



شبكة المعلومات الجامعية  
التوثيق الإلكتروني والميكروفيلم

# بسم الله الرحمن الرحيم



**MONA MAGHRABY**



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# جامعة عين شمس التوثيق الإلكتروني والميكروفيلم

## قسم

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# **Hyperspectral Unmixing using Deep Learning**

Thesis submitted to the Department of Scientific Computing  
Faculty of Computer and Information Sciences  
Ain Shams University

In partial fulfillment of the requirements for the degree  
of Master in Computer and Information Sciences  
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Cairo-2020

# Acknowledgment

First of all, I thank Allah, the most merciful and gracious, who gave me the knowledge, patience, and strength to complete this thesis, and blessed me with his inspired gifts to overcome the obstacles I encountered.

I would like to express my deep gratitude to my supervisors who I'm lucky to work under their supervision; Prof. Dr. Mohamed Tolba for his usual support, patience, encouragement, and guidance, Prof. Dr. Hala Mosher Ebied for her usual support, motivation and guidance and Dr. Marwa Sayed the one who I am lucky to have by my side not only a supervisor but an elder sister too, I extend my utmost gratitude and appreciation for your technical and scientific help, continuous supportive guidance in both technical and non-technical issues and for always believing in me. I am deeply thankful.

I would like to thank the world's best gift, the most supportive family. I would like to thank Mum and Dad, who have devoted themselves to support me in my whole life, not just this work for their endless passionate support and encouragement and the sleepless nights they spent to make it easier for me. And my brothers Islam, and Ayman for always being by my side in the downs and ups. Thanks, my brother, for your usual moral support. My family, thanks for being the shoulder I can always depend on and for constantly pushing me to become the person I want to become and create the life I want for myself. This thesis dedicated to you to make you proud. Without you, everything is nothing.

Last but not least, I would like to thank all my professors, colleagues, and students who kept on encouraging me. Thank you for being in my life.

# Abstract

Remote sensing applications have been enriched by the spectral information captured by hyperspectral cameras despite its limited spatial resolution. In each pixel, multiple ground materials generally mix to form the spectrum recorded. Hyperspectral Unmixing (HU) or Spectral mixture analysis is a challenging problem in determining the underlying material spectra, called endmembers from hyperspectral sensors and the abundances fraction of each pure material in each pixel.

The problem of Hyperspectral Unmixing (HU) has already been extensively researched. Different Hyperspectral Unmixing algorithms have been developed. In this thesis, a comprehensive investigation of HU methods was conducted. There are different categories for HU methods; the machine learning-based method offers more accurate estimation results compared to other traditional and statistical methods.

In this thesis, three different HU methods were proposed. First, a Deep Convolutional Autoencoder Network (DCAE) was presented to resolve the unmixed hyperspectral pixels. The proposed architecture composed of two sub-networks, namely: encoder and decoder. The encoder sub-network extracts a significant non-redundant feature vector. On the other hand, the decoder sub-network contains only one-layer to mimic the linear unmixing model. By utilizing the decoder layer weigh, one can extract both the endmembers and their abundance maps. Several experiments were performed to assess the proposed DCAE performance using synthetic and real hyperspectral datasets. The results demonstrated the significant performance of the proposed DCAE and that it outperforms benchmark unmixing methods even in a noisy environment in terms of both Root Mean Square Error (RMSE), and Mean Square Error (MSE). The achieved results of the proposed DCAE in terms of mean absolute error were

0.0097, 0.001, 0.0141, and 0.0145 for Samson, Cuprite, Urban, and Jasper Ridge datasets, respectively.

Second, a blind hyperspectral nonlinear unmixing method was proposed in [3]. The proposed autoencoder architecture composed of encoder and decoder. The encoder network contains three layers and the proposed decoder network has four fully connected layers, each with the number of neurons equal to the dimension of the end members. Several experiments were conducted using nonlinear synthetic dataset sampled from the USGS library, and the performance was evaluated using both SAD and SID metrics. The experiments evaluated the performance in terms of accuracy assessment, weight initialization techniques, learning rate, and robustness to the noise. The results verified that the proposed autoencoder outperforms traditional endmember extraction algorithms in nonlinear cases. After that, we introduced the application of hyperspectral image unmixing algorithm in the Internet of things (IoT) environment.

Finally, a novel band selection approach that extends the work proposed in [3]. The proposed band selection approach consists of two main steps. The unmixing step utilized the aforementioned nonlinear deep autoencoder unmixing method to extract accurate material spectra. In the cluster stage, the variance for each obtained endmember was calculated to construct a variances vector. Next, classical K- means was adopted to cluster the variances vectors. Finally, only one spectral band for each cluster was selected. To evaluate the effectiveness and generality of the proposed method, various experiments were conducted on seven benchmarks hyperspectral dataset. Results shows the proposed approach had suppressed mentioned methods by an average of 4% in terms of overall accuracy.

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## List of Abbreviations

<u>Abbreviation</u>	<u>Stands for</u>
HSI	Hyperspectral Image
HU	Hyperspectral Unmixing
ANN	Artificial Neural Network
VIS	Visible range
NIR	Near-Infrared Range
SWIR	Short-Wavelength Infrared
MIR	Mid-wavelength Infrared
TIR	Thermal Infrared (TIR)
PPI	Pixel Purity Index
MV	Minimum Volume
LMM	Linear Mixing Model
MNF	Maximum Noise Fraction
BMM	Bilinear Mixing Models
OPF	Optimum-Path Forest
DCAE	Deep Convolutional Autoencoder
ReLU	Rectified Linear Unit
ASC	Sum-to-one Constraint
SID	Spectral Information Divergence
MSE	Mean Square Error
RMSE	Root Mean Square Error
SAD	Spectral Angler Distance
SID	Spectral Information Divergence
VCA	Vertex Component Analysis

# **Chapter 1**

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## **Introduction**

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