Hyperspectral Image Classification with Low-Cost 3D-2D Convolutional Neural Networks

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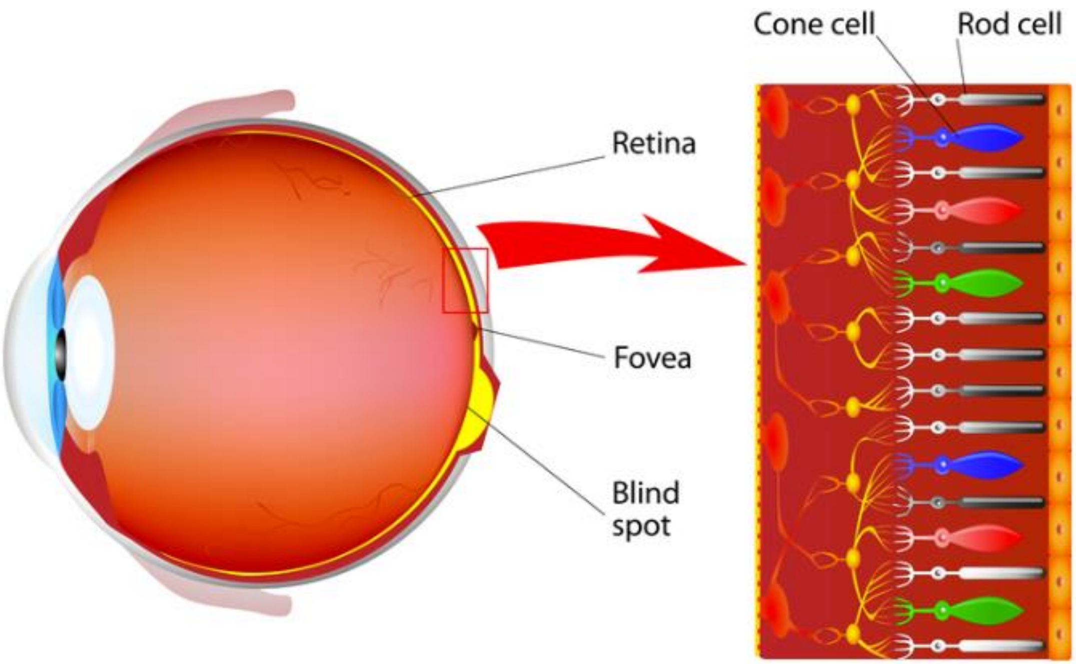
Contents

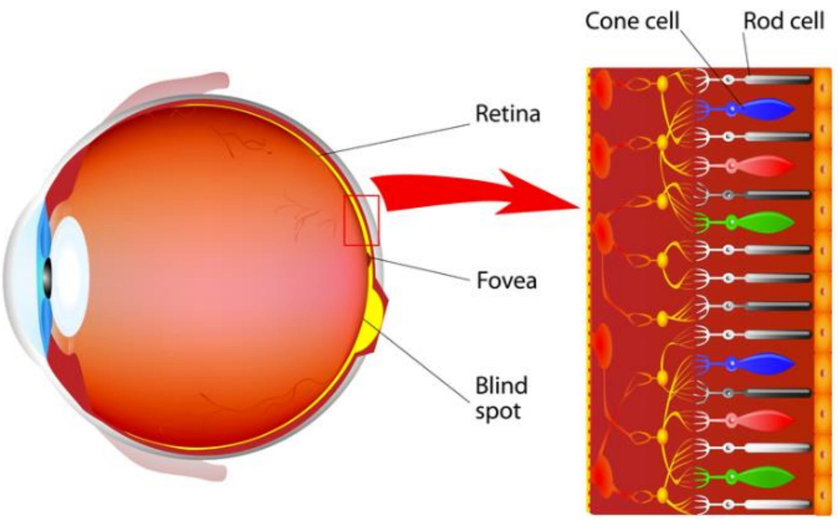
Introduction

- Human eye sees visible light in three bands: red, green, and blue.



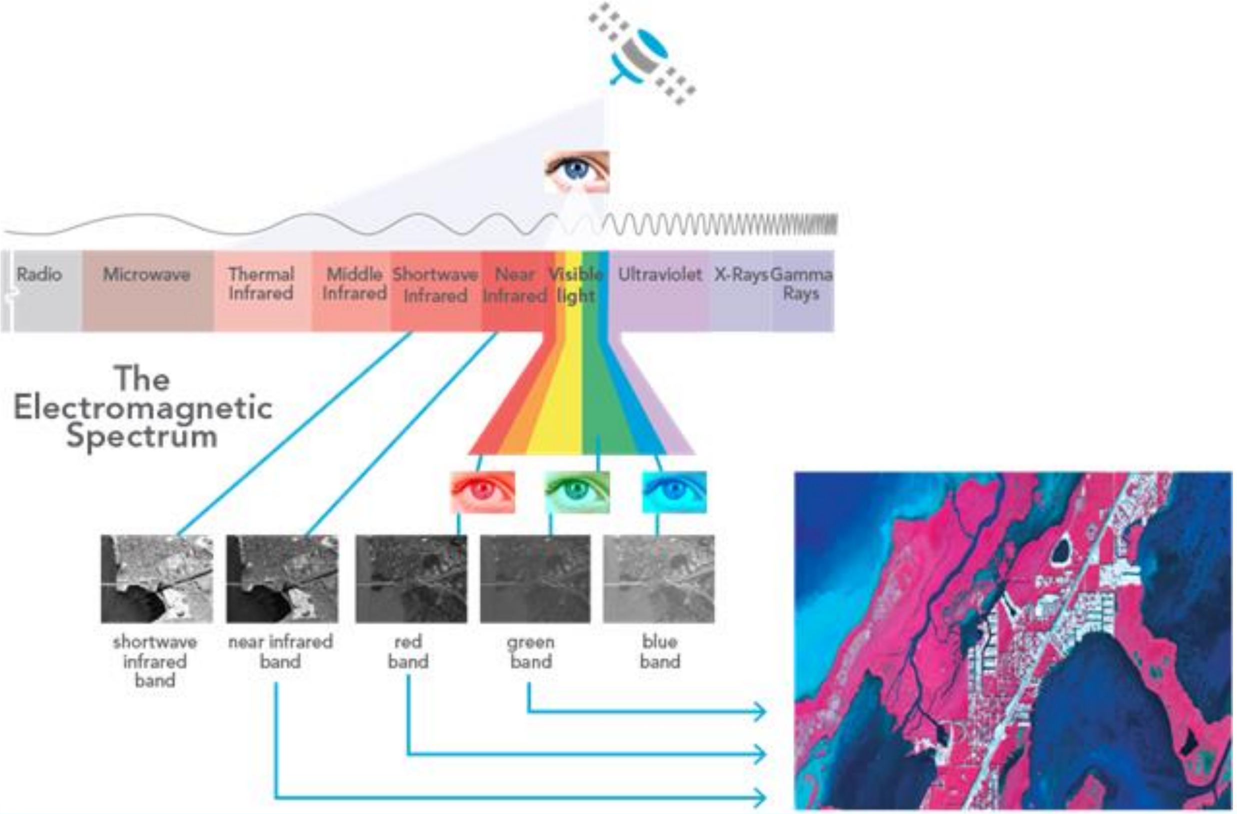
Introduction

- Human eye sees visible light in three bands: red, green, and blue.



Introduction

- Light spectrum contains much more information that humans are not able to see.



Introduction

What is hyperspectral imaging?

- Hyperspectral imaging is the collecting and processing of information from across the electromagnetic spectrum.

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- Hyperspectral images (HSIs) originated from the combination of spectroscopy and digital imaging.

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What is hyperspectral imaging?

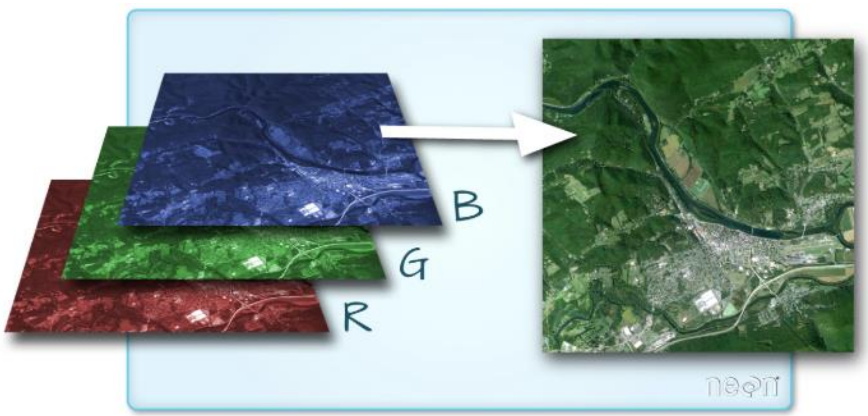
- Hyperspectral imaging is the collecting and processing of information from across the electromagnetic spectrum.
- Hyperspectral images (HSIs) originated from the combination of spectroscopy and digital imaging.

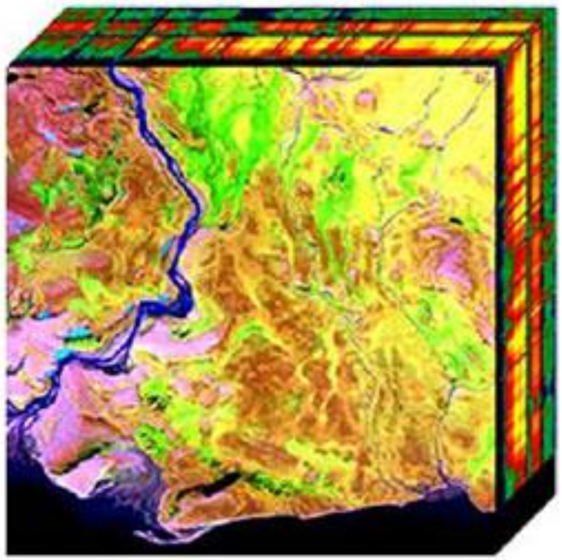
- Two advantages:
  - Spectral resolution: Allows us to identify some materials (or their properties) by their absorption-band characteristics.
  - Spatial resolution: Captures details such as shapes or textures.

Introduction

What is hyperspectral imaging?

- HSIs consist of hundreds of narrow contiguous spectral channels (400 – 2500 nm).

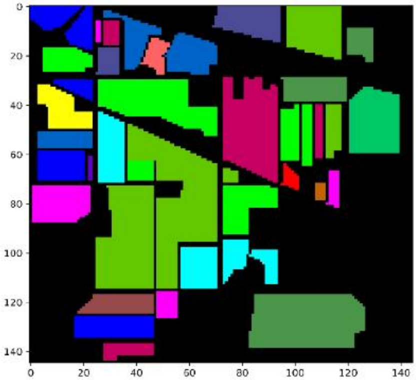


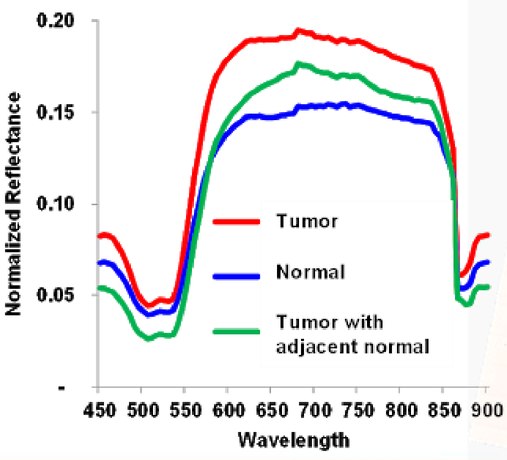


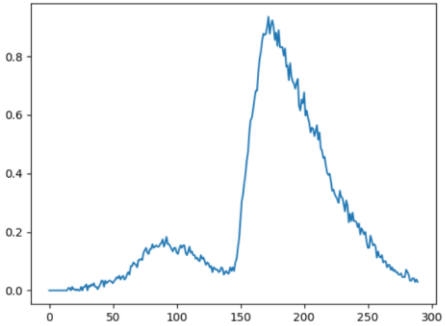
Introduction

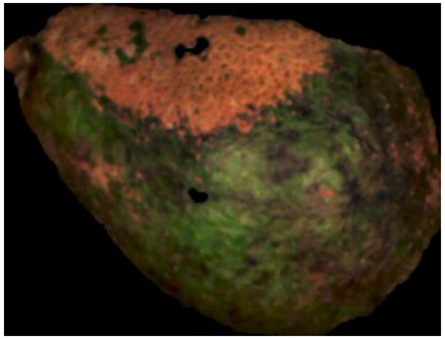
Applications

- Remote sensing (aerial images, satellite images).
- Agriculture.
- Food quality.
- Biomedicine.









Introduction

RESONON

Hyperspectral Cameras ▼ Systems ▼ Machine Vision Software Applications ▼

Founded in 2002, Resonon is located in Bozeman, Montana in the heart of the Rocky Mountains.

We provide complete hyperspectral imaging systems as well as custom hardware and software solutions. Our hyperspectral imaging cameras are compact, cost effective and provide excellent performance.

Resonon provides systems globally through our **distributor** network.

Technical excellence. Superior Support.

Introduction

- Dealing with HSIs becomes a challenge due to the increased volume of data.

- Fine spectral resolution: Redundancy.

- We should prioritize the computational efficiency when storing and processing hyperspectral images.

- We propose a CNN model called Hyper3DNet with two sections: a 3-D feature extractor and a 2-D spatial encoder.

Hypothesis

- We hypothesize that the Hyper3DNet architecture could lead us to train more efficient HSI classification models than the compared methods given a set of different HSI datasets.

Background

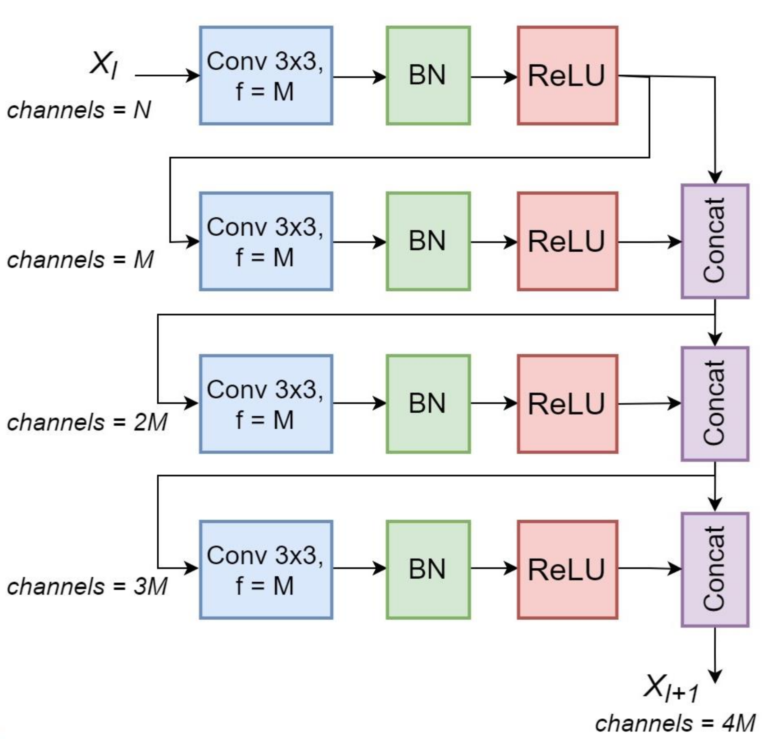
Densely connected blocks

- Facilitates sharing information from low levels of the network to the higher ones.
- Connects all layers directly with each other using short paths while preserving the feature-map sizes.
- The preservation of the preceding information of each block is ensured by the concatenation.

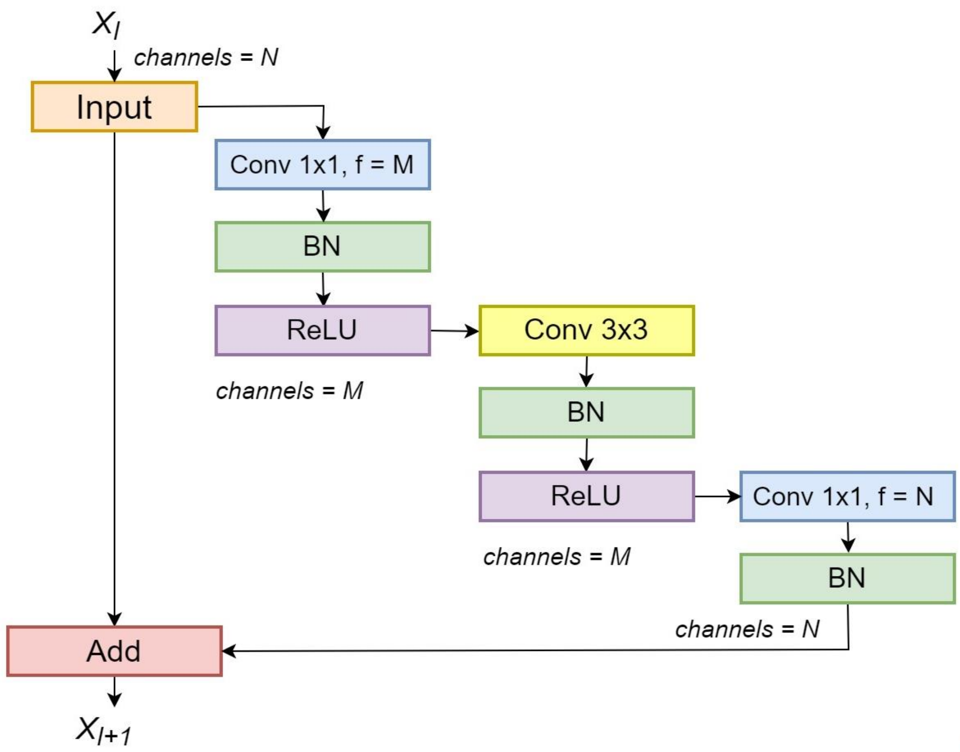
Background

Densely connected blocks

Densely connected block



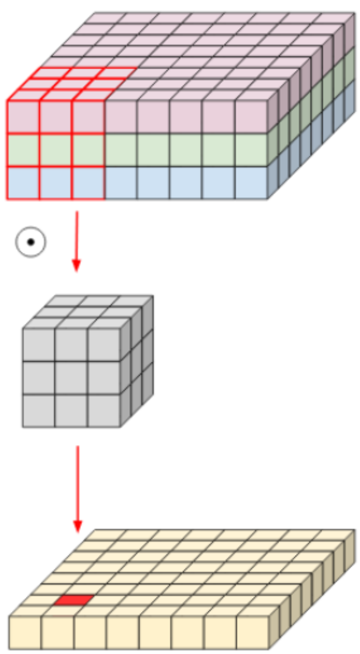
Residual block



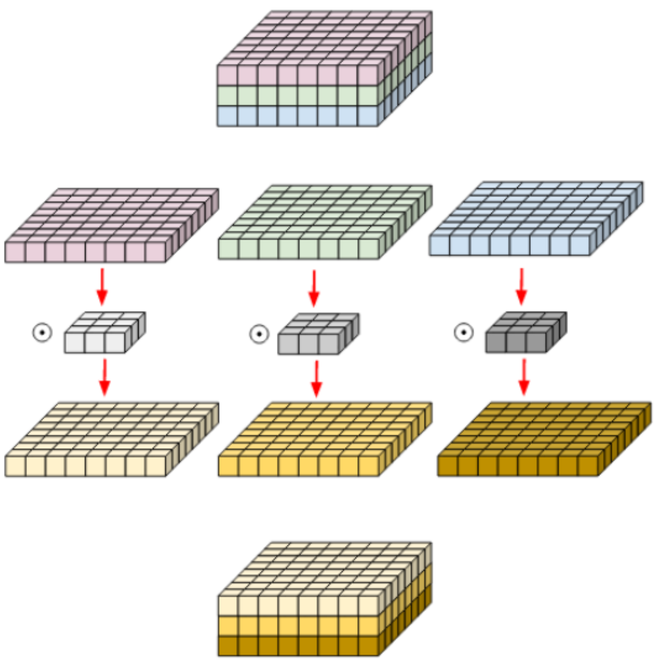
Background

Dephtwise convolutions

Normal convolution



Depthwise convolution

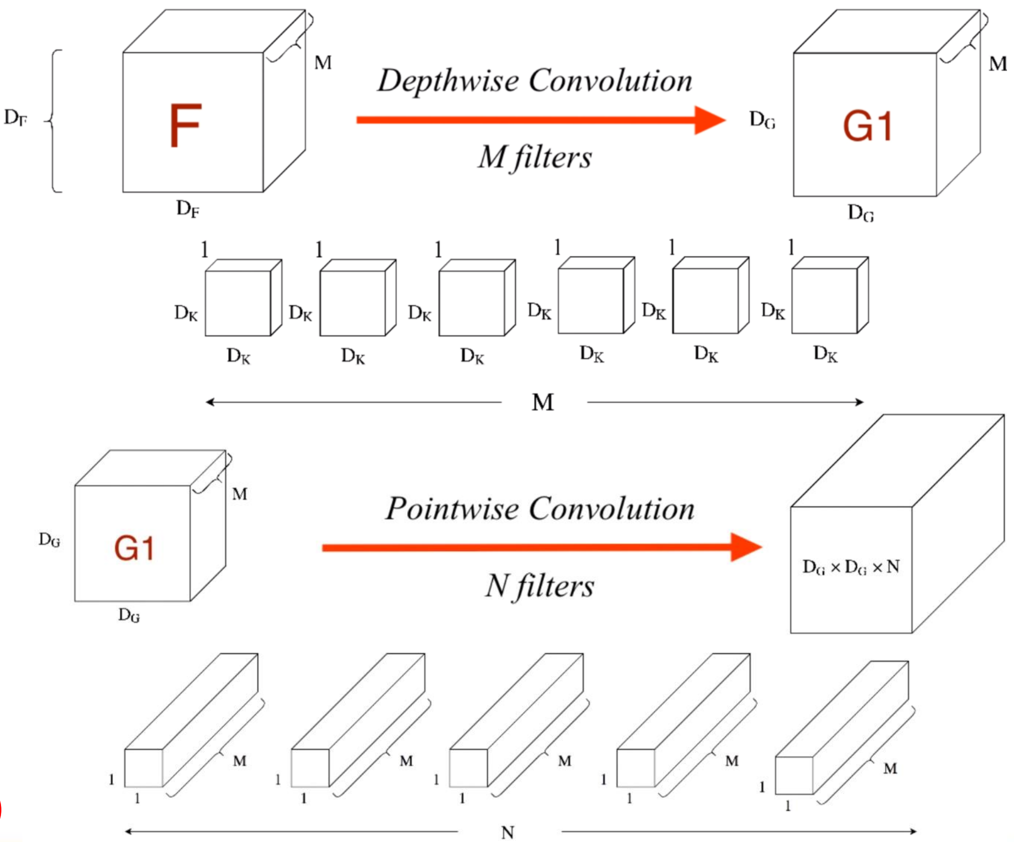


Background

Separable convolutions

Step 1: Depthwise.

Step 2: Pointwise.

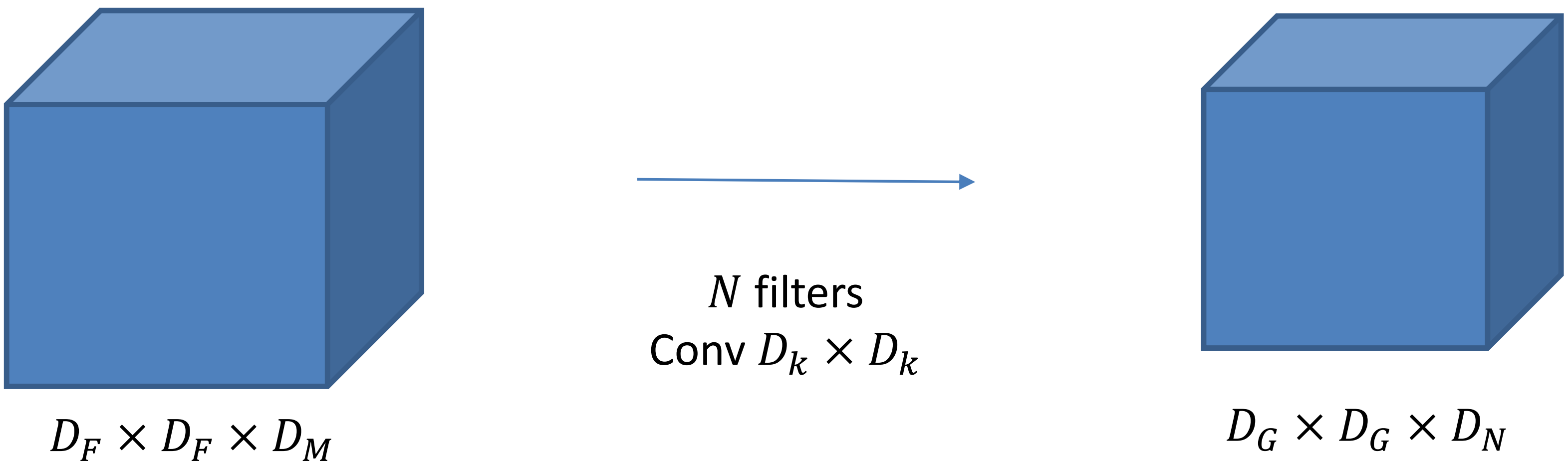


$$Total = D_G^2 \times M \times (Dk^2 + N)$$

Background

Separable convolutions

Normal convolution



#Total operations $= N \times M \times D_G^2 \times Dk^2$

Background

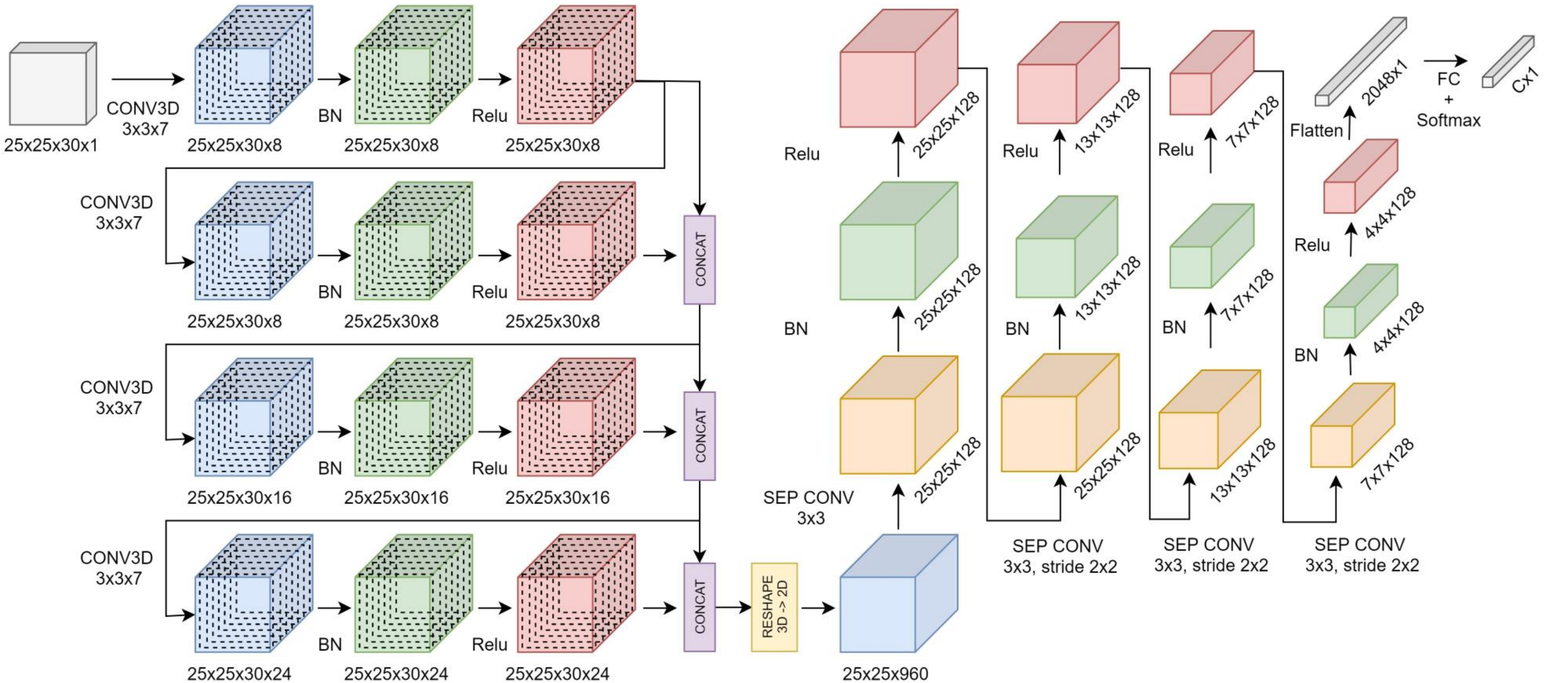
Separable convolutions

$$\frac{\#Op.\,Separable\ conv.}{\#Op.\,normal\ conv.} = \frac{1}{N} + \frac{1}{Dk^2}$$

$N = 1024 \qquad Dk = 3$

$$\frac{\#Op.\,Separable\ conv.}{\#Op.\,normal\ conv.} = \frac{1}{1024} + \frac{1}{3k^2} = 0.112$$

Proposed Framework



Hyper3DNet

Experimental Design

Datasets:

1. Indian Pines.
2. Pavia University.
3. Salinas.
4. EuroSAT.
5. Kochia.

Experimental Design

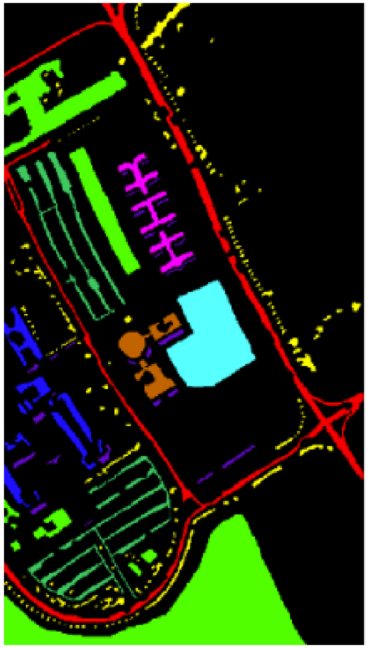
Datasets: HIS for remote sensing

- Indian Pines: 224 bands. ⅔ agriculture and ⅓ forest or other perennial vegetation. 16 classes. AVRIS sensor.
- Pavia University: 103 bands. Urban images, high resolution (1.3 m). 9 classes. ROSIS sensor.
- Salinas: 224 bands. Only agriculture. 16 classes. AVRIS sensor.

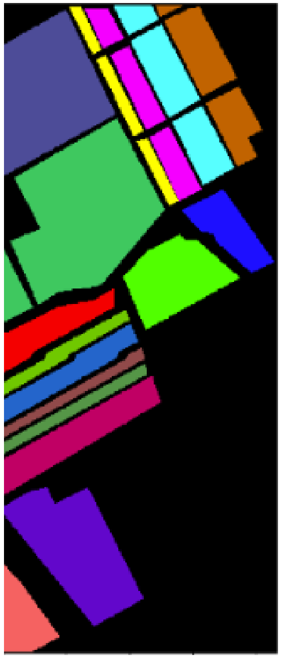
Experimental Design

Datasets: HIS for remote sensing

Indian Pines



Pavia University



Salinas

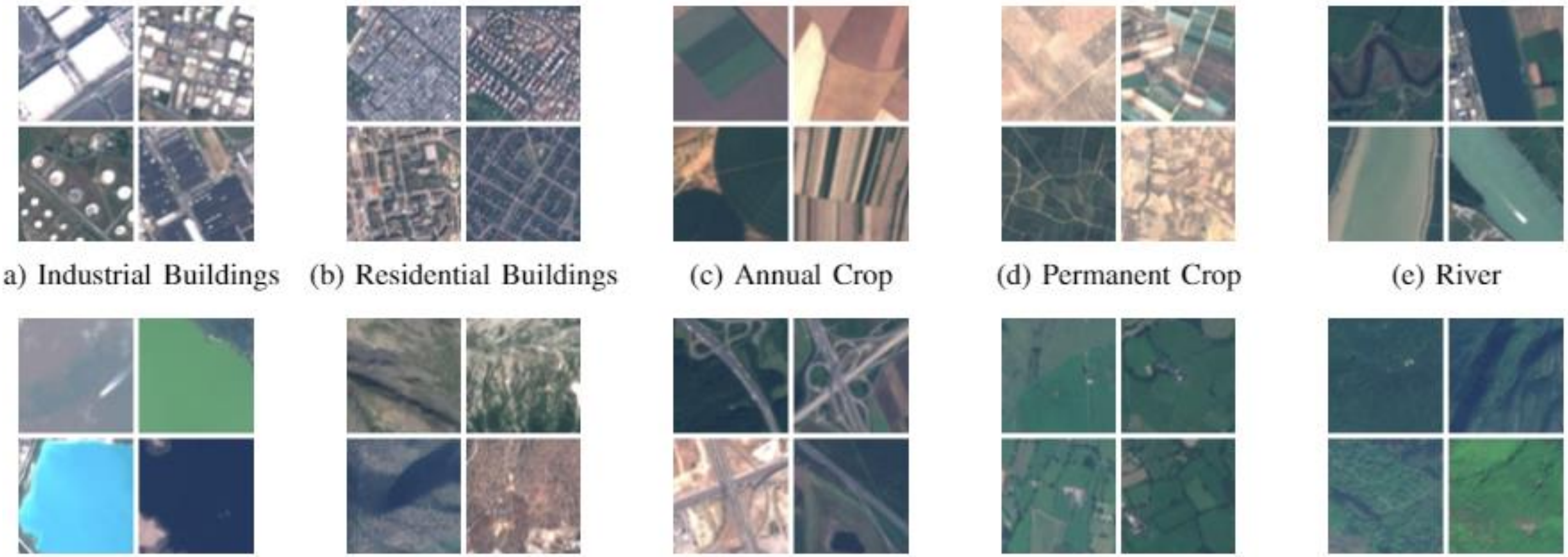
Experimental Design

Datasets: EuroSAT

- Based on Sentinel-2 satellite images covering 13 spectral bands. It consists of 27,000 64×64 - images classified in 10 classes.
- By definition, three of the spectral bands (i.e. aerosol, water vapor, and cirrus) do not present relevant information for our problem.
- Based on a previous work, we discarded the B08A band (red edge 4).

Experimental Design

Datasets: EuroSAT



a) Industrial Buildings (b) Residential Buildings (c) Annual Crop (d) Permanent Crop (e) River

(f) Sea & Lake (g) Herbaceous Vegetation (h) Highway (i) Pasture (j) Forest

Experimental Design

Datasets: Kochia

- Objective: Discriminate between herbicide-susceptible and herbicide-resistant biotypes of the weed kochia (glyphosate-resistant and dicamba-resistant).

- A total of 76 images of kochia with varying spatial resolution and 300 spectral bands ranging from 387.12 to 1023.5 nm were captured at Montana State University Southern Agricultural Research Center (SARC).

Experimental Design

Datasets: Kochia

A Resonon Pika L hyperspectral imager mounted on a tripod and a drone imaging weeds

Experimental Design

Preprocessing: Remote sensing datasets

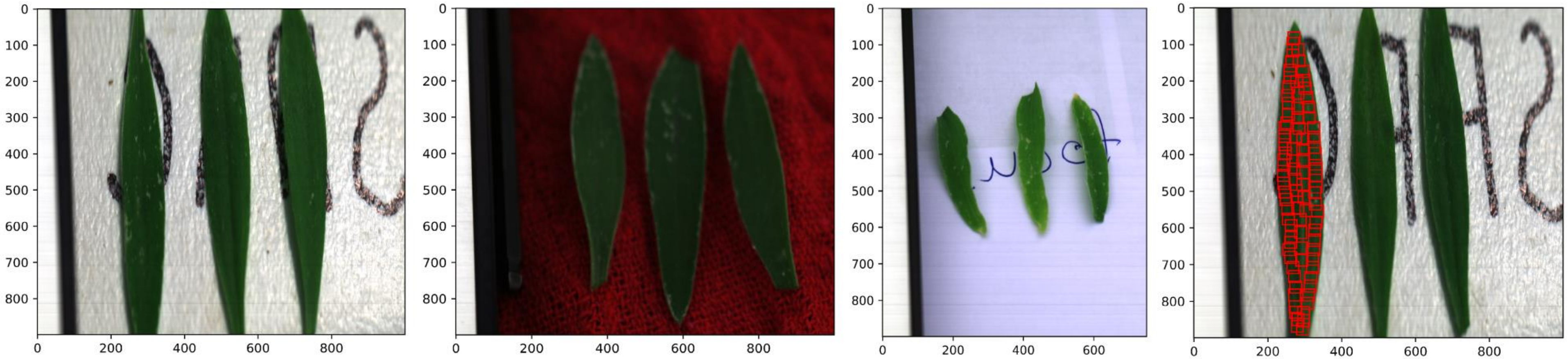
- IP, PU, SA: We reduced the number of channels to 30 applying PCA, retaining 99.285%, 99.966%, and 99.99% of the variance, respectively.

- The aforementioned datasets are big images, so we divided them in small overlapping 25x25 3-D patches.

- The modified IP dataset consists of 10,249 patches; the new PU dataset, on 42,776; and the new SA dataset, on 54,129.

Experimental Design

Preprocessing: Kochia dataset



- We manually extracted 6,316 25×25 - pixel overlapping patches.
- We applied PCA to reduce the number of spectral bands from 300 to 100 with an explained variance of 99.565%.

Experimental Design

Training details

- Python 3.6. KRAKEN: Intel(R) Xeon(R) CPU E5- 2603 v4 at 1.70GHz, 128GB RAM and two NVIDIA GeForce GTX 1080 Ti GPUs.
- Adam optimizer with a learning rate of 0.0001, a momentum term β_1 of 0.9.
- Mini-batch size of 4, for Indian Pines, Pavia University, and Salinas; 8, for EuroSAT; and 128, for the Kochia dataset.
- We used a 10-fold stratified cross-validation approach to train all the networks.

Results and Discussion

Compared methods

1. SpectrumNet.
2. HybridSN.
3. ResNet50.
4. KochiaFC

Results and Discussion

Efficiency comparison

Table 1 Comparison of number of trainable parameters and FLOPS of different networks trained on the IP, PU, SA, and EuroSAT datasets.

Dataset	**IP, SA**		**PU**		**EuroSAT**	
Method	**# Param.**	**MFLOPS**	**# Param.**	**MFLOPS**	**# Param.**	**MFLOPS**
ResNET50	23,705,168	199.56	23,637,705	199.53	23,573,898	337.15
HybridSN	5,122,176	105.44	5,121,273	105.44	15,965,562	**191.04**
SpectrumNet	741,040	**30.10**	737,449	**30.07**	729,898	205.61
Hyper3DNet	**243,240**	89.85	**228,897**	89.82	**200,322**	193.63

Table 2 Comparison of number of trainable parameters and FLOPS of different networks trained on the Kochia dataset.

Method	**# Param.**	**MFLOPS**
KochiaFC	**402,503**	**0.8**
HybridSN	6,410,739	311.35
SpectrumNet	1,479,907	28.44
Hyper3DNet	523,483	213.73

Results and Discussion

Efficiency comparison

TABLE I
THE SPECTRUMNET ARCHITECTURE.

Layer name/type	**Output size/filters**	**Filter size/stride** (if not a spectral module)	1×1 **Squeeze**	1×1 **Expand**	3×3 **Expand**
Input	$64 \times 64 \times 10$				
conv1	$32 \times 32 \times 96$	$2 \times 2/1$			
spectral2	$32 \times 32 \times 128$		16	96	32
spectral3	$32 \times 32 \times 128$		16	96	32
spectral4	$32 \times 32 \times 256$		32	192	64
maxpool4	$16 \times 16 \times 256$	$2 \times 2/2$			
spectral5	$16 \times 16 \times 256$		32	192	64
spectral6	$16 \times 16 \times 384$		48	288	96
spectral7	$16 \times 16 \times 384$		48	288	96
spectral8	$16 \times 16 \times 512$		64	385	128
maxpool8	$8 \times 8 \times 512$	$2 \times 2/2$			
spectral9	$8 \times 8 \times 512$		64	385	128
conv10	$8 \times 8 \times 10$	$1 \times 1/1$			
avgpool10	$1 \times 1 \times 10$	$8 \times 8/1$			

Results and Discussion

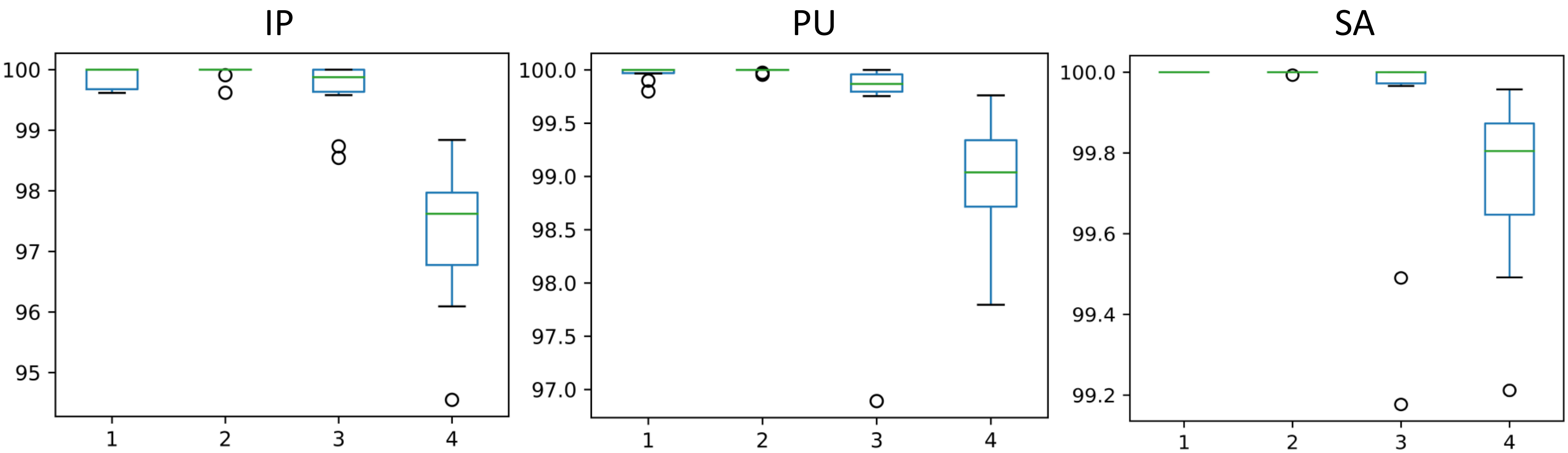
Results on the IP, PU, and SA datasets

Table 3 Metrics comparison on the IP, PU, and SA datasets.

Dataset	**Indian Pines**				**Pavia University**				**Salinas**			
Method	**OA**	**Prec**	**Rec**	**F1**	**OA**	**Prec**	**Rec**	**F1**	**OA**	**Prec**	**Rec**	**F1**
SpectrumNet	98.75 $\pm$ 0.39	95.95 $\pm$ 1.33	98.37 $\pm$ 0.92	96.54 $\pm$ 1.10	99.57 $\pm$ 0.23	99.21 $\pm$ 0.45	98.97 $\pm$ 0.58	99.08 $\pm$ 0.51	99.72 $\pm$ 0.23	99.48 $\pm$ 0.42	99.44 $\pm$ 0.50	99.45 $\pm$ 0.46
ResNET50	99.84 $\pm$ 0.12	99.51 $\pm$ 0.63	99.50 $\pm$ 0.65	99.47 $\pm$ 0.56	99.79 $\pm$ 0.27	99.83 $\pm$ 0.10	99.60 $\pm$ 0.51	99.71 $\pm$ 0.30	99.72 $\pm$ 0.09	99.63 $\pm$ 0.19	99.66 $\pm$ 0.11	99.64 $\pm$ 0.13
HybridSN	99.98 $\pm$ 0.04	99.98 $\pm$ 0.04	99.93 $\pm$ 0.19	99.95 $\pm$ 0.11	99.98 $\pm$ 0.04	99.98 $\pm$ 0.04	99.93 $\pm$ 0.19	99.95 $\pm$ 0.11	99.95 $\pm$ 0.04	99.93 $\pm$ 0.04	99.92 $\pm$ 0.05	99.93 $\pm$ 0.05
Hyper3DNet	99.94 $\pm$ 0.08	99.84 $\pm$ 0.26	99.89 $\pm$ 0.19	99.86 $\pm$ 0.19	99.99 $\pm$ 0.01	99.99 $\pm$ 0.02	99.98 $\pm$ 0.04	99.98 $\pm$ 0.03	99.96 $\pm$ 0.04	99.94 $\pm$ 0.06	99.94 $\pm$ 0.05	99.94 $\pm$ 0.06

Results and Discussion

Results on the IP, PU, and SA datasets



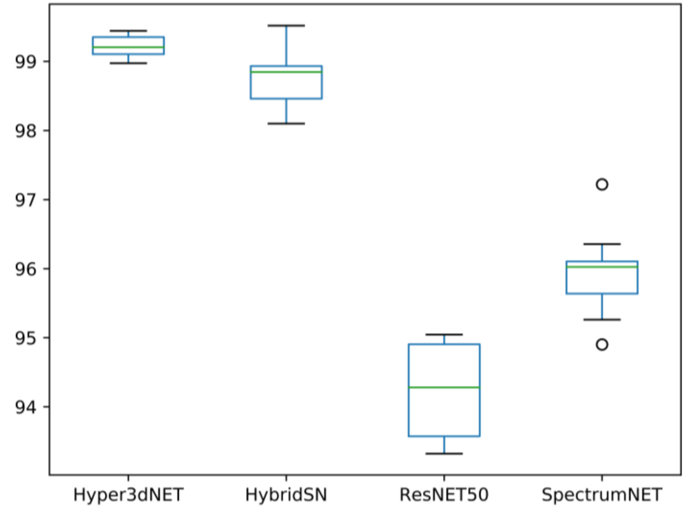
1) Hyper3DNet. 2) HybridSN. 3) ResNET50. 4) SpectrumNET.

Results and Discussion

Results on the EuroSAT dataset

Table 4 Metrics comparison on the EuroSAT dataset.

Method	OA	Prec	Rec	F1
SpectrumNet	96.08 (± 0.58)	96.08 (± 0.49)	95.87 (± 0.57)	95.94 (± 0.56)
ResNET50	94.48 (± 0.62)	94.49 (± 0.52)	94.15 (± 0.72)	94.24 (± 0.66)
HybridSN	98.84 (± 0.37)	98.85 (± 0.38)	98.74 (± 0.41)	98.78 (± 0.39)
Hyper3DNet	99.57 (± 0.21)	99.58 (± 0.20)	99.54 (± 0.24)	99.56 (± 0.22)

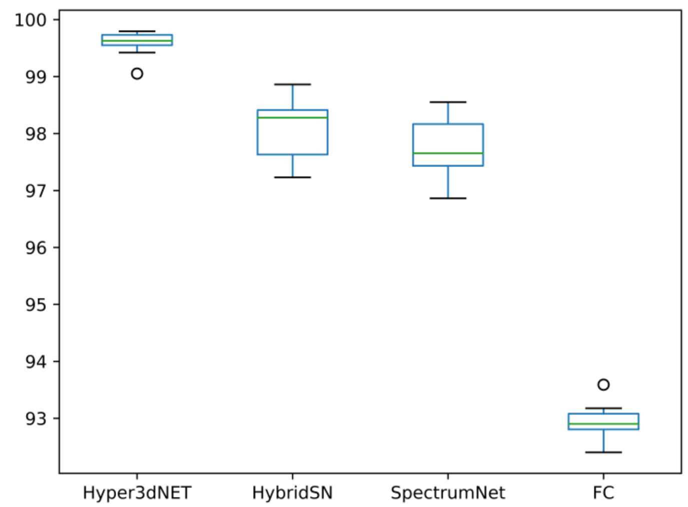


Results and Discussion

Results on the Kochia dataset

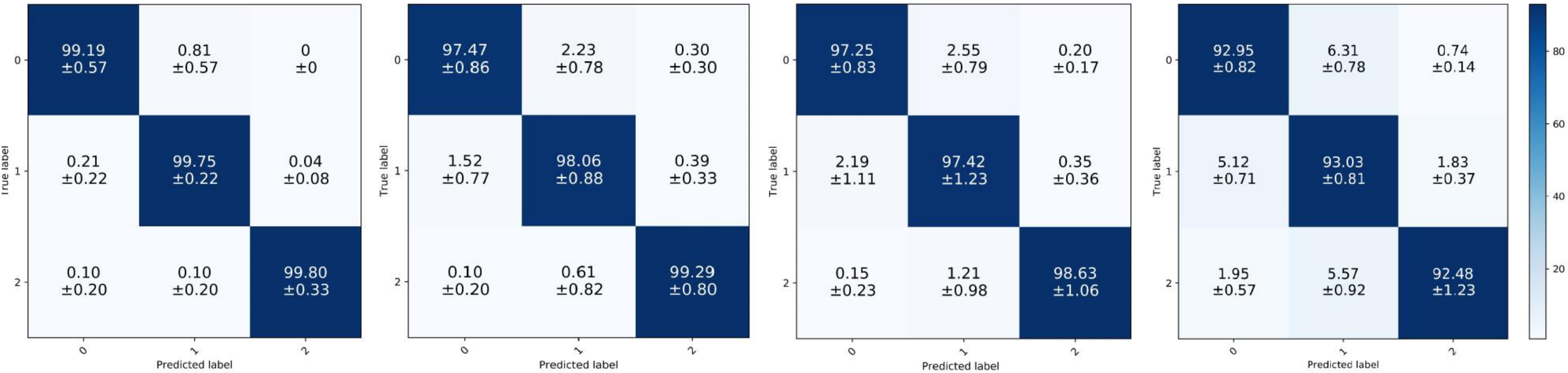
Table 5 Metrics comparison on the Kochia dataset.

Method	OA	Prec	Rec	F1
KochiaFC	92.89 (± 0.29)	93.09 (± 0.30)	92.82 (± 0.40)	92.95 (± 0.29)
HybridSN	98.09 (± 0.62)	98.18 (± 0.61)	98.28 (± 0.56)	98.22 (± 0.58)
SpectrumNet	97.59 (± 0.55)	97.81 (± 0.59)	97.77 (± 0.46)	97.78 (± 0.51)
Hyper3DNet	99.55 (± 0.22)	99.62 (± 0.19)	99.57 (± 0.23)	99.59 (± 0.21)



Results and Discussion

Results on the Kochia dataset



1) Hyper3DNet. 2) HybridSN. 3) SpectrumNET. 4). KochiaFC.

Conclusions

- We have presented a novel trainable deep neural network, called Hyper3DNet, for addressing the problem of HSI classification.
- Our network architecture has been designed explicitly to reduce the number of trainable parameters and computational operations.
- The experimental results show that Hyper3DNet consistently achieves the highest classification accuracy within a variety of HSI scenarios, proving that the reduced complexity of the model not only does not affect its performance, but also reduces the propensity to overfit.
- Future work will focus on reducing the number of FLOPS required by the first convolution layer of the 2-D spatial encoder immediately after the 3-D feature extractor.

Acknowledgements

Thanks to Dr. John Sheppard for his advice and valuable comments about this work. I also thank the members of the Optical Remote Sensor Laboratory of the Department of Electrical and Computer Engineering, Bryan Scherrer and Dr. Joseph Shaw, for providing the hyperspectral images of kochia, some scripts, and information about the project in general.