Integrating Metadata for Enhanced Phytoplankton Classification:

A Comparative Study of Machine Learning Models

Ashley Nguyen, Christopher Kverne, Emily Hong, Ethan Feldman, Lorraine Yang
2025 Data Science in Oceanography

Motivation • *What are phytoplanktons?*

- Aquatic Microorganisms
- Between 3,444 and 4,375 species
- Use sunlight and carbon dioxide to produce food and release oxygen

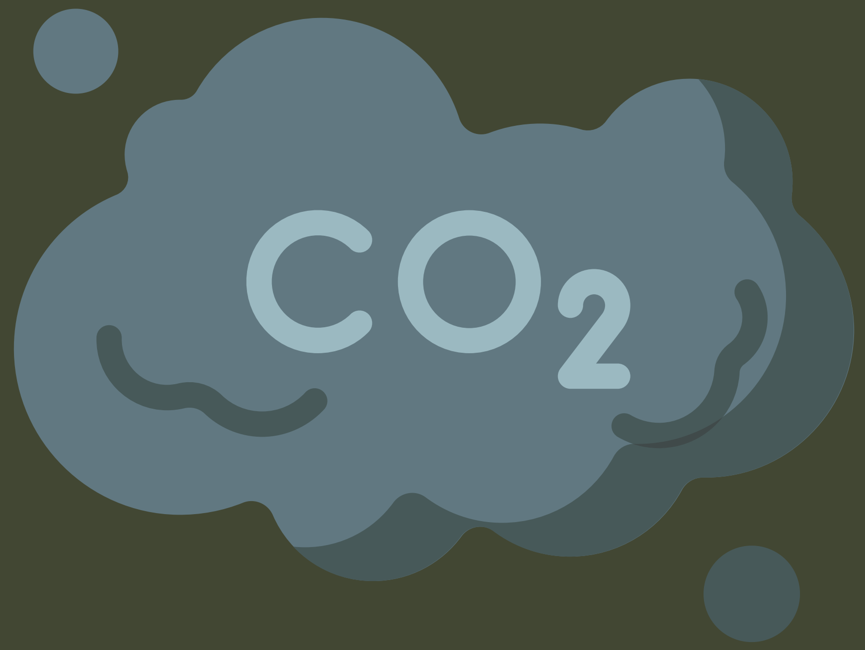
Motivation • *Why do we study phytoplanktons?*

Food Web Foundation

bottom of the marine food web

Climate Bio Sensors

used to determine ecological status (Racault et al. 2014; HELCOM 2021) + Harmful Algea Blooms



Carbon Regulation

contribute nearly half of Earth's carbon fixation (~ 50 Pg C yr−1; Falkowski 1994)

Literature Review • *an active field of research*

AI facilitated fluoro-electrochemical phytoplankton classification†

Check for updates

Haotian Chen, ‡[a] Samuel Barton, ‡[b] Minjun Yang, [a] Rosalind E. M. Rickaby, [b] Heather A. Bouman [b] and Richard G. Compton *[a]

RESEARCH ARTICLE | AUGUST 04 2020

Deep learning for plankton and coral classification

Alessandra Lumini; Loris Nanni; Gianluca Maguolo

+ Author & Article Information

Article | Open access | Published: 22 July 2020

Annotation-free learning of plankton for classification and anomaly detection

Vito P. Pastore, Thomas G. Zimmerman, Sujoy K. Biswas & Simone Bianco

Scientific Reports 10, Article number: 12142 (2020) | Cite this article

Current Evidence | Open Access

Deep-learning-powered data analysis in plankton ecology

Harshith Bachimanchi, Matthew I. M. Pinder, Chloé Robert, Pierre De Wit, Jonathan Havenhand, Alexandra Kinnby, Daniel Midtvedt, Erik Selander, Giovanni Volpe

First published: 18 April 2024 | https://doi.org/10.1002/lol2.10392 | Citations: 7

RAPID: real-time automated plankton identification dashboard using Edge AI at sea

Convolutional neural networks and vision transformers for Plankton Classification

Loris Nanni [a], Alessandra Lumini [b], Leonardo Barcellona [a], Stefano Ghidoni [a]

Show more

Objectives

1. Compare performances between neural network architectures for plankton classification to determine model efficiencies.

2. Determine whether addition of environmental parameters (e.g. temperature, salinity, etc) will improve classification accuracies.

Methodology • *Data Collection*

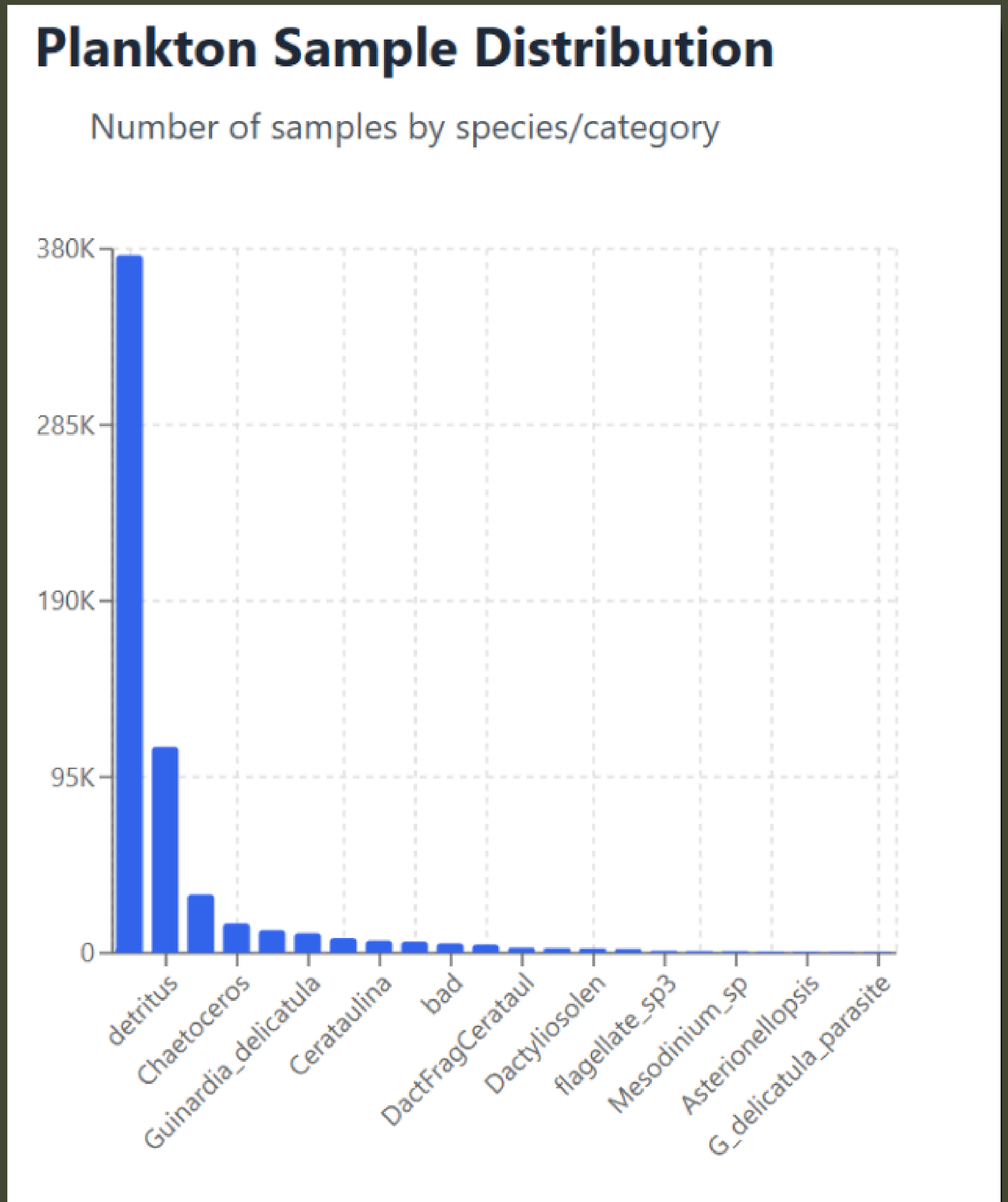
Phytoplankton Images

WOODS HOLE OCEANOGRAPHIC INSTITUTION®

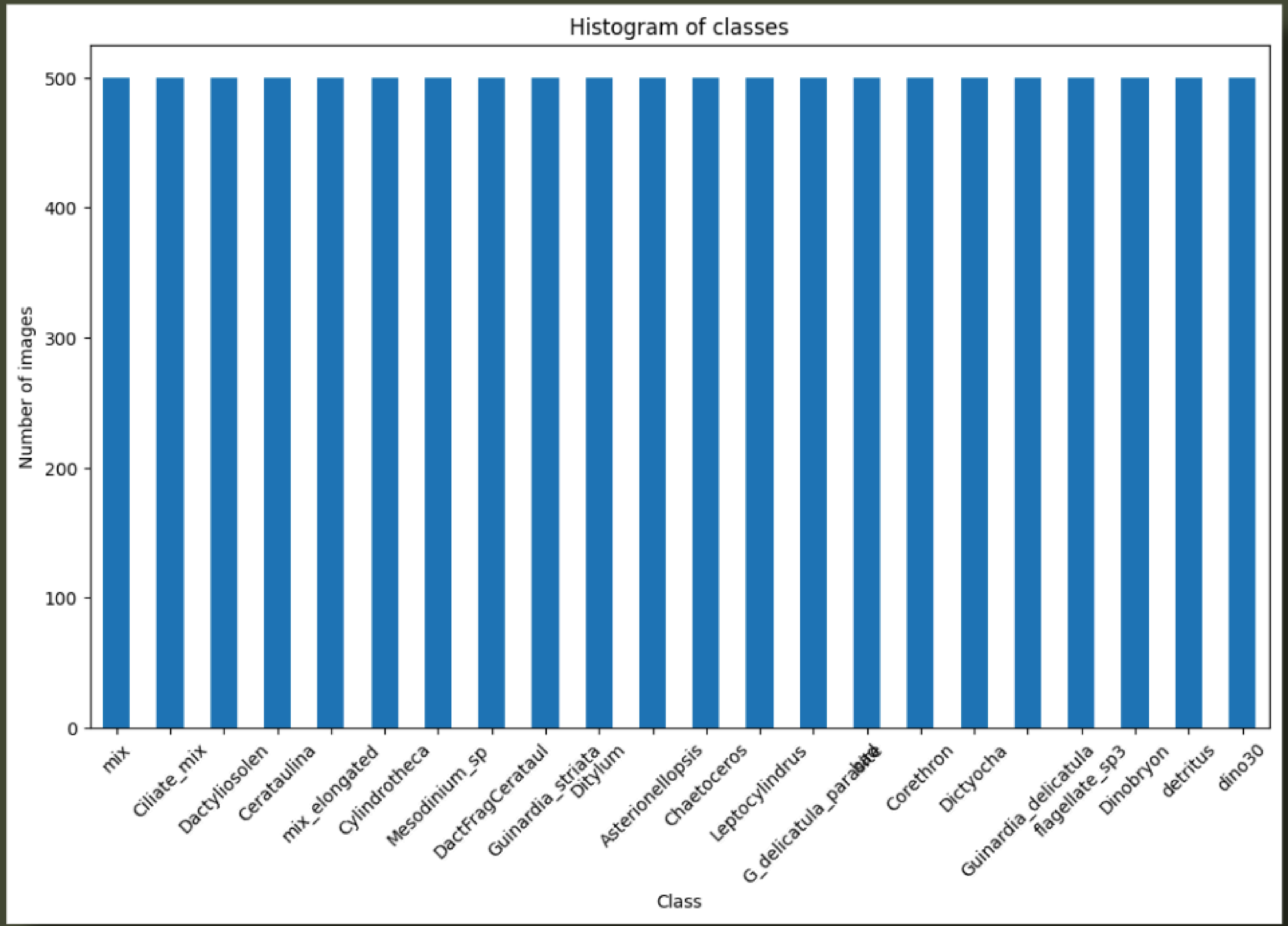
- 3.5 million images of marine plankton
- 103 categories
- Time: 2006-2014

1. Literature review
2. **Data collection & processing**
3. Exploratory data analysis
4. Model training
5. Metadata Integration

Methodology • *Data Cleaning Process*



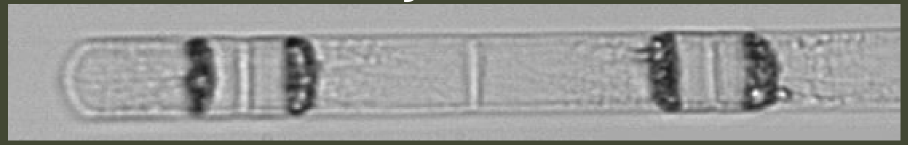
→



Dates	**# of Classes**	**# of Images Per Class**	**Total Images**
2007, 2013, 2014	17 (22-5)	500	10,500

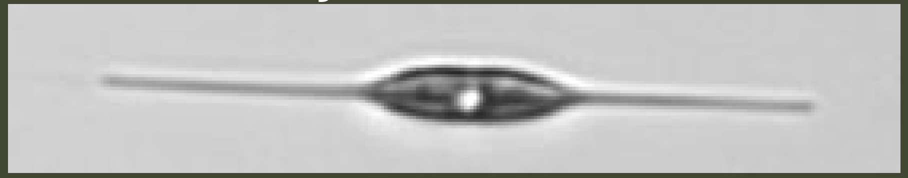
Data • *Meet the Phytoplankton Species*

Dactyliosolen

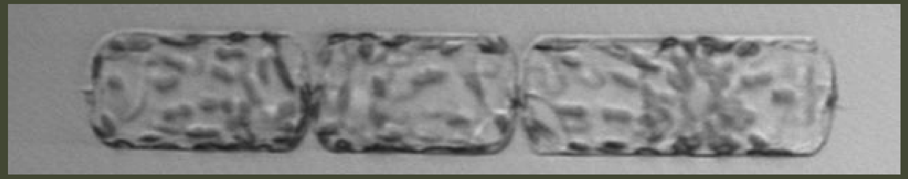


Cerataulina

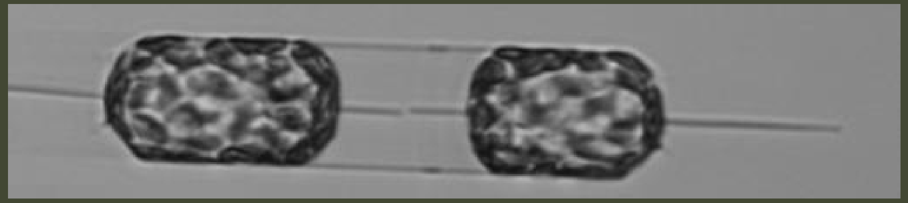
Cylindrotheca



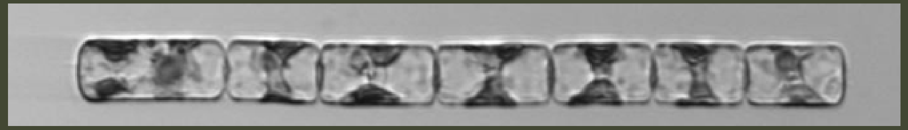
DactFragCerataul



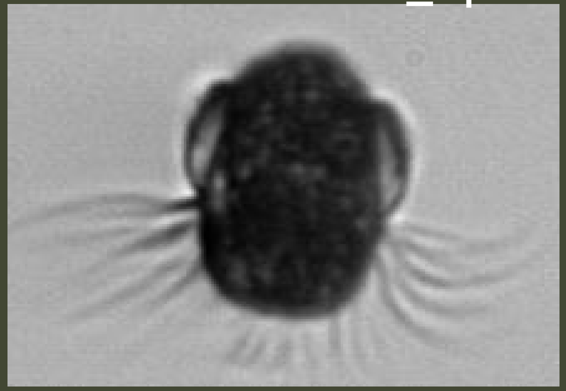
Ditylum



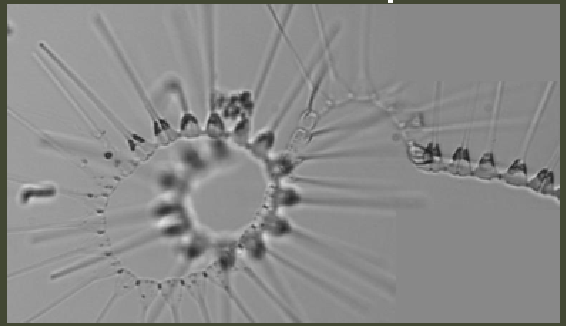
Guinardia_delicatula



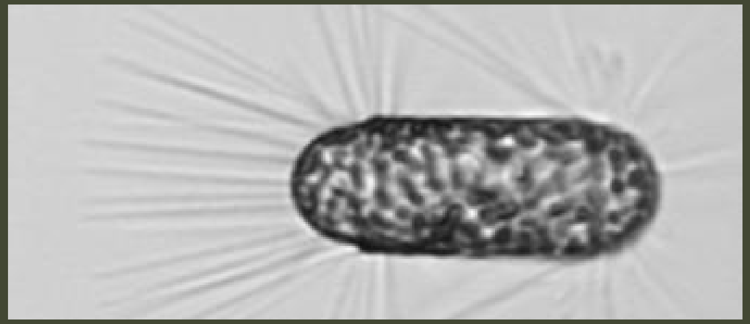
mesodinium_sp



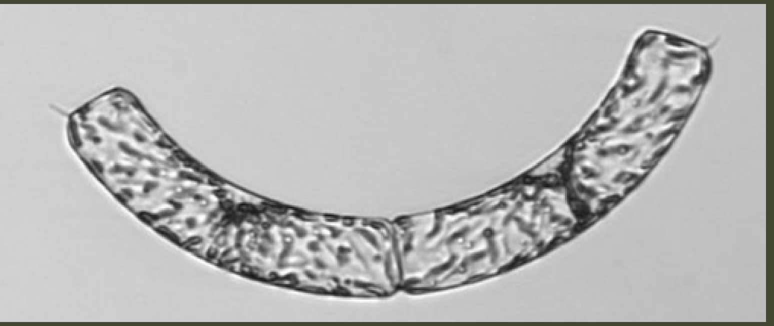
Asterionellopsis



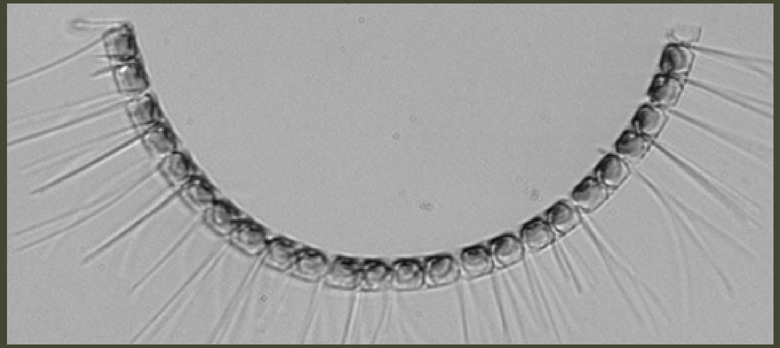
Corethron



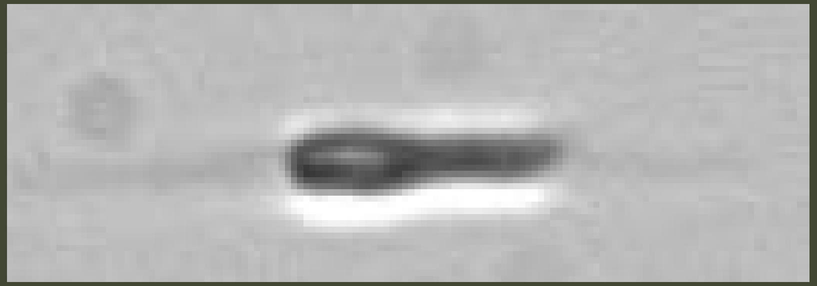
Guinardia_striata



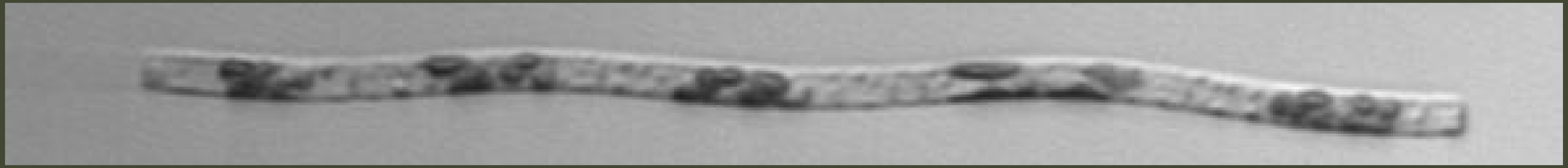
Chaetoceros



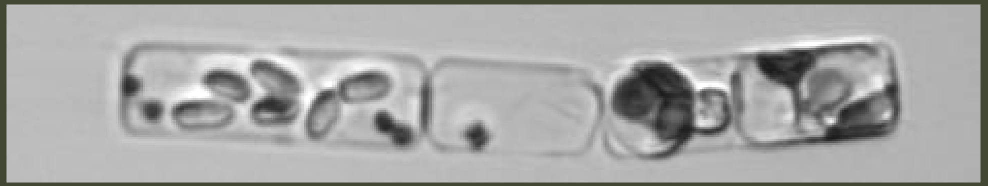
flagellate_sp3



Leptocylindrus

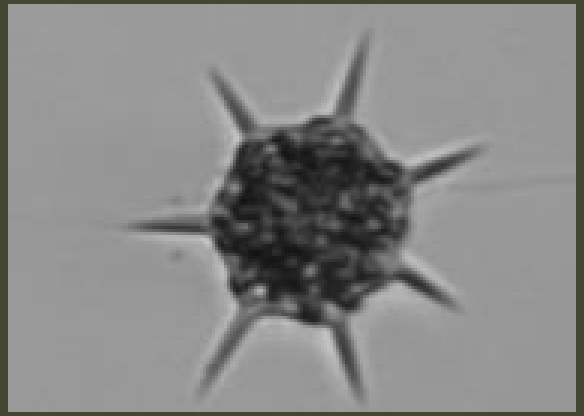


G_delicatula_parasite

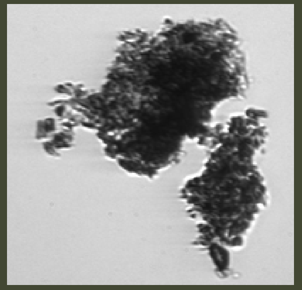


dino30

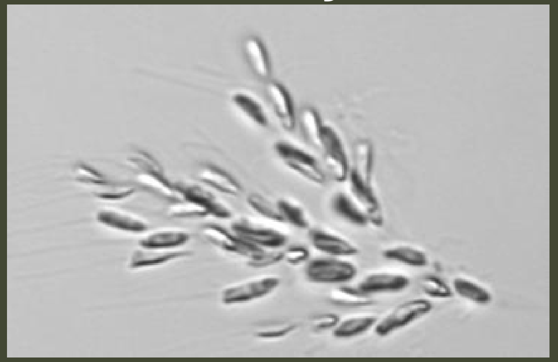
Dictyocha



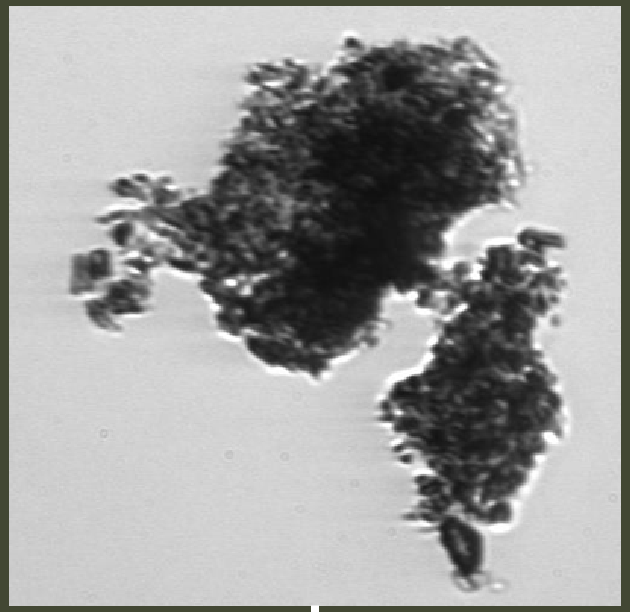
detritus

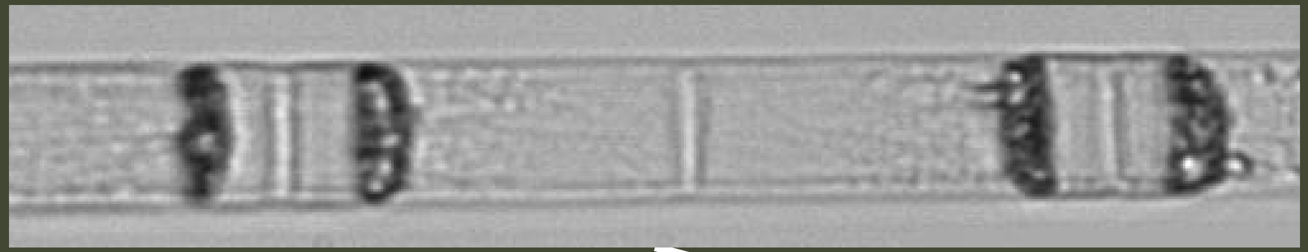


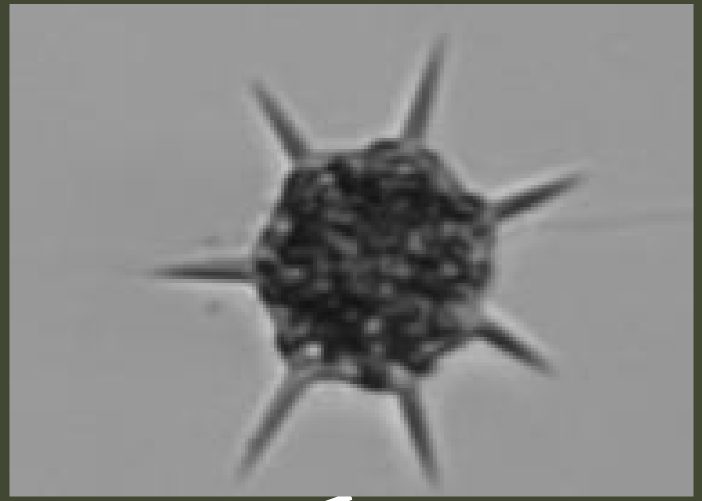
Dinobryon



Methodology • *Data Cleaning Process*







Compression

[1,64, 64]

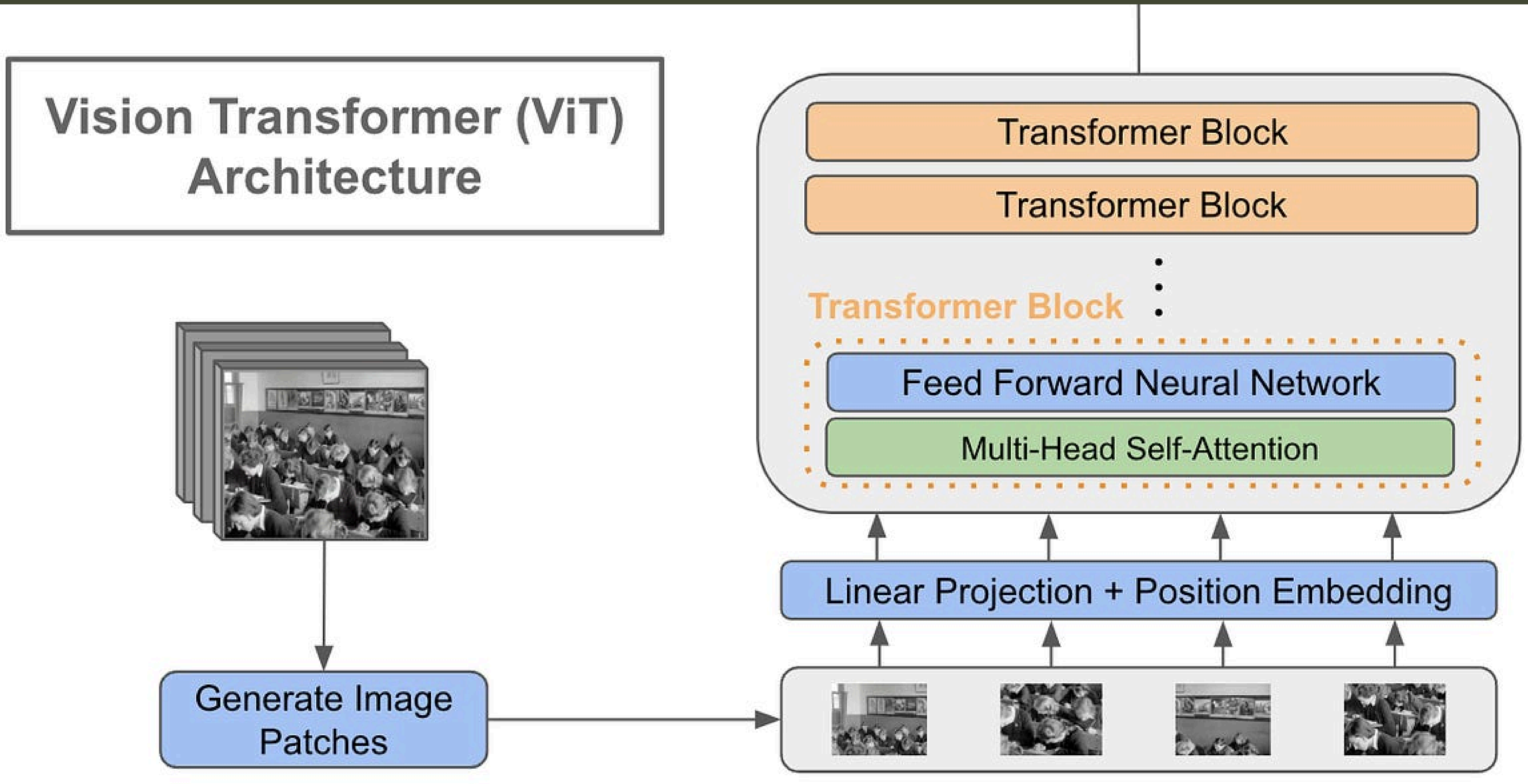
Modeling • *7 NN Architectures*

	Name	Function
From Scratch	**Multilayer Perceptron**	Fully connected feedforward neural network that maps inputs to outputs though hidden layers.
	Vision Transformer	Transformer-based model that treats images as sequences of patches and applies self-attention to capture global context.
	CNN	Image-specialized network that uses convolutional layers to learn hierarchical spatial features.
Pre-trained	**ResNet50**	50-layer CNN that uses residual skip connections to enable deep networks without vanishing gradients.
	ResNeXt	ResNet variant that improves efficency and accuracy by using grouped convolutions.
	DenseNet121	Layer connected to every other layer in a feed-forward fashion, with a focus on accuracy and feature reuse.
	MobileNetV2	Optimized for mobile devices using depthwise separable convolutions and inverted residuals with fewer parameters.

Modeling • *Training and Fine-Tuning*

	Models	Method
From Scratch	Multilayer Perceptron Vision Transformer CNN	• Removed “bad”, “detritus”, “parasite”, and “mixed” classes
Pre-trained	ResNet50 ResNeXt DenseNet121 MobileNetV2	• Removed “bad”, “detritus”, “parasite”, and “mixed” classes • Altered batch size, epochs, lower learning rate, • Unfroze the last 30 layers, earlier stop, and data augmentation

VISION TRANSFORMER



One Step Further • *Metadata*

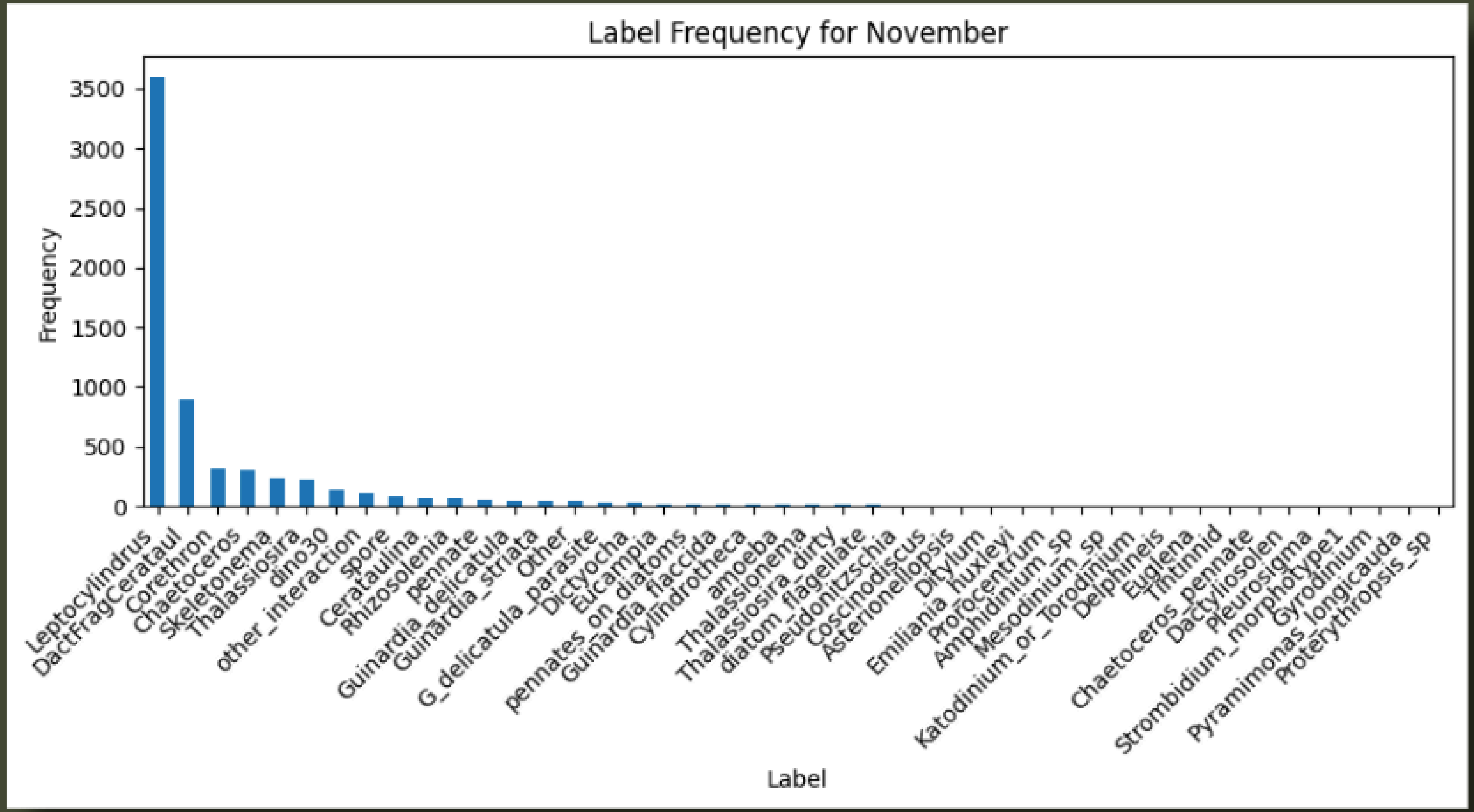
Remember Martha's Vineyard?

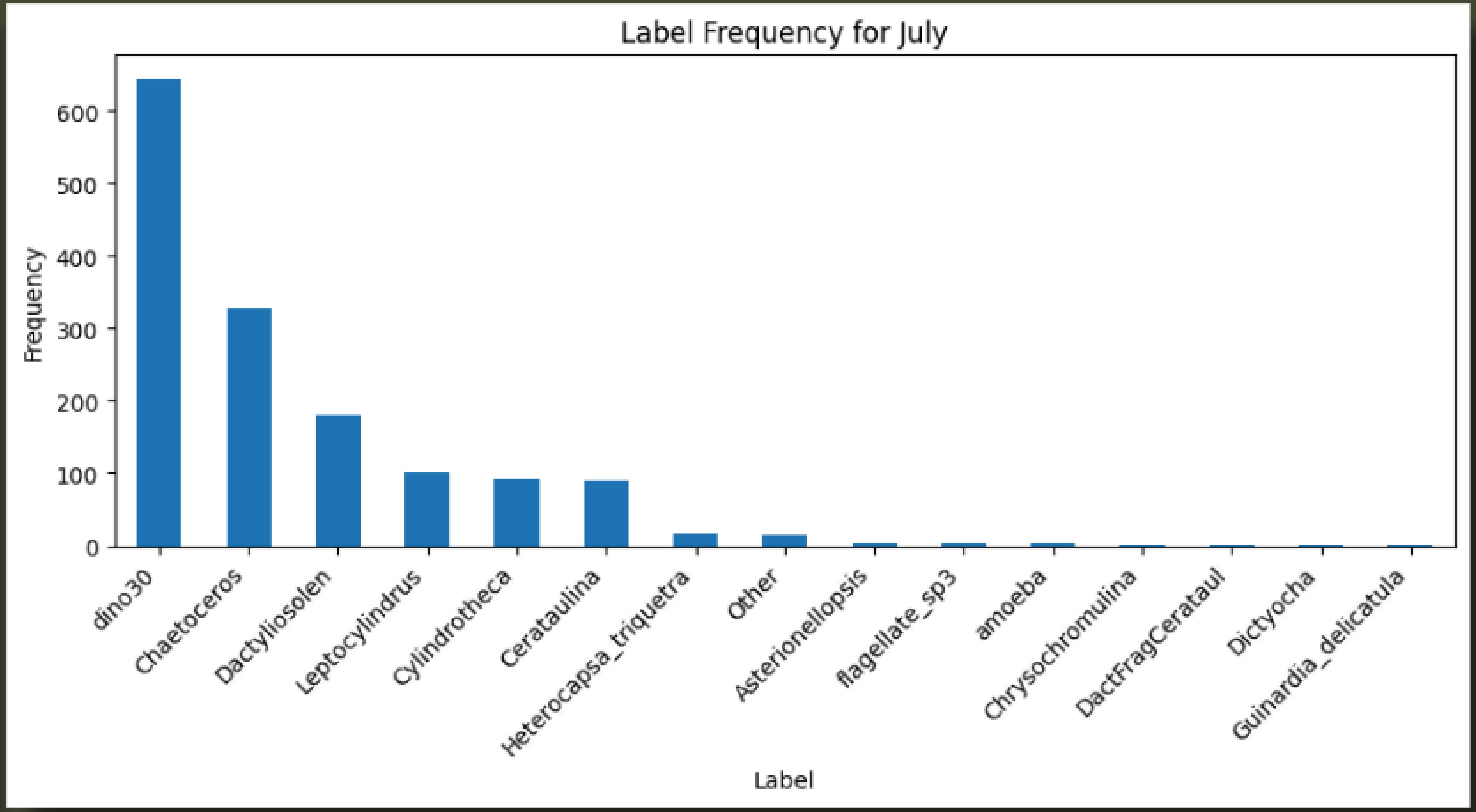
Imaging FlowCytobot (IFCB)

It collects more than just plankton pictures!

→ also temperature, salinity, time of year, etc....

One Step Further • *Metadata*

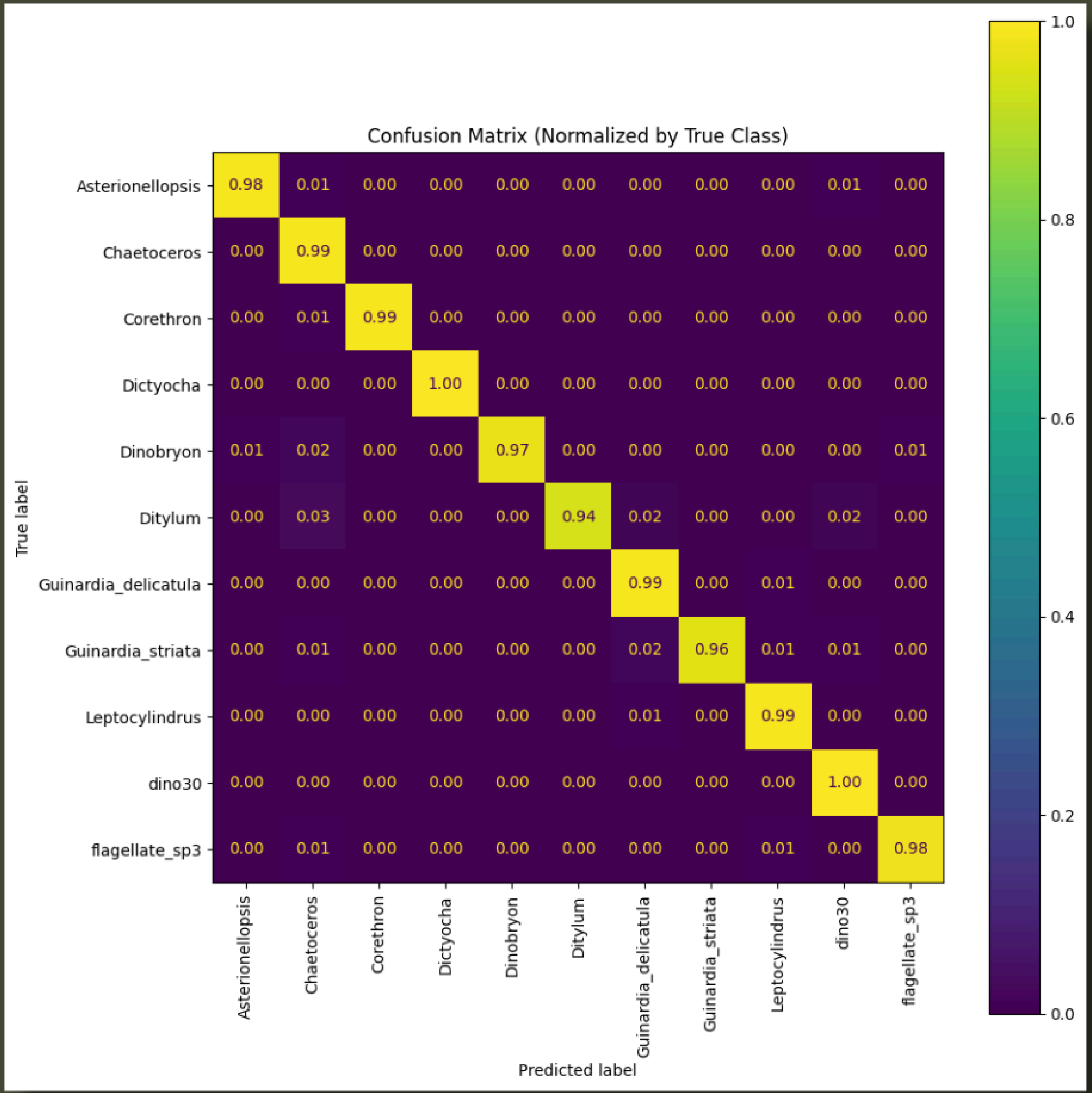




Seasonal variation of data

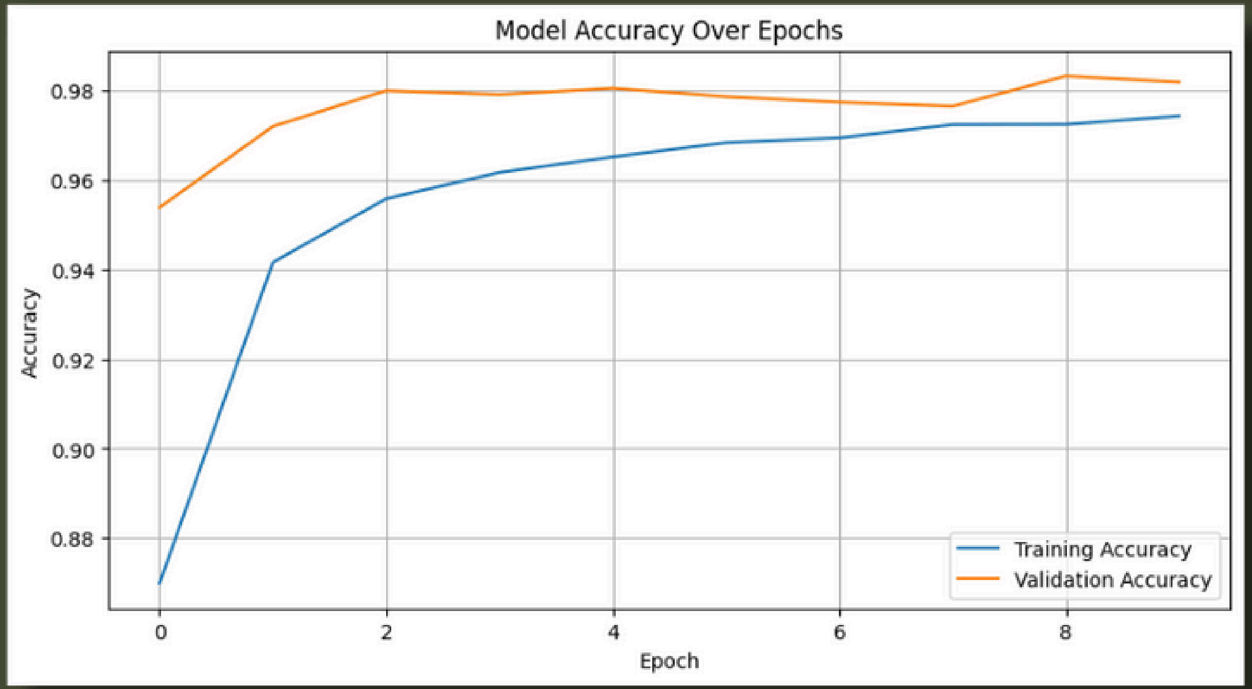
Results • *Metadata*

accuracy: **0.9915** loss: **0.0157** val_accuracy: **0.9894** val_loss: **0.0371**

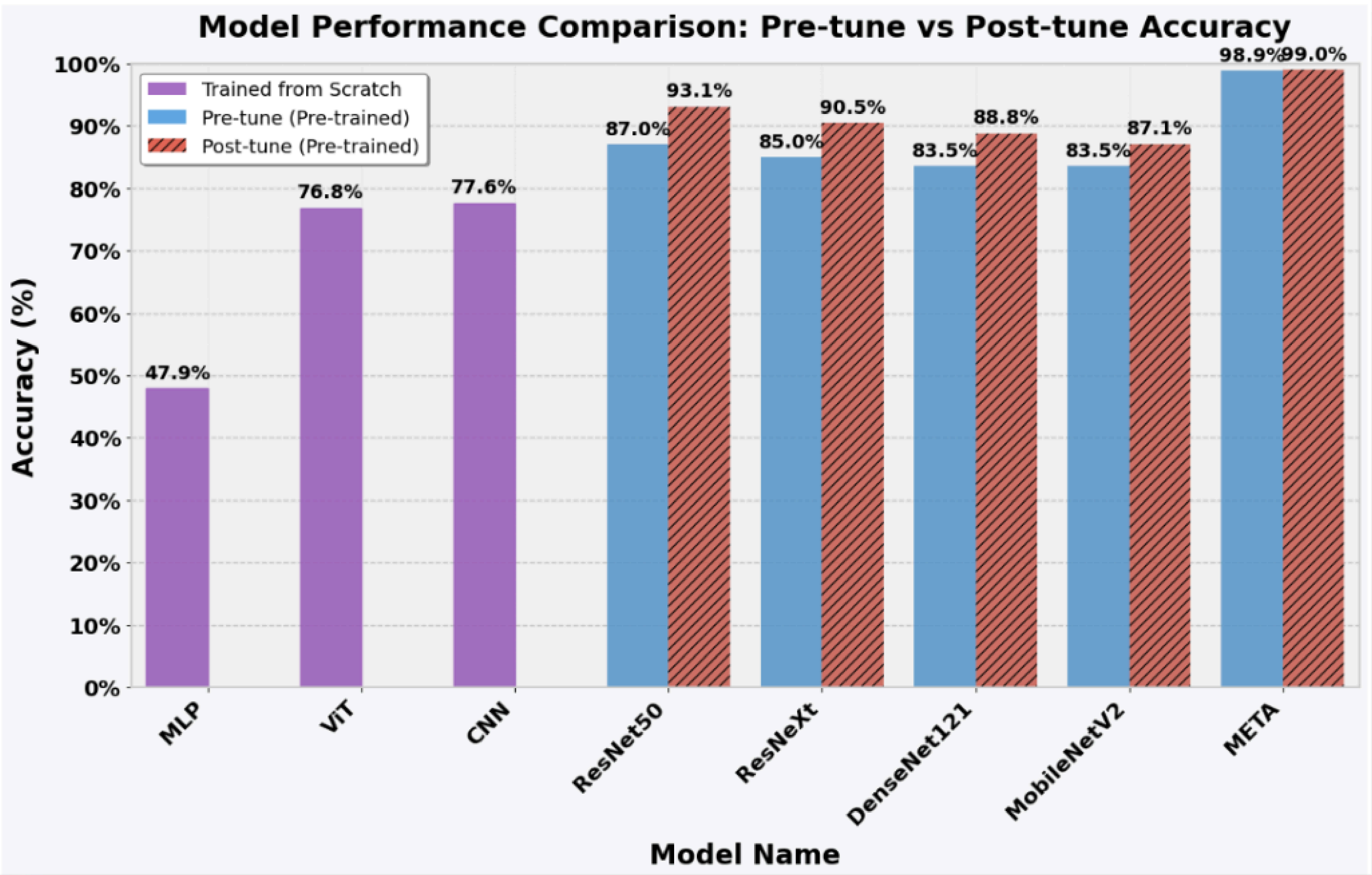


Classification report:

	precision	recall	f1-score	support
Asterionellopsis	0.94	0.98	0.96	132
Chaetoceros	0.99	0.99	0.99	2050
Corethron	0.99	0.99	0.99	228
Dictyocha	1.00	1.00	1.00	33
Dinobryon	0.98	0.97	0.97	199
Ditylum	0.98	0.94	0.96	65
Guinardia_delicatula	0.97	0.99	0.98	760
Guinardia_striata	0.97	0.96	0.96	119
Leptocylindrus	1.00	0.99	0.99	3150
dino30	0.99	1.00	1.00	1950
flagellate_sp3	0.98	0.98	0.98	226
accuracy			0.99	8912
macro avg	0.98	0.98	0.98	8912
weighted avg	0.99	0.99	0.99	8912

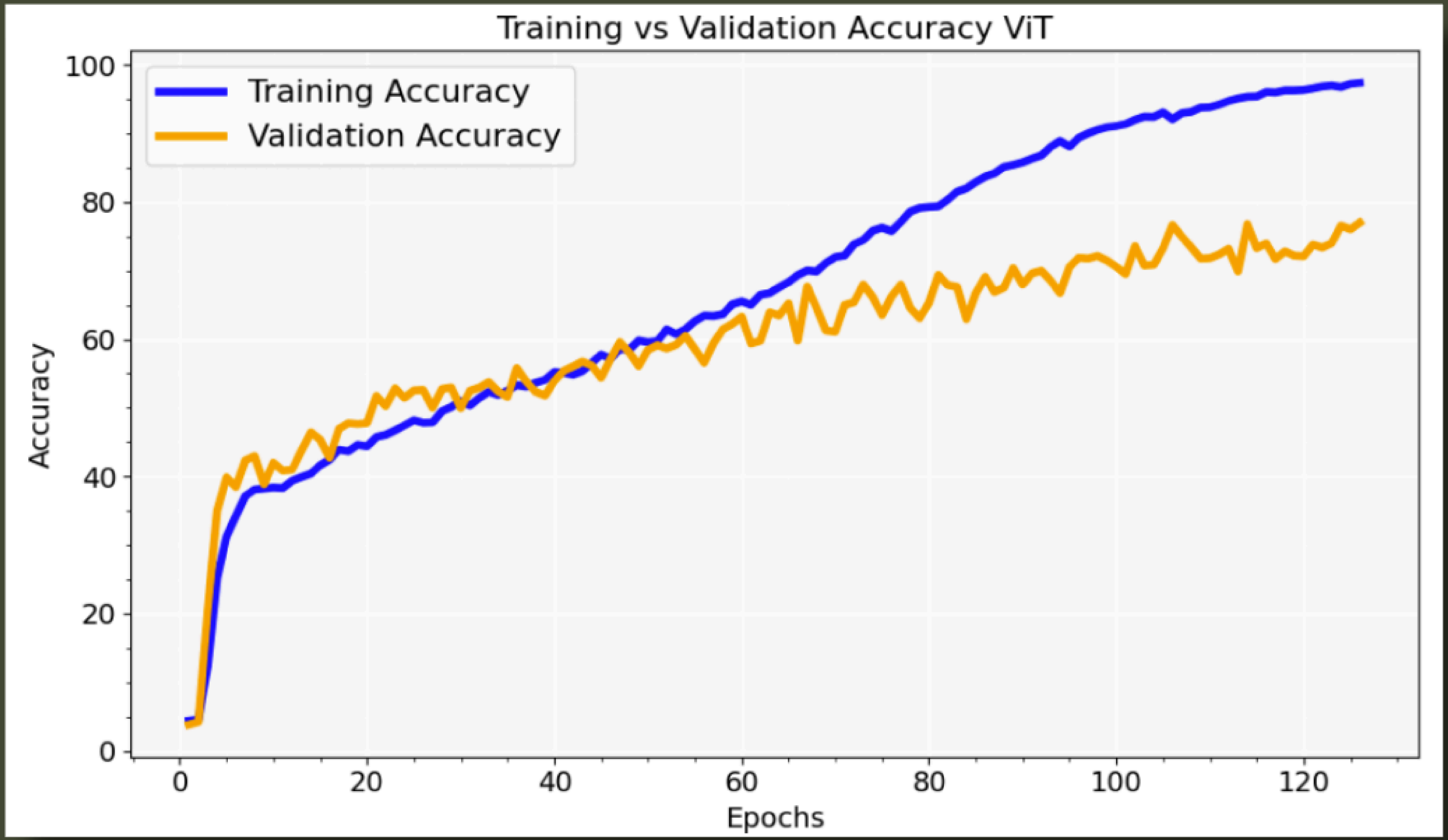


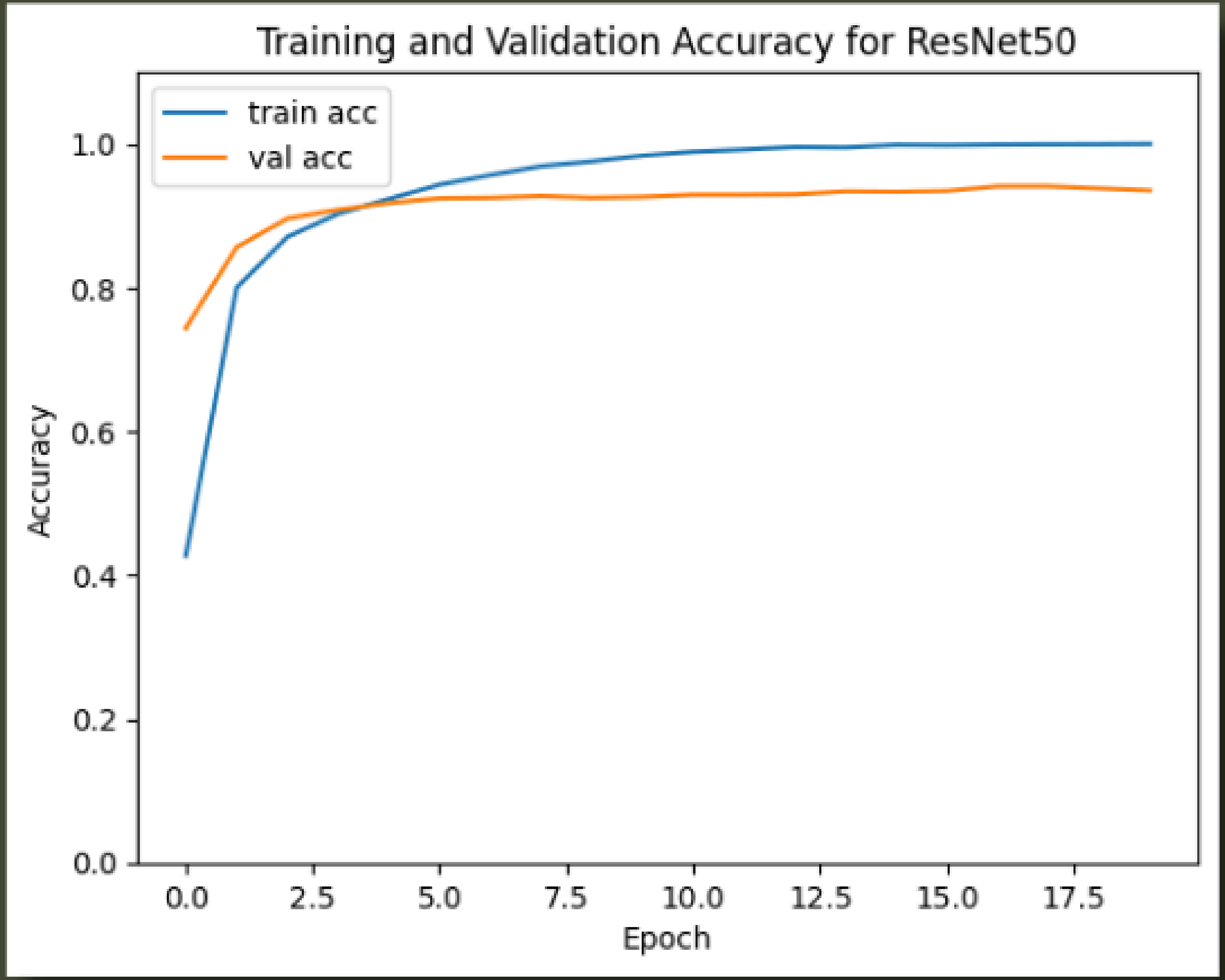
Results • *All Models*



Discussion • *Pre-train v.s. From Scratch*

Why do pre-trained models perform better than our models trained from scratch?





Conclusion

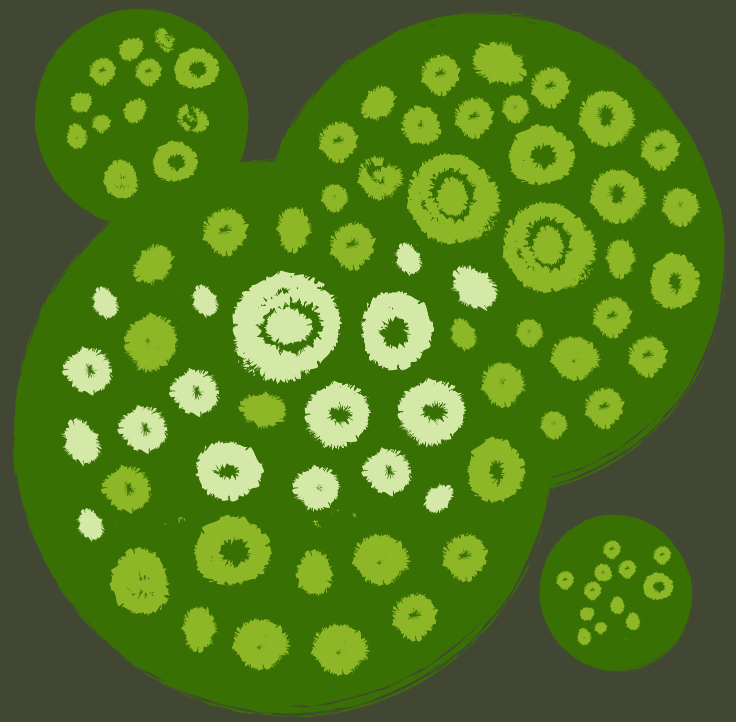
✅ Compare performances between neural network architectures for plankton classification to determine model efficiencies.
--> Pre-trained outperformed from scratch models

✅ Determine whether addition of environmental parameters (e.g. temperature, salinity, etc) will improve classification accuracies.
--> Yes, it did!

Limitations and Future Steps

Limitations:

- Downloading data = time-intensive
- Unfamiliar species with limited images

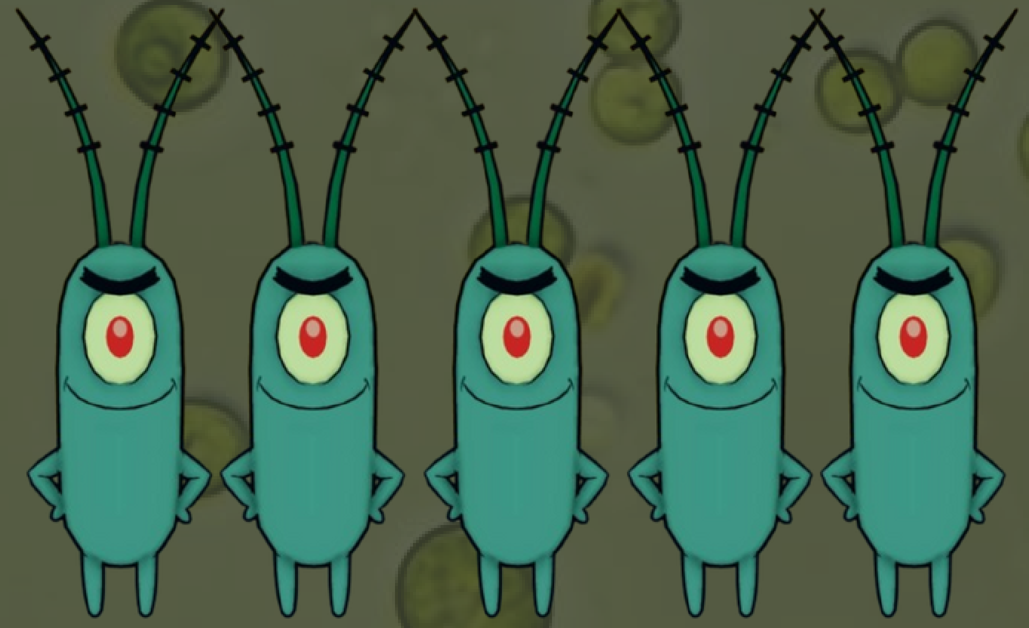


Future Steps:

- Consider the Family or Genus class to broaden classification for other dataset
- Unsupervised approach (k-means fuzzy)
- Increase data samples to improve species diversity

Thank you!

we hope you learned something new



Citations

Nanni, et al. “Convolutional neural networks and vision transformers for Plankton Classification”, 2025, https://www.sciencedirect.com/science/article/pii/S157495412500281X

Alageshan, J. K., A. K. Verma, J. Bec, and R. Pandit. 2020. Machine learning strategies for path-planning microswimmers in turbulent flows. Phys Rev E 101: 43110. doi:10.1103/PhysRevE.101.043110

Pastore, V.P., Zimmerman, T.G., Biswas, S.K. et al. Annotation-free learning of plankton for classification and anomaly detection. Sci Rep 10, 12142 (2020). https://doi.org/10.1038/s41598-020-68662-3

Alessandra Lumini, Loris Nanni, Gianluca Maguolo; Deep learning for plankton and coral classification. *Applied Computing and Informatics* 9 June 2023; 19 (3-4): 265–283. https://doi.org/10.1016/j.aci.2019.11.004