

Diatom classification via deep learning using raw holograms captured by a lenless holographic system

B. Bogue-Jimenez¹, Raúl Castañeda², Carlos Trujillo², Ana Doblas¹.

¹Department of Electrical & Computer Eng., UMass Dartmouth, USA. ²School of Applied Sciences and Eng., Universidad EAFIT, Medellin, Colombia.

Al and Optical Data Sciences V: Paper 12903-46 in Session 8 – Analog Optical Computing

Presentation Date/Time: 31 January 2024 8 AM

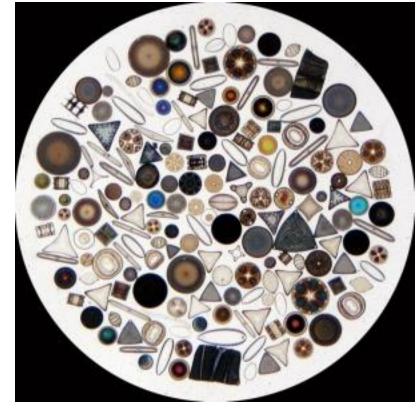






Monitoring of Diatoms is Crucial in Understanding the Overall Health of Aquatic Ecosystems

- □ Diatoms are microscopic algae that play a crucial role in aquatic ecosystems.
- Diatoms' **size** depends on the **species**, ranging from 2 to 200 μm.
- ☐ Diatoms are **sensitive to changes** in water quality, including nutrient levels, temperature, and pollution.
- ☐ Their abundance and diversity indicate the overall health of aquatic ecosystems.
- Monitoring diatom communities can help assess water quality and identify potential environmental problems.



https://underthecblog.org/2013/10/21/diatom-detectives/

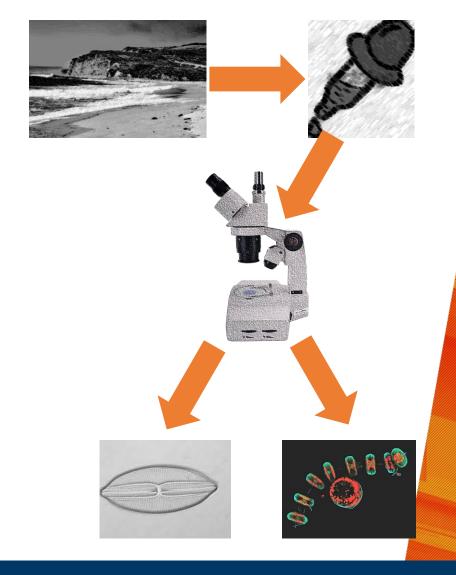






Diatoms are traditionally identified based on their morphology in a third-party lab

- ☐ Conventional identification of diatoms requires the collection of water samples from the target environment.
- ☐ Traditional **brightfield microscopy** is typically used to inspect the **morphological features** of diatoms.
- Widefield fluorescence microscopy has been used to study live diatoms and assess their physiological status, providing insights into the health and vitality of diatom populations.
- ☐ Limitation: diatom cells should be mounted on microscope slides for their analysis.





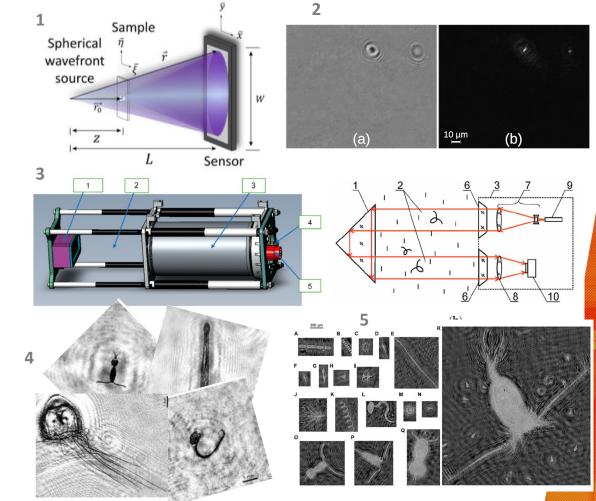




Digital Holographic Microscopy (DLHM) enables the

study of diatoms

- □ **DLHM** systems **preserve** the **natural state** of the **diatoms**¹, minimizing artifacts that may be introduced by sample preparation techniques.
- □ DLHM systems have been implemented in submersible systems³
- ☐ Monitoring of micro-organisms in potable water, aiming to reduce water-related diseases²
- Quantitative measurements for biodiversity and ecosystem monitoring³: plankton concentration, average size and size dispersion of individuals, particle size dispersion, water turbidity, suspension statistics.



- 1. Credit to Maria Josef Lopera Acosta, Master dissertation, 2022.
- 2. Pitkaaho et al., Digital Holography and 3D Imaging 2027, paper W2A.4
- 3. Dyomin, *et. al.*, Sensors 21, 4863 (2021) & Dyomin *et al.*, Appl. Sci. 12 (2022) & Nayak *et al.*, Frontiers in Marine Science 7, 572146 (2021)
- 4. Schnitzler et al., Marine Pollution Bulletin 163, 111950 (2021)).

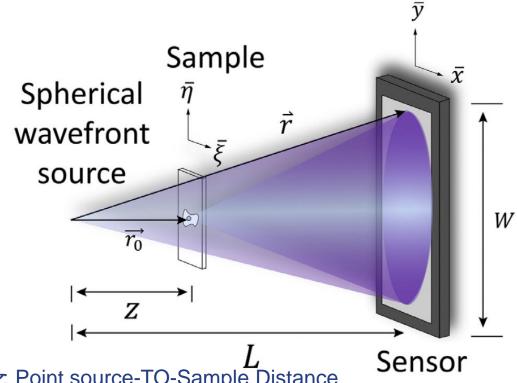






Principle of Digital Lensless Holographic Microscopy

(DLHM)



z. Point source-TO-Sample Distance

L: Point source-TO-Sensor Distance

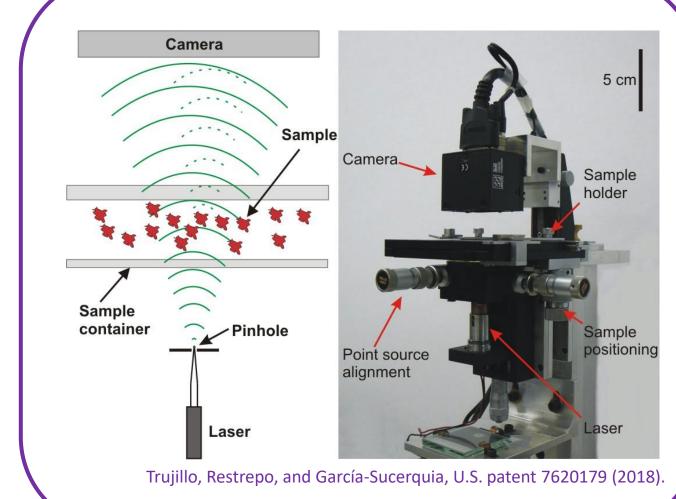
M = z/L: Lateral Magnification. λ: Laser's wavelength

W: Sensor size $(M \Delta_{xv})$.

M: Number of pixels

 Δ_{xy} : pixel size

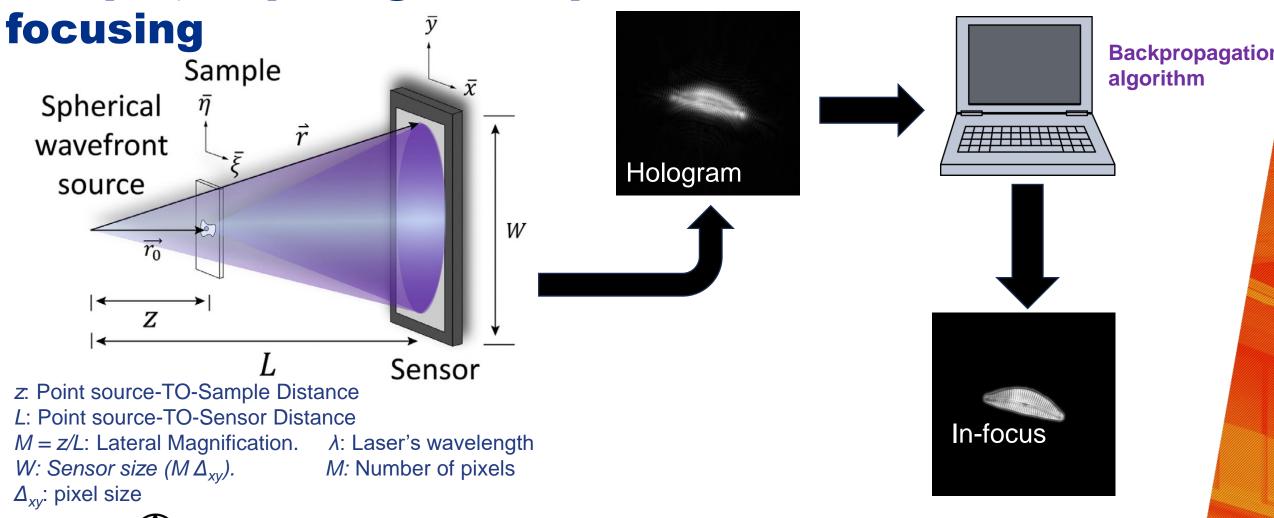








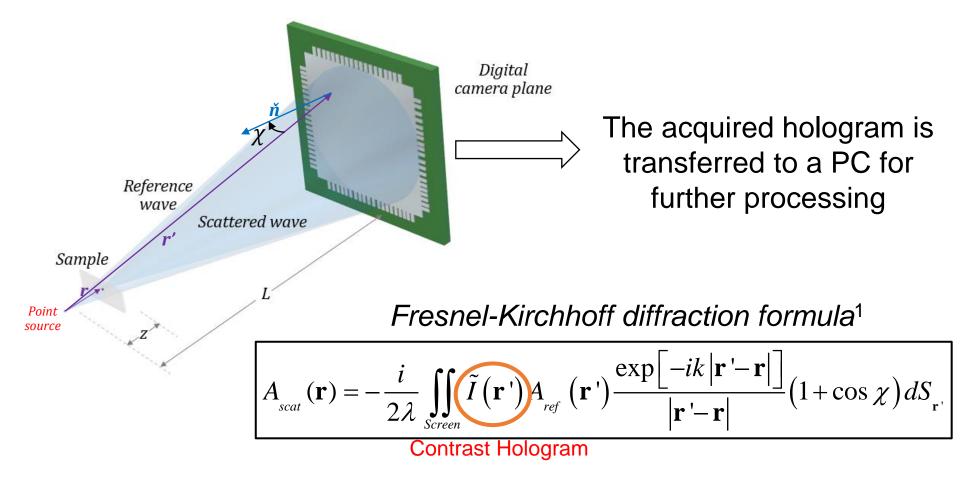
DLHM system records the diffraction pattern of a sample, requiring a computational method for







The backpropagation algorithm aims to solve the Fresnel-Kirchhoff diffraction formula

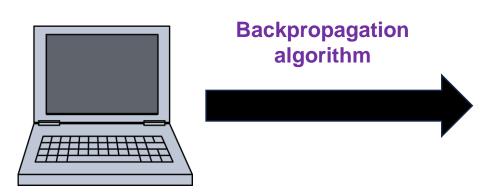




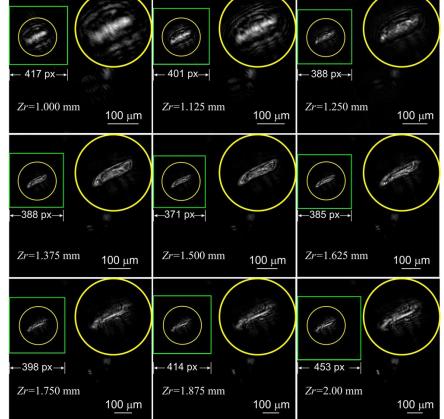


¹Garcia-Sucerquia, et al., Appl. Opt. 45, 836–850 (2006).

The backpropagation algorithm is expensive in terms of computational complexity and processing time if one has not prior knowledge of the sample distance (z) _____



How many manual reconstructed images should one estimate to find the correct propagation distance?



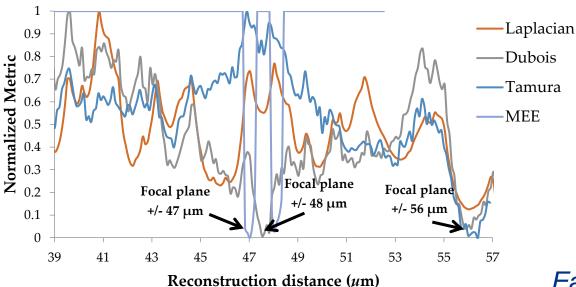
Trujillo and Garcia-Sucerquia, Opt. Lett. 39, 2569–2572 (2014)

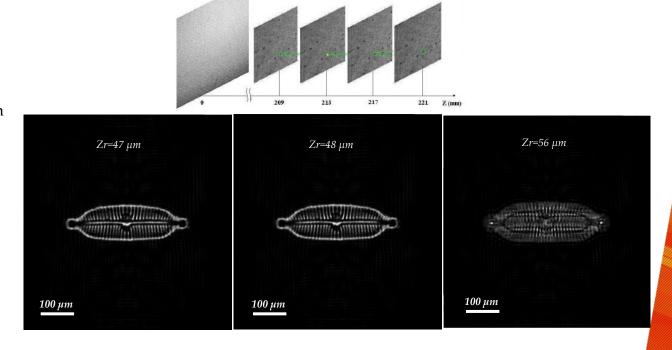




Although DLHM allows a numerical focusing, it is required to define a metric to reconstruct in-focus lensless holograms

MEE: Modified Enclosed Energy





Each metric provides a different reconstruction distance The best metric changes with the sample¹

¹Trujillo and Garcia-Sucerquia, Opt. Lett. 39, 2569–2572 (2014)

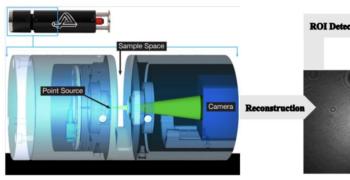


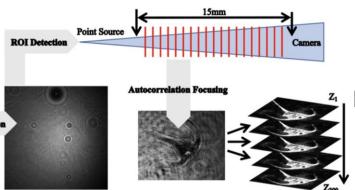




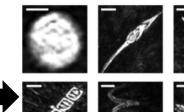
Diatoms have been able to classify with high accuracy using in-focus images from a DLHM system

DLHM system





Reconstructed in-focus images





















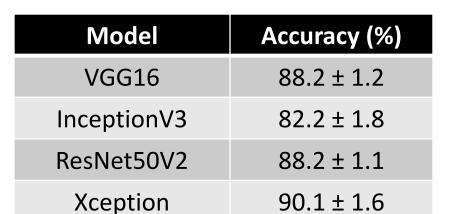


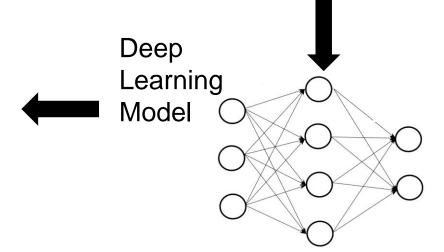










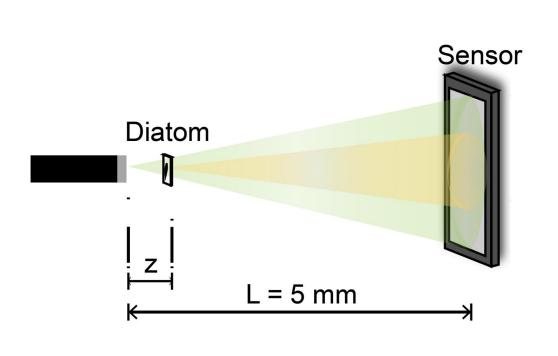


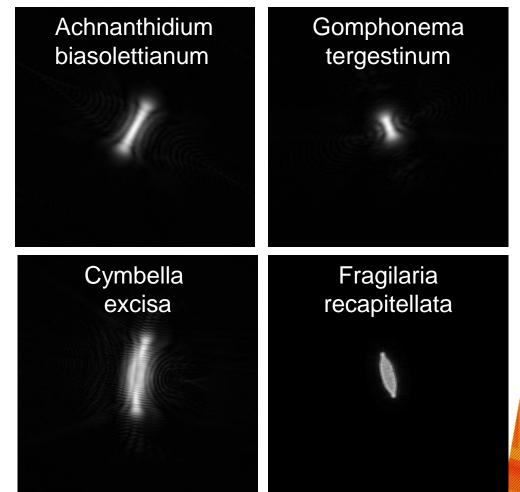




Results from MacNeil, Missan, Luo et al. BMC Ecol Evo 21, 123 (2021).

Research Question: Can we classify diatoms from the raw holograms? Do the raw holograms have enough classification information?

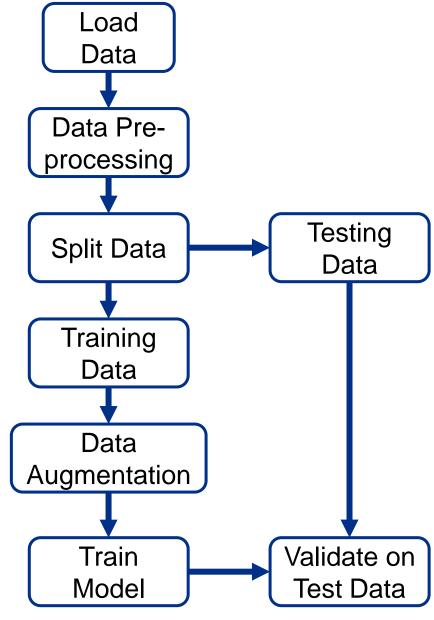








Research Study Framework



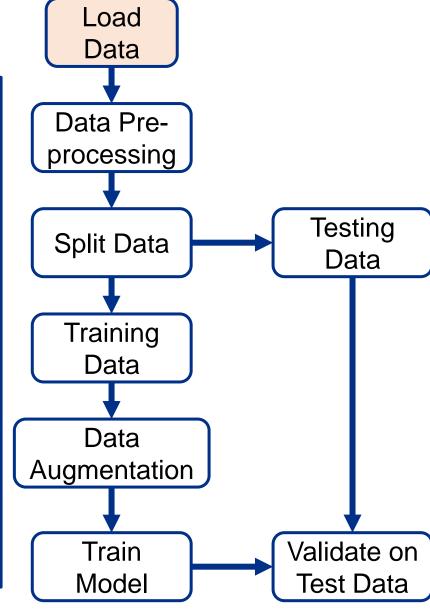






Loading the diatom dataset

- Dataset from a public dataset of segmented diatoms located in Turkey water.^{1,2}
- The image size for each segmented diatom is 1583x1583.²
- We converted the color images to monochrome images.
- Our dataset contains 1,816 images from 36 classes.
- [1] Gunduz et al., Turkish J. E.E.C.S. 30 2268 (2022)
- [2] Akinlar et al., Intern. J. of P.R. and A.I. 26 (2012)
- [3] https://www.kaggle.com/huseyingunduz/diatom-dataset





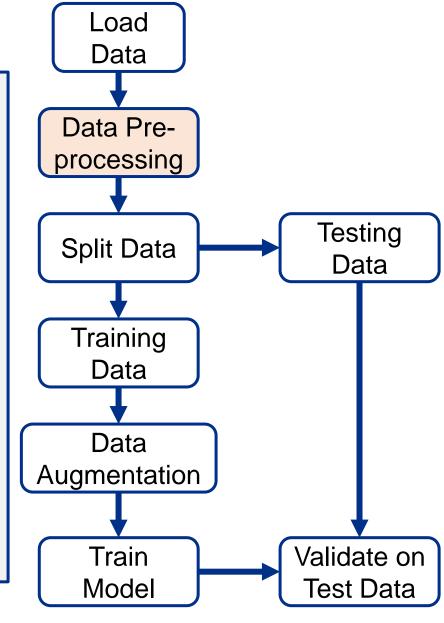






Creating the DLHM dataset

- Diatoms images were transformed into DLHM holograms using the Bluestein method¹ and the modified Angular Spectrum method² depending on the distance z to properly emulate the location of the specimen within the inspection volume.
- Diatoms were considered amplitude cells.
- Raw holograms were simulated at 5 evenly spaced axial depths, ranging from z = 0.5 – 4.1 mm.
- DLHM configuration:
 - Source Wavelength = 528 nm
 - Sensor Width = 1583 x 1583
 - Sensor placed at L = 5 mm from the spherical point source
- [1] Restrepo et al., Appl. Opt. 50, 1745-1752 (2011).
- [2] Mendlovic et al., J Mod Opt. 44(2):407–414 (1997).







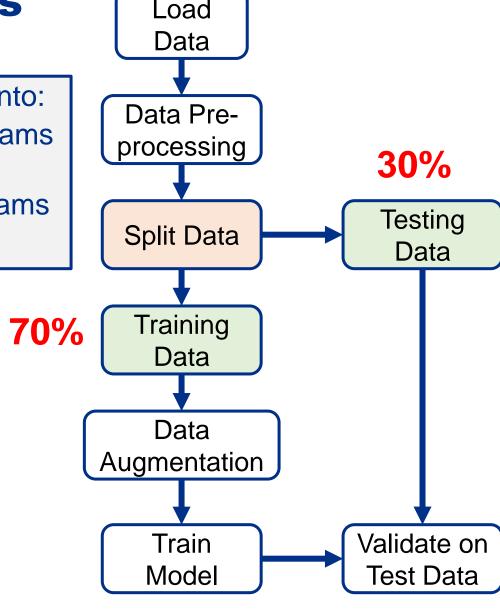




Training/Testing Datasets

The total **9,080 holograms** are divided into:

- **Training** dataset with **6,356** holograms (= 1,816*5*0.7).
- **Testing** dataset with **2,724** holograms (= 1,816*5*0.3).





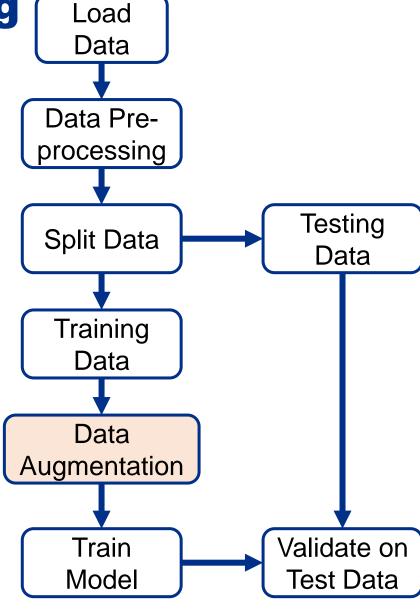






Further increased of training instances

Training dataset was randomly flipped vertically and horizontally to further increased the training dataset, improving generalization.











Training classification models

- Selected classification models: AlexNet, VGG16, and ResNet18.
- Transfer learning was used by taking previously MATLAB trained models and replacing their last learning layers, allowing the initial weight and bias learning rates to be higher.
- Bayesian Optimization was used to select the best model hyperparameters.
- Hyperparameters Optimization:

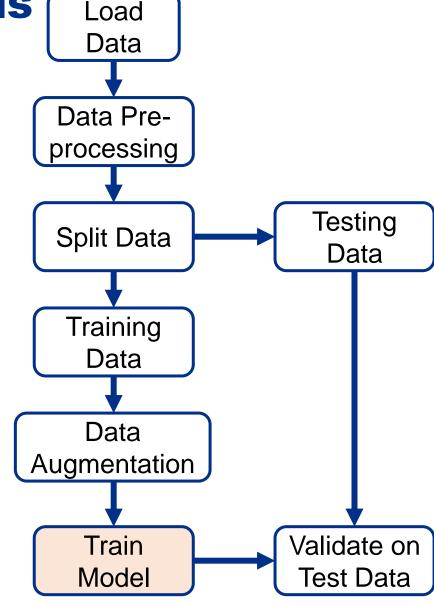
Initial Learning Rate: [0.0001,0.01, 0.01]

Epochs: [3,50,1]

Batch Size: [16,128,16]

Validation Frequency: [16,128, 16]

Optimizer: adam, rmsprop and sgdm

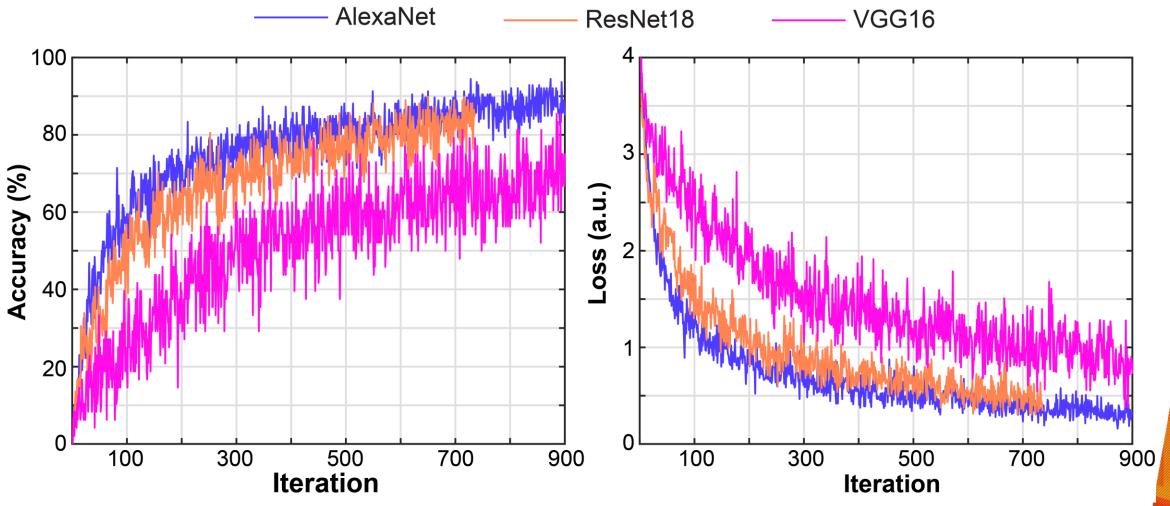








Healthy Trained Models for all the selected models



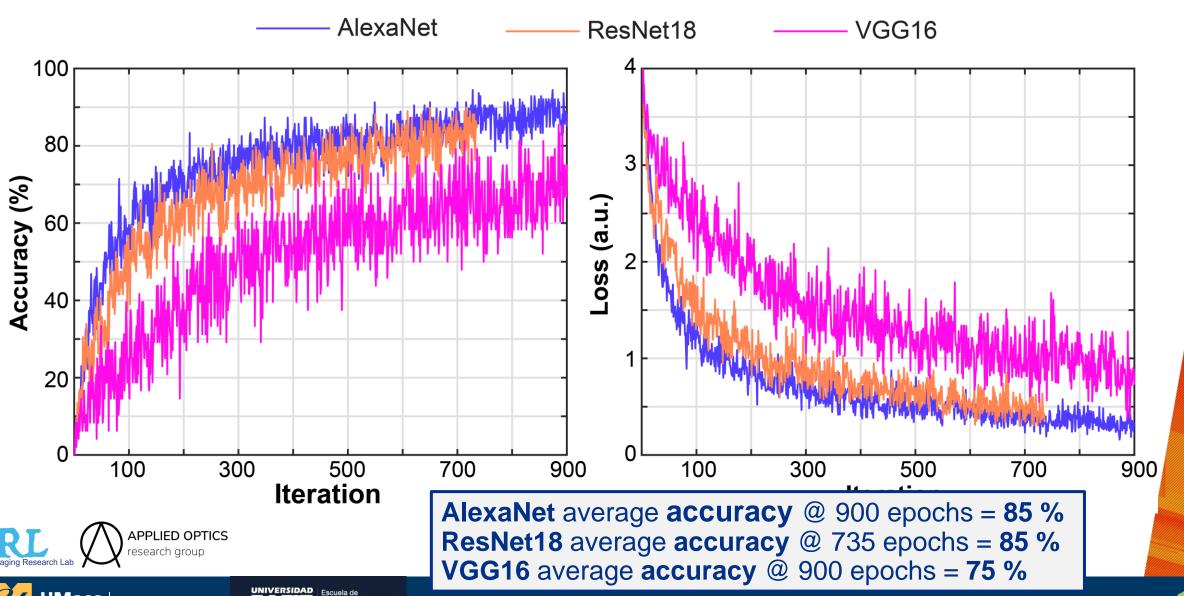






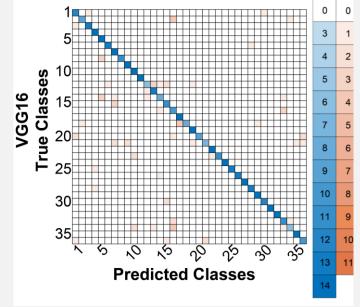


Healthy Trained Models for all the selected models



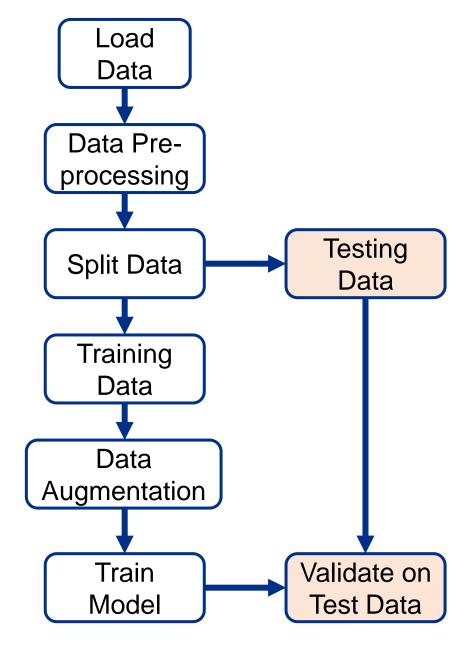
Testing the models

- Models are validated using the unseen testing dataset.
- Performance metrics used are the accuracy (AC) and confusion matrix.



$$AC(\%) = \frac{Predicted True Values}{Total Values}$$

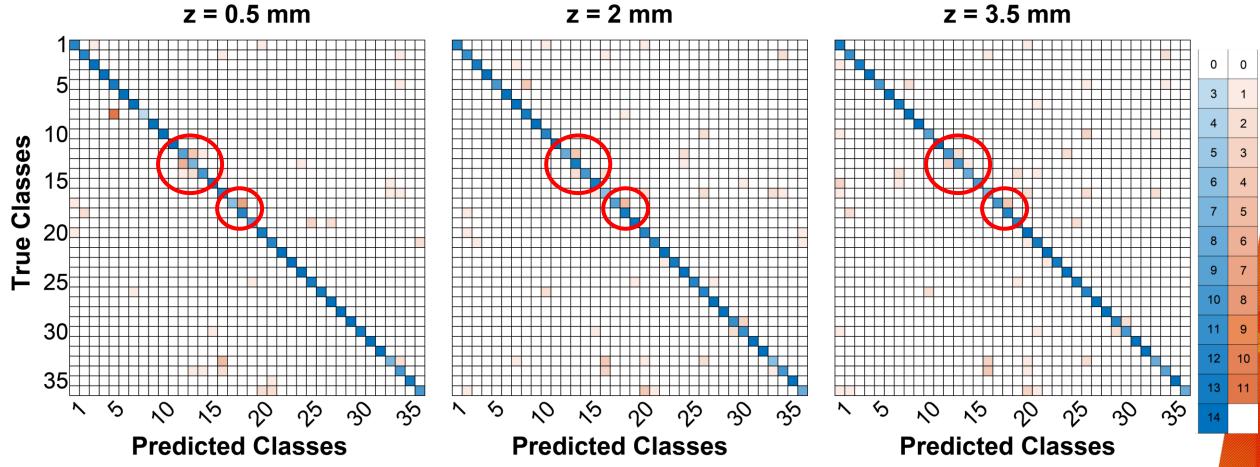








Can the trained AlexaNet model identify diatoms?



The classification accuracy does not depend on the axial position of the diatom

87.2 ± 15.1 %



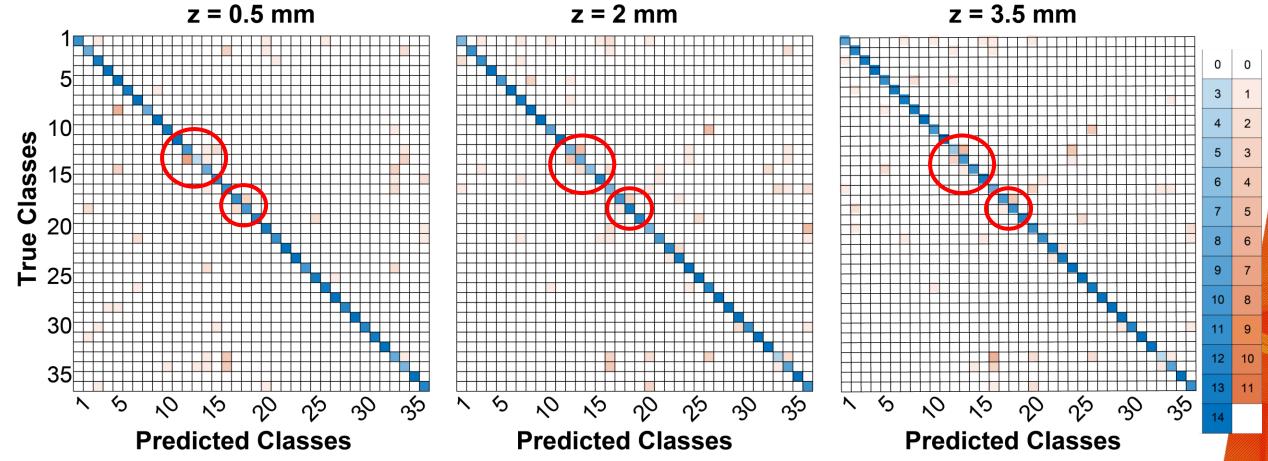
87.7 ± 15.4 %





86.7 ± 14.5 %

Can the trained ResNet18 model identify diatoms?



85.3 ± 17.2 %

83.4 ± 18.1 %

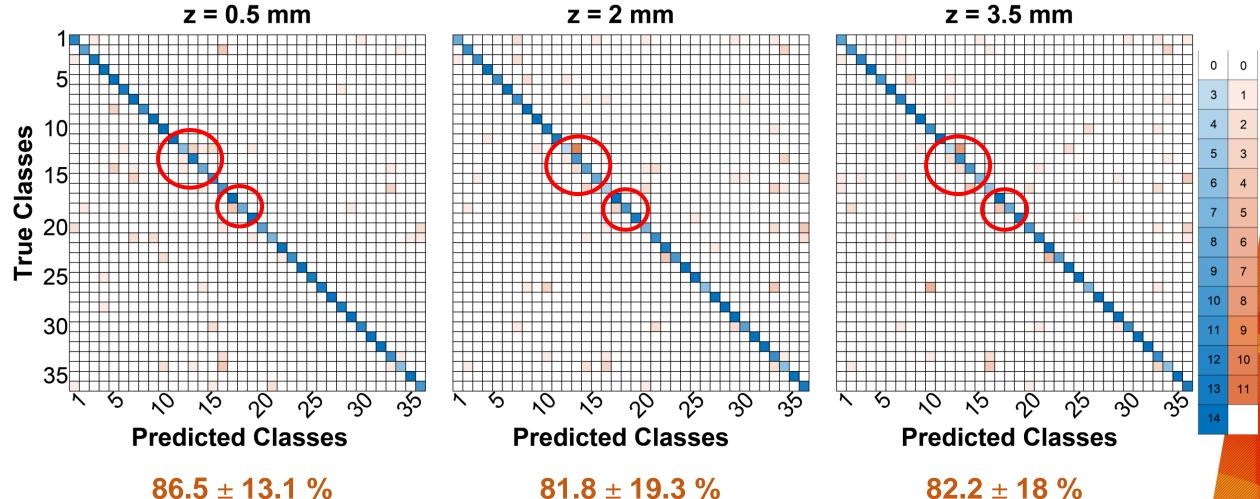
84.8 ± 16.3 %

The ResNet18 model has a lower performance than the AlexaNet one – lower





Can the trained VGG16 model identify diatoms?



The VGG16 model provides the lowest accuracy to the raw holograms that were closer to the sensor.

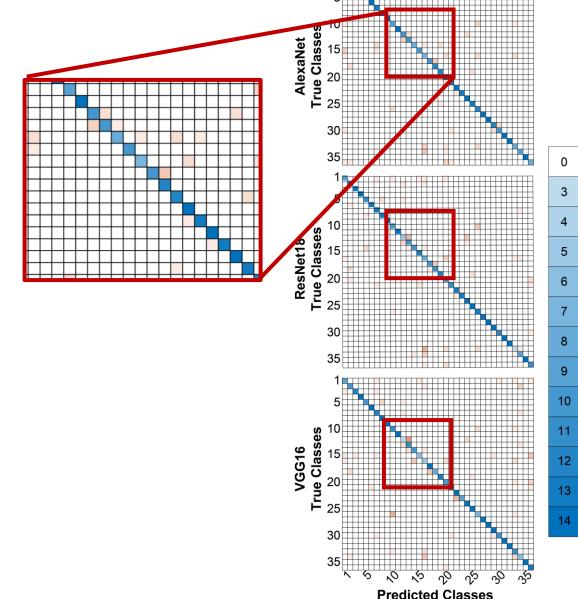




Challenges to recognize some diatoms

Models fail to predict

- The Gomphonema drutelingense diatom, prediciting it as Gomphonema micropus or Navicula moskalii diatom.
- The Halamphora paraveneta diatom, predicting as the Halamphora veneta diatom.
- The Nitzschia hantzschiana diatom, predicting as the Achnanthidium biasolettianum or Nitzschia archibaldii diatom.



z = 3.5 mm

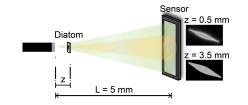


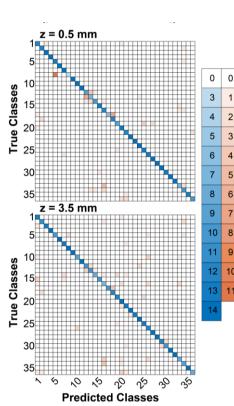




Summary

- We have investigated the potential use of lensless imaging systems for underwater monitoring by identifying diatom species and their diversity
- We have shown the classification power of traditional classification models (i.e., AlexaNet, ResNet18, and VGG16) to predict diatom species using raw hologram recorded by a DLHM system.
- ☐ The AlexaNet model provides the highest accuracy, being independent of the axial position of the diatom.
- ☐ The mean accuracy of the AlexaNet model with raw holograms (87.7%, 87.2%, and 86.7%) is quite close to the one provided using reconstructed in-focus images (88.2%)¹.
- ☐ We have had difficulty identifying some diatoms, regardless of the models.
- ☐ Future work: analyze the classification accuracy for transparent diatoms and real experimental dataset







¹MacNeil et al. BMC Ecol Evo 21, 123 (2021).



Acknowledgments





This work has been funded in part by:

- UMass Dartmouth (Doblas' startup fund)
- National Science Foundation (2042563)
- Vicerrectoría de Ciencia, Tecnología e Innovación, Universidad EAFIT, Colombia.





Minciencias



OIRL Research Group

Assistant Professor: Dr. A. Doblas (adoblas@umassd.edu) Graduate Students in OIRL Group: B. Bogue-Jimenez, Undergraduate Students in OIRL Group: C. Joseph, O. Kramer.



EAFIT's Applied Optics Research Group

Associate Professor: Dr. C. Trujillo (catrujilla@eafit.edu.co) Assistant Professor: Dr. R. Castaneda (<u>racastaneq@eafit.edu.co</u>) Professors: R. Restrepo and E. Montilla.

Graduate Students: M. Lopera-Acosta, S. Obando-Vasquez and D. Pulgarín.

