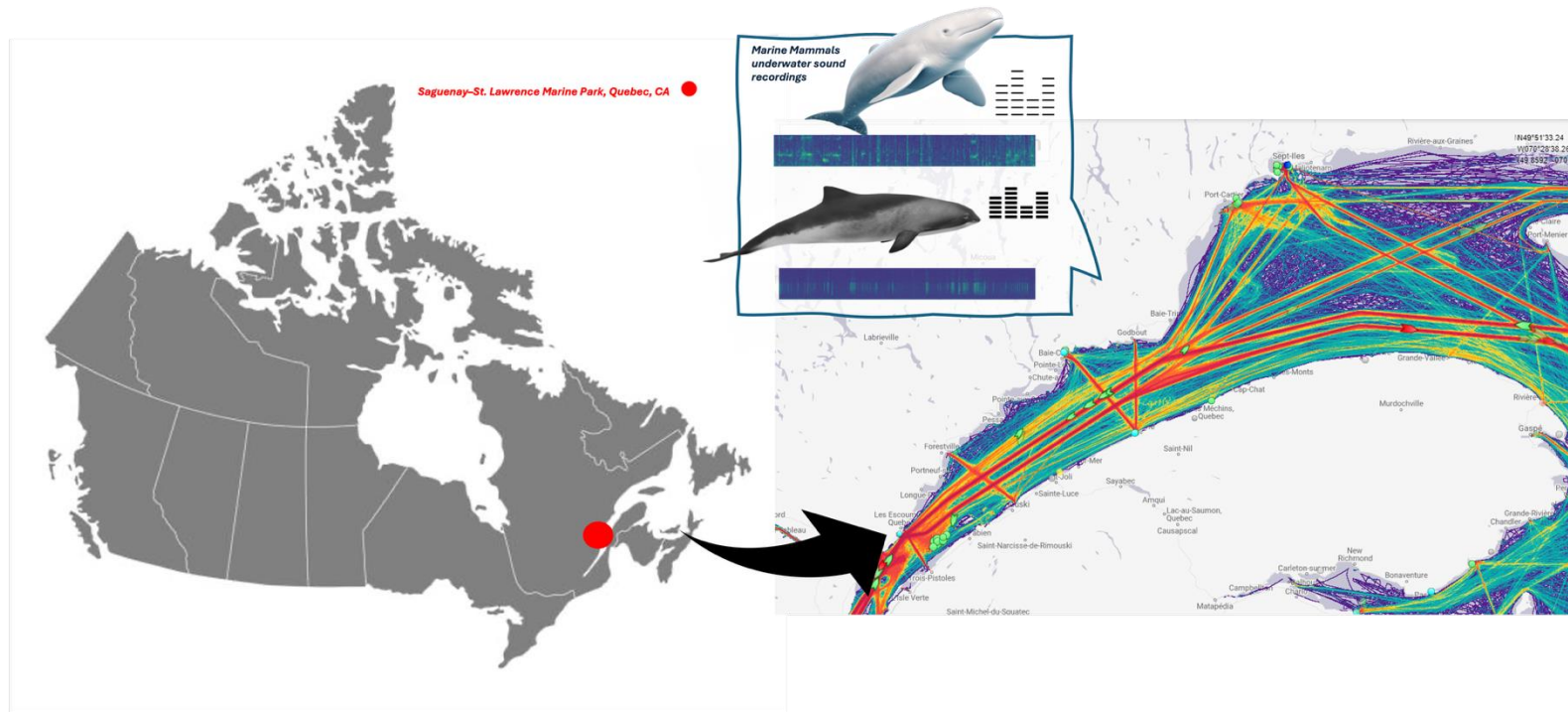


Bioacoustic Multi-Step Attention : Underwater Ecosystem Monitoring in Climate Change Context

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General context



St. Lawrence Estuary: a unique and ecologically sensitive region. One of the world's largest navigable waterways.

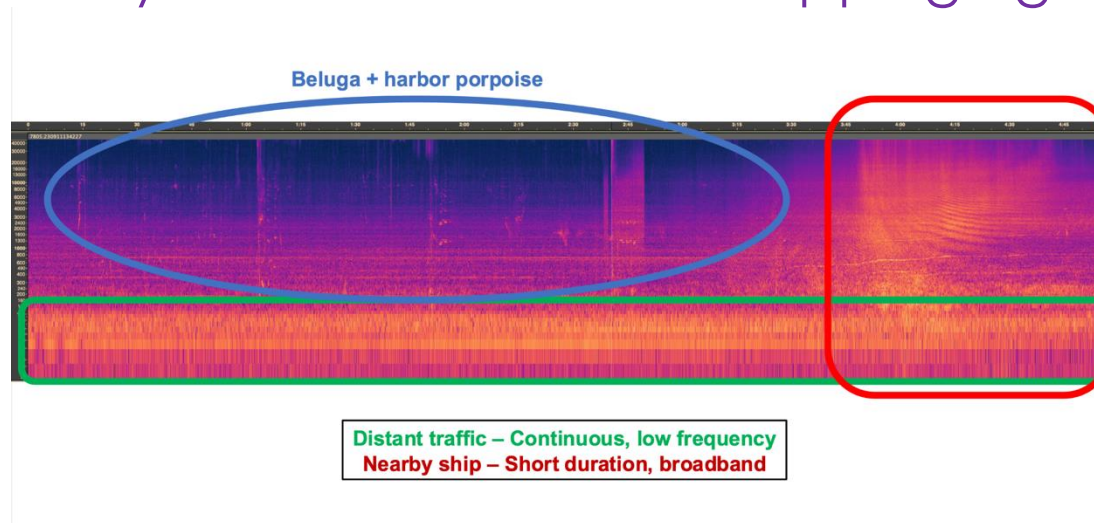
Increasing pressures:

- Shipping traffic $\Rightarrow$ acoustic pollution
- Climate change $\Rightarrow$ altered soundscapes and species distribution

Problem Statement and Objectives

In addition to being a high-traffic area, St. Lawrence Estuary is critical acoustic habitat for marine mammals

- Main challenges: Noisy conditions and overlapping signals



- General objective:
Automatically detect and classify marine mammal vocalizations in noisy, multi-species recordings (Porpoise and Beluga Clicks, Whistles)

Problem Statement and Objectives

The available data comes from hydrophone networks that continuously record underwater soundscapes.

Dataset: Exclusive subset of the SSLMP monitoring program

- ~1,500 h passive acoustic monitoring (hydrophones)
 - ~ 500 h shore-based visual surveys
 - ~10,000 annotated 5-min segments (Beluga, Harbour Porpoise)
 - Frequency range: 10 Hz – 150 kHz (whistles, clicks, vessel noise)
-
- **multi-label setup** (Whistle, Beluga Click, Porpoise Click) 
 - **multi-class** by encoding all label combinations ($2^3 = 8$ categories)

Problem Statement and Objectives

- In order to study mammals, we must first **establish a reliable methodology for detecting them.**
- End-to-end multi-step framework combining spectrograms + pseudo attention masks

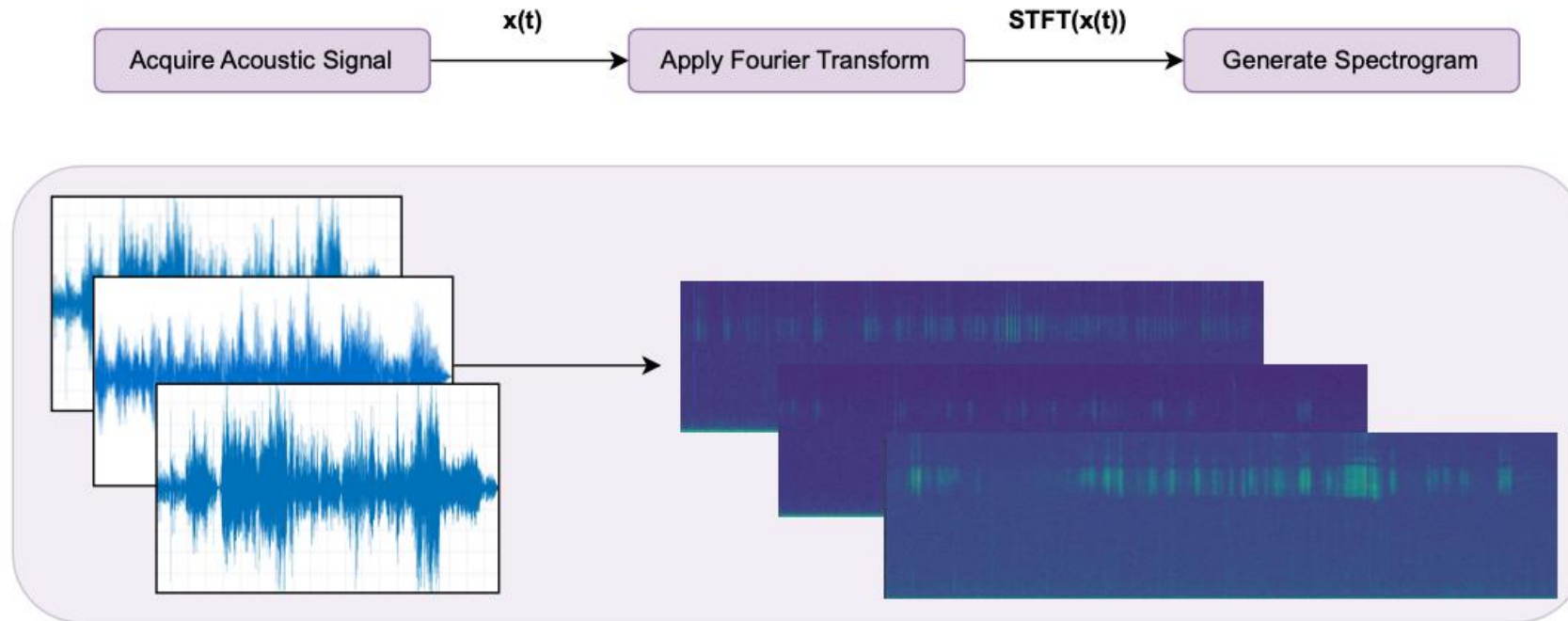
Problem Setup:

$$\hat{y} = \mathcal{C}\left(\text{Fuse}\left(\mathcal{E}_{\text{spec}}(\mathcal{T}(x(t))), \mathcal{E}_{\text{mask}}(\mathcal{M}_{\text{seg}}(\mathcal{T}(x(t))))\right)\right), \quad \hat{y} \in \mathbb{R}^K$$

where $\mathcal{T}$ is the STFT, $\mathcal{E}_{\text{spec}}$ and $\mathcal{E}_{\text{mask}}$ are the embedding functions for the spectrogram and mask, respectively, and $\text{Fuse}(\cdot, \cdot)$ denotes the mid-level embedding fusion. $\mathcal{M}_{\text{seg}}$ a segmentation model and $\mathcal{C}$ a classifier. [▶ see](#)

Framework description

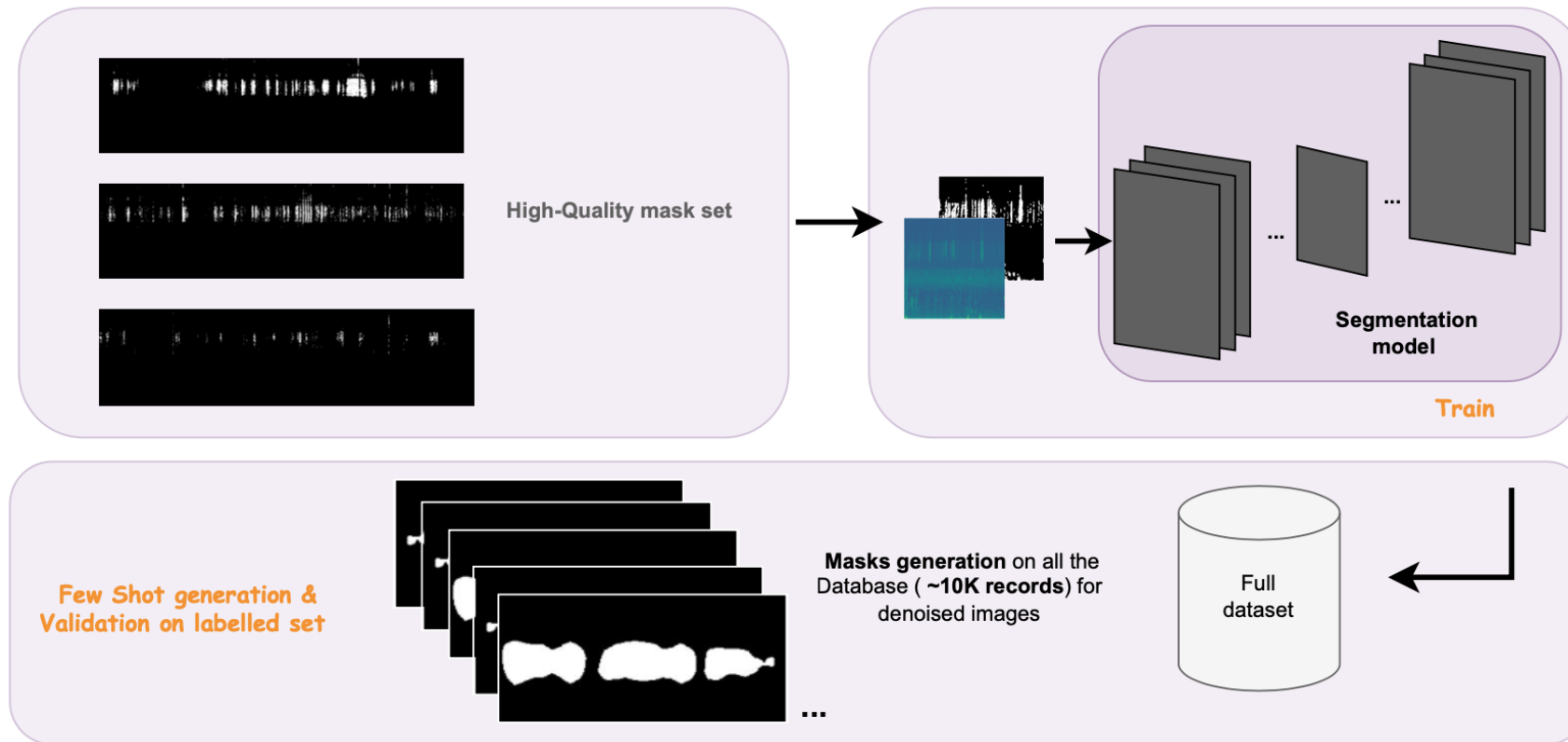
Time–frequency representation of raw acoustic signals



STEP 1 : From audio to spectrogram representation

Framework description

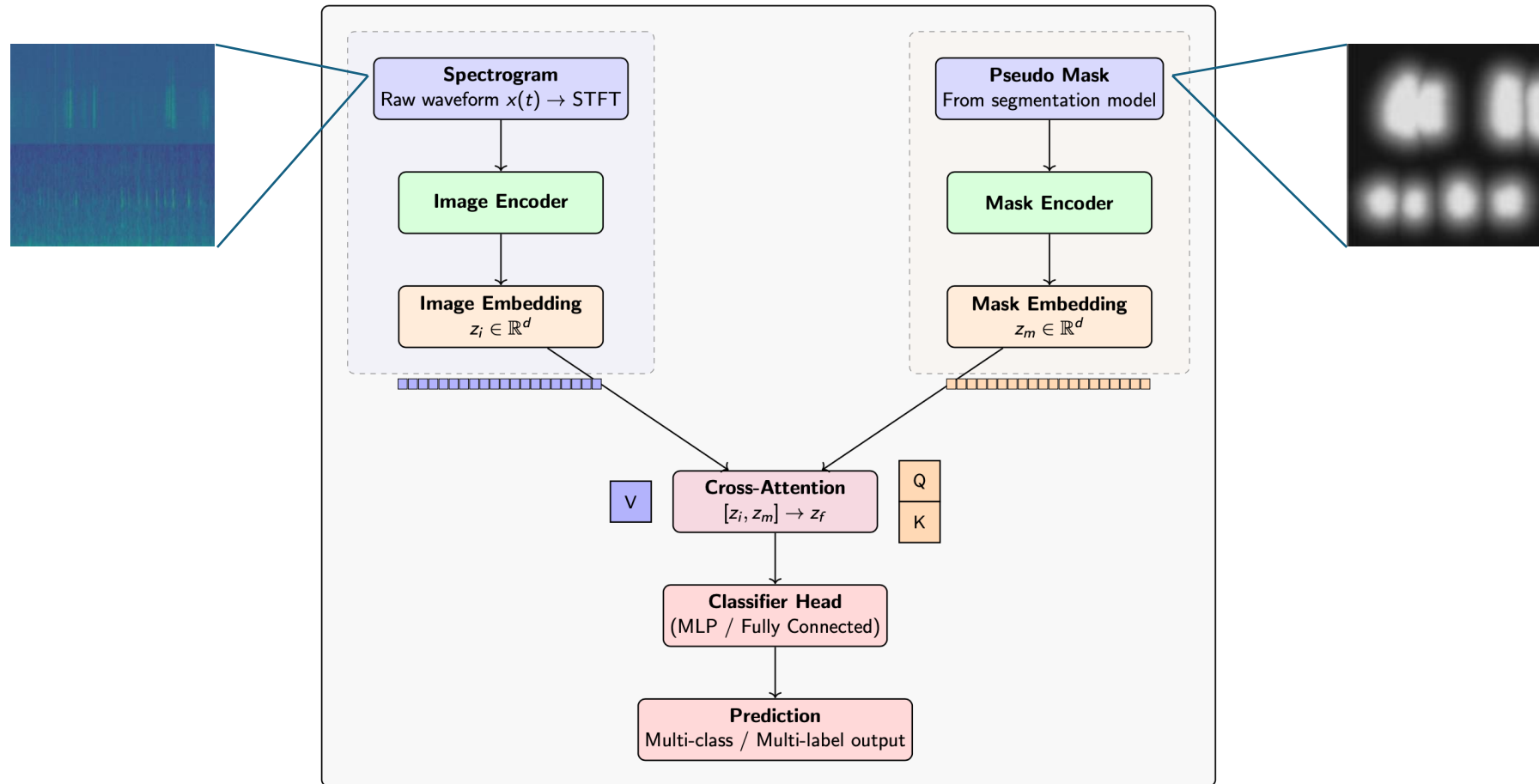
Few-shot learning strategy for segmenting vocalization regions of interest



STEP 2 : Generation of the masks

Framework description

Fusing spectrograms with generated masks to enrich signal representation



STEP 3 : Cross Attention Fusion and classification

Results

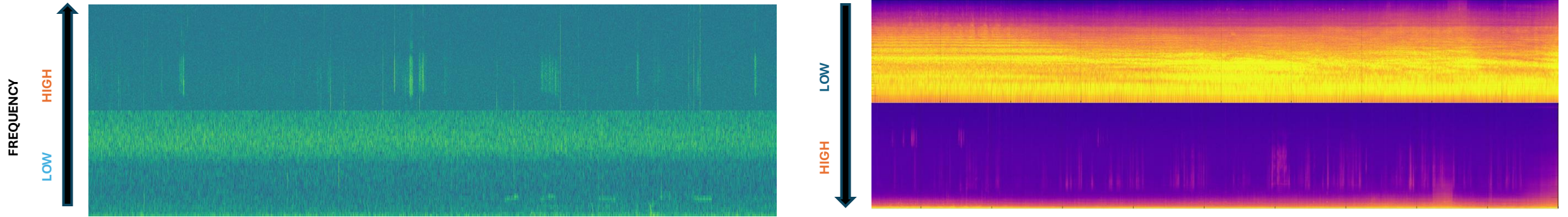
Comparison of baseline models with **our approach**

Model	Accuracy	F1 macro	
Resnet50	0.588	0.562	
ConvNext	0.625	0.591	
ViT	0.788	0.787	
Multi-step (Gen. Masks)	0.837	0.816	↑
Multi-step (HQ Maks)	0.897	0.890	↑↑

- Comparison of single-step baseline models and the proposed multi-step approach with cross-attention using either generated or a subset with high-quality masks.

Results

Generalization properties in OOD setting

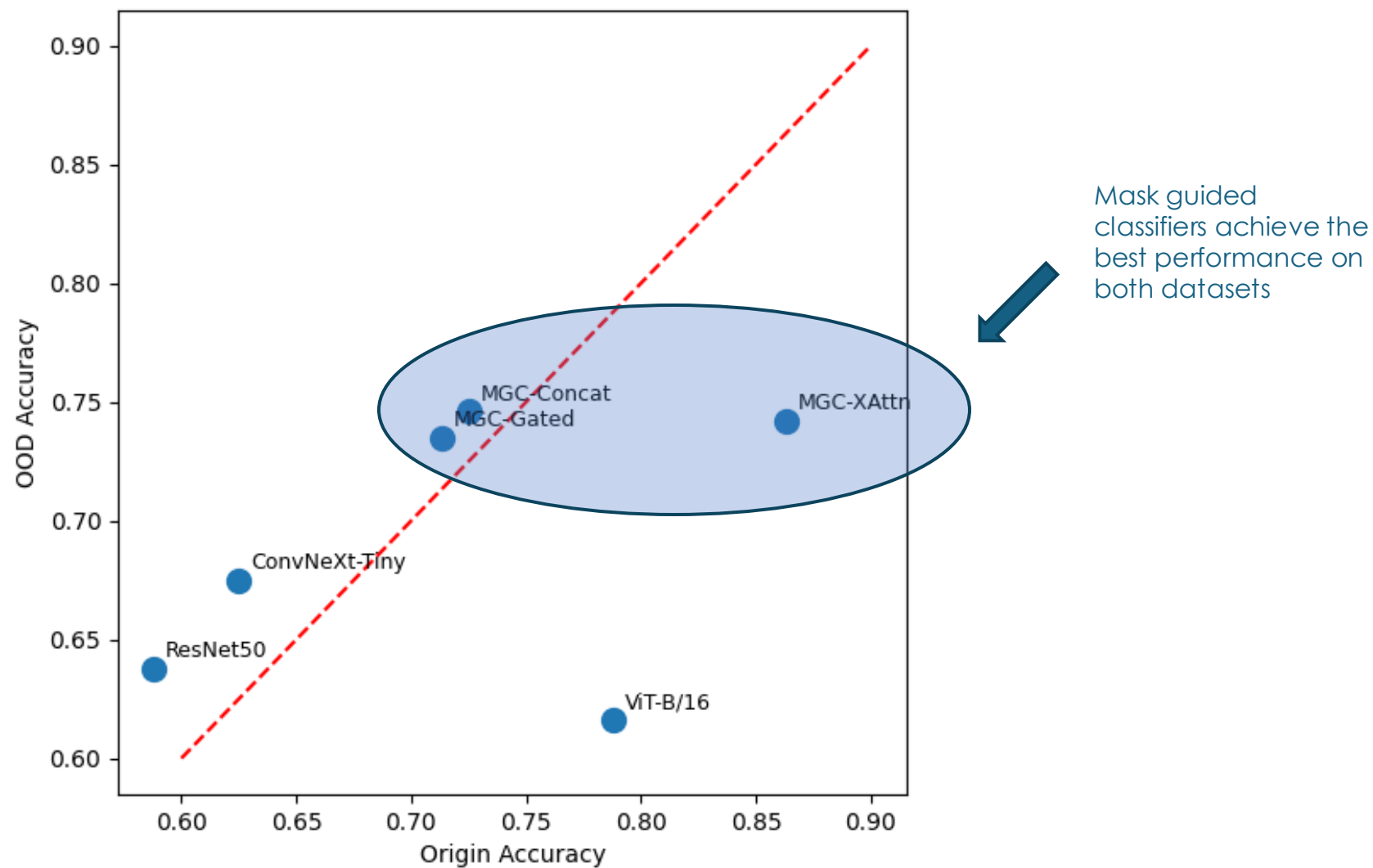


Aim of the Experiment :

- Assess robustness of models under distributional shift.
- Compare performance on original vs. OOD (out-of-distribution) data generated by alternative spectrogram transformations.

Results

Generalization properties in OOD setting



Conclusion

- Complexity of marine mammal vocalizations: Overlapping calls and variable noise make automated analysis challenging.
- Effectiveness of multi-step framework: Despite complexity, the proposed multi-step approach reduces ambient noise impact and improves classification robustness.
- Promising directions: Improving mask quality and integrating models that process raw audio can further enhance signal representation.

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