as well as detect cancer cells in tissue samples.
4. **Remote sensing**: HSI can be used to collect data about the Earth's surface from space, allowing us to monitor environmental changes on a global scale.
5. **Forensics**: HSI can be used to analyze crime scene evidence, such as bloodstains, to identify substances that may not be visible under normal lighting conditions.

Overall, hyperspectral imaging has numerous applications that are revolutionizing various industries and fields, and its potential for innovation and discovery is vast.





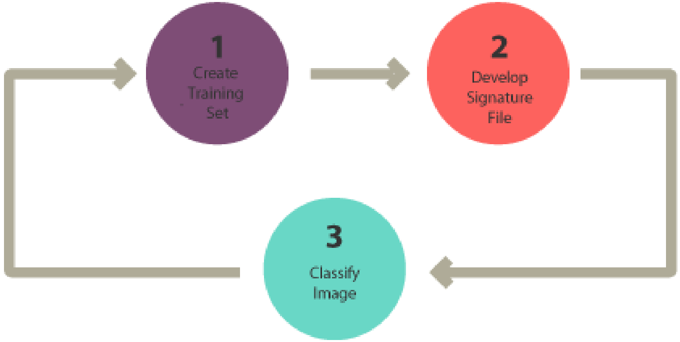


Source: https://youtu.be/0gs-Ohg8KIM

Image Classification

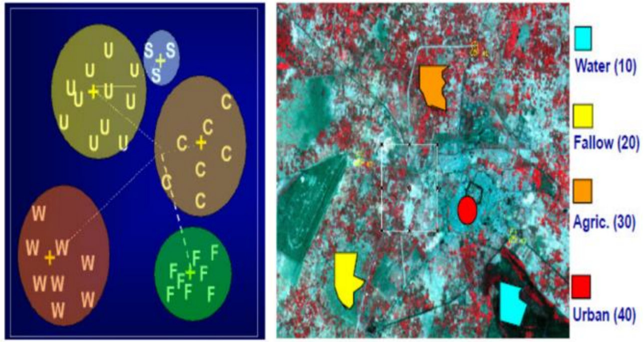
Image classification is the process of categorizing and labeling groups of pixels or vectors within an image based on specific rules. The categorization law can be devised using one or more spectral or textural characteristics.

- Each pixel of the image is assigned to a particular class.
- Classification transforms the image data into an information



1. Supervised Classification

- Identify training set (information class),
- Select sample pixels in an image representing specific class,
- Direct the image processing software to use training sets as references for the classification of all other pixels in the image.



Training Sets

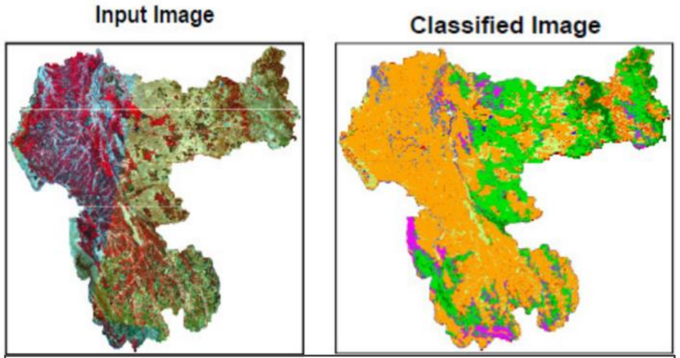


Image Classification

Source: https://gisgeography.com/supervised-unsupervised-classification-arcgis/

2. Unsupervised classification

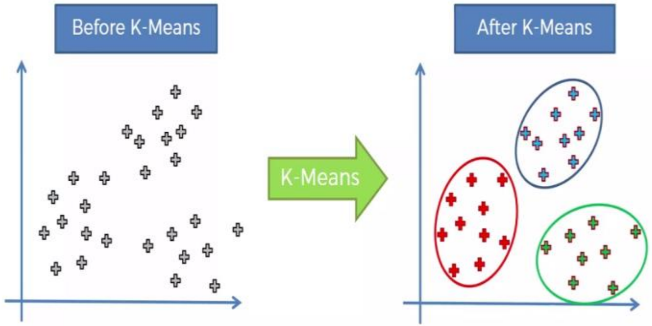
Unsupervised classification requires no advance information about the classes of interest. Rather, it examines the data and breaks it into the most prevalent natural spectral groupings, or clusters, present in the data.

k-means clustering

***k*-means** is a commonly used partitioning based clustering technique that tries to find a user specified number of clusters *(k)*, which are represented by their centroids, by minimizing the square error function. Although *k*-means is simple and can be used for a wide variety of data types.

The steps of the k-means algorithm are written below:

- Initialization: choose randomly *k* pixel vectors (data points) to initialize the clusters.
- Nearest-neighbor search: for each input vector, find the cluster center that is closest, and assign that input vector to the corresponding cluster.
- Mean update: update the cluster centers in each cluster using the mean (centroid) of the input vectors assigned to that cluster.



k-means clustering algorithm

Why Unsupervised Classification?

There are several benefits of unsupervised classification over supervised classification:

1. **No prior knowledge needed**: It does not require any prior knowledge of the classes or features to be identified in the image. This can be particularly useful in situations where the data is **complex** and difficult to interpret.
2. **Time-saving**: Supervised classification requires the user to **manually select training areas**, which can be t**ime-consuming** and **costly** especially in large datasets. Unsupervised classification is faster and can be automated, reducing the time and effort required for classification.
3. **Objective**: Unsupervised classification is **more objective** than supervised since it does not rely on human interpretation. This reduces the potential for bias and ensures that the classification is based purely on data.

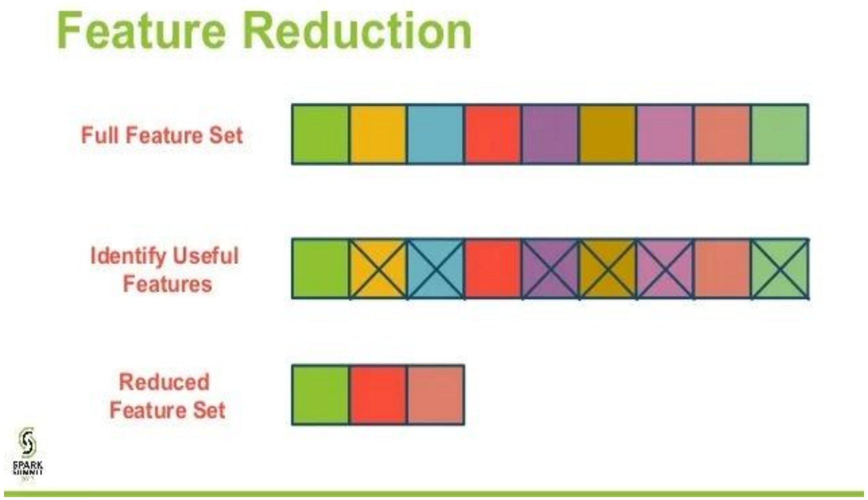
Overall, unsupervised classification has several benefits over supervised classification and can be a useful tool in various fields, especially when dealing with large and complex data sets.

Feature Reduction

Hyperspectral image is considered in the form of a matrix which comprises information in rows and columns with number of pixels and bands. To reduce the number of features in dataset without loss of significant amount of information, feature reduction is performed.

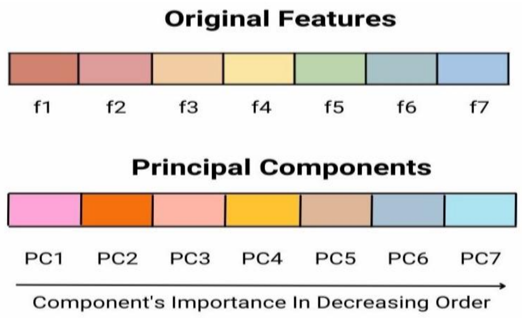
Many Machine Learning problems involve thousands or even millions of features for each training instance.

- These features make training extremely slow.
- Harder to find a good solution.
- These problems are often referred to as the curse of dimensionality.



PCA

Principal Component Analysis(PCA) is a technique which generally transforms original attributes into new attributes of same numbers known as PC's but this time there is correlation between the attributes.



The steps of PCA are:

- To standardize the data for comparison.
- To find the covariance in order to determine the correlation.
- To know the principal components of the datapoints by obtaining eigenvector and eigenvalues.
- Sorting the eigen values in decreasing order and determining the percentage of variance /information each PC constitutes.

PCA Parameters and psuedocode:

```
pca = PCA(n_components=0.99)
pca.fit(X)
```

Parameters

n_components : (int, float, default=None)
    Number of components to keep.

X : (array-like of shape (n_samples, n_features)
    Training data, where n_samples is the number of samples and n_features is the number of features

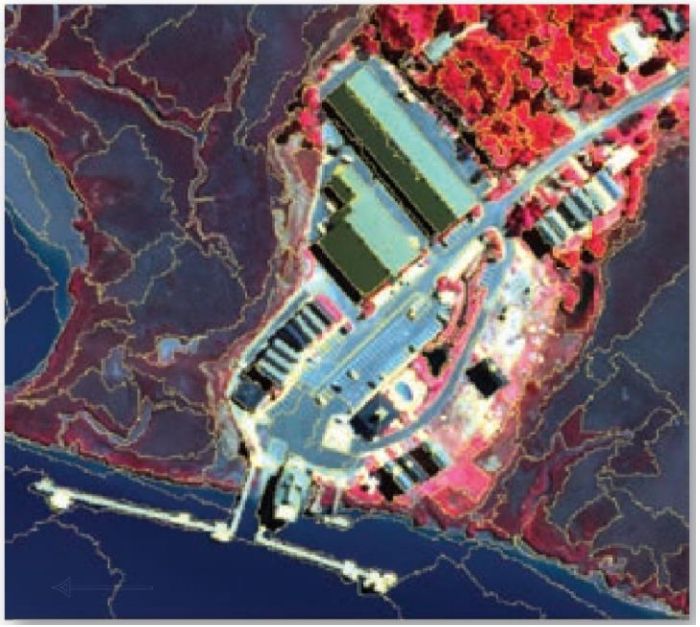
Returns

X_new : ndarray of shape (n_samples, n_components)
    Transformed values.

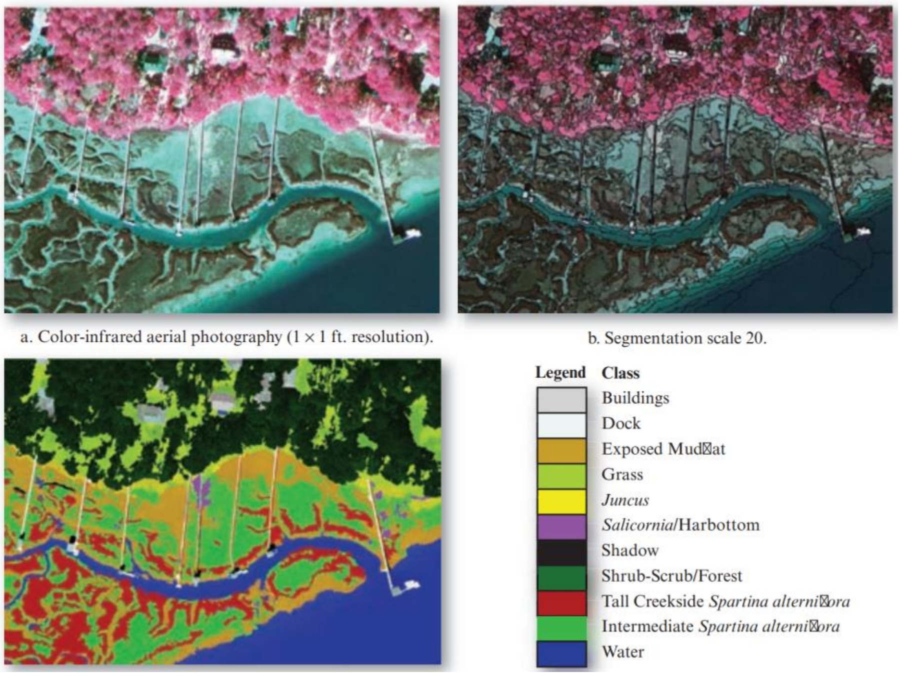
Image Segmentation

Image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics. The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image.

Each of the pixels in a region is similar with respect to some characteristic or computed property, such as color, intensity, or texture.



Object-based Image Analysis (OBIA) of Estuarine Intertidal Habitat near Bluffton, SC



John R. Jensen. 2016.Introductory digital image processing: A remote sensing perspective. Pearson, 4th edition.

Literature Review

Sr No.	Year of Publication	Paper/Book	Remarks
1	August, 2022	Yao Ding; Zhili Zhang; Xiaofeng Zhao; Yaoming Cai; Siye Li; Biao Deng; Weiwei Cai, "Self-Supervised Locality Preserving Low-Pass Graph Convolutional Embedding for Large-Scale Hyperspectral Image Clustering“, IEEE Transactions on Geoscience and Remote Sensing.	Compared with supervised or semi-supervised methods, HSI clustering is often a fundamental but challenging task, due to prior knowledge deficiency, large spectral variability, and high dimension of HSI.
2	February, 2022	Sen Jia; Yue Yuan; Nanying Li; Jianhui Liao; Qiang Huang; Xiuping Jia; Meng Xu, "A Multiscale Superpixel-Level Group Clustering Framework for Hyperspectral Band Selection", IEEE Transactions on Geoscience and Remote Sensing.	Principal Component Analysis (PCA) was introduced as a linear dimensionality reduction technique for HSI which projects the high-dimensional data to a low-dimensional subspace with principal components maximizing the variance of the projected data.
3	April, 2020	J. Chang, G. Meng, L. Wang, S. Xiang and C. Pan, "Deep self-evolution clustering", IEEE Trans. Pattern Anal. Mach. Intel.	The key to the HSI clustering is to measure the similarity between data points.
4	July, 2017	Y. Li, L. Zhang, C. Tian, C. Ding, Y. Zhang and W. Wei, "Hyperspectral image super-resolution extending: An effective fusion based method without knowing the spatial transformation matrix", Proc. IEEE Int. Conf. Multimedia Expo (ICME)	The abundant spectral information of HSIs comes at the cost of greatly reducing spatial resolution which hinders the widespread applications of HSIs.

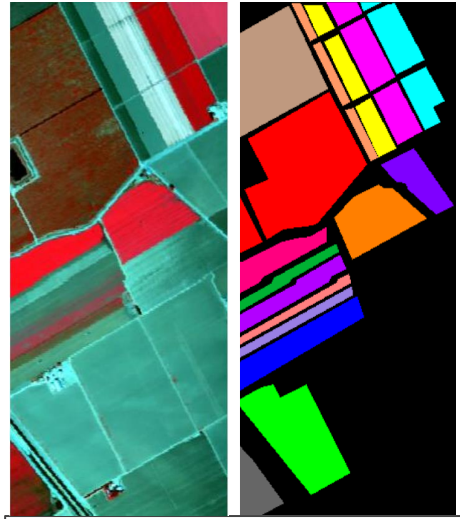
Literature Review

Sr No.	Year of Publication	Paper/Book	Remarks
5	January, 2013	B. Luo, C. Yang, J. Chanussot and L. Zhang, "Crop yield estimation based on unsupervised linear unmixing of multidate hyperspectral imagery", IEEE Trans. Geosci. Remote Sens.	HSIs can provide rich band information from different wavelengths and thus get widely used in various research field, such as biological analysis.
6	October, 2011	J. Khodr and R. Younes, "Dimensionality reduction on hyperspectral images: A comparative review based on artificial datas".	Moreover, due to the high correlation among the neighboring bands, which not only increases the computational complexity of the classifiers but also may have a negative impact on the classification accuracy, dimensionality reduction (DR) should be applied as a preprocessing step to discard the redundant information.
7	December, 2007	A. Martínez-usó, F. Pla, J. M. Sotoca and P. García-sevilla, "Clustering-based hyperspectral band selection using information measures", IEEE Trans. Geosci. Remote Sens.	The importance of a band obtained by unsupervised methods is evaluated by various statistical measures or clustering quality assessment which is unrelated to the labeled sample size.

Dataset

The experiments were conducted over three sets of hyperspectral images respectively are Salinas, Pavia center and Pavia University.

Salinas scene was collected by the 224-band AVIRIS sensor over Salinas Valley, California, and is characterized by high spatial resolution (3.7-meter pixels). The area covered comprises 512 lines by 217 samples. This image was available only as at-sensor radiance data. It includes vegetables, bare soils, and vineyard fields. Salinas ground truth contains 16 classes.



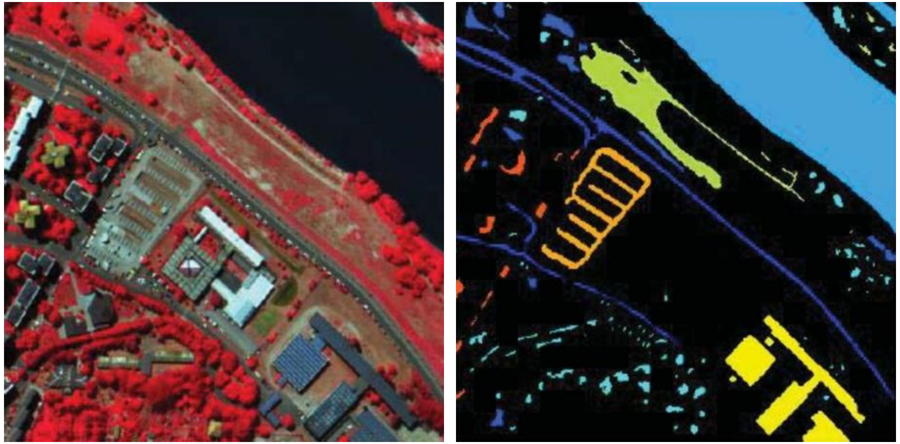
Salinas and Ground Truth

Broccoli green weeds 1	Broccoli green weeds 2	Fallow	Fallow rough plow	Fallow smooth
Stubble	Celery	Grapes untrained	Soil vineyard develop	Corn senesced green weeds
Lettuce romaine 4 weeks	Lettuce romaine 5 weeks	Lettuce romaine 6 weeks		
Lettuce romaine 7 weeks	Vineyard untrained	Vineyard vertical trellis	Unlabeled	

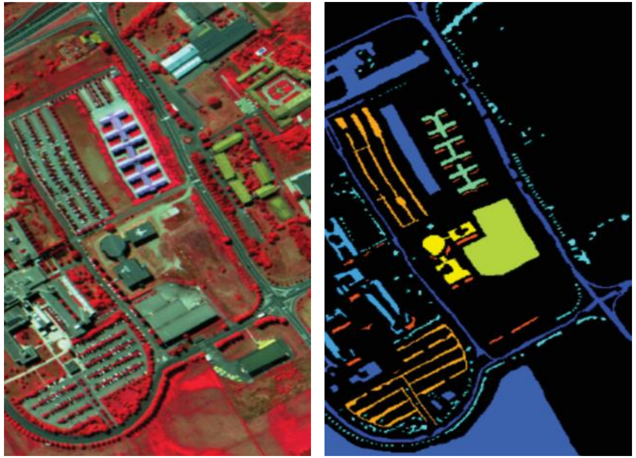
Source: Salinas Dataset, 2021: www.ehu.eus/Hyperspectral_Remote_Sensing_Scenes

Dataset

Pavia Centre and Pavia University are two scenes acquired by the ROSIS sensor during a flight campaign over Pavia, northern Italy. The number of spectral bands is 102 for Pavia Centre and 103 for Pavia University. Pavia Centre is a 400 × 400 pixels image, and Pavia University is 610 × 340 pixels. The geometric resolution is 1.3 meters. Pavia centre ground truth contains 8 classes while Pavia university ground truth contains 9 classes.



Pavia Centre and Ground Truth

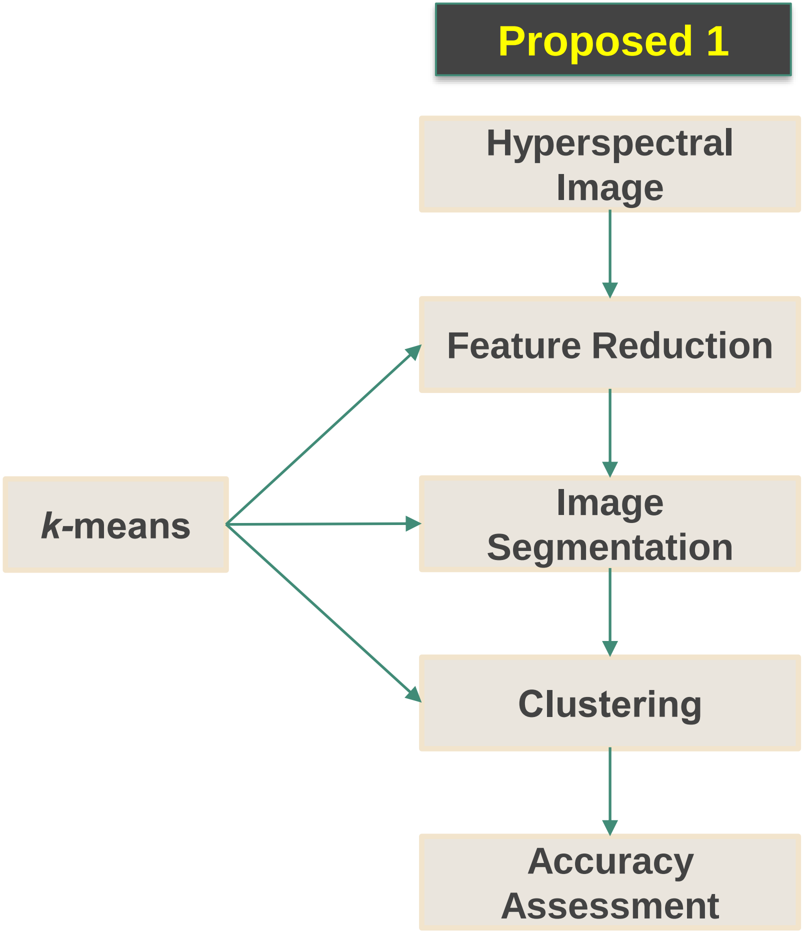


Pavia University and Ground Truth

Source: Pavia University and Pavia center datasets 2021.
www.ehu.eus/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scenes

Methodology

Proposed Methodology



Segmentation using *k*-means Proposed 1

Algorithm Utilizing *k*-means for feature reduction, segmentation and clustering:

1. Input dataset of Salinas.
2. For feature reduction, perform *k*-means clustering on bands (features).
3. Now to create segments on reduced dataset perform *k*-means clustering.
4. Obtain cluster map.
5. Convert the cluster map into segmentation map using connected component.
6. Apply *k*-means clustering.

Cluster Map

1	1	2	2	2	2
1	1	2	2	2	2
1	1	2	2	5	5
4	4	2	2	5	5
4	4	2	2	1	1
4	4	2	2	1	1

Segmentation Map

1	1	2	2	2	2
1	1	2	2	2	2
1	1	2	2	5	5
4	4	2	2	5	5
4	4	2	2	6	6
4	4	2	2	6	6

Simple linear iterative clustering (SLIC)

Simple linear iterative clustering (SLIC), adapts *k*-means clustering to generate superpixels.

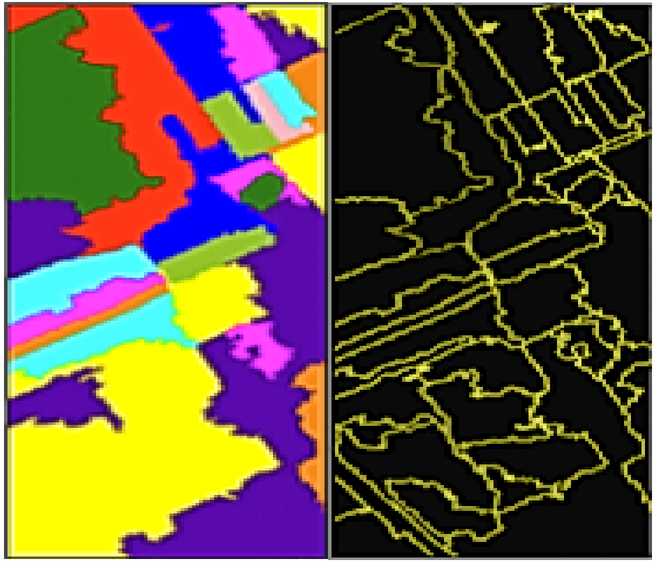
- It is faster and more memory efficient than existing methods.
- SLIC is easy to use, offers flexibility in the compactness and number of the superpixels it generates,
- it straightforward to extend to higher dimensions, and is freely available.

R. Achanta, A. Shaji, K. Smith, A. Lucchi, P. Fua and S. Süsstrunk, "SLIC Superpixels Compared to State-of-the-Art Superpixel Methods," in IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 34, no. 11, pp. 2274-2282, Nov. 2012, doi: 10.1109/TPAMI.2012.120.

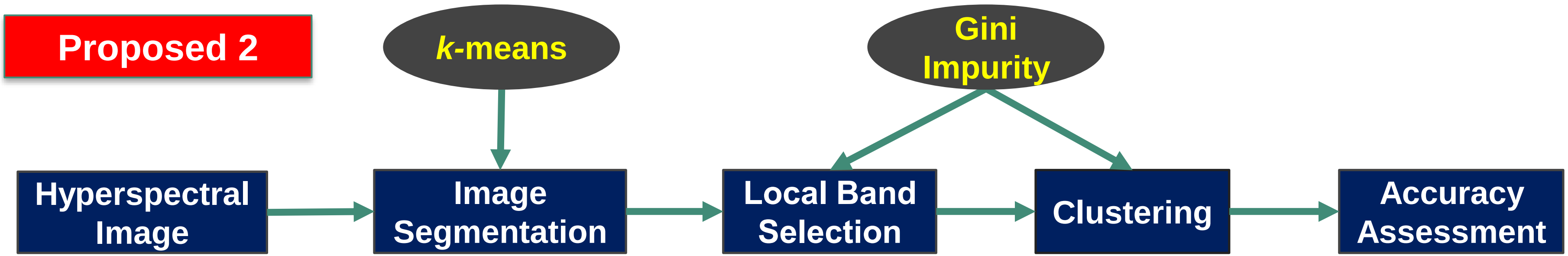
Segmentation using SLIC

Algorithm Utilizing PCA and SLIC:

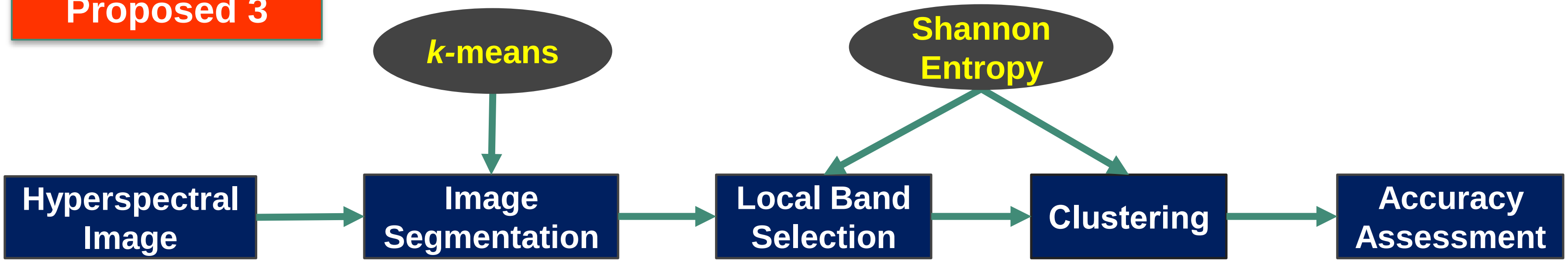
1. Apply PCA on input dataset to reduce features
2. Create Segmented Image Using SLIC.
3. Out of n Segments created, find best 16 (Salinas) segments by arranging all segments in ascending order of 'Ginni Index'.
4. Calculate Euclidian distances between remaining segments to each of best 16 segments and assign that segment to nearest best segment.
5. Now take mean of all pixel within a segment..



Proposed 2



Proposed 3



NMI and Purity

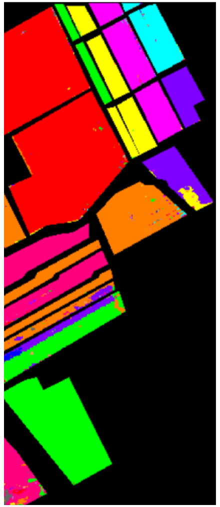
- **Purity** is a measure of the extent to which clusters contain a single class.
- **Mutual Information** is a function that measures the agreement of the two assignments.

$$NMI(\Omega, C) = \frac{MI(\Omega, C)}{\mathrm{mean}(H(\Omega), H(C))}$$

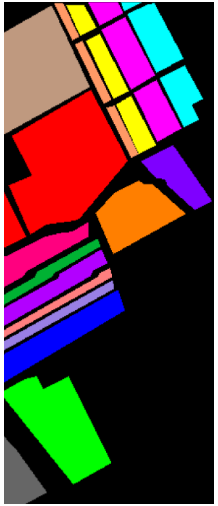
$$MI(\Omega, C) = \sum_k \sum_j p(\omega_k \cap c_j) \log_2 \frac{p(\omega_k \cap c_j)}{p(\omega_k)\, p(c_j)}$$

$$H(\Omega) = -\sum_k p(\omega_k) \log_2 p(\omega_k)$$

$$Purity(\Omega, C) = \frac{1}{N} \sum_k \max_j |\omega_k \cap c_j|$$



Classified



Reference

Broccoli green weeds 1	Broccoli green weeds 2	Fallow	Fallow rough plow	Fallow smooth
Stubble	Celery	Grapes untrained	Soil vineyard develop	Corn senesced green weeds
Lettuce romaine 4 weeks	Lettuce romaine 5 weeks	Lettuce romaine 6 weeks		
Lettuce romaine 7 weeks	Vineyard untrained	Vineyard vertical trellis	Unlabeled	

$\Omega = \{\omega_1, \omega_2, \omega_3, \ldots\ldots, \omega_k\}$ is the set of clusters.

$C = \{c_1, c_2, c_3, \ldots\ldots\ldots, c_j\}$ is the set of classes obtained from reference image

N is total number of pixel sample image

http://nlp.stanford.edu/IR-book/html/htmledition/evaluation-of-clustering-1.html

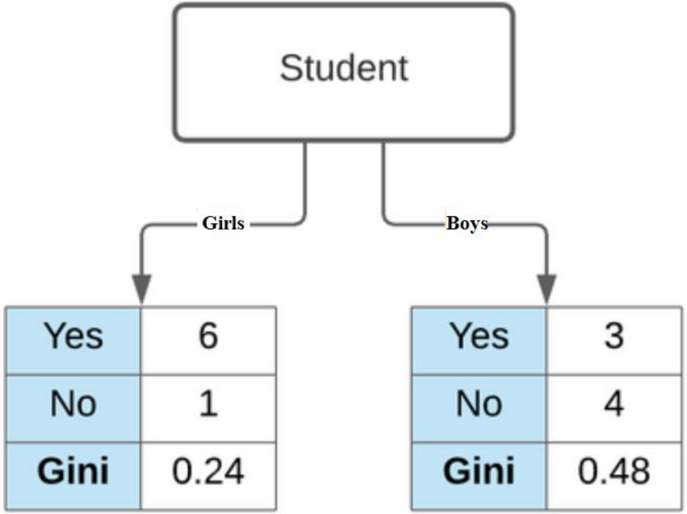
Cai, D., X. He, and J. Han. 2005. "Document Clustering Using Locality Preserving Indexing." IEEE Transactions on Knowledge and Data Engineering, 17 (12): 1624-1637.

Gini Impurity

Gini Impurity measures the probability for a random instance being misclassified when chosen randomly. The **lower** the **Gini Impurity**, the **lower** the **likelihood** of misclassification.

Consider a dataset D that contains samples from k classes. The probability of samples belonging to class i at a given node can be denoted as pi. Then the Gini Impurity is defined as:

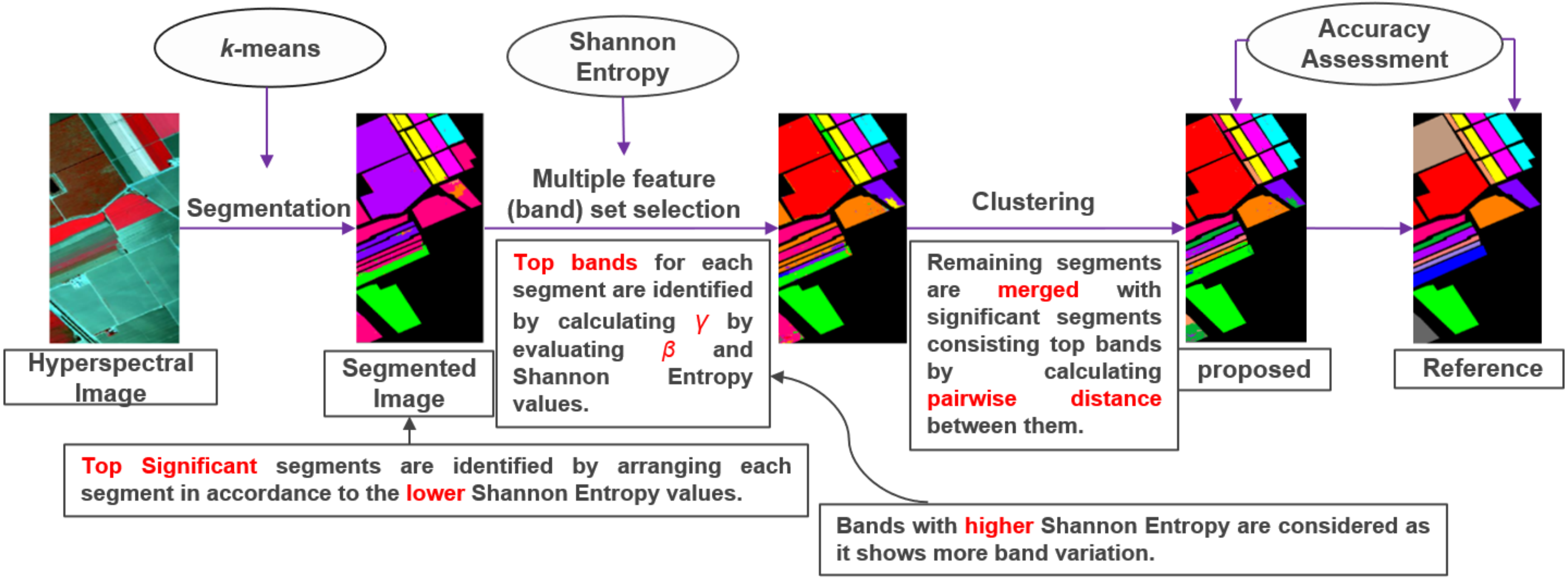
$$Gini\ (D) = 1 - \sum_{i=1}^{k} p_i^2$$



Gini Impurity for Student is 0.367

Source: https://www.learndatasci.com/glossary/gini-impurity/

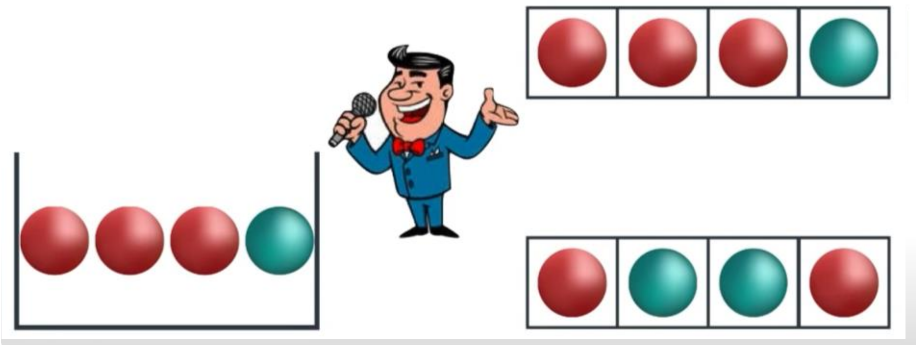
Proposed 3



Source: https://www.learndatasci.com/glossary/gini-impurity/

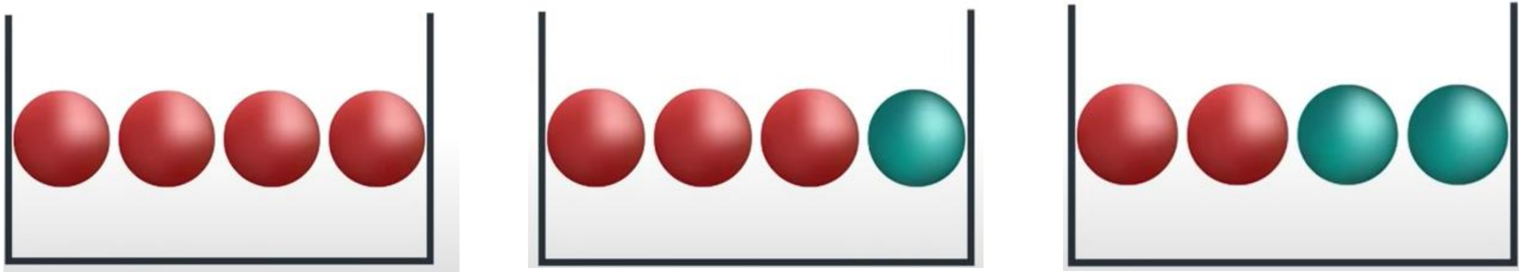
Shannon Entropy

Shannon entropy is employed in methodology which basically is a measure of the uncertainty associated with a random variable. Specifically, Shannon entropy **quantifies** the **expected** value of the information contained in a message.



← Expected Outcome

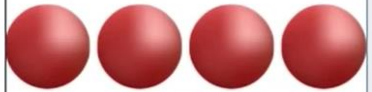
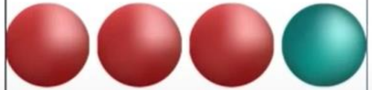
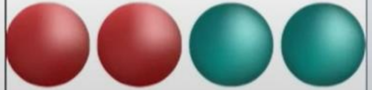
← Unexpected Outcome



BEST MEDIUM WORST

We can see that **Product of** Probabilities is results in a **very small number.**
And It keeps getting smaller if **number of sample** is **very high**

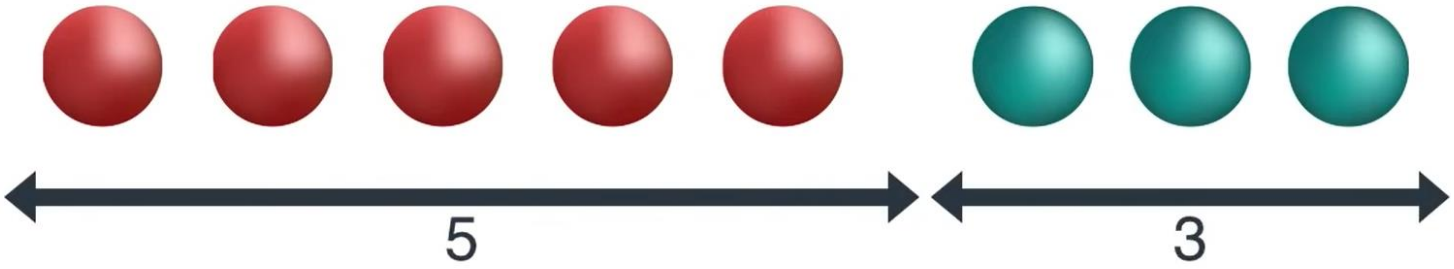
$$\log(ab) = \log(a) + \log(b)$$

	P(red)	P(blue)	P(winning)	$-\log_2(P(\text{winning}))$	Entropy
	1	0	$1 \times 1 \times 1 \times 1 = 1$	0+0+0+0	0
	0.75	0.25	$0.75 \times 0.75 \times 0.75 \times 0.25 = 0.105$	0.415+0.415+0.415+2	0.81
	0.5	0.5	$0.5 \times 0.5 \times 0.5 \times 0.5 = 0.0625$	1+1+1+1	1

Source: https://youtu.be/9r7FIXEAGvs

Consider a dataset X that contains samples from k classes. The probability of samples belonging to class i at a given node can be denoted as pi. Then the Shannon Entropy of is defined as:

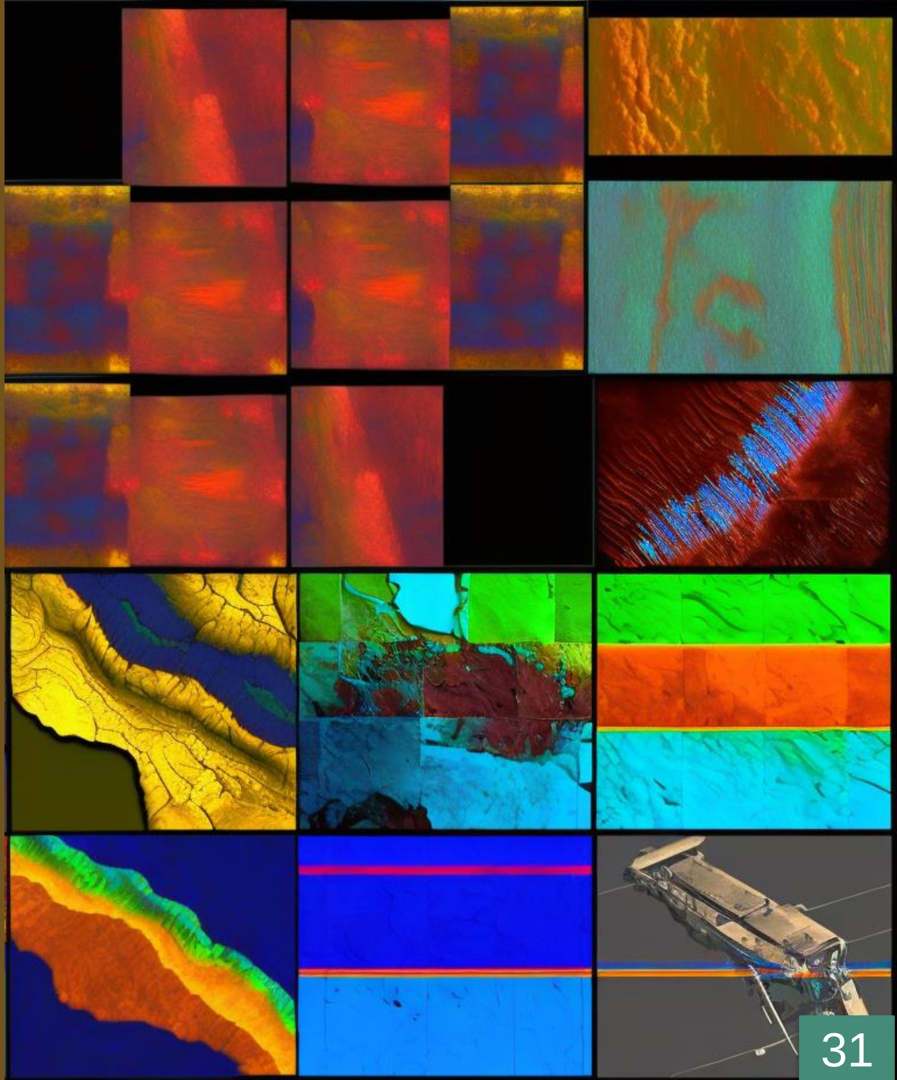
$$H(X) = -\sum_{i=1}^{k} p_i \log_2(p_i)$$



$$\text{Entropy} = -\frac{5}{8}\log_2\left(\frac{5}{8}\right) - \frac{3}{8}\log_2\left(\frac{3}{8}\right) = 0.9544$$

Source: https://youtu.be/9r7FIXEAGvs

LOCAL BAND SELECTION



Local Band Selection

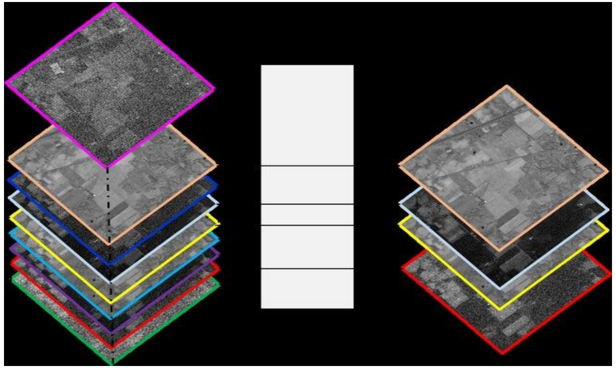
A hyperspectral image has a very high spectral resolution due to the number of pixels and bands it contains. As a result, it's important to arrange number of bands in a dataset without drastically reducing the amount of information maintained.

It is necessary to perform band selection method as:

- These bands make training extremely slow.
- Harder to find a good solution.

Steps for selecting top-ranked bands:

- Shannon Entropy is used as a ranking criteria to select the top-ranked bands in a sorted sequence containing relevancy and less redundancy.
- A distance-weighted parameter called score is introduced to prevent bands with same Shannon entropy.



Band Selection Technique

Source:
https://www.researchgate.net/profile/PedramGhamisi/publication/322281687/figure/fig1/AS:580431734743040@1515397117915/Hyperspectral-image-dimensionality-reduction_W640.jpg

Local Band Selection

To calculate ***score***, *delta* function is used that stores maximum distance for a test band from all bands whose Shannon entropy is higher than that of test band.

Formally, score is formulated in equation as :

$$delta = \max_{H_j > H_i} d$$

$$score = (delta) \times (H_i)$$

where,

d is distance between mean vectors of all pixels in a cluster for particular segment to remaining bands of the segment,

Hi is the Shannon entropy for corresponding bands,

i and j are band indexes.

```python
for prop in regions:
    pxIdLst = prop.coords
    for j in range(d):
        band = mat[pxIdLst[:,0],pxIdLst[:,1],j];
        entropy_band[i,j] = shannon_entropy(band) # matrix for entropy of segment and band


    i = i + 1
```

```python
for i in range(k_cl):
    t = int(sig_entropy[i])
    b_dist = np.zeros((d,d))  # to store euclidean distance among all band for a particular segment
    for x in range(d):
        for y in range(d):
            b_dist[x,y] = np.linalg.norm(seg_nxk[t,x] - seg_nxk[t,y])

    for j in range(d):
        max = 0
        for k in range(d):
            if entropy_band[t,k] > entropy_band[t,j] :    #first condition for band whose entropy greater than jth band
                if b_dist[j,k] > max :   #finding max distance among band whose entropy is greater than jth band
                    max = b_dist[j,k]
        temp_array[i,j] = max

scaler = MinMaxScaler()
m = scaler.fit(temp_array)
new_dist = m.transform(temp_array)
```

Calculation of delta function, that stores maximum distance for a test band from all bands whose Shannon Entropy is higher than that of test band.

```python
score = np.zeros((k_cl,d))     #creating a parameter for sorting by multiplying entropy and max distance.
for i in range(k_cl):
    t = int(sig_entropy[i])
    for j in range(d):
        score[i,j] = entropy_band[t,j] * new_dist[i,j]
```

Calculation of score, that stores delta × Shannon Entropy for each band.

```python
score = np.argsort(-score) #sorting in decreasing order
```

Bands and their Shannon Entropy→

	195	196	197	198	199	200	201	202	203
1	0.021692	0.0230723	0.0335522	0.0219146	0.0144928	0.020979	0.0384615	0.0880503	0.0229885
2	0.00789323	0.00562622	0.00534442	0.0134615	0.00415007	0.0141213	0.0131356	0.0331633	0.0212264
3	8.20811e-06	8.94757e-06	1.29875e-05	1.45632e-05	1.02886e-05	1.32118e-05	2.68666e-05	5.76632e-05	6.85619e-05
4	0.000737585	0.00070852	0.000668785	0.000666158	0.00067554	0.000713212	0.000872111	0.000294318	0.000585651

Top 12 Significant Bands (L = 12) →

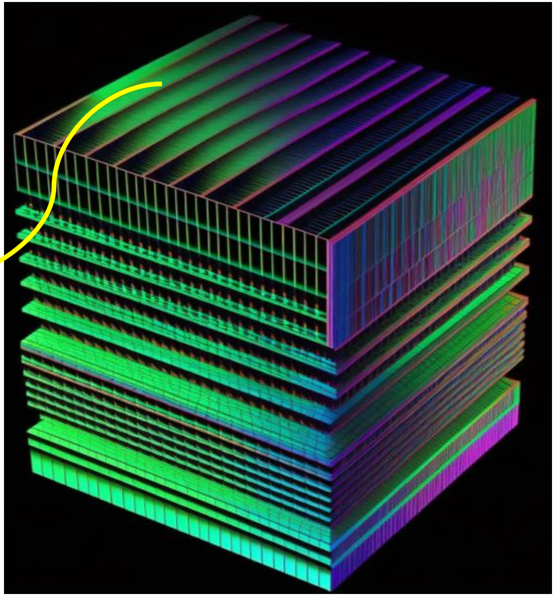
Top 16 Significant Segments (*k*_cl = 16) →

	0	1	2	3	4	5	6	7	8	9	10	11
0	203	31	30	33	29	28	27	32	34	1	26	25
1	0	130	131	132	133	134	135	136	137	138	139	140
2	203	56	59	57	55	54	51	74	58	47	52	50
3	203	31	30	33	29	28	27	32	34	1	26	25
4	203	31	30	33	29	28	27	32	34	1	26	25
5	0	130	131	132	133	134	135	136	137	138	139	140
6	203	31	30	33	29	28	27	32	34	1	26	25
7	203	31	30	33	29	28	27	32	34	1	26	25
8	0	130	131	132	133	134	135	136	137	138	139	140
9	0	130	131	132	133	134	135	136	137	138	139	140
10	203	31	30	33	29	28	27	32	34	1	26	25
11	203	31	30	33	29	28	27	32	34	1	26	25

SEGMENTATION

Small Part of input image (in matrix form of size 512 x 217)

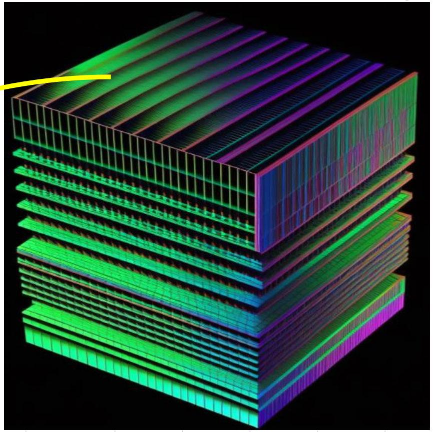
	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100	101	102	103
64	304	304	375	375	375	375	304	446	304	304	375	304	304	375	375	304	304	304	375	375
65	374	231	303	374	303	303	303	231	303	303	231	303	374	303	374	374	303	303	303	303
66	308	308	379	308	308	308	308	308	379	308	308	308	379	308	451	308	308	308	308	379
67	308	308	298	298	298	369	298	298	298	298	298	298	298	298	441	298	298	298	298	369
68	369	298	298	298	298	369	298	298	298	298	298	298	298	298	441	298	298	298	298	369
69	369	227	369	298	298	298	298	441	298	298	369	298	298	227	298	227	298	298	298	298
70	365	365	294	365	294	365	365	365	365	365	294	365	294	365	294	222	365	294	294	436
71	300	300	372	372	372	300	300	300	372	300	300	300	372	300	372	300	372	372	300	372
72	300	300	372	372	372	300	300	300	372	300	300	300	305	305	233	305	305	376	305	447
73	305	305	305	233	305	305	376	376	305	376	376	376	305	305	233	305	305	376	305	447
74	316	245	387	316	387	316	316	316	387	316	387	245	316	316	316	316	316	316	387	387
75	306	306	306	306	235	449	377	377	306	306	306	306	306	306	377	306	306	306	306	306
76	306	306	306	306	305	376	376	305	305	305	305	305	376	305	233	233	376	305	305	305
77	305	233	305	305	305	376	376	305	305	305	305	305	376	305	233	233	308	308	308	308



Small part of segmented image (in matrix form of size 512 x 217)

	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98
64	25	25	23	23	23	23	23	23	16	16	16	21	21	21	21
65	25	25	25	23	23	23	23	23	23	16	16	21	21	21	21
66	25	25	25	25	25	23	23	23	23	16	16	21	21	21	21
67	25	25	25	25	25	25	23	23	23	23	16	16	16	21	21
68	25	25	25	25	25	25	23	23	23	23	16	16	16	21	21
69	25	25	25	25	25	25	23	23	23	23	23	16	16	21	21
70	25	25	25	25	25	25	25	23	23	23	23	16	16	23	21
71	25	25	25	25	25	25	23	23	23	23	23	23	23	23	21
72	25	25	25	25	25	25	23	23	23	23	23	23	23	23	23
73	25	25	25	25	25	25	23	23	23	23	23	23	23	23	23
74	25	25	25	25	25	25	25	23	23	23	23	23	23	23	23
75	25	25	25	25	25	25	25	23	23	23	23	23	23	23	23
76	25	25	25	25	25	25	25	25	23	23	23	23	23	23	23
77	25	25	25	25	25	25	25	25	23	23	23	23	23	23	23

Total 170 Segments



Pixel No.	Pixels Location		Pixel Values in different bands					
	x	y	1	2	3	4	5	6
1	64	92	304	308	306	312	298	305
2	64	93	306	307	303	309	299	305
3	64	94	312	317	315	308	313	308
4	65	93	298	296	299	294	302	300
5	65	94	295	300	295	308	299	296
6	66	93	408	412	409	405	407	406
7	66	94	350	356	354	348	352	349
8	67	94	360	360	362	369	358	365
9	67	95	298	294	296	289	292	293
10	68	94	320	322	322	325	324	320

Sample Matrix of a **segment** containing **pixel's location** and corresponding **band** value in different bands

```
entropy_mat = np.zeros((numRegns,1)) #Shannon Entropy for all segment

n_pix = np.zeros((numRegns,1))
k_cl = 24
i = 0
L = ab # Top bands
L_entropy_band = np.zeros((k_cl,L))


temp_array = np.zeros((k_cl,d)) #temp matrix to store band number
#for significant segments
for prop in regions:
    pxIdLst = prop.coords
    matrix = np.zeros((len(pxIdLst),d))
    for j in range(d):
        band = mat[pxIdLst[:,0],pxIdLst[:,1],j];
        for aa in range(len(band)):
            matrix[aa,j] = band[aa] #matrix for each segment
    entropy_mat[i] = shannon_entropy(matrix) #Shannon entropy for each segment
    n_pix[i] = len(pxIdLst)

    i = i + 1

sig_entropy = np.zeros(numRegns)
for i in range(numRegns):
    sig_entropy[i] = 50
    if(n_pix[i]> 5):
        sig_entropy[i] = entropy_mat[i]

sig_entropy = np.argsort(sig_entropy)
```

Calculation of Shannon Entropy for each segments.

Considering only those segments in which no. of pixels is greater than 5 and calculating Significant Segments on the basis of Shannon Entropy and number of pixels.

Segments are arranged (Ascending) based on their Entropy

Shannon Entropy | No. of Segments

	0	1
0	0.000524715	0
1	0.000280672	1
2	5.01864e-05	2
3	8.64598e-05	3
4	0.000393657	4
5	0.000217093	5
6	0.000101229	6
7	0.00185795	7
8	0.000696704	8
9	7.55814e-05	9
10	7.44806e-05	10

Shannon Entropy | No. of Segments

	0	1
0	1.1574e-05	120
1	2.46516e-05	98
2	2.54236e-05	162
3	2.57029e-05	115
4	2.633e-05	135
5	3.01953e-05	21
6	3.22963e-05	130
7	3.43106e-05	12
8	3.48677e-05	108
9	3.75538e-05	125
10	3.77923e-05	136

Best 16 Segments

Pairwise distances of remaining segments from best 16 Segments.

Remaining Segments (16 to 169) →

	164	165	166	167	168	169
4	14766.9	12539.6	15167	16576.8	15707.1	22521.2
5	14938.9	12559.9	15317.2	14621.5	15873.9	23154.6
6	15332	12879.2	15689.3	13183	16255.2	23814.5
7	9925.26	8490.33	10352.3	21179.7	10766.6	16306.1
8	15810.6	13306.8	16150.9	11852.6	16712.8	24468.2
9	9334.36	6868.82	9632.57	14259.5	10174.3	18345.8
10	14626.6	12303.9	15013.8	15421	15567	22685.2
11	14833.3	12702.4	15241.6	17580	15767.7	22305.2
12	9836.59	7815.7	10249.1	18398.5	10781.3	17427.4
13	14978.2	12641.6	15363.9	15235.1	15914.7	23048.5
14	15284.5	12840.3	15647.7	13453.2	16206.1	23705.5
15	14475.1	12440.1	14891.1	18426.5	15404.8	21708.9

Labels are assigned to remaining segments according to minimum distance from best 16.

	0
159	9
160	9
161	7
162	7
163	9
164	9
165	9
166	9
167	8
168	9
169	7

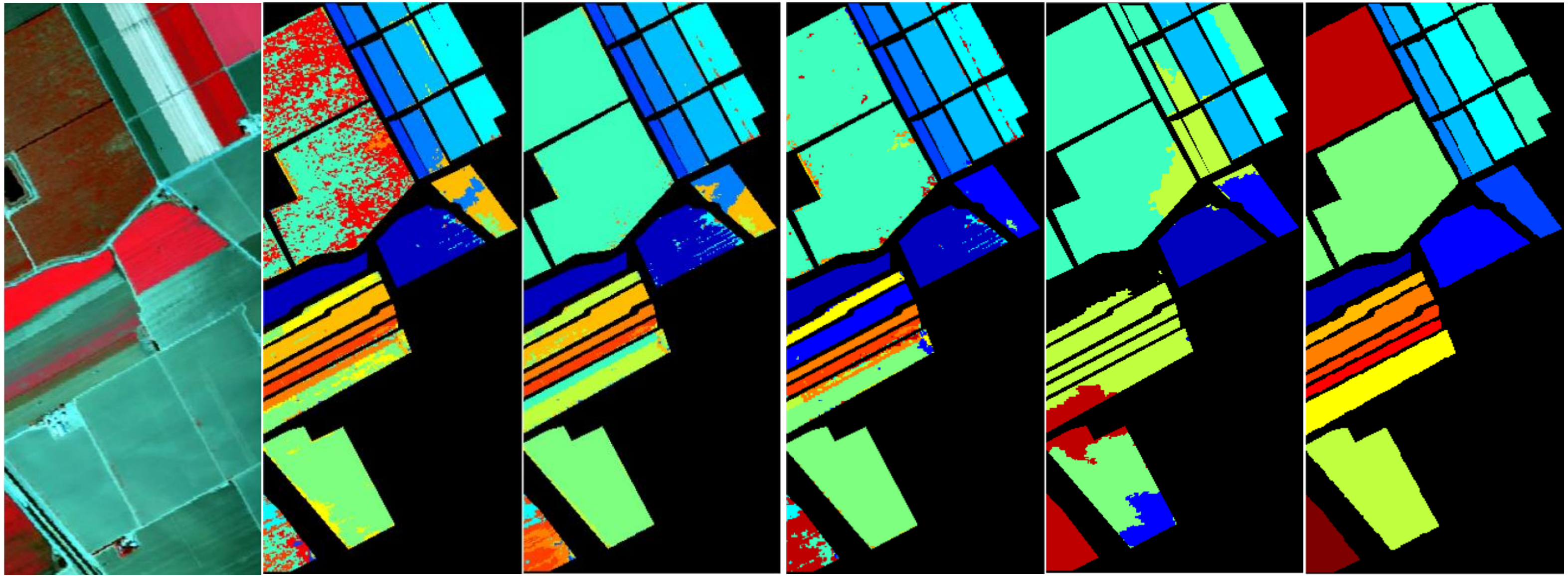
- Best 16 out 170 segments are identified.
- Labels (0 to 15) are given to remaining segments according to minimum distance from best 16.

Relabelled Segmented image (in matrix form of size 512 x 217)

Total 16 Segments

	84	85	86	87	88	89	90	91	92	93	94	95	96	97	98	99	100	101	102	103
64	9	9	14	14	14	14	14	14	15	15	15	4	4	4	4	4	4	4	4	4
65	9	9	9	14	14	14	14	14	14	15	15	4	4	4	4	4	4	4	4	4
66	9	9	9	9	9	14	14	14	14	15	15	4	4	4	4	4	4	4	4	4
67	9	9	9	9	9	9	14	14	14	14	15	15	15	4	4	4	4	4	4	4
68	9	9	9	9	9	9	14	14	14	14	15	15	15	4	4	4	4	4	4	4
69	9	9	9	9	9	9	14	14	14	14	14	15	15	4	4	4	4	4	4	4
70	9	9	9	9	9	9	9	14	14	14	14	15	15	14	4	4	4	4	4	4
71	9	9	9	9	9	9	14	14	14	14	14	14	14	14	4	4	4	4	4	4
72	9	9	9	9	9	9	14	14	14	14	14	14	14	14	14	4	4	4	4	4
73	9	9	9	9	9	9	14	14	14	14	14	14	14	14	14	4	4	4	4	4
74	9	9	9	9	9	9	9	14	14	14	14	14	14	14	14	4	4	4	4	4
75	9	9	9	9	9	9	9	14	14	14	14	14	14	14	14	14	4	4	4	4
76	9	9	9	9	9	9	9	9	14	14	14	14	14	14	14	14	4	4	4	4
77	9	9	9	9	9	9	9	9	14	14	14	14	14	14	14	14	14	14	14	4

Results And Discussion



Salinas | *k*-means | *k*-means + PCA | proposed 1 | SLIC | Reference

Broccoli green weeds 1	Broccoli green weeds 2	Fallow	Fallow rough plow	Fallow smooth
Stubble	Celery	Grapes untrained	Soil vineyard develop	Corn senesced green weeds
Lettuce romaine 4 weeks	Lettuce romaine 5 weeks	Lettuce romaine 6 weeks		
Lettuce romaine 7 weeks	Vineyard untrained	Vineyard vertical trellis	Unlabeled	

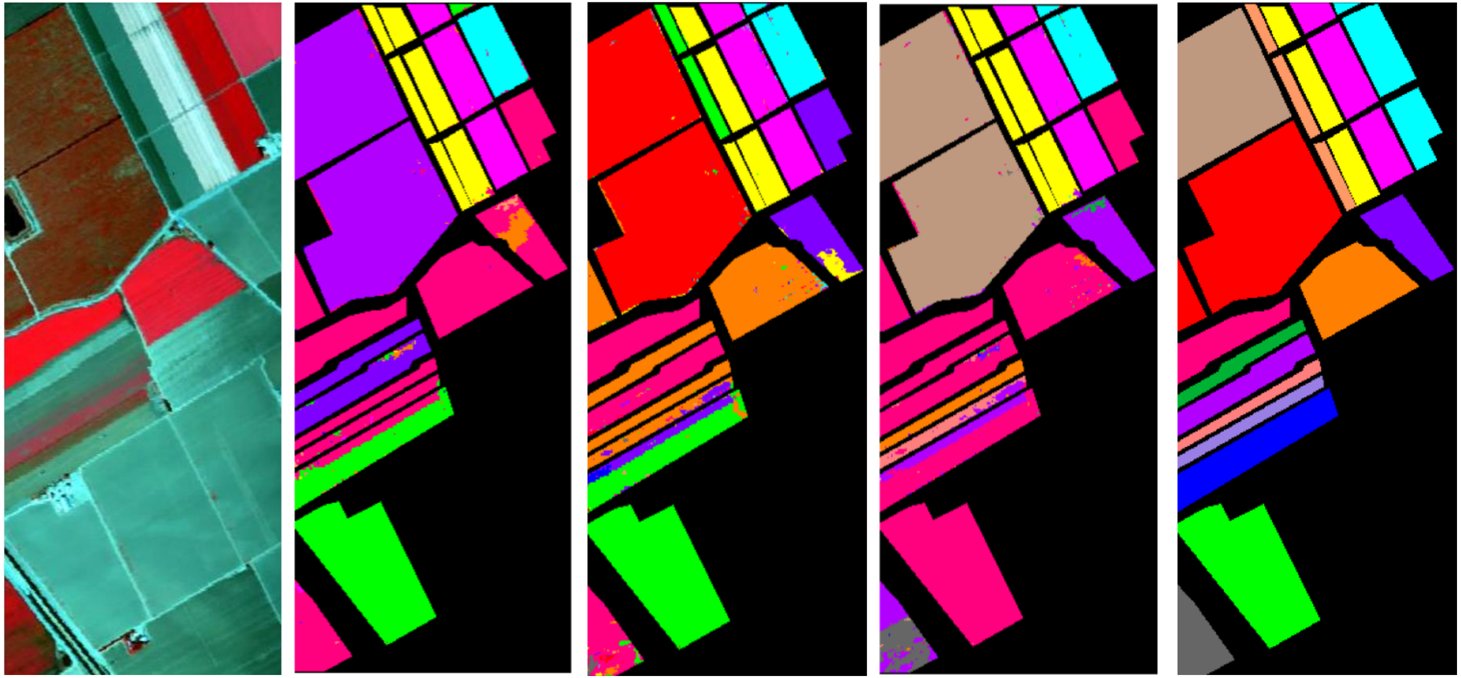
Results And Discussion

Datasets	Salinas	
Methods	**NMI**	**Purity**
k-means	0.7242	0.6734
k-means + PCA	0.7656	0.6785
Proposed 1 (*k*-means + *k*_fr + *k*_seg)	**0.8115**	**0.6835**
(PCA + SLIC + Clustering)	**0.6876**	**0.5875**

Parameter Settings

Methods	Variables	Salinas
*k*means	*k*_cl	16
*K*means + PCA	*k*_cl	16
	% of Variance Data	99
SLIC	No. of Segments	100
	Compactness	10

Results And Discussion



Salinas | k_seg | k_seg + LBS_R | proposed 2 | Reference

Broccoli green weeds 1	Broccoli green weeds 2	Fallow	Fallow rough plow	Fallow smooth
Stubble	Celery	Grapes untrained	Soil vineyard develop	Corn senesced green weeds
Lettuce romaine 4 weeks	Lettuce romaine 5 weeks	Lettuce romaine 6 weeks		
Lettuce romaine 7 weeks	Vineyard untrained	Vineyard vertical trellis	Unlabeled	

Results And Discussion

Datasets	Salinas	
Methods	**NMI**	**Purity**
k-means	0.7242	0.6734
*k*_seg	0.7921	0.6738
*k*_seg + LBS_R	0.7932	0.6426
Proposed 2 (*k*_seg+ LBS)	**0.8130**	**0.7011**

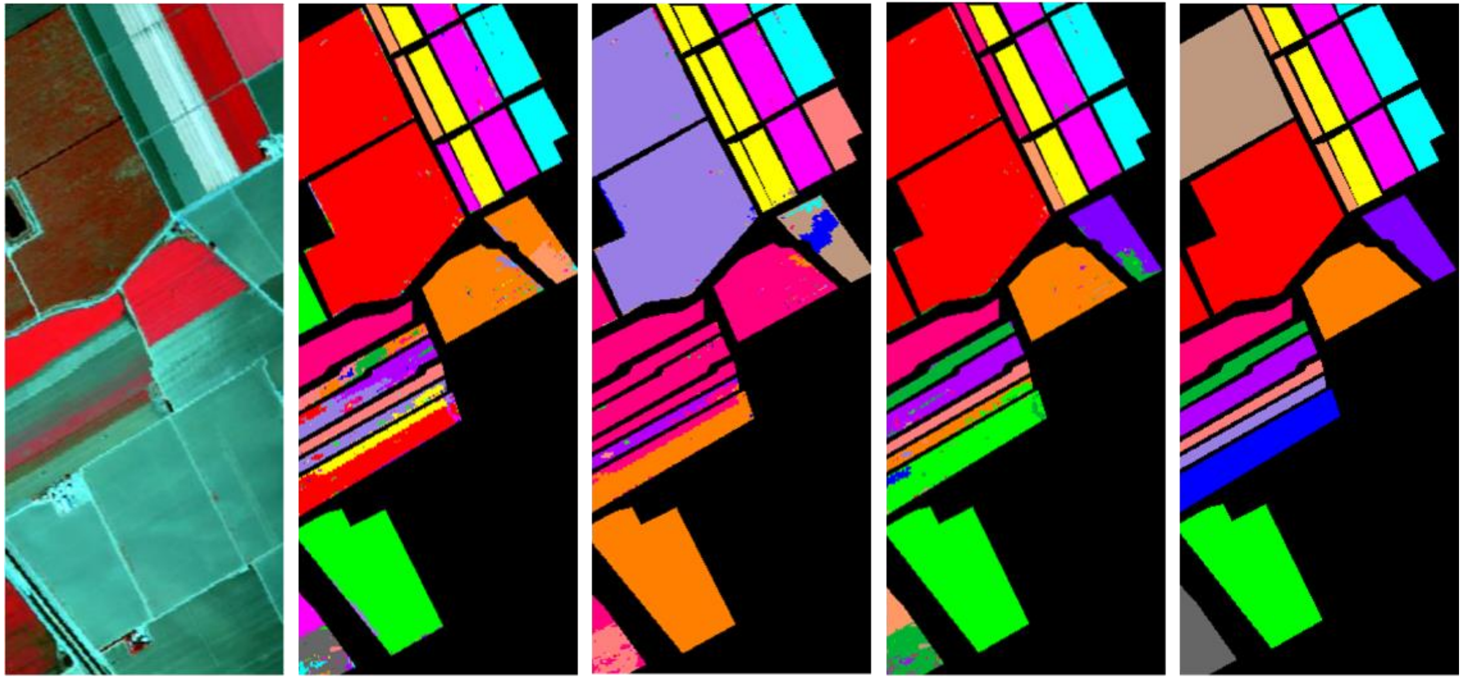
Parameter Settings

↓ Methods

Variables →	*k_seg*	*k*_cl	L
k-means	-	16	All bands
*k*_seg	5	28	All bands
*k*_seg + LBS_R	7	18	12
Proposed 2 (*k*_seg+ LBS)	**6**	**26**	**12**

*k*_seg is number of segments,
*k*_cl is number of significant clusters,
L is number of significant bands taken,
LBS_R is Local Band Selection with Redundant bands,
LBS is Local Band Selection without Redundancy.

Results And Discussion



Salinas k_seg k_seg + LBS_R proposed 3   Reference

Broccoli green weeds 1	Broccoli green weeds 2	Fallow	Fallow rough plow	Fallow smooth
Stubble	Celery	Grapes untrained	Soil vineyard develop	Corn senesced green weeds
Lettuce romaine 4 weeks	Lettuce romaine 5 weeks	Lettuce romaine 6 weeks		
Lettuce romaine 7 weeks	Vineyard untrained	Vineyard vertical trellis	Unlabeled	

Results And Discussion

Datasets	Salinas	
Methods	**NMI**	**Purity**
k-means	0.7242	0.6734
*k*_seg	0.7408	0.6795
*k*_seg + LBS_R	0.8210	0.6905
Proposed 3 (*k*_seg+ LBS)	**0.8430**	**0.7288**

Parameter Settings

← **Methods**

Variables →	***k*_*seg***	***k*_cl**	**L**
k-means	-	16	All bands
*k*_seg	8	16	All bands
*k*_seg + LBS_R	6	25	10
Proposed 3 (*k*_seg+ LBS)	**7**	**24**	**13**

*k*_seg is number of segments,
*k*_cl is number of significant clusters,
L is number of significant bands taken,
LBS_R is Local Band Selection with Redundant bands,
LBS is Local Band Selection without Redundancy.

Results And Discussion

Dataset	Salinas			Pavia Center			Pavia University		
	k cl	NMI	Purity	k cl	NMI	Purity	k cl	NMI	Purity
kM	16	0.7242	0.6734	8	0.7694	7961.0000	9	0.5203	0.6696
PCA + kM	16	0.7656	0.6785	7	0.7750	0.8048	8	0.5663	0.7150
k_seg	28	0.7921	0.6738	17	0.7388	0.8641	17	0.5042	0.7087
k_seg + LBS_R	18	0.7932	0.6426	19	0.7538	0.8208	19	0.5242	0.7009
H2NMF	26	0.6372	0.5877	8	0.7596	0.8592	9	0.4641	0.6261
Proposed 1	**16**	**0.8115**	**0.6835**	**8**	**0.8097**	**0.8155**	**9**	**0.6166**	**0.7362**
SLIC	**16**	**0.7185**	**0.6112**	**8**	**0.6743**	**0.8060**	**9**	**0.4375**	**0.6582**
Proposed 3	**26**	**0.8130**	**0.7011**	**18**	**0.7976**	**0.9001**	**19**	**0.5303**	**0.7141**
Proposed 4	**24**	**0.8430**	**0.7288**	**20**	**0.7903**	**0.8956**	**13**	**0.5407**	**0.6832**

Followings are the acronyms for abovementioned methods:

- Proposed 1 (k-means + k_fr + k_seg)
- Proposed 2 (PCA + SLIC + Clustering)
- Proposed 3 (k_seg+ LBS using Gini Impurity)
- Proposed 4 (k_seg+ LBS using Shannon Entropy)
- SLIC is Simple Linear Iterative Clustering,
- PCA is Principle Component Analysis,
- H2NMF Hierarchical rank 2 non-negative matrix factorization,
- LBS_R is Local Band Selection with Redundant bands,

Conclusion

In this study several approaches of image classification based on **segmentation, clustering** with **local band selection** techniques through **gini impurity and Shannon entropy** are preformed.

- In **Proposed 1** methodology i.e., image segmentation, feature reduction and clustering are performed using ***k*-means**.
- In **Proposed 2** methodology i.e., image segmentation is performed using *k*-means, Local Band Selection and clustering are performed using **Gini Impurity**.
- In **Proposed 3** methodology i.e., image segmentation is performed using *k*-means, Local Band Selection and clustering are performed using **Shannon Entropy**.

Experiments were performed on three dataset and the results were compared on the basis of accuracy assessment.

- Among the evaluated methods, higher accuracy is achieved by **Proposed 3** methodology.
- The accuracy measurements in terms of **NMI** for dataset **Salinas** is significantly increased from **0.7242** to **0.8430** respectively.

TIMELINE OF WORK

Mar. – Oct. 2022

- *k*-means based clustering & segmentation with Feature Reduction.
- Presented work at International Conference on Advances in Mechanics, Modelling, Computing and Statistics (ICAMMCS-2022).
- Received Undergraduate Research Award (URA-1) for this work.

Nov. – Dec. 2022

- Improved Algorithm by utilizing PCA and DBSCAN.
- Published work at International Conference on Computing, Communication, and Intelligent System (ICCIS-2022). https://doi.org/10.1109/ICCCIS56430.2022.10037590

Jan. – Feb. 2023

- Improved algorithm and worked on Simple Linear Iterative Clustering (SLIC).
- Utilized Gini Impurity for local feature selection & Segment Merging.
- Published work at 7th International Conference on Trends in Electronics and Informatics (ICOEI-2023).

Mar. – Apr. 2023

- Utilized Shannon Entropy for local feature selection & Segment Merging.
- Improved Algorithm and overall accuracies.
- Conference Paper accepted at International Conference on Computational Intelligence and Sustainable Engineering Solutions (CISES-2023).

Future of Hyperspectral Imaging

The future of hyperspectral imaging (HSI) looks promising, as advancements in technology and new applications continue to emerge. Here are some potential developments in the field:

1. Integration with other technologies: HSI could be combined with other technologies such as **artificial intelligence** and **machine learning** to improve data analysis and interpretation, leading to faster and more accurate results.

2. Increased applications: HSI has already been applied in numerous fields, but there is still potential for new applications. For example, HSI could be used **to monitor air and water quality**, **detect defects in materials**, or identify counterfeit products.

3. Enhanced spectral resolution: Advances in sensor technology could lead to even higher spectral resolution, enabling more detailed analysis of chemical composition and more precise classification of materials.

4. Space exploration: HSI could also have potential applications in **space exploration**, such as **identifying mineral deposits on other planets or detecting atmospheric gases in exoplanets**.

Overall, the future of HSI is exciting, with new applications and advancements on the horizon that could have a significant impact in multiple fields.

Reference

[1] A. Femenias and S. Mar´ın, "Hyperspectral imaging," Electromagnetic Technologies in Food Science, 2021.
[2] M. Mateen, J. Wen, D. Nasrullah, and M. Azeem Akbar, "The role of hyperspectral imaging: A literature review," International Journal of Advanced Computer Science and Applications, vol. 9, p. 51, 09 2018.
[3] A. Mehta and O. Dikshit, "Comparative study on projected clustering methods for hyperspectral imagery classification," Geocarto International, vol. 31, pp. 296–307.
[4] A. F. Alkarkhi and W. A. Alqaraghuli, "Cluster analysis, chapter 11," in Easy Statistics for Food Science with R, A. F. Alkarkhi and W. A. Alqaraghuli, Eds. Academic Press, 2019, pp. 177–186.
[5] A. Mehta and O. Dikshit, "Projected clustering of hyperspectral imagery using region merging," Remote Sensing Letters, vol. 7, no. 8, pp. 721–730, 2016.
[6] C. D. Manning, P. Raghavan, and H. Sch¨utze, Introduction to Information Retrieval. Cambridge University Press, 2008, cambridge Books Online. [Online]. Available: http://dx.doi.org/10.1017/CBO9780511809071
[7] A. Mehta and O. Dikshit, "Segmentation-based projected clustering of hyperspectral images using mutual nearest neighbour," IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, vol. 10, no. 12, pp. 5237–5244, 2017.
[8] Y. Li and H. Wu, "A clustering method based on k-means algorithm," Physics Procedia, vol. 25, pp. 1104–1109, 12 2012.
[9] S. Lloyd, "Least squares quantization in pcm," IEEE Transactions on Information Theory, vol. 28, pp. 1104–1109, 1982.
[10] A. K. Jain, M. N. Murty, and P. J. Flynn., Data Clustering: A Review, 1999, pp. 264–323.
[11] J. A. Richards, Remote Sensing Digital Image Analysis: An Introduction Springer-Verlag, Berlin, Heidelberg, 5th Edition, 2013, pp. 403–446.
[12] Ehu, "Salinas, pavia university and pavia center datasets," Accessed on 2021. [Online]. Available: https://www.ehu.eus/ccwintco/index.php?title=Hyperspectral_Remote_Sensing_Scenes


THANK YOU