Advancing Retinal Disease Diagnosis through Hyperspectral Imaging

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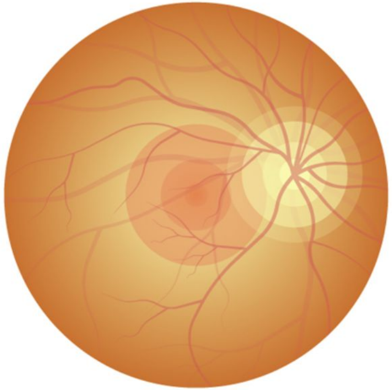
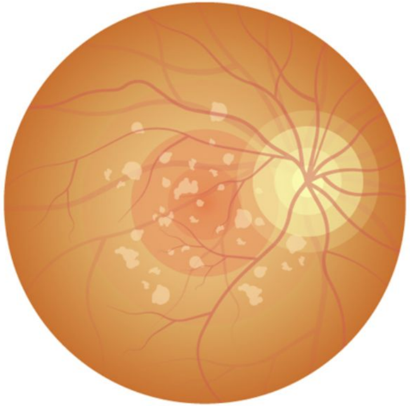
Introduction

- Age-Related Macular Degeneration (AMD)
    - Characterized by drusen lesions
    - Leads to deterioration of cells in the macula
- Currently no treatment for AMD
- Early diagnosis can slow disease progression

Healthy Eye

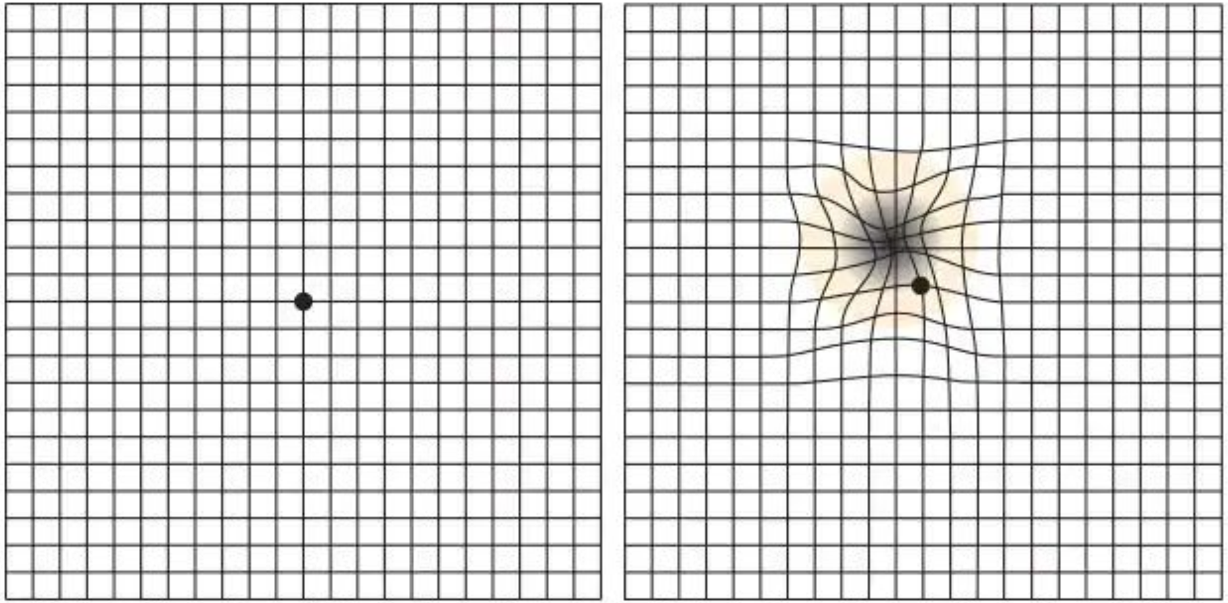




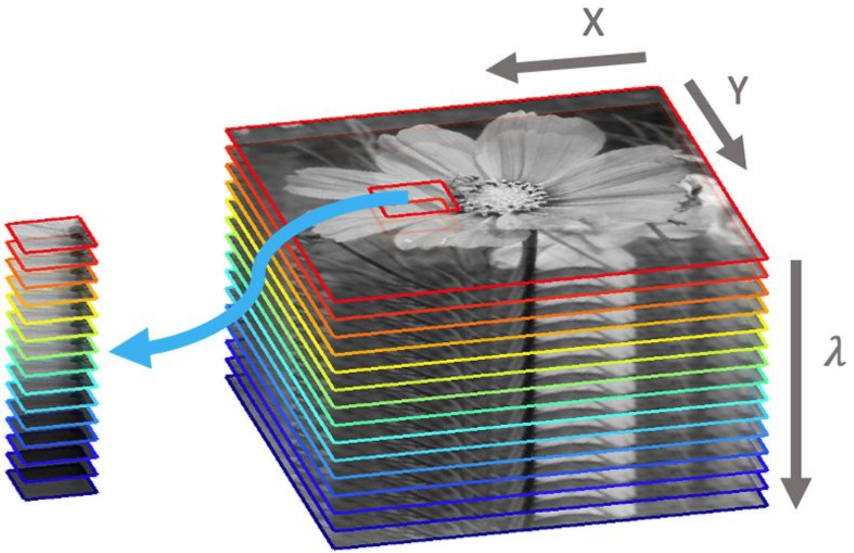
Eye with Drusen

Eye Physicians of Long Beach

Current AMD Diagnostic Landscape



Hyperspectral Imaging for AMD Diagnosis



Polder and Gowen 2021

- Hyperspectral imaging (HSI) captures dozen wavelengths on axes x, y, λ
- Drusen biochemical composition produces unique spectra
- Images need to be reconstructed and spectra need to be extracted

Gaps in Knowledge

AMD Current Diagnostic Limitations	Relies mainly on assessing visual function and struggles with clear drusen lesion identification.
Imaging Techniques	Traditional methods don't capture complexities; hyperspectral imaging enhances detail yet struggles with live patients
Current Spectral Analysis Methods	Techniques like Non-negative Matrix Factorization (NMF) take a long time and are not computationally efficient.
Need for Improved Diagnostic Methods	Highlights the critical need for more precise, efficient, and dependable diagnostic tools.

Significance and Innovation

Reconstruction Methods

- Novel pathway for diagnosing AMD using CASSI technology.
- Reconstruction of 3D hyperspectral data from 2D images.

Imaging Techniques

- Development of a fundus camera to image drusen lesions.
- Importance of identifying autofluorescence signatures.

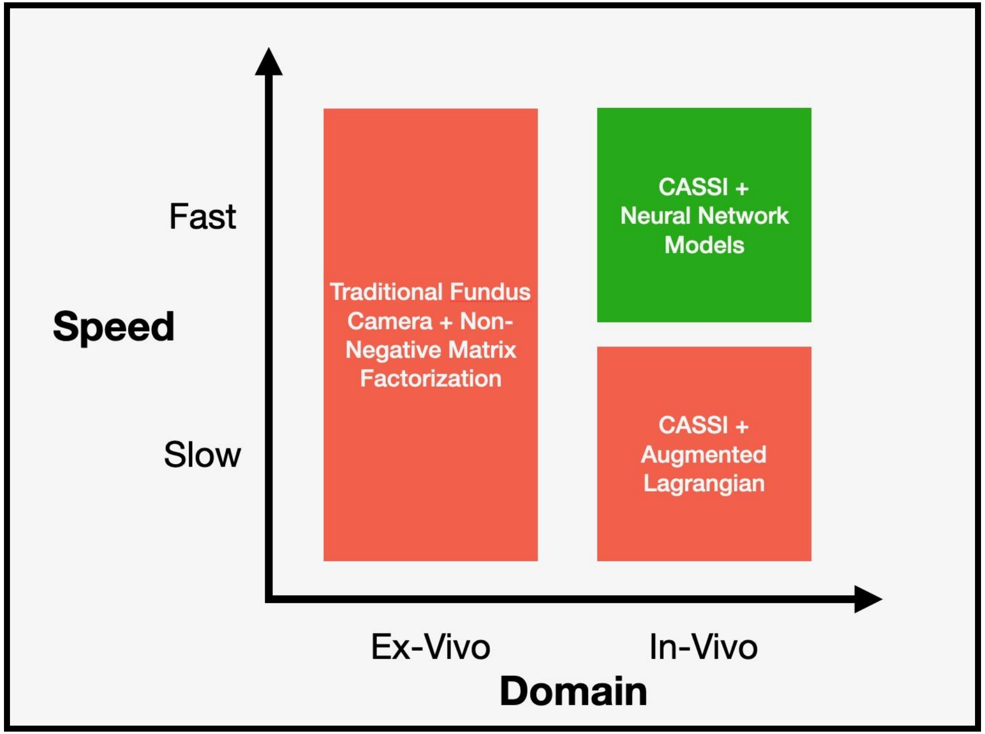
Image Reconstruction and Analysis

- Building upon neural networks and deep learning models.
- Aiming for higher resolution and spectral accuracy with less resource intensiveness.

Methodological Innovations

- Appling a deep learning algorithm to compare its computational efficiency to traditional iterative algorithms for matrix factorization to extract spectra

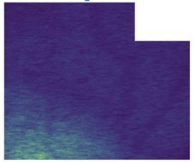
Comparative Analysis of AMD Diagnostic Techniques



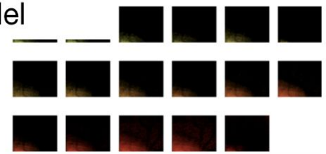
Experimental Design

1

Decompress image using convolutional neural network model



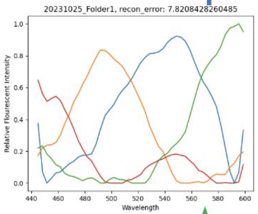
2D Compressed Retina Image (x, y)



3D Hyperspectral Datacube (x, y, λ)

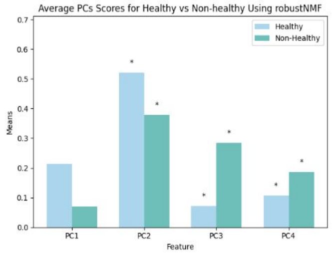
2

Extract spectra from datacube using deep learning-based matrix factorization methods



3

Analyze matrix factorization results to diagnose patients



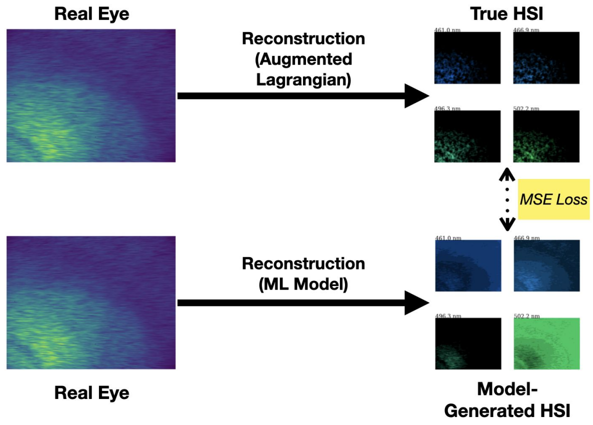
Experimental Design (Hyperspectral Image Reconstruction)

Models Evaluated:
1. Supervised U-Net
2. Self-Supervised U-Net
3. Self-Supervised Deep Unfolding

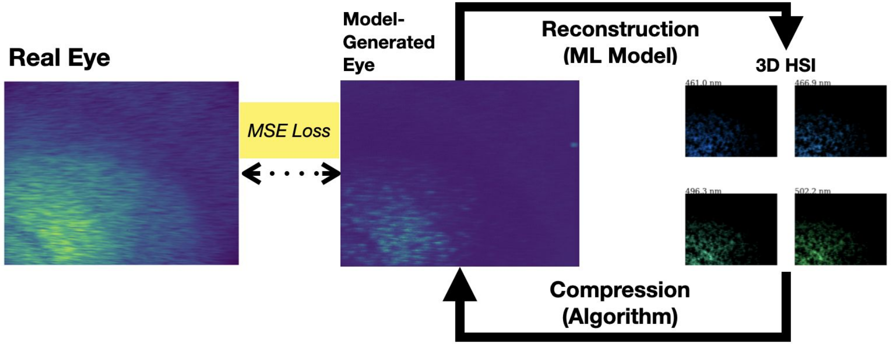
Metrics:
1. Training Time
2. Validation Loss
3. Model Size

U-Net: Standard Image Generation Network
Deep Unfolding: ML + AL Network made for HSI Reconstruction

Supervised



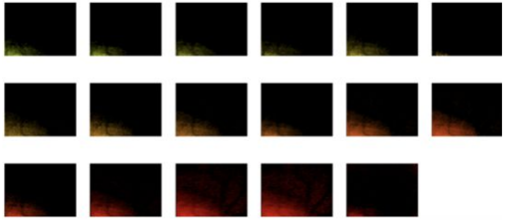
Self-Supervised



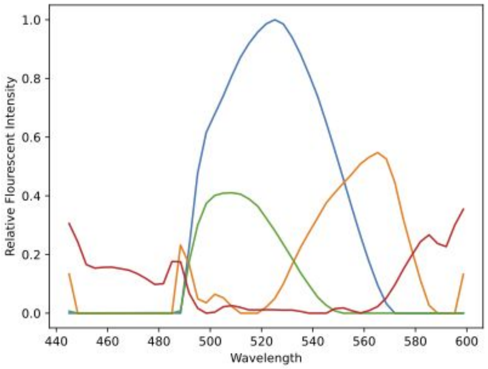
Experimental Design (cont.)

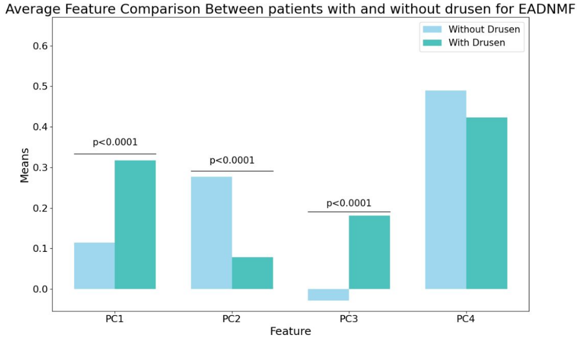
Spectral Extraction from Hyperspectral Images

Step 1	Step 2	Step 3
Convert the reconstructed hyperspectral data cube into a matrix using mode-3 matricization.	**Extract spectra** from data cube using nonnegative matrix factorization (NNMF) algorithms: 1. iterative: **Robust-NMF** 2. deep learning: **Elastic Adversarial Deep Nonnegative Matrix Factorization (EADNMF)**	**Statistical analysis** to compare spectra between algorithms and diagnose patients with AMD using functional principal component analysis (fPCA)



3D Hyperspectral Datacube (x, y, λ)





Results

Only the traditional model produces eye images comparable to the true eye captured by the fundus camera

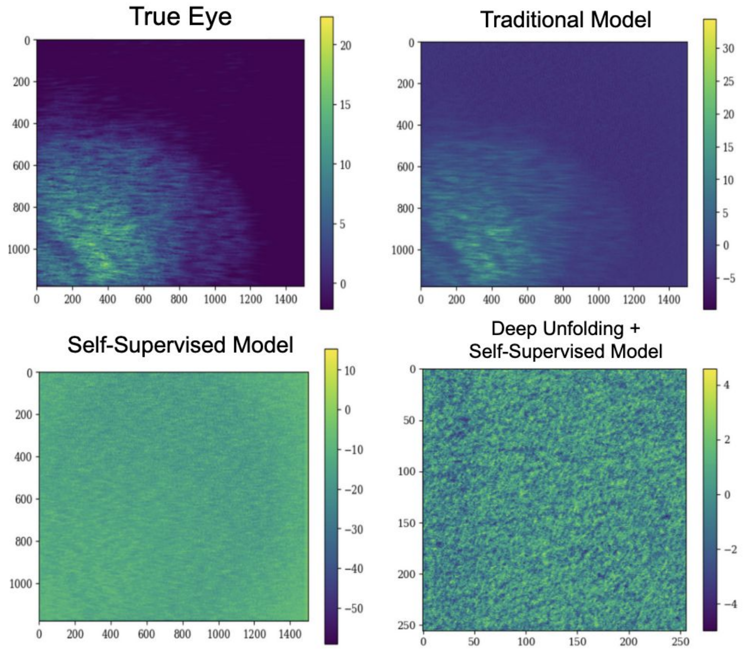


Figure 5. True and predicted eye images.

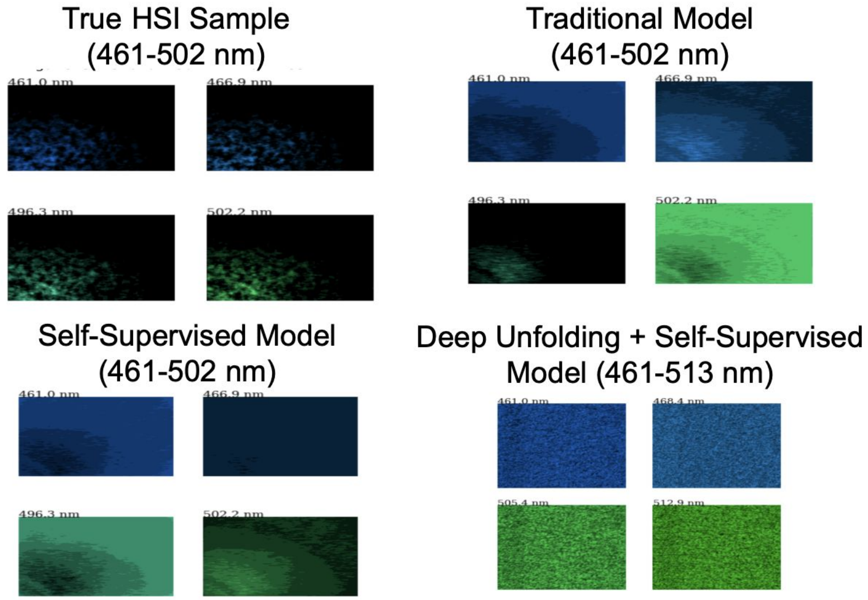


Figure 6. True (Augmented Lagrangian) and predicted eye HSIs.

Machine learning models demonstrate computational efficiency, U-Net model significantly smaller than Deep Unfolding model

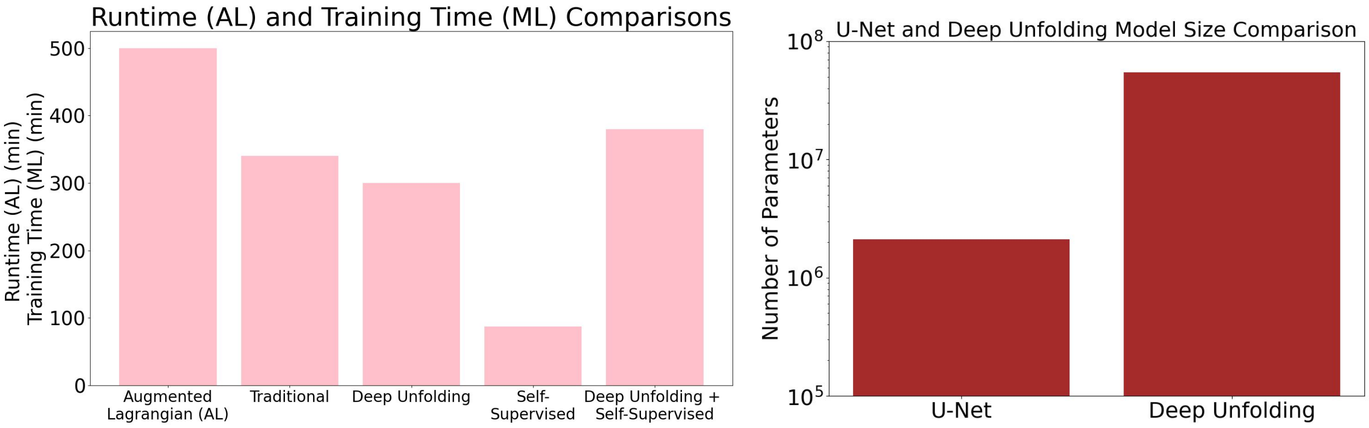


Figure 7. Comparison of model run and train times (left). Comparison of model size (right).

Self-Supervised algorithms avoid overfitting and achieve decreases in only training loss

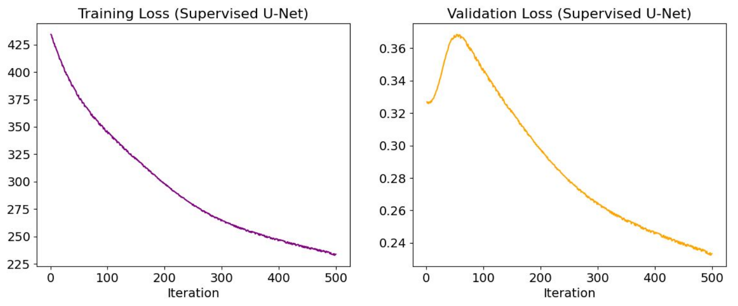


Figure 8. MSE Training loss and validation loss of supervised U-Net model after 500 iterations. Model is overfitting despite decreasing validation loss.

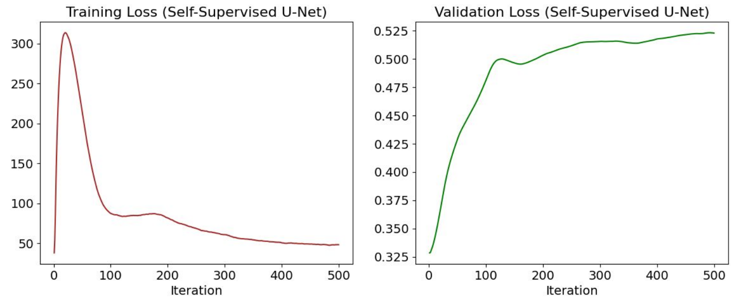


Figure 9. MSE Training loss and validation loss of self-supervised U-Net model after 500 iterations.

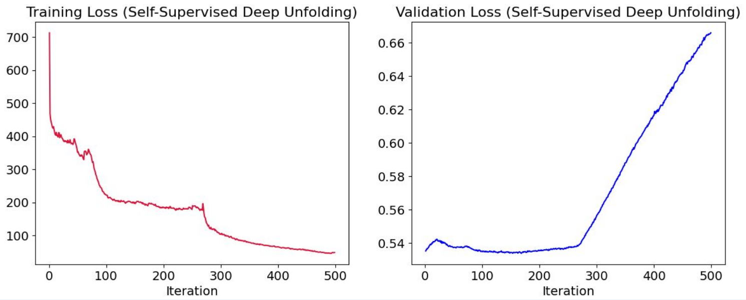
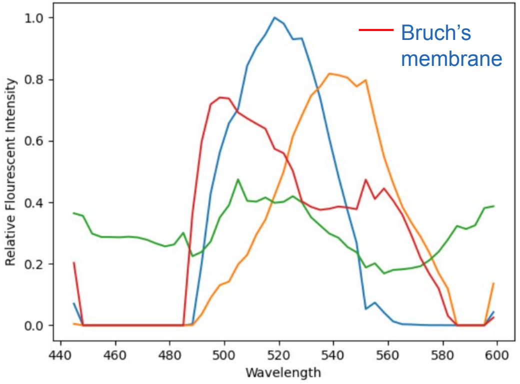
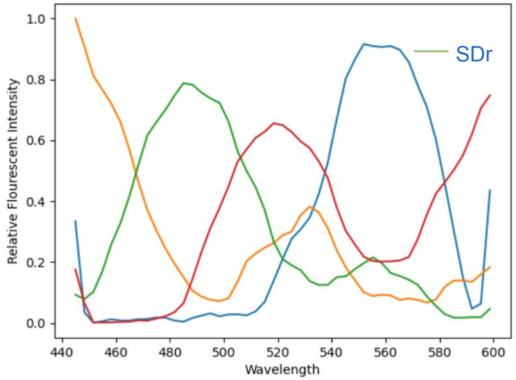
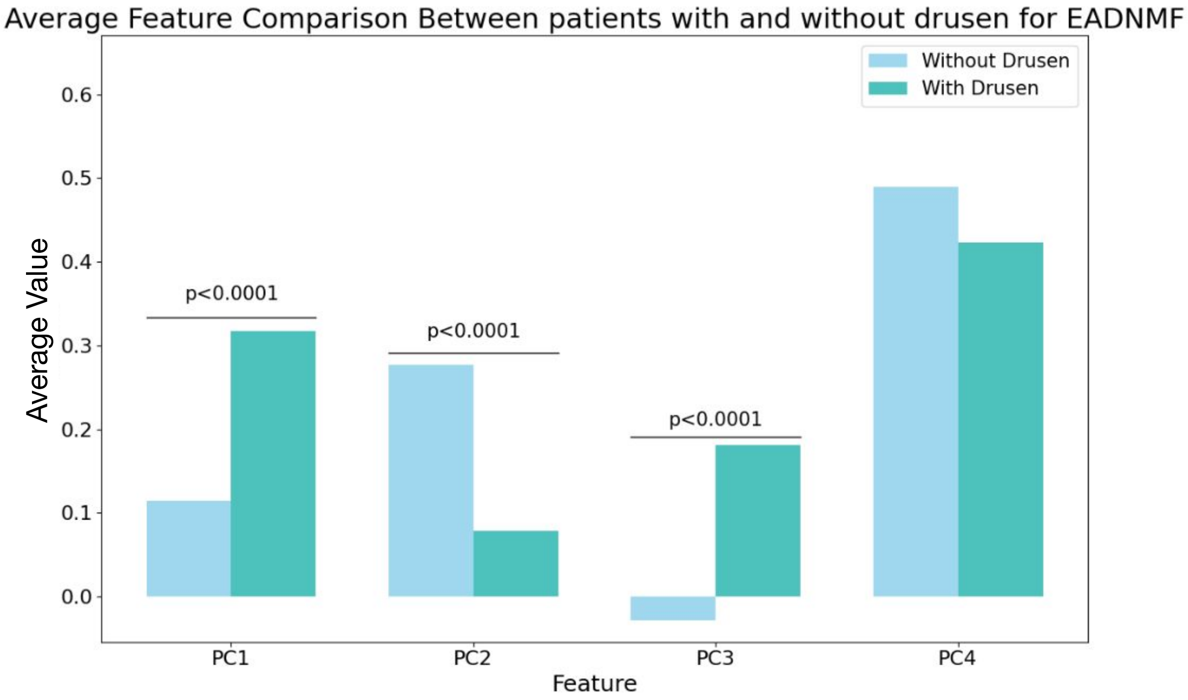


Figure 10. MSE Training loss and validation loss of self-supervised Deep Unfolding model after 500 iterations.

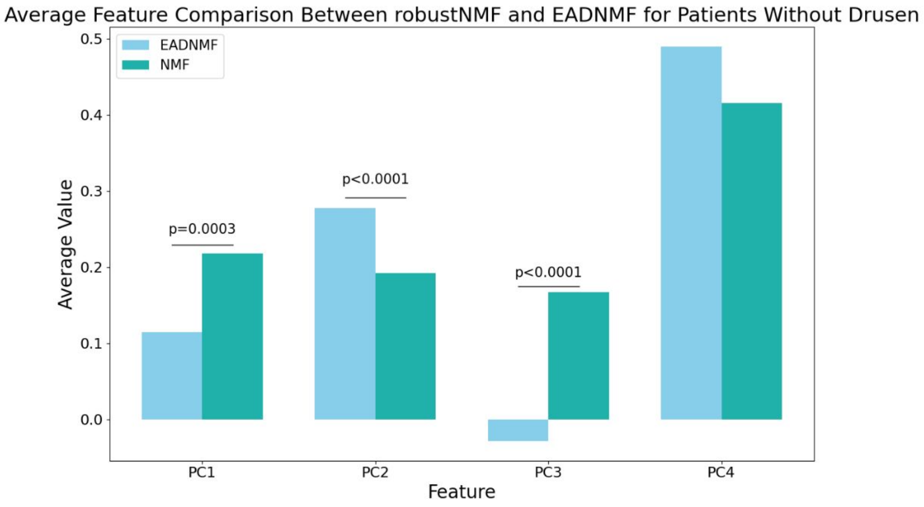
Distinct spectra extracted using deep learning for an eye with drusen and an eye without drusen

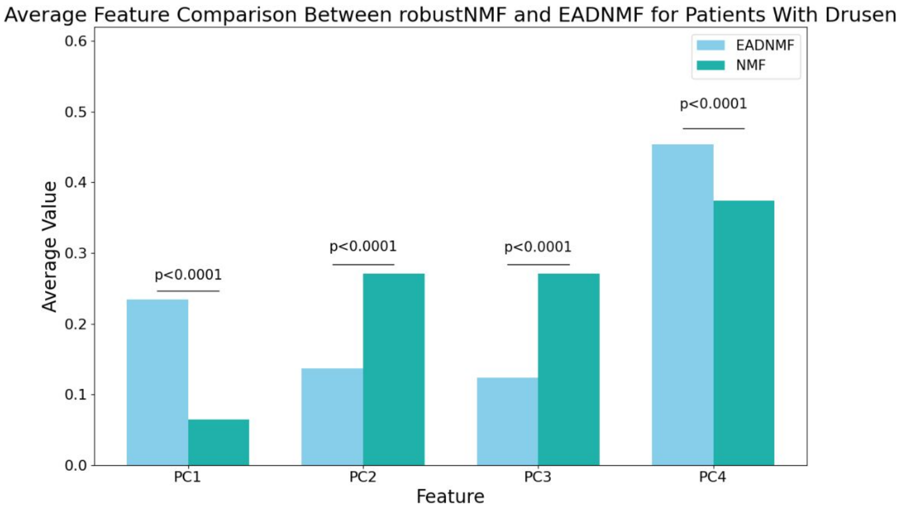




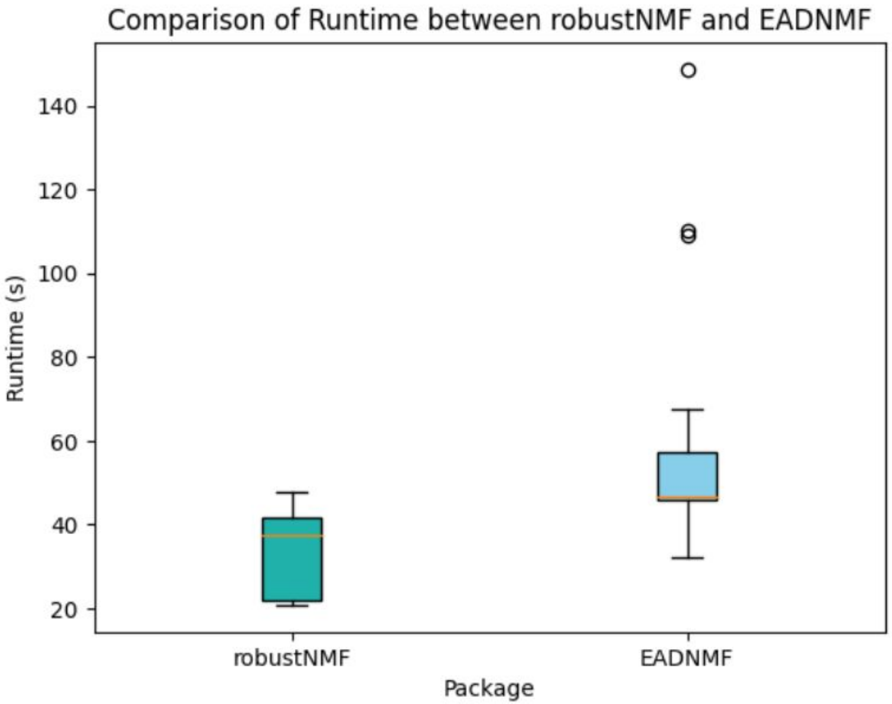


Deep learning spectra did not closely approximate NNMF spectra





Reduced spread in runtime for deep learning indicates that its efficiency is not data-dependent



Future Directions

Future work:

- Future work will focus on refining these techniques for broader clinical application.
- Ongoing research aims to optimize spectral extraction and enhance diagnostic accuracy.

Potential Future Tasks:

1. Utilize deep learning techniques to improve hyperspectral data reconstruction and AMD spectral signature extraction.
2. Tailor non-negative matrix factorization (NMF) algorithms for in-vivo data to achieve precise diagnostic outcomes.
3. Refine analysis methods for representative spectra to gain more valuable insights.
4. Collaborate with relevant stakeholders to refine techniques for broader clinical use and ensure seamless integration in diverse settings.
5. Focus on optimizing spectral extraction methods to enhance diagnostic accuracy.

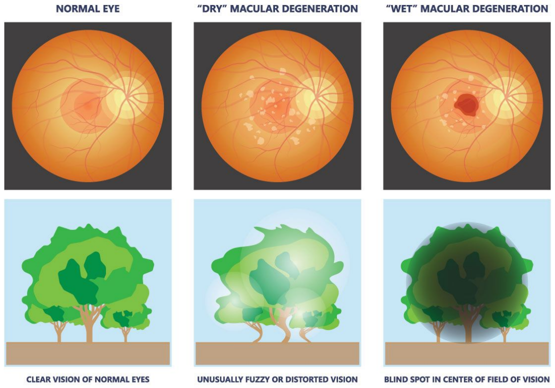
Conclusion

Return to the big picture:

- Computational models enable early intervention in AMD, a critical measure given the absence of a cure.
- Aiding in disease progression mitigation, as it has been shown that early diagnosis can both decrease disease progression and increase quality of life.

Conclusions:

- The integration of hyperspectral imaging and machine learning has potential for early AMD diagnosis.
- Deep learning methods have improved computational efficiency and quality of reconstruction.



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Thank you for listening!

Any questions?

References

Mohammed, T., et al., “Ex Vivo Hyperspectral Autofluorescence Imaging and Localization of Fluorophores in Human Eyes with Age-Related Macular Degeneration,” Vision, vol. 2, no. 4, 2018, https://doi.org/10.3390/vision2040038

N. Dey et al., “Tensor decomposition of hyperspectral images to study autofluorescence in age-related macular degeneration,” vol. 56, pp. 96–109, Aug. 2019, doi: https://doi.org/10.1016/j.media.2019.05.009. Dey, N., et al., “Robust-NMF”, Github Repository, September 2019, https://github.com/neel-dey/robust-nmf

Seyedi, S., “EADNMF”, Github Repository, December 2022, https://github.com/amjadseyedi/EADNMF/tree/master

Seyedi, S., et al., “Elastic adversarial deep nonnegative matrix factorization for matrix completion,” Information Sciences, vol. 621, pp. 562-579, April 2023, https://doi.org/10.1016/j.ins.2022.11.120

Xie H, Zhao Z, Han J, Xiong F, Zhang Y. Dual camera snapshot high-resolution-hyperspectral imaging system with parallel joint optimization via physics-informed learning. Opt Express. 2023 Apr 24;31(9):14617-14639. doi: 10.1364/OE.487253. PMID: 37157322.