Deep Learning for Multi Crop Classification using Hyperspectral Data

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Overview

Hyperspectral Remote Sensing

- Hyperspectral remote sensing is one of the most exciting field of remote sensing due to the enormous amounts of data it produces due to its high spectral resolution.
- The large number of bands (400 bands) allow us to identify and distinguish spectrally similar materials which enhances the capability to distinguish ground objects more accurately.

Motivation

- Till date , many standard machine learning techniques and neural network models have been tried out on hyperspectral images in order to further improve the classification accuracies.
- Classification using Classical Machine Learning Methods on Hyperspectral Datasets is done to set benchmark results.
- Then to use Deep Learning and computational models on hyperspectral datasets.

Datasets

Table: Dataset comparison table

Information	Indian Pines	Pavia	Salinas
Number of Classes	16	9	16
Number of Bands	200	103	224
Frequency range	0.4 to 2.5 um	0.43 to 0.86 um	0.43 to 2.5 um
Spectral Resolution	9.5 nm	4.1 nm	9.2 nm
Size of site	145x145	610x610	512x217
Spatial Resolution	20m	1.3m	3.7m
Classes with min. sample	Alfalfa/Oats	Shadows	Lettuce romaine
Type of this class	Crop	Shadows	Thin crop strip

Datasets

AVIRIS-NG Dataset

Complete AVIRIS-NG Phase 1 over Agricultural University, Anand District , Gujarat (15 classes and 6 classes as per spectra collected from ground visits)

Table reading key

- SVM-l refers to Linear kernel SVM
- SVM-p refers to Polynomial kernel SVM
- SVM-r refers to Radial Basis Function kernel SVM
- RF refers to Random Forest Classifier
- OA refers to Overall Accuracy and AA refers to Average Accuracy
- 'neigh' refers to the number of neighbours used in kNN algorithm
- 'est' refers to the maximum estimators chosen by the Random Forest classifier
- 'f' refers to the maximum features chosen by the Random Forest classifier

Training Samples Variation

- We train the model using randomly selected 10, 10%, 30%, 50% and 60% samples per class from training set.

- There is a mismatch in the inter-class distribution of samples .For example , the small sample size classes i.e. Alfaalfa (0.4% of total samples), grass-pasture-mowed (0.2%), oats (0.2%) and stonesteel-towers (0.8%), the accuracy is seen when the number of training samples is less (Indian Pines dataset).

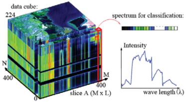


Figure: Less number of samples illustration

- The classifiers which perform better with input 30% to 50% of the training samples will fare better in the vastly unlabelled hyperspectral datasets of AVIRIS sensors

Classification Results on Indian Pines dataset

Table: Indian Pines Dataset with train size 2% (Classifier class accuracy shown in %)

Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN
Alfalfa	0	46	0	0	0	0	0
Corn-notill	28	1400	45	53	0	70	41
Corn-mintill	16	814	45	15	0	0	38
Corn	4	233	39	21	0	0	41
Grass-pasture	9	474	51	48	0	73	44
Grass-trees	14	716	72	70	0	48	59
Grass-pasture-mowed	0	28	0	0	0	0	0
Hay-windrowed	9	469	82	83	0	72	80
Oats	0	20	0	0	0	0	0
Soybean-notill	19	953	47	53	0	0	30
Soybean-mintill	49	2406	48	41	24	38	51
Soybean-clean	11	582	20	37	0	0	13
Wheat	4	201	70	73	0	0	63
Woods	25	1240	82	82	0	77	76
Blds-grass-drives	7	379	40	45	0	0	0
Stone-steel-towers	1	92	0	0	0	0	0
OA			55.73	51.30	23.93	48.37	51.885
AA			52	50	6	39	46
Kappa			0.48	0.41	0.00	0.36	0.4389
Parameter grid			C=0.05 G=0.01	C=0.01 G=0.05	C=0.01 G=0.01	est= 700 f=log2	

Classification Results on Indian Pines dataset

Table: Indian Pines Dataset with train size=10 samples (Classifier class accuracy shown in %)

Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN	GMM
Alfalfa	10	36	18	16	14	15	9	0
Corn-notill	10	1418	68	60	29	21	43	5
Corn-mintill	10	820	30	37	39	12	23	0
Corn	10	227	29	25	18	0	9	0
Grass-pasture	10	473	52	64	61	39	39	0
Grass-trees	10	720	87	86	77	67	70	0
Grass-pasture-mowed	10	18	39	2	27	27	7	0
Hay-windrowed	10	468	96	93	91	61	92	0
Oats	10	10	5	3	3	3	2	0
Soybean-notill	10	962	35	36	31	0	29	0
Soybean-mintill	10	2445	62	72	58	0	57	0
Soybean-clean	10	583	26	36	15	0	17	0
Wheat	10	195	51	77	73	53	56	0
Woods	10	1255	87	89	85	75	82	0
Blds-grass-drives	10	376	58	42	19	54	15	0
Stone-steel-towers	10	83	75	77	100	39	99	0
OA			54.19	51.24	41.65	34.0271	38.24	0.00
AA			60	63	52	26	50	0.01
Kappa			0.48	0.45	0.34	0.2605	0.31	0.03
Parameter grid			C=0.05 G=0.01	C=0.02 G=0.05	C=0.01 G=0.05	n_est 700 f=log2	neigh=8	comp=9 cov=full

Classification Results on Indian Pines dataset

Table: Indian Pines Dataset with train size 10% (Classifier class accuracy shown in %)

Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN
Alfalfa	4	42	34	36	0	0	0
Corn-notill	142	1286	67	62	62	52	48
Corn-mintill	83	747	68	68	0	0	59
Corn	23	214	58	29	0	0	32
Grass-pasture	48	435	81	86	0	0	81
Grass-trees	73	657	85	80	52	34	70
Grass-pasture-mowed	2	26	100	0	0	0	0
Hay-windrowed	47	431	88	88	0	0	83
Oats	2	18	0	0	0	0	0
Soybean-notill	97	875	65	74	0	0	48
Soybean-mintill	245	2210	61	57	36	42	57
Soybean-clean	59	534	55	45	0	0	41
Wheat	20	185	94	91	0	0	77
Woods	126	1139	88	89	69	72	83
Blds-grass-drives	38	348	74	70	0	0	86
Stone-steel-towers	9	84	99	100	0	0	99
OA			71.3	68.57	45.05	46.70	62.8534
AA			71	68	29	29	61
Kappa			0.66	0.63	0.31	0.35	0.5684
Parameter grid			C=0.05 G=0.01	C=0.02 G=0.05	C=0.05 G=0.01	est 700 f=log2	Neigh=11

Classification Results on Indian Pines dataset

Table: Indian Pines Dataset with train size=30% (Classifier class accuracy shown in %)

Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN
Alfalfa	13	33	81	43	0	0	0
Corn-notill	428	1000	80	73	59	54	51
Corn-mintill	249	581	76	66	0	0	69
Corn	71	166	71	64	0	0	48
Grass-pasture	144	339	85	87	0	0	81
Grass-trees	219	511	92	87	55	35	72
Grass-pasture-mowed	8	20	100	100	0	0	0
Hay-windrowed	143	335	94	89	78	0	84
Oats	6	14	75	57	0	0	0
Soybean-notill	291	681	75	80	0	0	55
Soybean-mintill	736	1719	68	66	41	42	61
Soybean-clean	177	416	67	69	0	0	67
Wheat	61	144	95	97	91	0	79
Woods	379	886	91	93	70	72	86
Blds-grass-drives	115	271	85	71	0	0	82
Stone-steel-towers	27	66	100	100	0	0	100
OA			78.75	76.30	51.11	46.86	66.7919
AA			79	76	36	29	67
Kappa			0.75	0.72	0.40	0.35	0.6146
Parameter grid			C=0.05	C=0.05	C=0.05	est 700	Neigh=10
			G=0.01	G=0.05	G=0.05	f=log2	

Classification Results on Indian Pines dataset

Table: Indian Pines Dataset with train size=50% (Classifier class accuracy shown in %)

Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN
Alfalfa	23	23	100	50	0	0	67
Corn-notill	714	714	81	79	60	0	51
Corn-mintill	415	415	82	71	0	0	66
Corn	118	119	75	64	0	0	42
Grass-pasture	241	242	89	93	89	0	84
Grass-trees	365	365	93	93	65	35	74
Grass-pasture-mowed	14	14	100	100	0	0	67
Hay-windrowed	239	239	95	92	80	0	86
Oats	10	10	100	50	0	0	0
Soybean-notill	486	486	76	84	0	0	58
Soybean-mintill	1227	1228	75	73	41	38	63
Soybean-clean	296	297	72	78	0	0	64
Wheat	102	103	95	94	88	0	84
Woods	632	633	92	94	71	73	86
Blds-grass-drives	193	193	86	78	100	0	87
Stone-steel-towers	46	47	100	98	100	0	100
OA			82.58	81.25	53.95	42.84	67.6321
AA			83	81	46	21	68
Kappa			0.79	0.78	0.44	0.29	0.6263
Parameter grid			C=0.05	C=0.05	C=0.05	est 700	
			G=0.01	G=0.05	G=0.01	f=log2	

Classification Results on Indian Pines dataset

Table: Indian Pines Dataset with train size 60% (Classifier class accuracy shown in %)

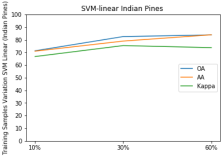
Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN	GMM
Alfalfa	27	19	100	94	0	0	100	14
Corn-notill	856	572	83	91	59	0	61	29
Corn-mintill	498	332	87	84	97	0	73	39
Corn	142	95	74	81	0	0	55	18
Grass-pasture	289	194	92	95	91	0	88	61
Grass-trees	438	292	94	96	72	34	80	77
Grass-pasture-mowed	16	12	100	100	0	0	86	27
Hay-windrowed	286	192	96	96	82	0	87	91
Oats	12	8	100	70	0	0	80	3
Soybean-notill	583	389	80	92	65	0	70	31
Soybean-mintill	1473	982	76	75	46	38	72	58
Soybean-clean	355	238	73	88	0	0	78	15
Wheat	123	82	98	95	86	0	84	73
Woods	759	506	91	95	78	73	90	85
Blds-grass-drives	231	155	87	80	100	0	75	19
Stone-steel-towers	55	38	100	100	100	0	100	100
OA			83.87	86.48	60.49	30	75.45	41.65
AA			84	87	62	9	75	52
Kappa			0.81	0.84	0.52	0.3	0.71	0.34
Parameter grid			C=0.05 G=0.01	C=0.05 G=0.05	C=0.05 G=0.02	est =700 f=log2	neigh=9	comp=9 cov=full

Classification Results on Indian Pines dataset

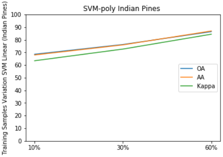
Table: Indian Pines Dataset with train size=80% (Classifier class accuracy shown in %)

Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN	GMM	Decision Tree
Alfalfa	36	10	91	83	0	0	86	91	86
Corn-notill	1142	286	80	67	62	11	68	80	68
Corn-mintill	664	166	73	67	90	6	62	73	62
Corn	189	48	78	67	50	2	51	78	51
Grass-pasture	386	97	87	87	93	0	84	87	84
Grass-trees	584	146	92	84	78	0	93	92	93
Grass-pasture-mowed	22	6	83	56	0	0	50	83	50
Hay-windrowed	382	96	99	95	83	0	95	99	95
Oats	16	4	57	67	0	0	50	57	50
Soybean-notill	777	195	79	72	82	0	73	79	73
Soybean-mintill	1964	491	79	74	57	51	73	79	73
Soybean-clean	474	119	84	70	51	24	54	84	54
Wheat	164	41	98	83	89	0	93	98	93
Woods	1012	253	95	92	86	0	91	95	91
Blds-grass-drives	308	78	81	80	82	0	64	81	79
Stone-steel-towers	74	19	100	100	100	0	79	100	100
OA			84.62	89	69.92	46.86	74	10.96	74.89
AA			82	87.13	72	47	77	15	75
Kappa			0.81	0.86	0.64	0.35	0.73	0.03	0.71
Parameter grid						est 700 f=log2			

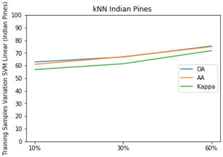
OA , AA and Kappa variation on increasing number of training samples (Indian Pines)



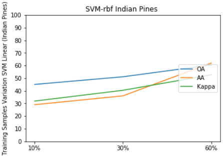
(a) SVM linear



(b) SVM poly



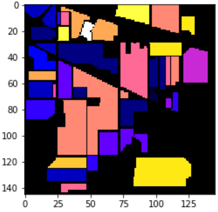
(c) kNN



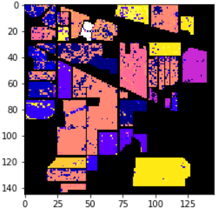
(d) SVM rbf

Error Images Indian Pines Dataset 10%

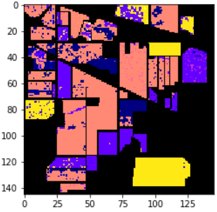
Figure: Classification results on Indian Pines dataset



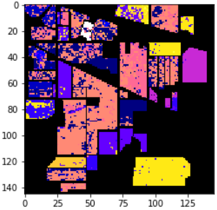
(a) Reference Image



(b) SVM Linear



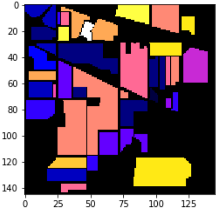
(c) RF



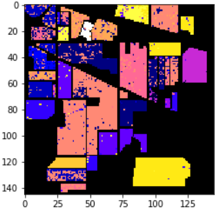
(d) kNN

Error Images Indian Pines Dataset 30%

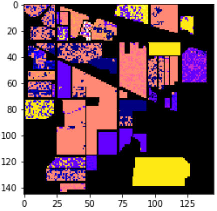
Figure: Classification results on Indian Pines dataset



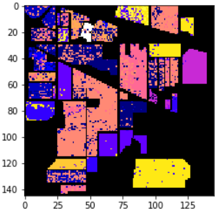
(a) Reference Image



(b) SVM Linear



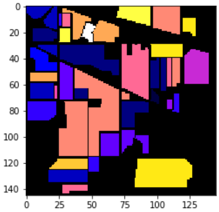
(c) RF



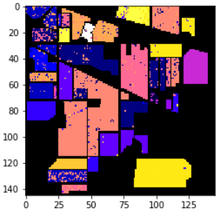
(d) kNN

Error Images Indian Pines Dataset 50%

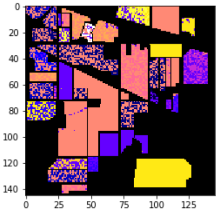
Figure: Classification results on Indian Pines dataset



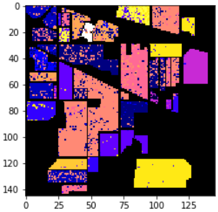
(a) Reference Image



(b) SVM Linear



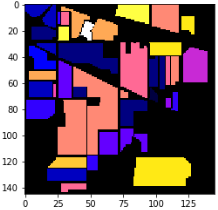
(c) RF



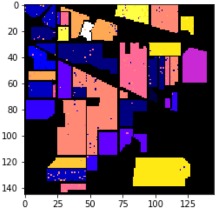
(d) kNN

Error Images Indian Pines Dataset 80%

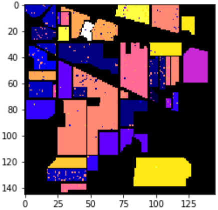
Figure: Classification results on Indian Pines dataset



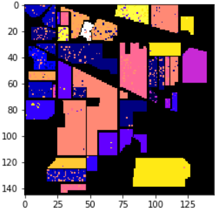
(a) Reference Image



(b) SVM Linear



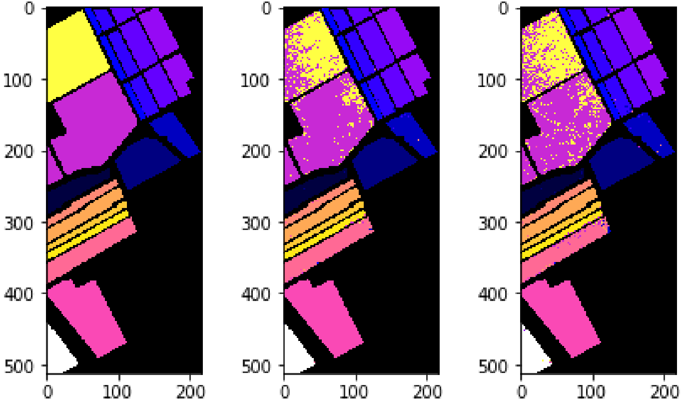
(c) SVM polynomial



(d) SVM rbf

Error Images Salinas Dataset 10%

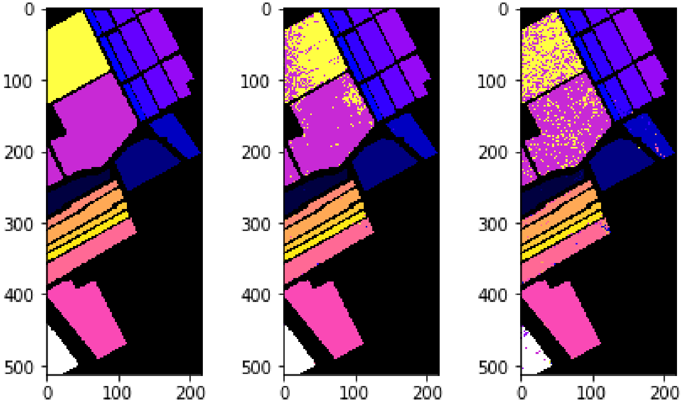
Figure: Classification results on Salinas dataset



(a) Reference Image (b) SVM Linear (c) SVM polynomial

Error Images Salinas Dataset 30%

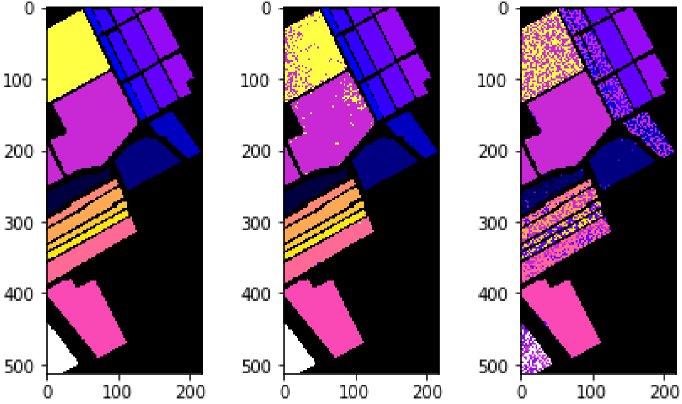
Figure: Classification results on Salinas dataset



(a) Reference Image (b) SVM Linear (c) kNN

Error Images Salinas Dataset 50%

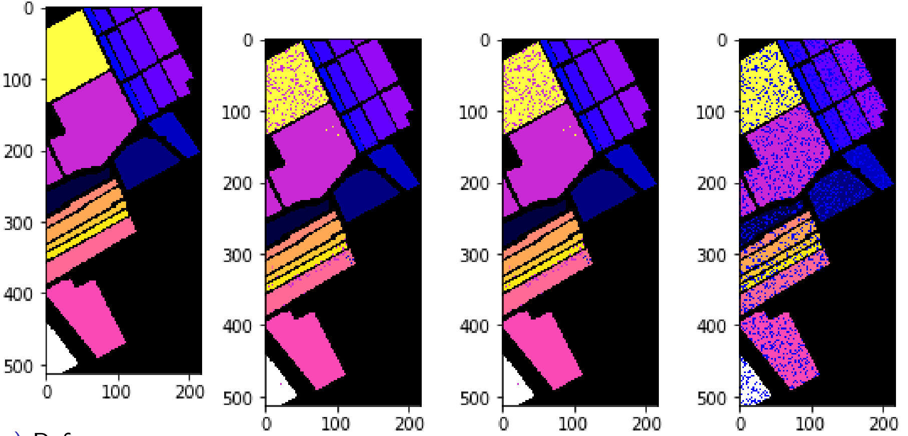
Figure: Classification results on Salinas dataset



(a) Reference Image (b) SVM Linear (c) Random Forest

Error Images Salinas Dataset 80%

Figure: Classification results on Salinas dataset



(a) Reference Image

(b) SVM Linear

(c) SVM Polynomial

(d) kNN

Methods performing the best for each dataset and each training sampling ratio

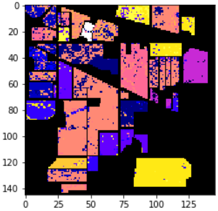
Table: Best performing classifiers

Training %	Indian Pines	Salinas	Pavia
2%	SVM-Linear	SVM-Linear	kNN/SVM-Linear
10 samples	SVM-Linear	SVM-Linear	kNN
10%	SVM-Linear	SVM-Linear	kNN
30%	SVM-Linear/SVM-poly	SVM-Linear/SVM-rbf	SVM-Linear/kNN
50%	SVM-Linear	SVM-Linear/SVM-poly	SVM-poly/SVM-Linear
60%	SVM-Linear	SVM-Linear and SVM-poly	kNN
80%	SVM-Poly	SVM-Poly	SVM-Poly

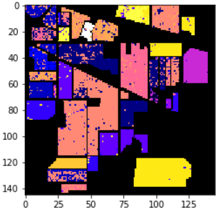
SVM- Linear and kNN are most viable algorithm for training sample taken to be 30% to 50% of total samples. SVM-poly performs better at higher training sample as it creates non-linear decision boundary.

SVM Linear Comparison

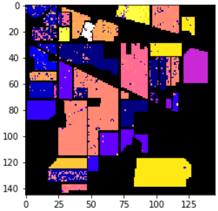
Figure: Classification results



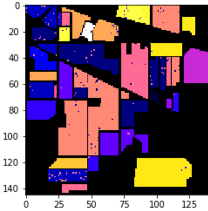
(a) 10%



(b) 30%



(c) 50%



(d) 80%

PCA on Indian Pines

Table: Indian Pines Dataset PCA (components=2)

Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN
Alfalfa	27	19	0	0	0	0	57
Corn-notill	856	572	42	0	0	41	45
Corn-mintill	498	332	0	0	0	0	40
Corn-mintill	142	95	0	0	0	0	39
Grass-pasture	289	194	22	0	0	0	65
Grass-trees	438	292	64	0	47	38	71
Grass-pasture-mowed	16	12	0	0	0	0	0
Hay-windrowed	286	192	76	0	74	0	83
Oats	12	8	0	0	0	0	0
Soybean-notill	583	389	0	0	0	0	48
Soybean-mintill	1473	982	37	24	36	43	57
Soybean-clean	355	238	0	0	0	0	33
Wheat	123	82	72	0	0	0	80
Woods	759	506	71	0	65	73	80
Blds-grass-drives	231	155	0	0	0	0	38
Stone-steel-towers	55	38	0	0	0	0	40
OA			48.733	23.91	43.47	46.7121	58.5728
AA			34	6	23	28	56
Kappa			0.3716	0	0.2998	0.3533	0.5224
Parameter grid			C=0.01 G=0.01	C=0.01 G=0.01	C=0.05 G=0.05		Neighbour=12

PCA on Indian Pines

Table: Indian Pines Dataset PCA (components=10)

Class	train	test	SVM-l	SVM-p	SVM-r	RF	kNN
Alfalfa	27	19	18	16	0	0	9
Corn-notill	856	572	68	60	59	50	43
Corn-mintill	498	332	30	37	0	0	23
Corn	142	95	29	25	0	0	9
Grass-pasture	289	194	52	64	68	0	39
Grass-trees	438	292	87	86	68	56	70
Grass-pasture-mowed	16	12	39	2	0	0	7
Hay-windrowed	286	192	96	93	81	80	92
Oats	12	8	5	3	0	0	2
Soybean-notill	583	389	35	36	0	0	29
Soybean-mintill	1473	982	62	72	43	39	57
Soybean-clean	355	238	26	36	0	0	17
Wheat	123	82	51	77	89	0	56
Woods	759	506	87	89	67	73	82
Blds-grass-drives	231	155	58	42	100	0	15
Stone-steel-towers	55	38	75	77	97	0	99
OA			54.19	51.2439	54.55	49.97	38.24
AA			60	63	45	33	50
Kappa			0.4831	0.4572	0.4493	0.3886	0.3133
Parameter grid			C=0.05 G=0.01	C=0.02 G=0.05	C=0.05 G=0.05		Neighbour=8

LDA on Indian Pines

Table: Indian Pines LDA (components=7)

Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN
Alfalfa	27	19	0	75	64	0	54
Corn-notill	856	572	0	53	52	46	48
Corn-mintill	498	332	0	0	33	0	24
Corn	142	95	0	52	59	0	51
Grass-pasture	289	194	0	48	62	0	57
Grass-trees	438	292	41	68	69	51	70
Grass-pasture-mowed	16	12	0	0	80	0	60
Hay-windrowed	286	192	0	89	90	66	88
Oats	12	8	0	0	0	0	0
Soybean-notill	583	389	0	56	56	0	55
Soybean-mintill	1473	982	34	48	53	42	63
Soybean-clean	355	238	0	24	45	0	47
Wheat	123	82	23	82	72	0	79
Woods	759	506	71	73	71	61	78
Blds-grass-drives	231	155	0	79	53	0	27
Stone-steel-towers	55	38	0	100	100	0	100
OA			41.0375	58.2318	60.4724	48.4413	61.2274
AA			20	53	58	31	58
Kappa			0.2752	0.5038	0.534	0.3735	0.5531
Parameter grid			C=0.05	C=0.5	C=1		Neighbours=9

Inference after Feature Extraction from input data using PCA and LDA

- The accuracy decreased by 20% to 30% when PCA or LDA is applied.
- Within 3 components, the variance ratio in PCA is drops to almost 1.
- There is slight drop in accuracy when 2 components are used instead of 10 components in PCA reduction.

Feature Selection

- The amount of information involved in hyperspectral imaging is large.
- Several information based measures such as mutual information have been proposed to reduce information redundancy among spectral bands.
- Recursive Feature Elimination select features by recursively considering smaller and smaller sets of features

ANOVA based feature extraction

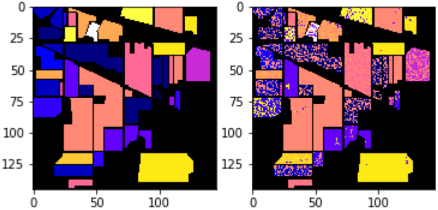


Figure: Indian Pines dataset (50 % training samples) and SVM classification

Class label index
Alfalfa , Corn-notill , Corn-mintill , Corn
Grass-pasture , Grass-trees , Grass-pasture-mowed , Hay-windrowed
Oats , Soybean-notill , Soybean-mintill , Soybean-clean
Wheat , Woods , Blds-grass-drives , Stone-steel-towers

OA = 42.25 % Kappa = 0.28

Recursive Feature Extraction and Cross Validation

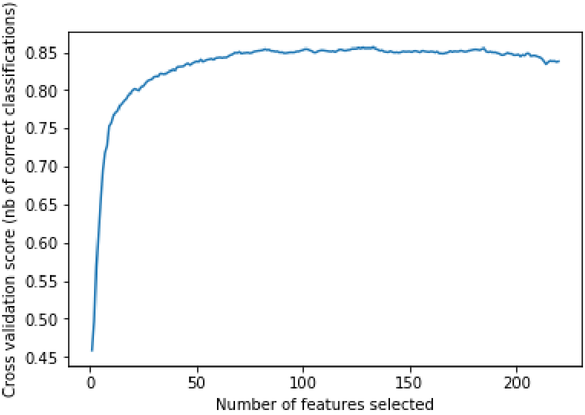
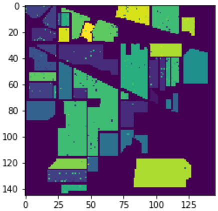


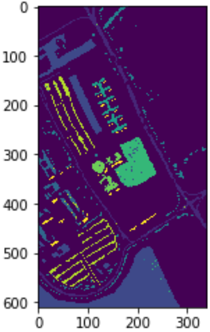
Figure: Indian Pines dataset and SVM classification

The CV score saturates at around 50 features extracted out of Indian Pines dataset.

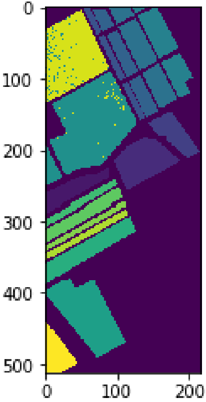
Separability Index in the three datasets



(a) Seperability of Indian Pines Classes



(b) Seperability of Pavia Classes



(c) Seperability of Salinas Classes

Some of the classes are have classified points in other classes , which we study using the Jeffries Matusita distance metric and see the separability of any two class.

Conclusion and Future Scope (Feature Reduction)

- t-SNE visualization
- Separability Index (JM Distance and Mahalanobis Distance for 2 highly misclassified class)
- Non linear Dimensionality reduction like LLE

Deep Learning

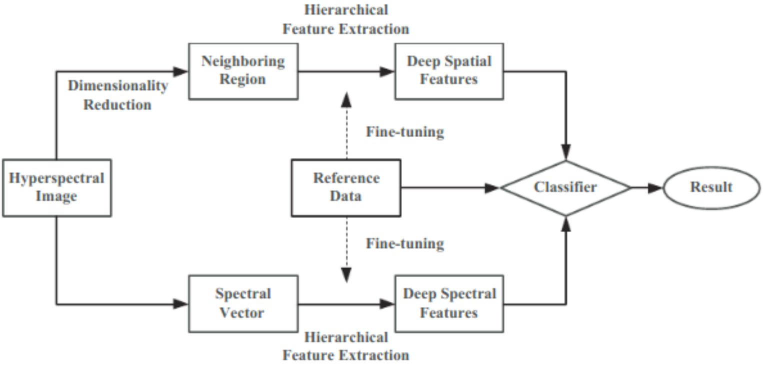


Fig. 1. General framework of HSI classification based on deep learning methods.

Figure: HSI Classification based on deep learning methods

Credit : HSI journal paper

Autoencoders

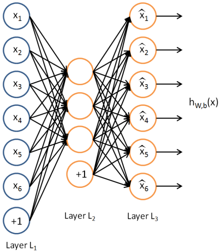


Figure: Image reference : http://ufldl.stanford.edu/tutorial/unsupervised/Autoencoders/

An autoencoder is an unsupervised learning algorithm that sets the target values of the neural network to be equal to the inputs.
Autoencoders can get useful high-level features and can be used to learn a hierarchical feature representation. It improves in the classification by training on unlabelled data. We have used softmax classifier to classify the encoded features with the labelled samples.

Commonly used Autoencoders in HSI classification

- Stacked Autoencoder
- PCA derived Autoencoder
- Convolutional (Patchwise) Autoencoder

Classification Methodology Description

- In the unsupervised classification approach, an autoencoder is trained against the Indian Pines dataset without the any class labels.
- The unlabelled patches are made by cutting the populated scene of Indian pines , into 8x8 patches(chosen arbitrarily). The patches are fed as input to the Autoencoder , and then training of input image till the encoded layer is done.
- Keras library in Python to build a neural network and reduce the representation of the spectral space to a few dimensions and then upsample it to get the new features.
- The encoded features are fed softmax classifier which will classify the encoded features with the training set of the labelled samples.
- When there are large number of unlabelled samples to train on, does the model give better prediction.

Autoencoder Results

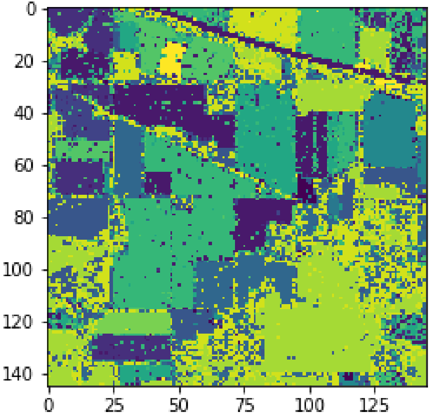


Figure: Classified Map Autoencoder

Autoencoder Results

Class	Train	test	SVM-l	SVM-p	SVM-r	RF	kNN	Autoencoder
Alfalfa	27	19	100	94	0	0	100	86
Corn-notill	856	572	83	91	59	0	61	68
Corn-mintill	498	332	87	84	97	0	73	62
Corn	142	95	74	81	0	0	55	51
Grass-pasture	289	194	92	95	91	0	88	84
Grass-trees	438	292	94	96	72	34	80	93
Grass-pasture	16	12	100	100	0	0	86	50
Hay-windrowed	286	192	96	96	82	0	87	95
Oats	12	8	100	70	0	0	80	50
Soybean-notill	583	389	80	92	65	0	70	73
Soybean-mintill	1473	982	76	75	46	38	72	73
Soybean-clean	355	238	73	88	0	0	78	54
Wheat	123	82	98	95	86	0	84	93
Woods	759	506	91	95	78	73	90	91
Blds-grass-drives	231	155	87	80	100	0	75	64
Stone-steel-towers	55	38	100	100	100	0	100	79
OA			83.87	86.48	60.49	30	75.45	74.89
AA			84	87	62	9	75	75
Kappa			0.81	0.84	0.52	0.3	0.71	0.71

1-D Convolutional NN on Hyperspectral Data

- In deep learning, the convolutional neural networks (CNN) play a dominant role for processing visual-related problems.
- Since CNNs have been only considered on visual-related problems, there are rare literatures on the technique with multiple layers for HSI classification. The HSI essence is better captured by the CNN when we consider various extended morphological features from the spectrally rich Hyperspectral data.

Conclusion Remarks

- The classical methods have faster training and are more reliable , but they have a limitation when the complexity of the data increases.
- Autoencoder requires lot of training samples in order to overcome the classical method accuracy.
- To use both spatial and spectral components and build a Neural Network that can have hyperparameters which can extract maximum features from spatial and spectral side , to attain better classification.

Timeline

- November : Develop 1D CNN for spectral feature learning over Anand Site.
- December : Develop 2D CNN for spatial feature learning.
- January : Develop 3D CNN over Anand Site.
- February : To compare CNN with other deep learning frameworks like RNN , LSTM , One-shot and Reinforcement Learning.
- March : Refine the model and see for increased number of classes or for crops with similar spectra
- April : Deriving conclusions and results and making report.