Faculty of Computer Science

Data Science

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Deep Learning on Hyperspectral Satellite Imagery

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Hyperspectral imaging (HSI)

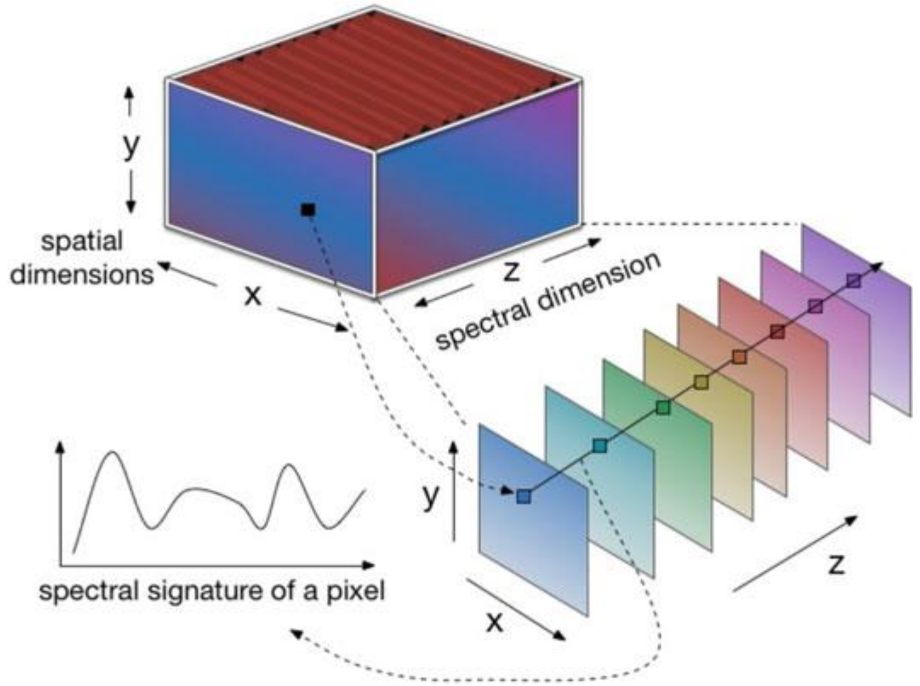
spectroscopic instrumentation

+

imaging systems

=

spatially resolved spectroscopic data



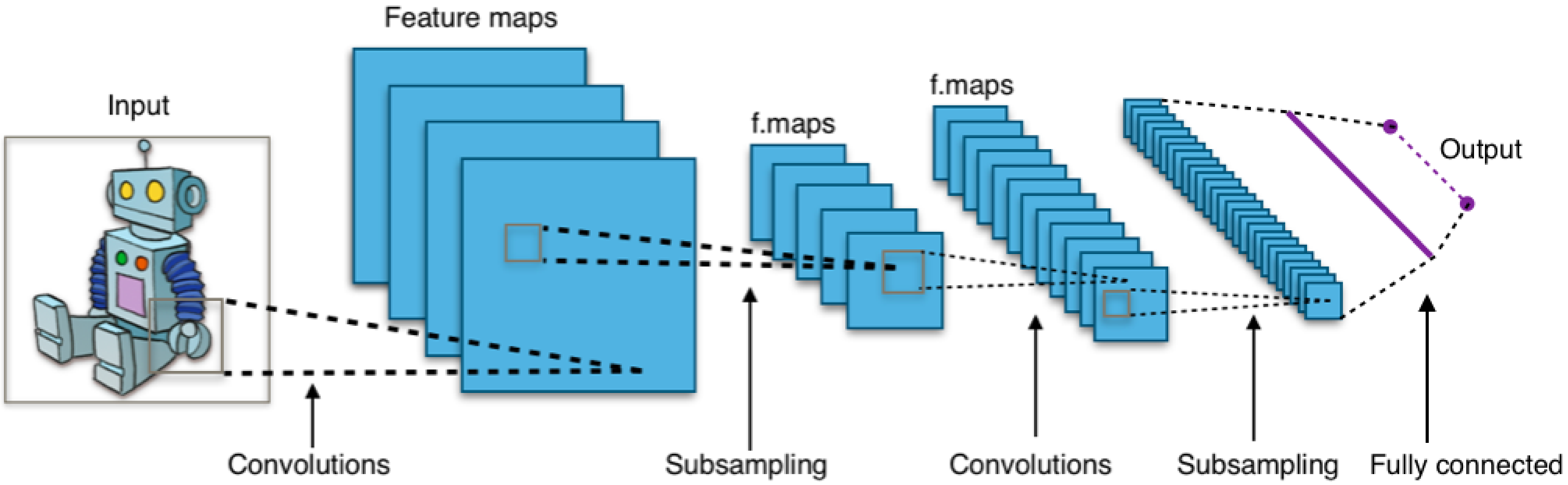
S. Berisha et al. Deep Learning for Hyperspectral Image Analysis, Part I: Theory and Algorithms

Challenges

more per-pixel data than traditional color imagery → larger input vectors → more trainable parameters → much more memory intensive optimization

Convolutional Neural Networks

- feed-forward neural network
- filter (kernel) optimization
- for processing data sampled on a uniform grid, such as an image

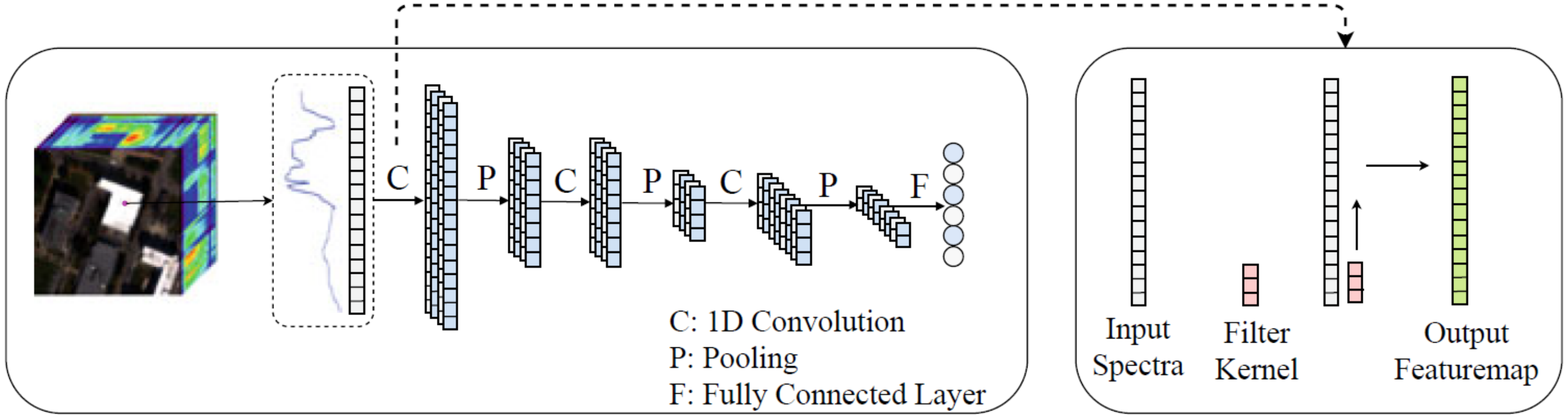


https://en.wikipedia.org/wiki/Convolutional_neural_network

1D CNN

Pros
- few parameters
- fast

Cons
- pixel-level extraction of spectral features
- weak in in extracting abstract deep features (spatial and spectra local features)



1D CNN Architecture **1D CNN Filtering Operation**

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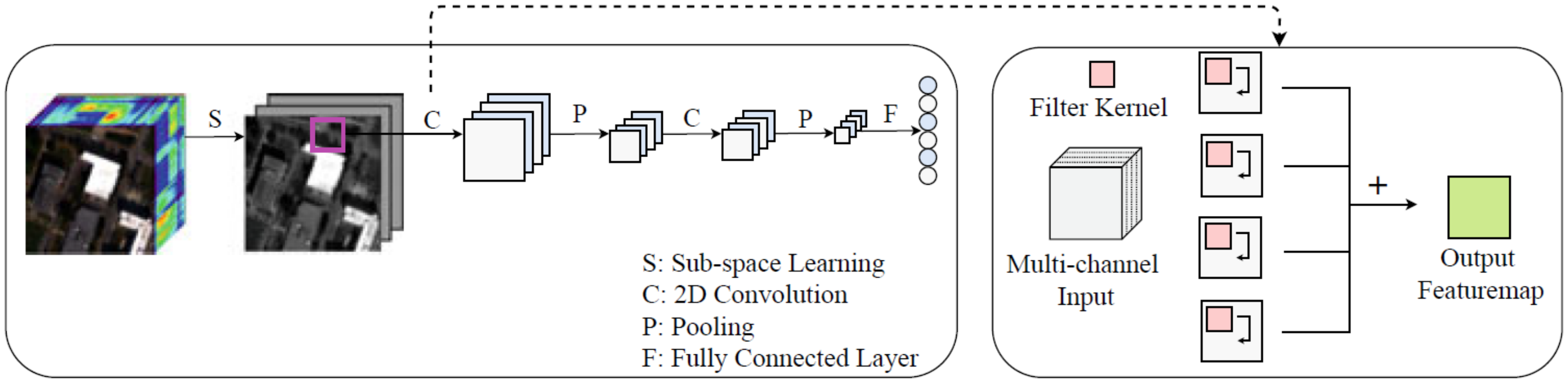
2D CNN

Pros

- extracts spatial local features
- produces a feature map for each band

Cons

- large number of parameters
- does not extracts spectral local features



2D CNN Architecture **2D CNN filtering Operation**

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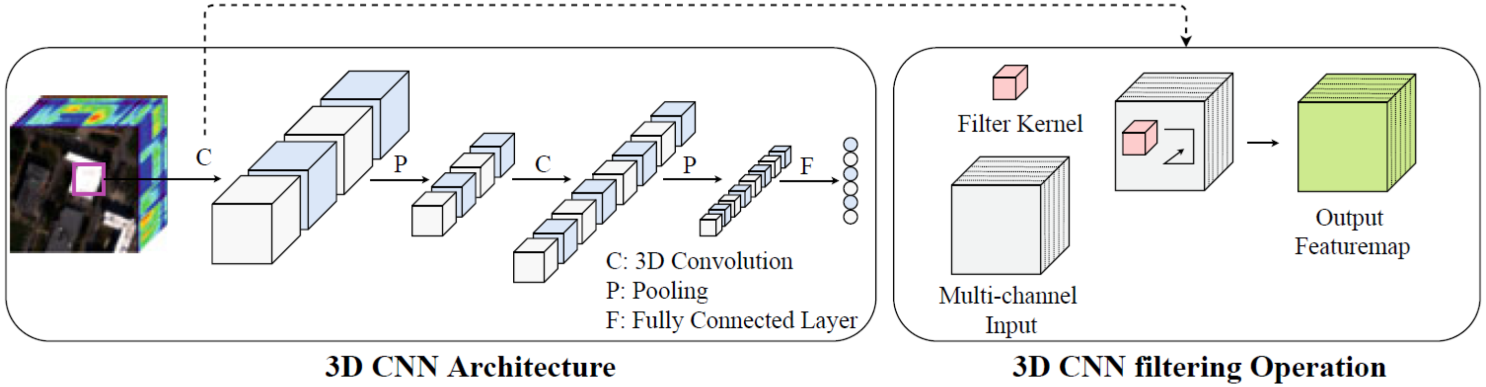
3D CNN



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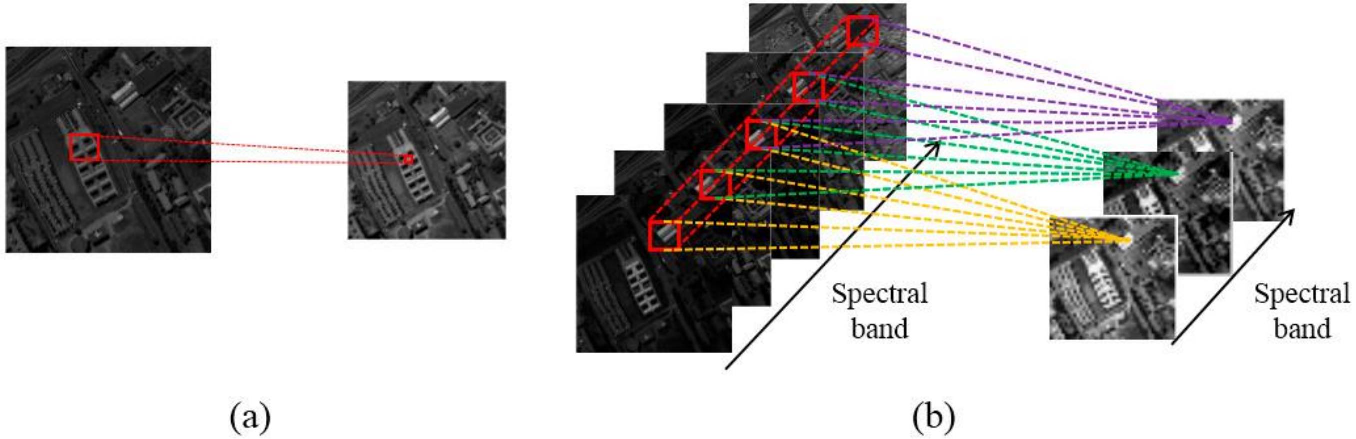
Pros

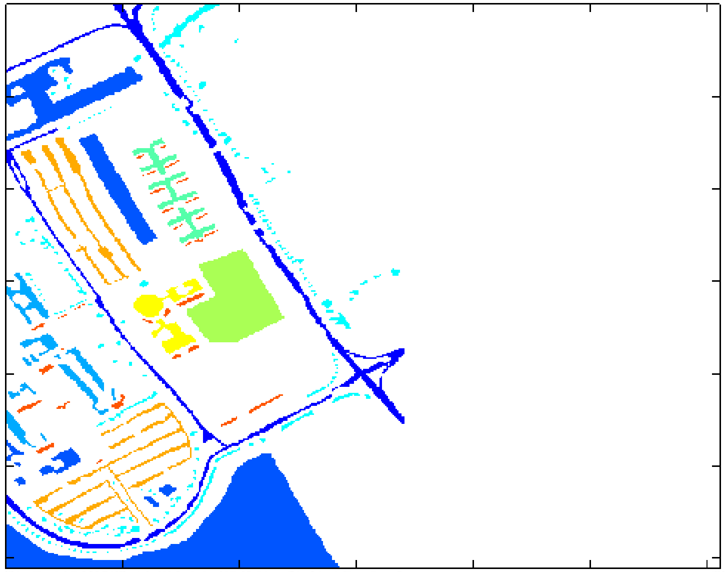
- is able to extract spectral–spatial information
- fewer parameters than 2D CNN
- faster convergence



Spectral–Spatial Classification of Hyperspectral Imagery with 3D Convolutional Neural Network

Dataset

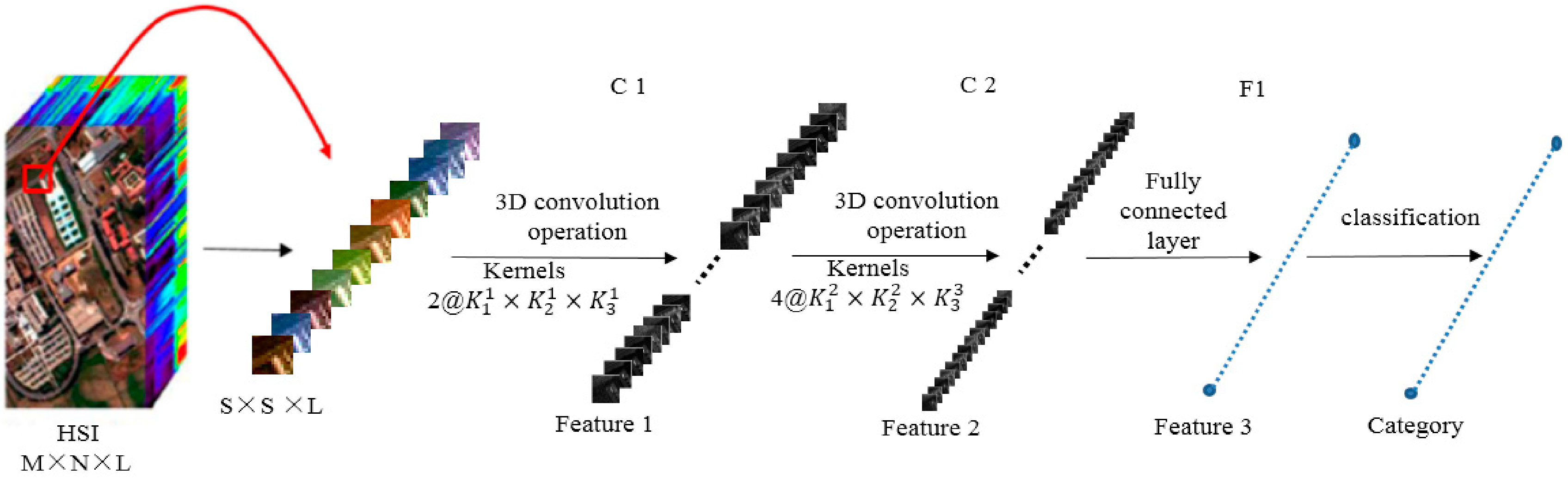
- 115 spectral bands (0.43 to 0.86 μm), 10 % of noisiest bands removed => 103 bands
- spatial resolution 1.3 m per pixel
- 610 × 340 pixels
- 9 Classes
- 1:1 stratified train-test split



https://www.ehu.eus/ccwintco/index.php/Hyperspectral_Remote_Sensing_Scenes#Pavia_Centre_and_University

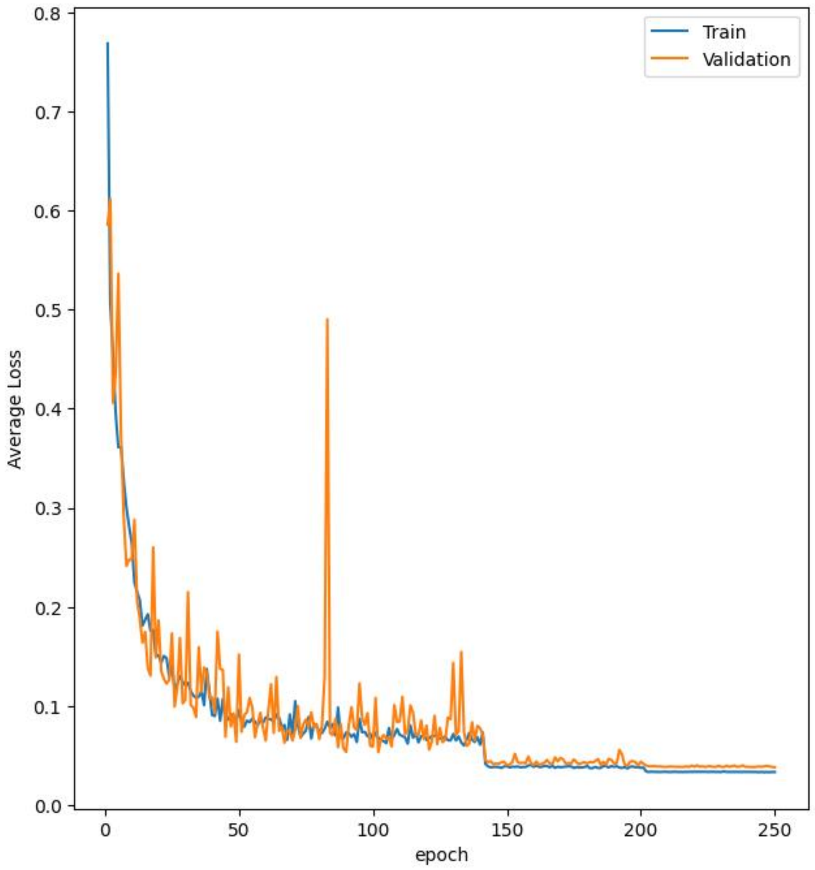
Architecture

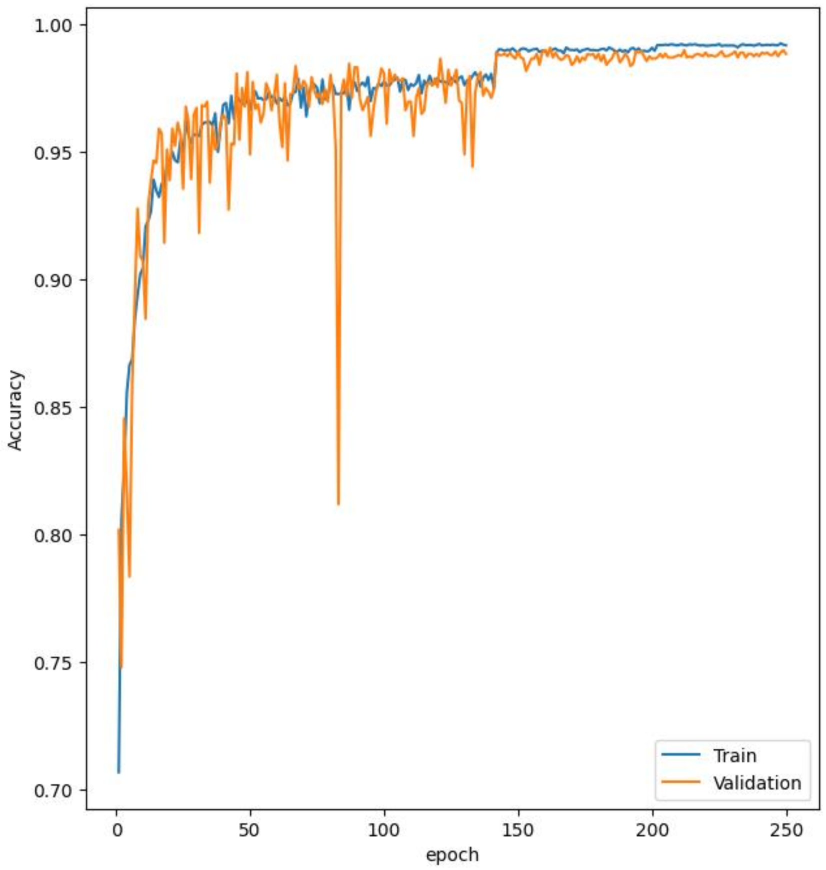
Layer	Kernel Size	Kernel #	Stride	Output Size	Feature Volumes	Param #
Input	-	-	-	5 × 5 × 103	1	-
Conv3d-1	3 × 3 × 7	2	1	3 × 3 × 97	2	128
Conv3d-2	3 × 3 × 7	4	1	1 × 1 × 95	8	220
Linear	-	-	-	1 × 1 × 1	144	3,810
Classification	-	-	-	1 × 1 × 1	9	-
Total params						4,158



Spectral–Spatial Classification of Hyperspectral Imagery with 3D Convolutional Neural Network

Results


Train
Validation
Average Loss
epoch
0.0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0
50
100
150
200
250


Train
Validation
Accuracy
epoch
0.70
0.75
0.80
0.85
0.90
0.95
1.00
0
50
100
150
200
250

	Predicted									
Observed	**Class**	Asphalt	Meadows	Gravel	Trees	Painted metal sheets	Bare Soil	Bitumen	Self-Blocking Bricks	Shadows
	Asphalt	**6436**	0	3	2	0	0	15	24	0
	Meadows	0	**17728**	0	21	0	70	0	0	0
	Gravel	4	0	**1926**	0	0	0	0	87	0
	Trees	0	54	0	**2964**	0	5	0	0	0
	Painted metal sheets	0	0	0	0	**1345**	0	0	1	0
	Bare Soil	0	51	0	3	0	**4972**	0	3	0
	Bitumen	23	0	0	0	0	0	**1307**	0	0
	Self-Blocking Bricks	18	4	14	0	0	1	1	**3644**	0
	Shadows	0	0	0	0	0	0	0	0	**947**

Class\Score	Precision	Recall	F1	Support
Asphalt	0.9938 ± 0.0022	0.9916 ± 0.0024	0.9927 ± 0.0011	6480
Meadows	0.9925 ± 0.0025	0.9977 ± 0.0016	0.9951 ± 0.0011	17819
Gravel	0.9846 ± 0.0064	0.9547 ± 0.0155	0.9693 ± 0.0068	2017
Trees	0.9938 ± 0.0023	0.9835 ± 0.0036	0.9887 ± 0.0028	2964
Painted metal sheets	0.9999 ± 0.0003	0.9996 ± 0.0009	0.9997 ± 0.0004	1345
Bare Soil	0.9918 ± 0.0047	0.9817 ± 0.0081	0.9867 ± 0.0033	5029
Bitumen	0.9880 ± 0.0057	0.9893 ± 0.0055	0.9887 ± 0.0044	1330
Self-Blocking Bricks	0.9682 ± 0.0118	0.9846 ± 0.0072	0.9762 ± 0.0047	3682
Shadows	0.9989 ± 0.0013	0.9985 ± 0.0016	0.9987 ± 0.0007	947
Accuracy			**0.9904 ± 0.0015**	41672
Macro average	0.9902 ± 0.0008	0.9868 ± 0.0025	0.9884 ± 0.0017	41672

Home Assignment Results and Conclusions

Results:

- Different types of CNNs were overviewed
- 3DCNN was implemented and fitted to a dataset

Conclusions:

- 3D CNNs are very efficient for analyzing HSI data

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More Model information

- Optimizer: Adam, lr=0.01, weight_decay=0.001
- Loss: SoftMax (CrossEntropyLoss)
- Scheduler: threshold=0.02, patience=50
- Batch size: 100
- Epochs: 250
- Validation size : 10% of train size