Camera-Trap Species Recognition Over Time: An Online Continual Learning Benchmark and Analysis

Real-World ML-Ready Benchmark

PhD Applicant for AU 2026

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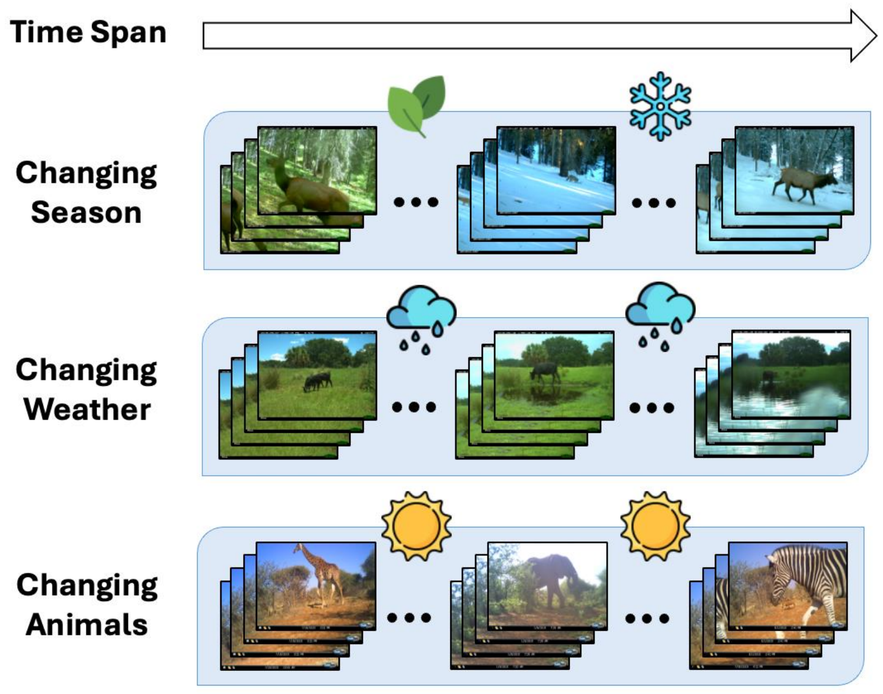
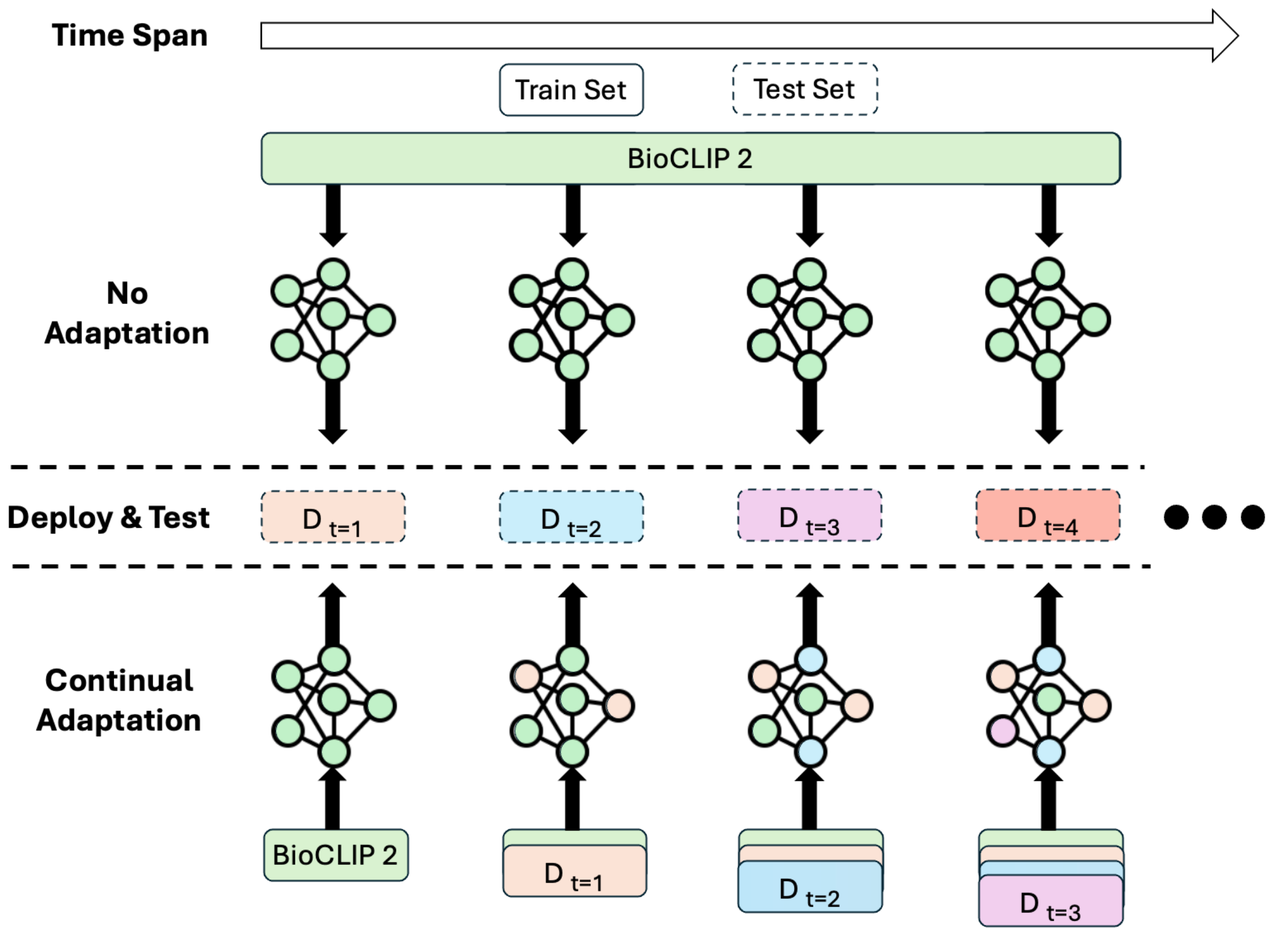
Motivation



- Camera traps change continuously over time (season, weather, species).
- Such non-stationary shifts make continual learning necessary.
- We provide **a unified ML-ready benchmark** to study this real-world continual setting.

Setup - Online Continual Learning

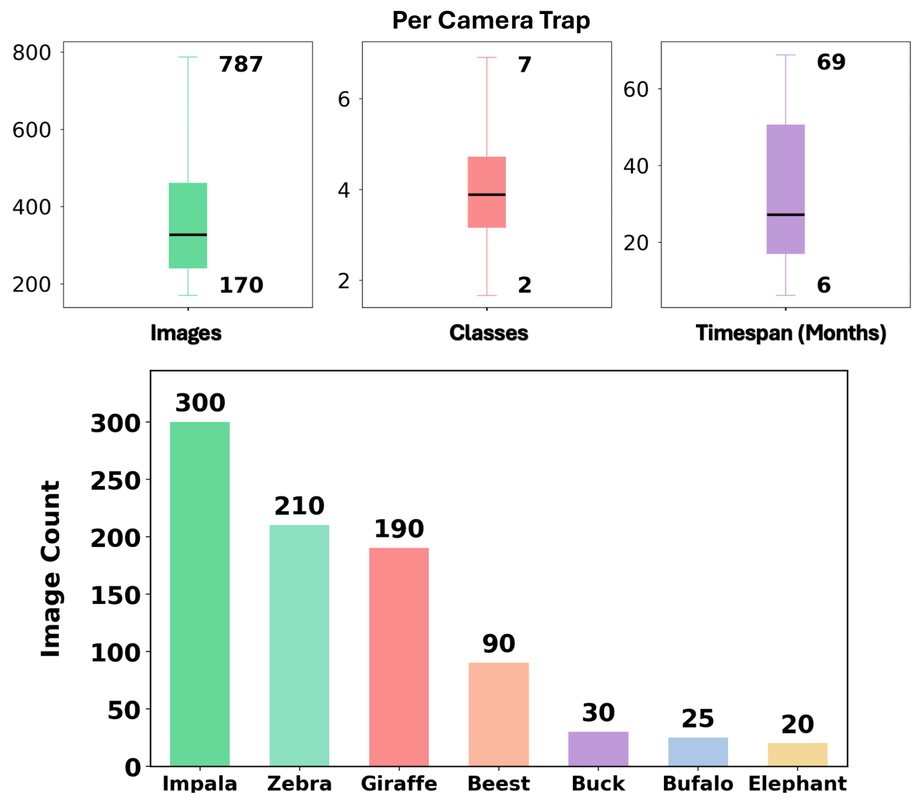


- **Real-world online continual learning setting** for a camera trap.
- **Train the current** month's data and **test with the next** month's data.

Benchmark Statistics

Benchmark Overview

Camera Traps	546
Continents	4
Images	3.32M
Classes	162

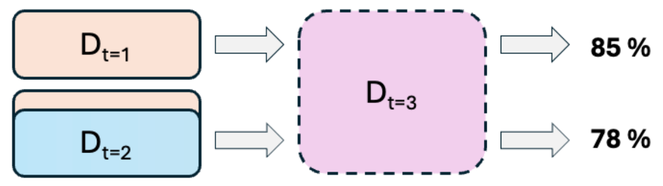


When Should We Adapt?

Do We Need to Continuously Adapt?

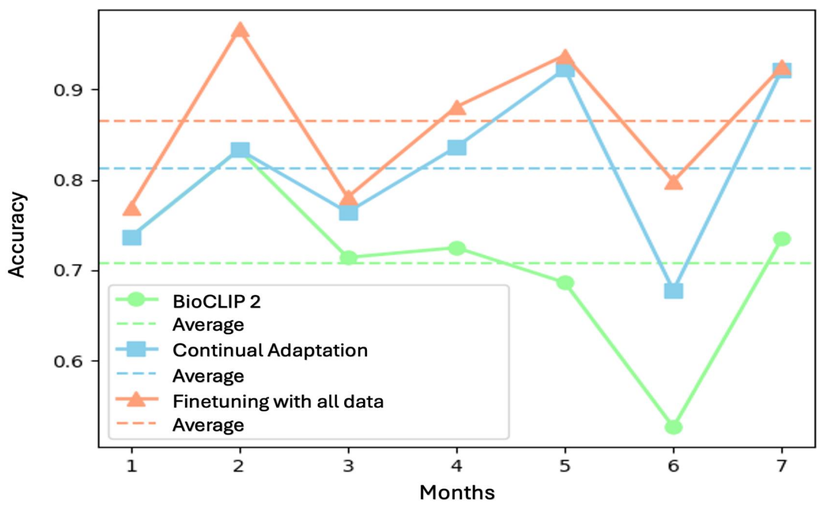
Adapted Months	0%	33%	66%	100%
Accuracy	73.1%	77.6%	79.7%	80.3%

Do We Need to Continuously Adapt **Every Month**?

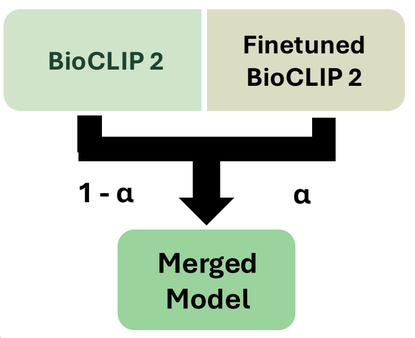


Continual Adaptation is Even Harder

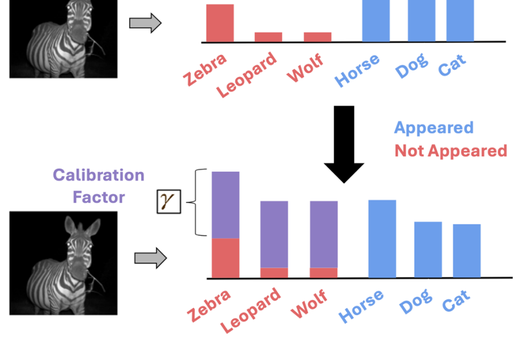
- Continual adaptation **may not work** every month!
- Techniques like **post-hoc methods** can be a solution.



Weight Interpolation (Model Merging)



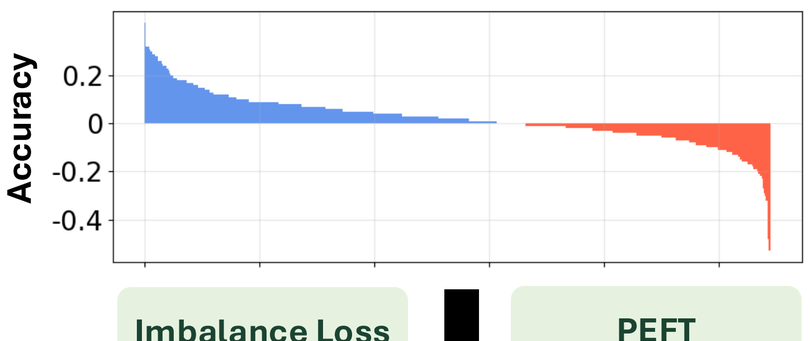
Logit Calibration



Naive Finetuning is Not Enough to Adapt

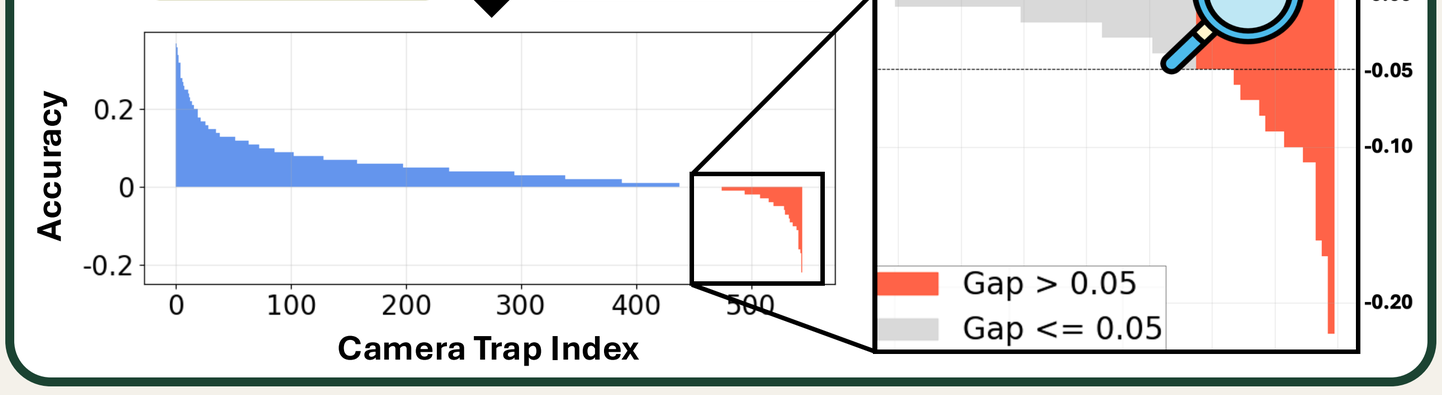
- Naive finetuning with **all data** may not be enough!
- Techniques like **imbalance loss** and **PEFT** can be a solution.

Finetuned BioCLIP 2 – BioCLIP 2



Poor Quality Images!

Imbalance Loss	PEFT
BSM	LoRA



Open Questions

- **Better imbalance loss or PEFT for stable adaptation?**
- **How to auto-select the best α or calibration factor?**
- **How often should a model adapt over time?**

Acknowledgement

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