University of Peradeniya
Sri Lanka

SLTC
SRI LANKA TECHNOLOGICAL CAMPUS

Convolutional Autoencoder for Blind Hyperspectral Image Unmixing

D.Y.L.Ranasinghe[1], S. Herath[2], H.M.H.K.Weerasooriya[2], E.M.M.B.Ekanayake[2], H.M.V.R Herath[2], G.M.R.I. Godaliyadda[2], M.P.B. Ekanayake[2]

[1]Office of Research and Innovation Services, Sri Lanka Technological Campus, Padukka, Sri Lanka
[2]Department of Electrical and Electronic Engineering, Faculty of Engineering, University of Peradeniya, Sri Lanka

Presenter : S. Herath

Abstract

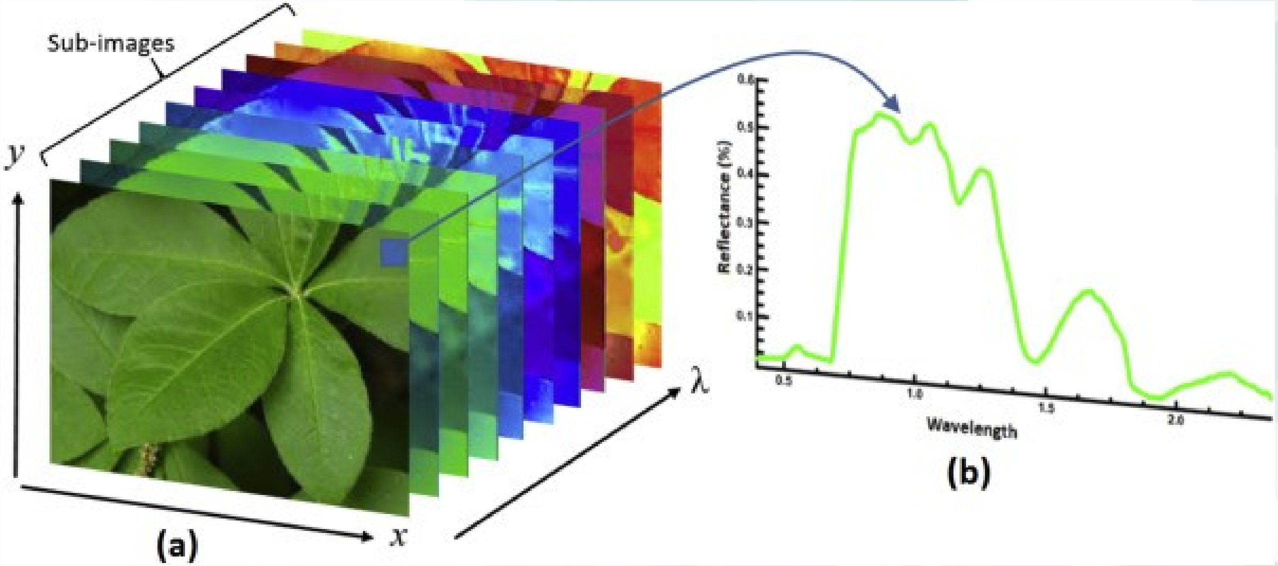
In the remote sensing context spectral unmixing is a technique to decompose a mixed pixel into two fundamental representatives: endmembers and abundances. In this paper, a novel architecture is proposed to perform blind unmixing on hyperspectral images. The proposed architecture consists of convolutional layers followed by an autoencoder. The encoder transforms the feature space produced through convolutional layers to a latent space representation. Then, from these latent characteristics the decoder reconstructs the roll-out image of the monochrome image which is at the input of the architecture; and each single-band image is fed sequentially. Experimental results on real hyperspectral data concludes that the proposed algorithm outperforms existing unmixing methods at abundance estimation and generates competitive results for endmember extraction with RMSE and SAD as the metrics, respectively.

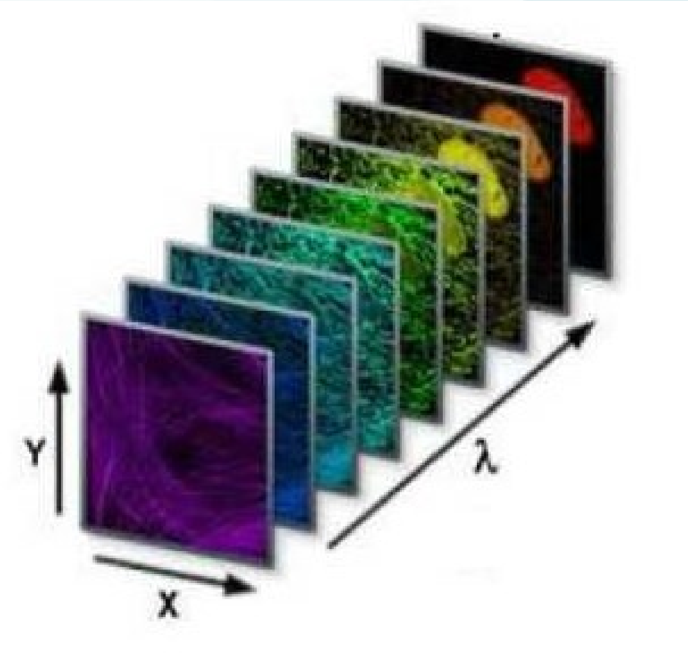
Outline of the Presentation

- Hyperspectral Unmixing Problem.
- Existing Solutions.
- Mathematical Foundation of the proposed method.
- Architecture of the Network.
- Results.
- Conclusion.

Hyperspectral Unmixing Problem

A hyperspectral image is a collection of images corresponding to a broad range of wavelengths

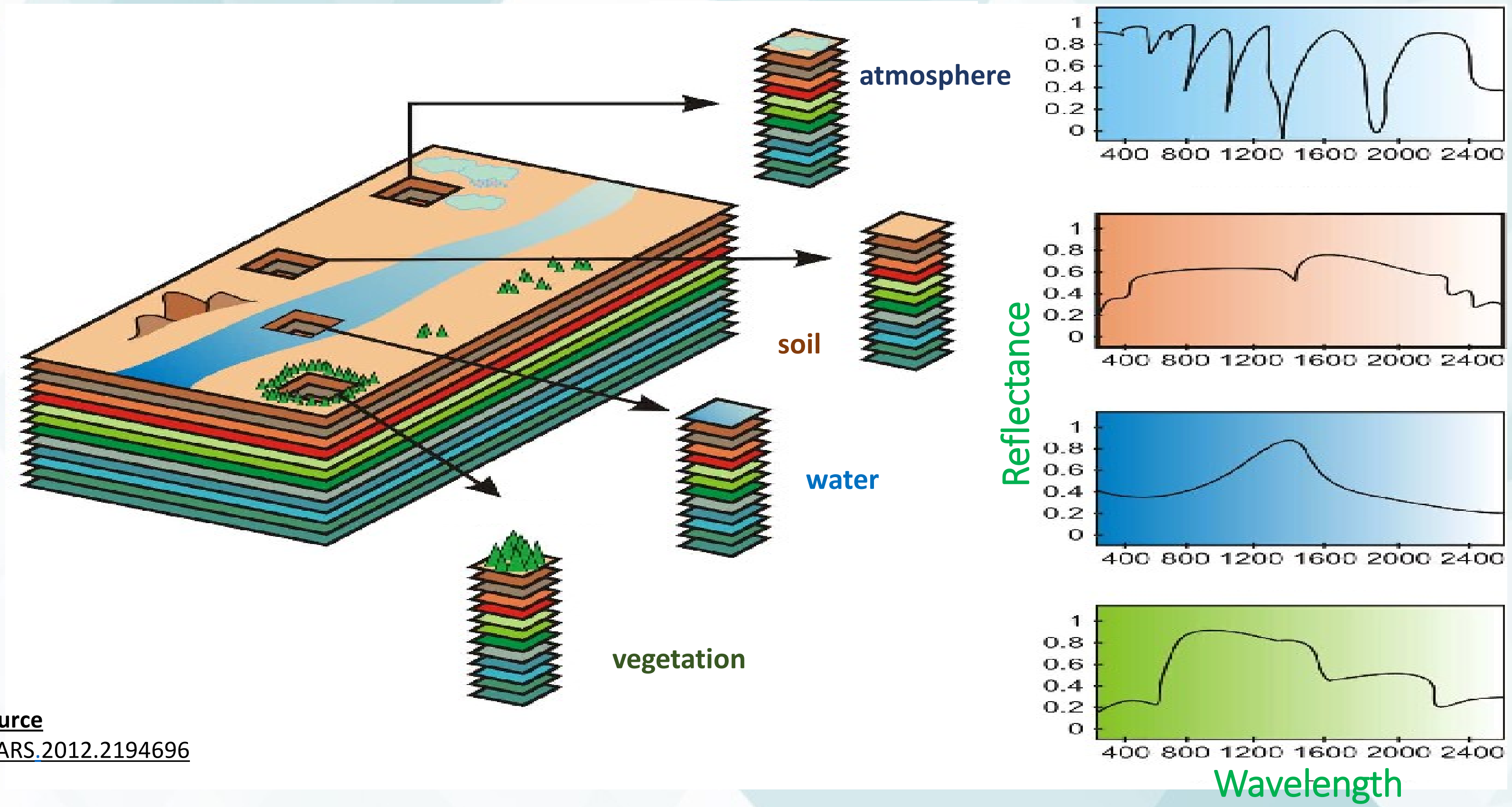




Hyperspectral Unmixing Problem Cont.

- Measured reflectance is a mixture of spectral signatures of the underlying substances

- HU aims to extract the measured reflectance into the materials' spectral signatures (endmembers); and to estimate the fractional contribution by each endmember to the mixture (abundances)



Source
DOI:10.1109/JSTARS.2012.2194696

Existing Solutions

- Statistical methods
  Interpret a mixed pixel by utilizing statistical representations
  Ex: ICA, BSOM

- Geometrical Methods
  exploit the geometric orientation of HSI data in an n-dimensional space
  Ex: VCA, NMF

- Deep Learning based methods
  Mostly supervised methods

Mathematical Foundation

- Objective: Given an HSI data matrix X, the objective is to decompose it into two matrices: endmember matrix A and abundance matrix S,

$$\boldsymbol{X_{m\times n}} = \boldsymbol{S_{m\times r}} \times \boldsymbol{A_{r\times n}}$$

  Here, n,m, and r are the no. of spectral bands, the no. of pixels and the no. of endmembers to be extracted, respectively

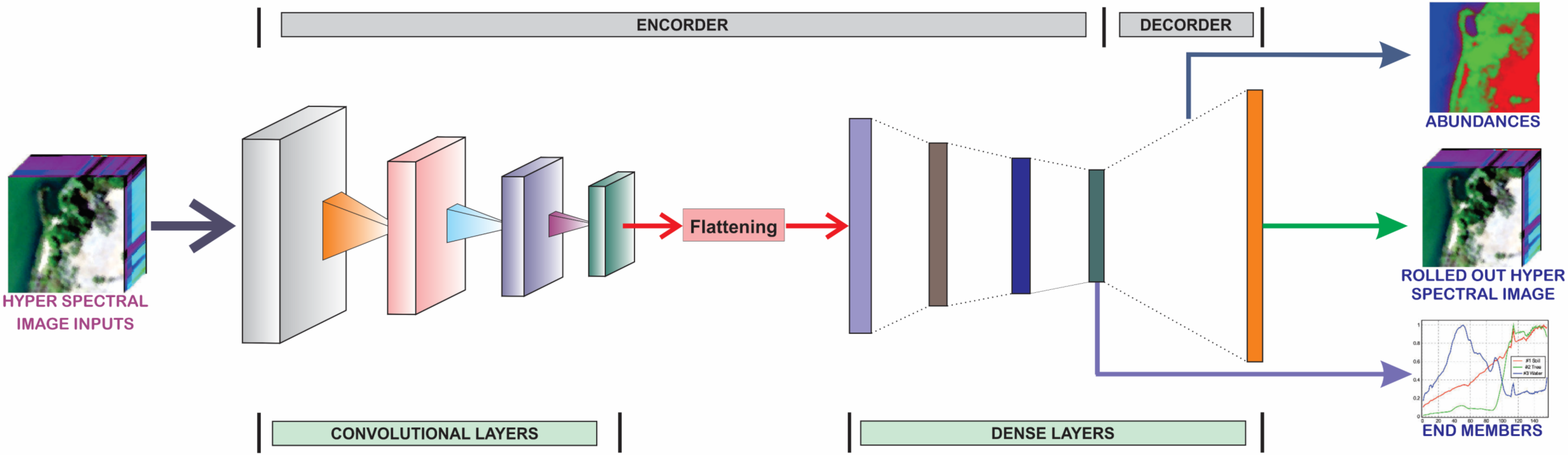
- Consider, the image corresponding to the b spectral band, x_b fed to a network with L layers. If a linear activation is used for the output layer, the transformation performed at the output layer can be written as,

$$\boldsymbol{\hat{x}_b} = \boldsymbol{W^{(L)} a^{(L-1)}}$$

  where, $a^{(L-1)}$ has the activations from the $(L-1)^{th}$ layer and $W^{(L)}$ are the weights of the output layer. If the $(L-1)^{th}$ layer has r neurons, then the reconstructed HSI $\hat{X}$ can be written as,

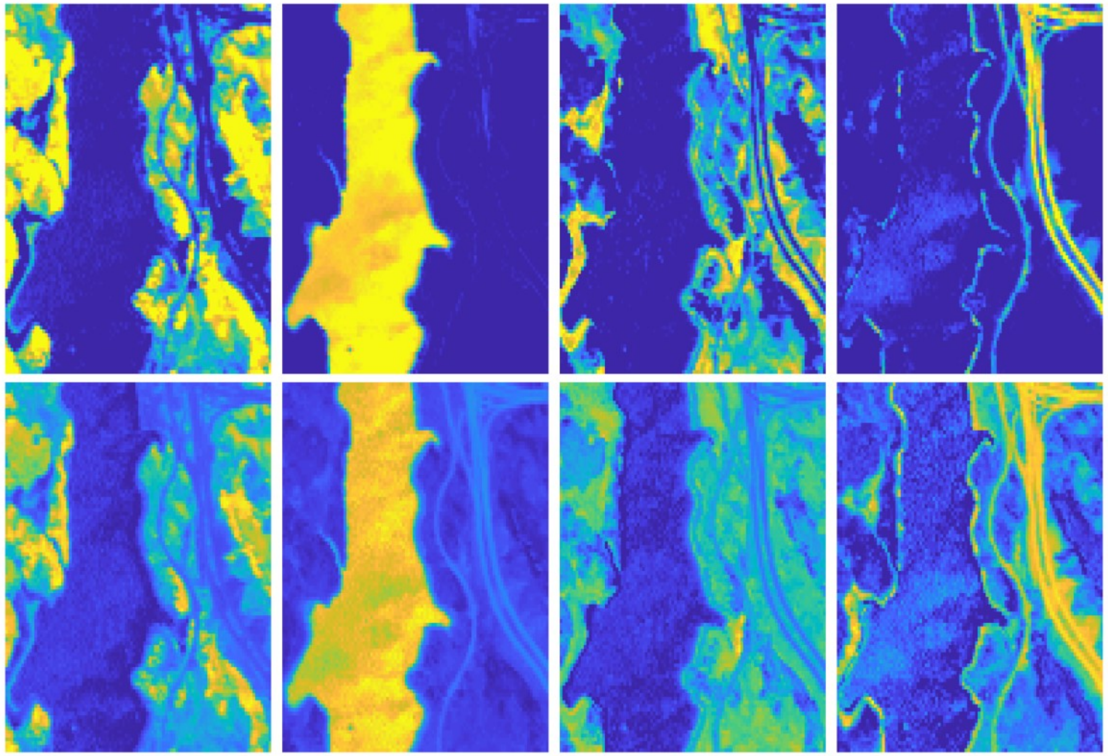
$$\boldsymbol{\hat{X}} = \boldsymbol{W^{(L)}_{m\times r}} \times \boldsymbol{H^{(L-1)}_{r\times n}}$$

Architecture of the Network

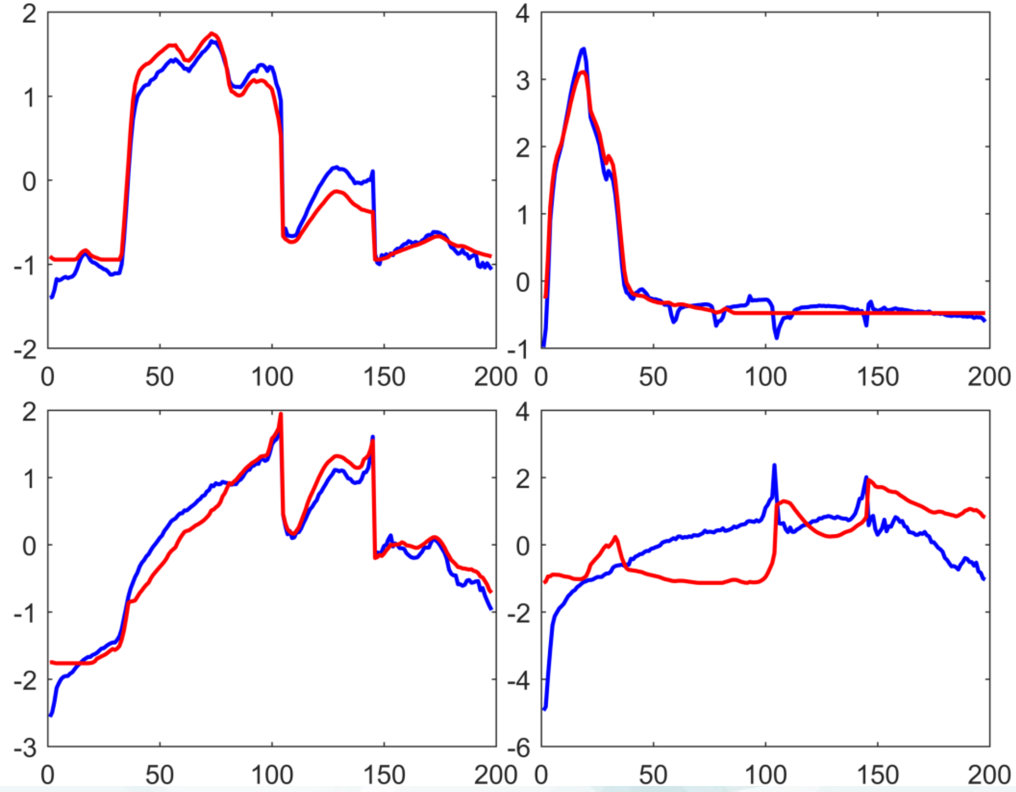


$$\hat{X} = W_{m\times r}^{(L)} \times H_{r\times n}^{(L-1)}$$

Results



Abundance Estimation
Top: Ground Truth
Bottom: Estimated



Endmember Estimation
Blue: Ground Truth
Red: Estimated

Results cont.

Unmixing Performance in terms of SAD

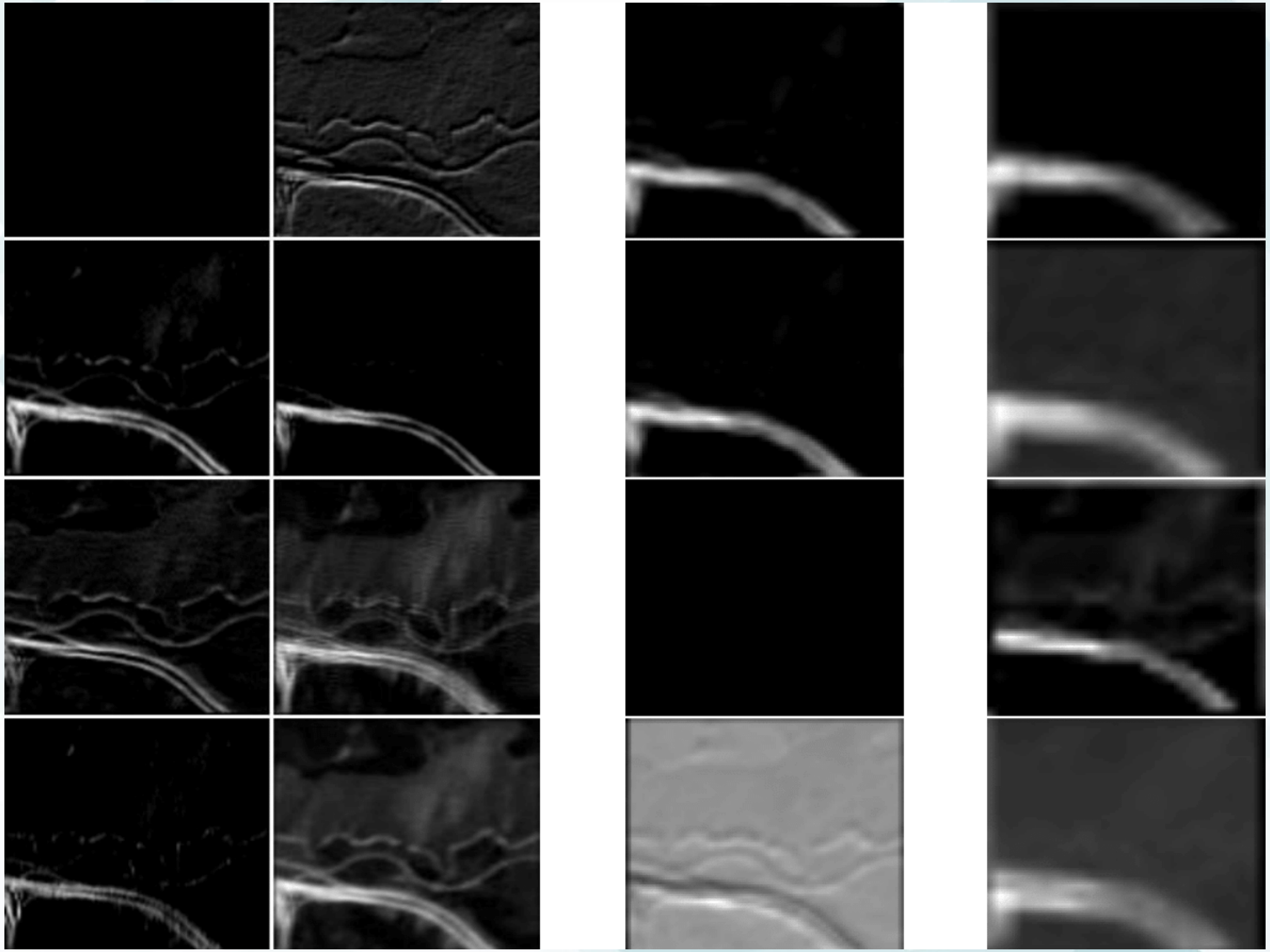
Method	CAE	DNAE	NMF	GNMF	RNMF	VCA
Dirt	**0.1474**	<u>0.3184</u>	1.6357	1.0105	1.2432	1.5352
Road	1.2473	**0.4118**	1.0747	1.2817	1.7852	<u>0.5302</u>
Tree	0.203	<u>0.1263</u>	**0.1110**	0.1353	0.2264	0.4046
Water	0.1426	<u>0.1003</u>	0.1413	0.1469	**0.0915**	0.1387
Average	<u>0.4351</u>	**0.2392**	0.7407	0.6436	0.8366	0.6522

Unmixing Performance in terms of RMSE

Method	CAE	DNAE	NMF	GNMF	RNMF	VCA
Dirt	**0.1926**	<u>0.2115</u>	0.4118	0.3388	0.2722	1.7537
Road	**0.1455**	0.2054	0.2502	<u>0.1541</u>	0.2047	0.2639
Tree	<u>0.2015</u>	**0.1991**	0.2792	0.3320	0.2630	0.3795
Water	0.1326	**0.1128**	0.1575	0.1798	<u>0.1270</u>	2.2116
Average	**0.1681**	<u>0.1822</u>	0.2747	0.2512	0.2167	1.1522

Results cont.

Visualization of the output of the intermediate convolutional layers



Conv layer 1 *Conv layer 2* *Conv layer 3*

Conclusion

- **A novel CNN based autoencoder architecture was proposed blind HU problem**
- **The weights of the output layer provides the abundances; and the activations from the layer before the output layer provides the endmember spectral signatures, simultaneously**
- **The proposed *CAE* outperforms existing HU methods in terms of abundance estimation**
- **Convolutional layers improve the abundance estimation by recognizing the spatial distribution of the endmembers**

References

[1] B. Rathnayake, E. M. M. B. Ekanayake, K. Weerakoon, G. M. R. I. Godaliyadda, M. P. B. Ekanayake, and H. M. V. R. Herath, "**Graph-Based Blind Hyperspectral Unmixing via Nonnegative Matrix Factorization**," IEEE Trans. Geosci. Remote Sens., pp. 1–19, 2020, doi: 10.1109/TGRS.2020.2976799..

[2] D. Y. L. Ranasinghe et al., "**Hyperspectral Imaging Based Method to Identify Potential Limestone Deposits**," in 2019 14th Conference on Industrial and Information Systems (ICIIS), Kandy, Sri Lanka, Dec. 2019, pp. 135–140, doi: 10.1109/ICIIS47346.2019.9063280.

[9] R. Heylen and M. Parente, "**A Review of Nonlinear Hyperspectral Unmixing Methods**," IEEE J. Sel. Top. Appl. EARTH Obs. REMOTE Sens., vol. 7, no. 6, p. 25, 2014.

[10] M. E. Paoletti, J. M. Haut, J. Plaza, and A. Plaza, "**Deep learning classifiers for hyperspectral imaging**: A review," ISPRS J. Photogramm. Remote Sens., vol. 158, pp. 279–317, Dec. 2019, doi: 10.1016/j.isprsjprs.2019.09.006.

Thank You