## Advancing Retinal Disease Diagnosis through Hyperspectral Imaging

Aditi Kumar, Martin Bourdev, Isabelle Liu, Aaron Park, Giovanna Sternberg, Dalia AlSaihati, Sanjana Kargi

**Abstract** In the expanding field of medical diagnostics, hyperspectral imaging (HSI) emerges as a pivotal innovation, particularly for its potential in early detection and monitoring of age-related macular degeneration (AMD). Current methods for reconstructing hyperspectral images of the eye and extracting spectral signatures from these images for diagnosis, face challenges related to speed, accuracy, and applicability to in vivo data. We propose a novel solution leveraging deep learning techniques to enhance image reconstruction and 2D Compressed Retina diagnostic algorithms, with the anticipation that our approach will improve AMD detection in-vivo. The results indicate that deep learning methods can enhance computational efficiency and

maintain quality of results obtained through traditional methods for

image reconstruction and diagnosis for AMD. This study lays the

groundwork for future research to refine these techniques and

Supervised U-Net Model

0 200 400 600 800 1000 1200 1400

Self-Supervised Deep

**Unfolding Model** 

#### Decompress image Analyze matrix using convolutional factorization results to neural network diagnose patients model des des des des des 3D Hyperspectral Datacube (x, y, λ) Extract spectra from datacube using deep learning-based matrix factorization methods

Figure 1. illustrates the process pipeline of preprocessing, analyzing, and diagnosing patients

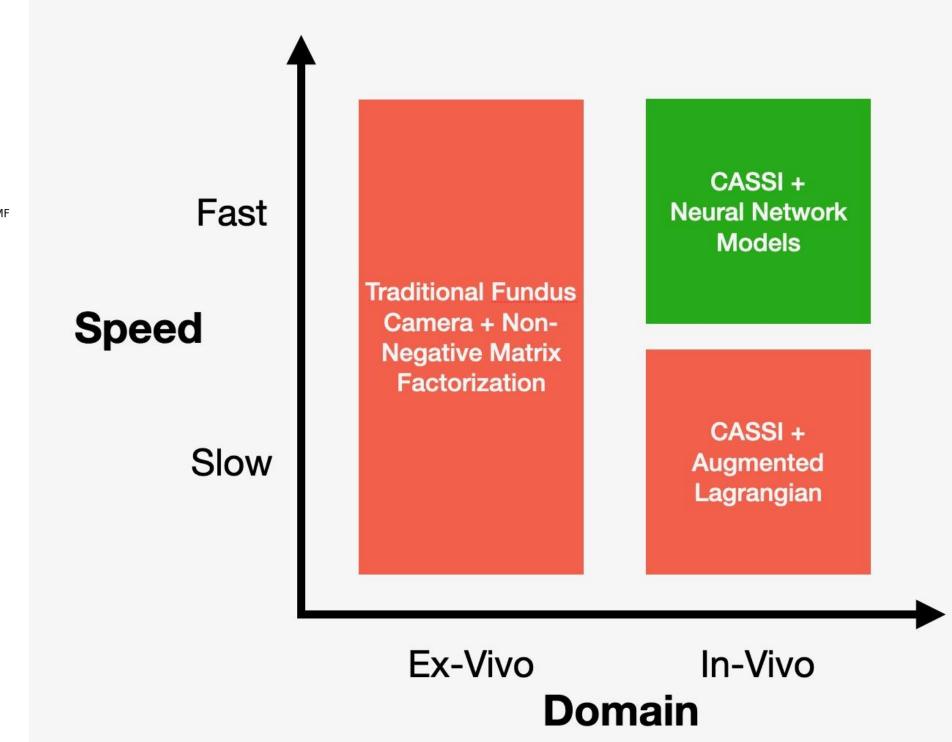


Figure 2. depicts the niche addressed by this research.



## Methods Reconstruction Generated **Real Eye** MSE Loss €……> Compression (Algorithm) Figure 4. Self-supervised training workflow.

Figure 3. U-Net (top) and Deep Unfolding (bottom) architectures.

Results

True Eye

0 200 400 600 800 1000 1200 1400

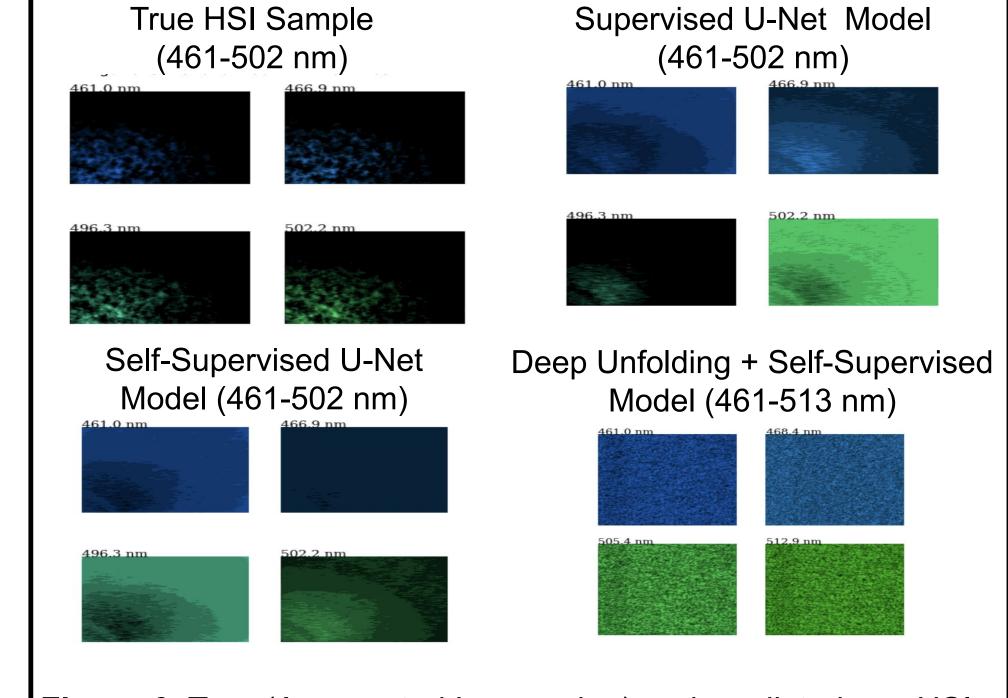
Self-Supervised

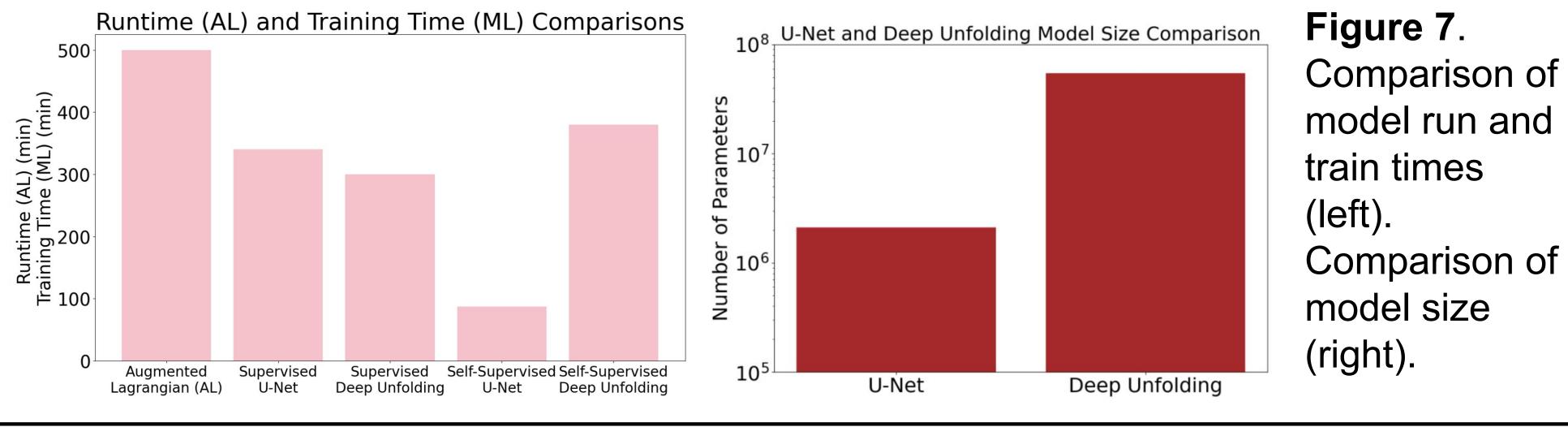
**U-Net Model** 

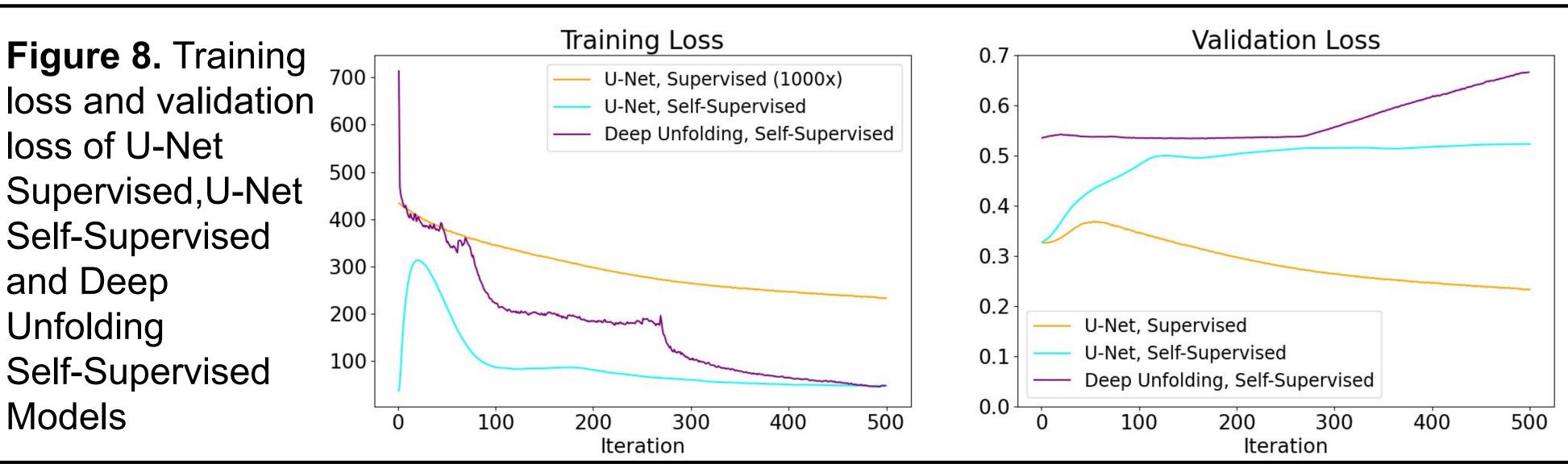
**Figure 5.** True and predicted eye images.

expand their application within clinical settings.

### **Models Evaluated:**







#### Conclusions

- Integration of hyperspectral imaging and machine learning holds promise for early AMD diagnosis.
- Increasing the training population can enhance model accuracy for early AMD diagnosis.
- Computational models enable early intervention in AMD, addressing the absence of a cure.
- Ongoing efforts in adapting NMF algorithms for in-vivo data aim for precision in diagnostic outcomes.

#### Acknowledgments

- - 1. U-Net + Supervised (Traditional)
- 2. U-Net + Self-Supervised
- 3. Deep Unfolding + Self-Supervised

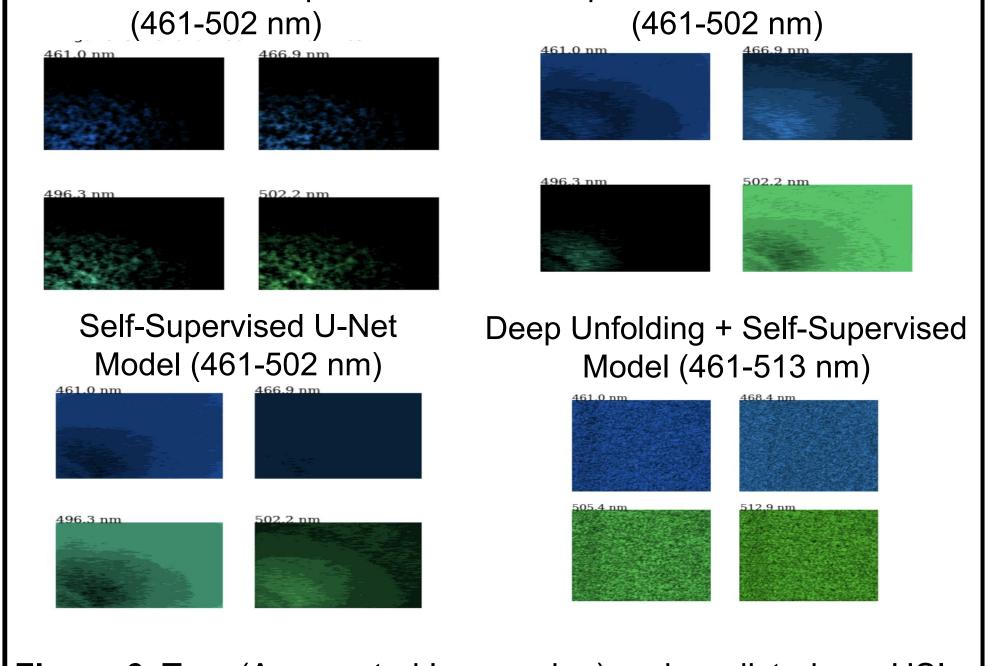


Figure 6. True (Augmented Lagrangian) and predicted eye HSIs.

# Without Drusen p<0.0001

Average Feature Comparison Between robustNMF and EADNMF for Patients Without Drusen

0.5 EADNMF

Figure 13. Average feature comparison between spectra extracted from patients with and without drusen lesions with EADNMF.

Part B: Spectral Extraction from Hyperspectral Images

Background

- Converted hyperspectral data cubes into matrices through mode-3 matricization.
- Extracted spectra from matrices using an iterative non-negative matrix factorization (NNMF) algorithm and a deep-learning based NNMF algorithm
- Performed functional-PCA on the unit-2 normalized spectra to compare the Robust-NMF and EADNMF algorithms as well as the spectra of patients with and without drusen lesions.
- Compared the runtime of the Robust-NMF and EADNMF algorithms for spectral extraction.

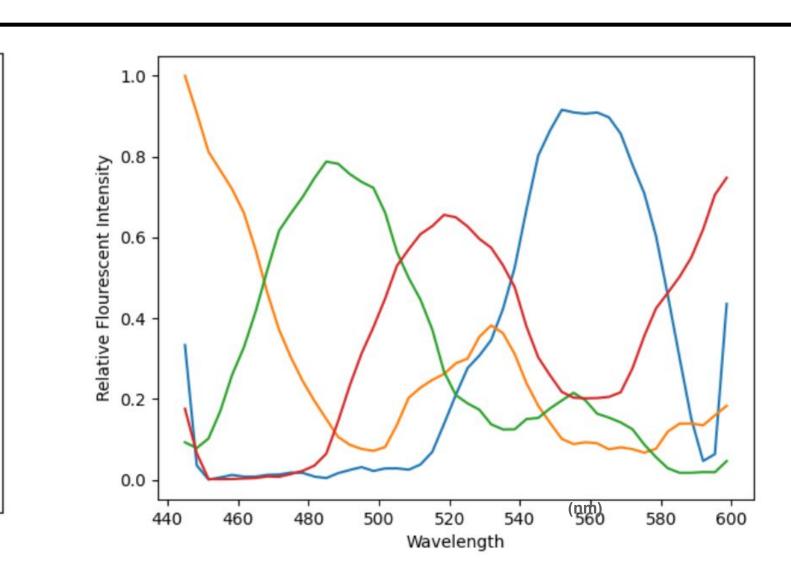


Figure 11. Representative spectra for a patient without (left) and with (right) drusen extracted using **EADNMF.** Potential drusen spectra shown in blue in the image on the right.

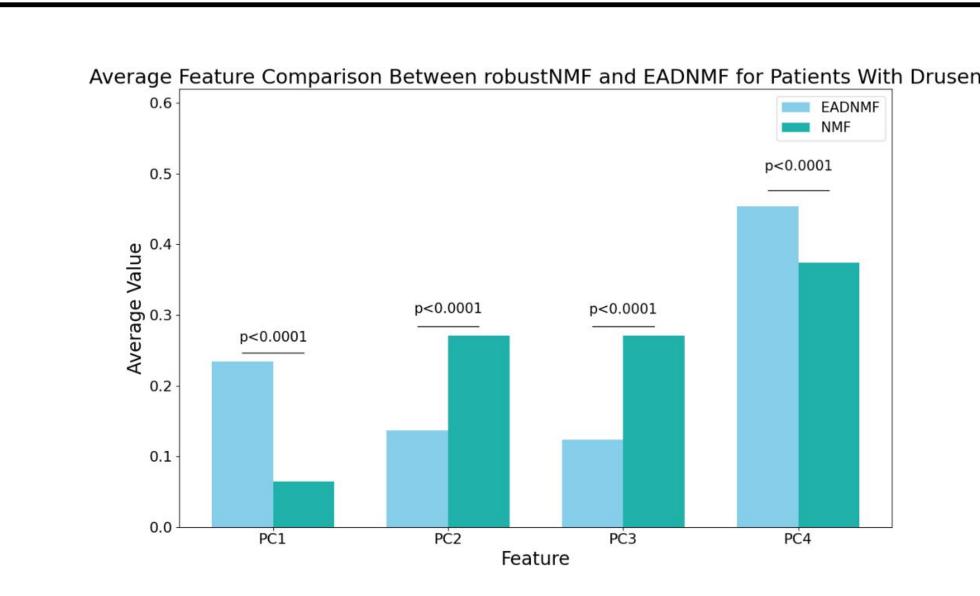


Figure 12. Average comparison feature between spectra extracted through robustNMF and EADNMF for patients with (left) and without (right) drusen lesions.

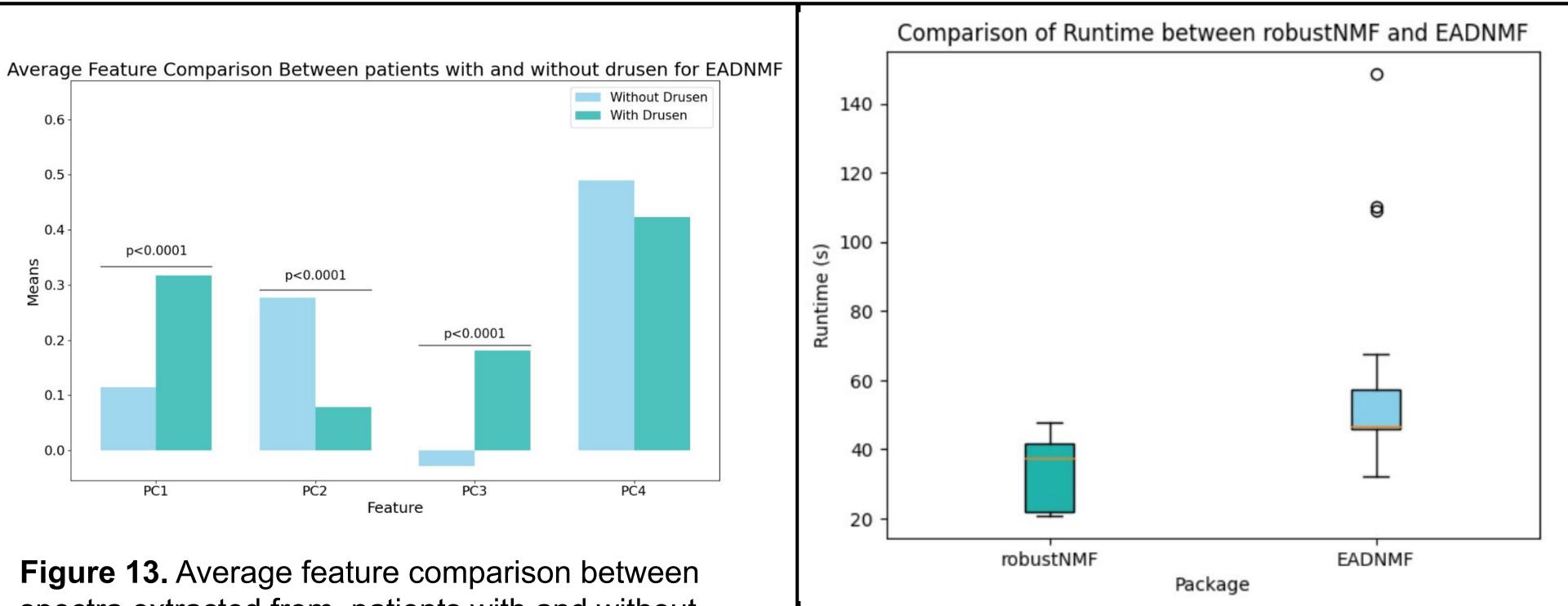


Figure 14. Runtime over all patients for spectra extraction using robustNMF and EADNMF

#### 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, <a href="https://doi.org/10.3390/vision2040038">https://doi.org/10.3390/vision2040038</a>
- 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, <a href="https://github.com/neel-dey/robust-nmf">https://github.com/neel-dey/robust-nmf</a> Seyedi, S., "EADNMF", Github Repository, December 2022, <a href="https://github.com/amjadseyedi/EADNMF/tree/master">https://github.com/amjadseyedi/EADNMF/tree/master</a>
- Seyedi, S., et al., "Elastic adversarial deep nonnegative matrix factorization for matrix completion," Information Sciences, vol. 621, pp. 562-579, April 2023, <a href="https://doi.org/10.1016/j.ins.2022.11.120">https://doi.org/10.1016/j.ins.2022.11.120</a>
- 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.

We would like to acknowledge Dr. Liang Gao, Ruixuan Zhao and the iOptics Lab, Dr. Mireille Kamariza, Austin Si, the New York Eye and Ear Infirmary of Mount Sinai, and the UCLA Department of Bioengineering.