SeagrassFinder: Deep Learning for Eelgrass Detection and Coverage Estimation in the Wild

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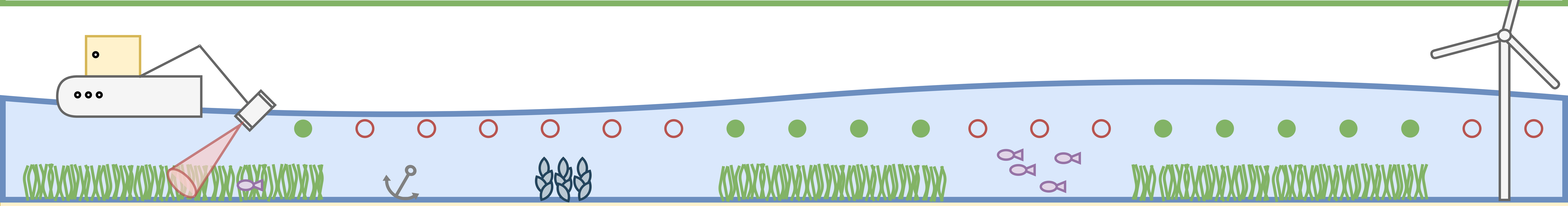


Introduction & Motivation

- **Seagrass meadows are vital** for coastal ecosystems health, biodiversity, and carbon sequestration
- Seagrass is **extremely vulnerable** to changes in water quality and temperature caused by human impact
- Manual video annotation for Environmental Impact Assessments (EIAs) is time-consuming and inconsistent
- **Goal**: Automate seagrass presence detection and coverage estimation using deep learning
- **Challenge**: Underwater footage is noisy, unstructured, and difficult to annotate and analyze at scale

Eelgrass

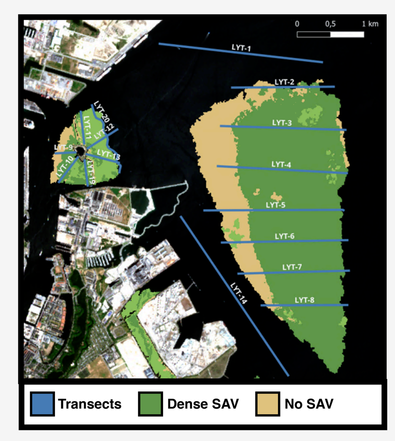
Eelgrass, or Zostera Marina, is a **seagrass species** growing in Lynetteholm, a new artificial peninsula constructed in Copenhagen. **DHI monitors** the health of eelgrass in the construction area to analyze the impact on the benthic habitat.

Process Pipeline

Data Collection via transect surveys | **Data Extraction** from transect videos | **Data Annotation** on custom app | **Deep Learning** benchmark analysis | **Coverage Estimation** as postprocessing

Environmental Impact Assessment

DHI regularly conducts Environmental Impact Assessments (EIAs) in the Lynetteholm area. During a **transect survey** a camera is towed behind a vessel to record video footage of the underwater environment and **submerged aquatic vegetation** (SAV).



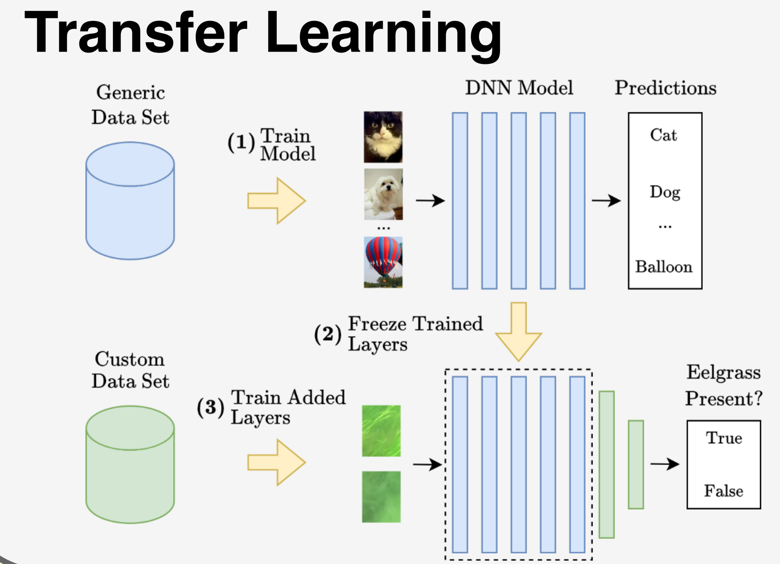
Dataset and Annotation

- **16,000 images** sampled from 6 underwater transects videos from Lynetteholm
- Our custom **browser-based app** enabled 19 annotators (experts & non-experts)
- Over **13,000 annotations** collected with **>76% agreement** and low error rates
- Images labeled as: **Eelgrass Present** **Eelgrass Absent**
- **Result:** a new annotated and publicly available eelgrass image dataset

Eelgrass Present

Eelgrass Absent

Transfer Learning



Deep Learning for Eelgrass Presence

- We train deep neural networks on the task of **classifying the presence of eelgrass**
- We apply **transfer learning** to fine tune models on our eelgrass dataset
- We use models pretrained on ImageNet and fine-tune two additional layers
- **Benchmark**: 1) ResNet, 2) InceptionNetV3, 3) DenseNet and 4) Vision Transformers (ViT)

Key Results

Model	Accuracy	AUROC	Calibration Error
ViT++	**90.2%**	**0.959**	**0.087**
DenseNet++	87.8%	0.955	0.110

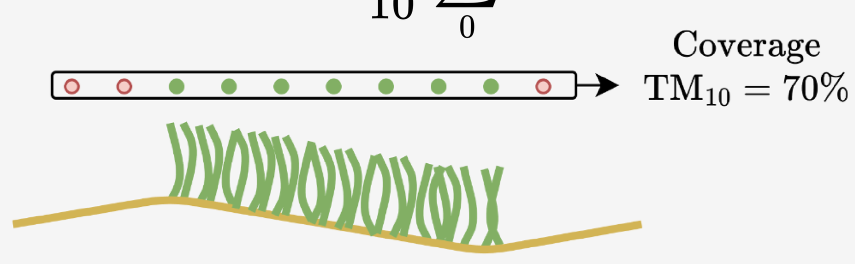
- Vision Transformer (ViT) outperforms traditional CNNs
- Fast training (< 30 mins)

++ Preprocessing images enhances performance

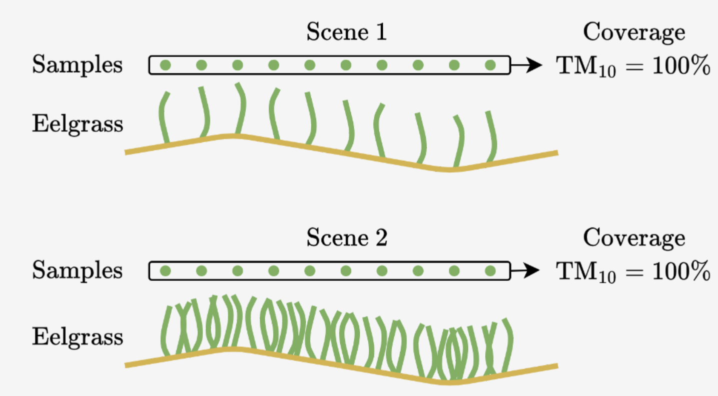
Eelgrass Coverage Estimation

- We **present a novel method** for eelgrass coverage estimation by
  - Using binary predictions from our trained ViT model
  - Calculating the temporal mean (TM) over consecutive frames
  - Considering **spatial coverage**, not pixel-based coverage
- **Advantages**: this process is automated, repeatable and scalable

$$\mathrm{TM}_{10}(i) = \frac{1}{10}\sum_{0}^{n=9} p_{i+n}$$



Same Coverage - Different Density



Conclusions

- Seagrass detection and coverage estimation **can be automated** with deep learning
- Our pipeline streamlines EIAs by **reducing time and financial resources**
- Paves the way towards environmental monitoring with **autonomous underwater vehicles**
- **Transferable technology** to other submerged vegetation species

Recommendations

- Invest in good camera equipment
- Underwater image enhancement slightly improves performance
- Read our pre-print: arxiv.org/abs/2412.16147
- Check our dataset: DOI:zenodo.org/records/13904604

[Full paper] [Data]

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