Data Collection Infrastructure for Feature Similarity Analysis in Satellite Images of Artic Sea Ice

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Sponsored by NSF Collaborative Research: Elements: Data: HDR: Developing On-Demand Service Module for Mining Geophysical Properties of Sea Ice from High Spatial Resolution Imagery, $127,966.00 (Jan 1, 2019 - Dec 31, 2021)

Introduction

- Sea Ice plays an important role in the Earth's climate: acting as both an indicator and an amplifier[1].

- Analyzing Sea Ice through novel computer-vision techniques including Deep Learning (DL) models can provide important capabilities when it comes to feature detection and classification[2][3].

- Doing this kind of analysis requires large amounts of manually labeled training data in order to "train" a model to detect features based on a pixel's similarity to a classified pixel within the training dataset.

- Creating this manually labeled training data using tools available within the status quo is an especially complicated task due to the intricate size and shape of features within HSR images of Artic sea ice.

[1]Dexuan Sha, Xin Miao, Mengchao Xu, Chaowei Yang, Hongjie Xie, Alberto M. Mestas-Nuñez, Yun Li, Qian Liu and Jingchao Yang, "An On-Demand Service for Managing and Analyzing Arctic Sea Ice High Spatial Resolution Imagery", Data, 5:39, 2020. doi:10.3390/

[2] Xin Miao, Hongjie Xie, Stephen F. Ackley, Songfeng Zheng, "Object-Based Arctic Sea Ice Ridge Detection From High-Spatial-Resolution Imagery", IEEE Geoscience and Remote Sensing Letters, 13(6): 787-791, 2016.

[3] Xin Miao, Hongjie Xie, Stephen F. Ackley, Donald K. Perovich, and Changqing Ke, "Object-Based Detection of Arctic Sea Ice and Melt Ponds Using High Spatial Resolution Aerial Photographs", Cold Regions Science and Technology, 119: 211-222, 2015.

Problem:

When it comes to training data for DL methods, labeling a sufficiently large dataset of normalized input images from dense and complicated High Spatial Resolution (HSR) images of Artic sea ice is almost impossible through current means.

Collecting such a dataset will require software that makes the process:

- Faster
- More Consistent
- More Tightly Integrated
- Specialized
- Collaborative

Goal:

- Create a quick and easy to use graphical user interface (GUI) to collect an enormous volume of training data.
- Implement an automated segmentation algorithm with user control over parameters to ensure data quality and consistency[2][3].
- Enforce a rigid data collection protocol to ensure uniformity.
- Collect training data that is easy to update, assess, append, etc.
- Deploy GUI in open-source to allow anyone to use.

[2] Xin Miao, Hongjie Xie, Stephen F. Ackley, Songfeng Zheng, "Object-Based Arctic Sea Ice Ridge Detection From High-Spatial-Resolution Imagery", IEEE Geoscience and Remote Sensing Letters, 13(6): 787-791, 2016.

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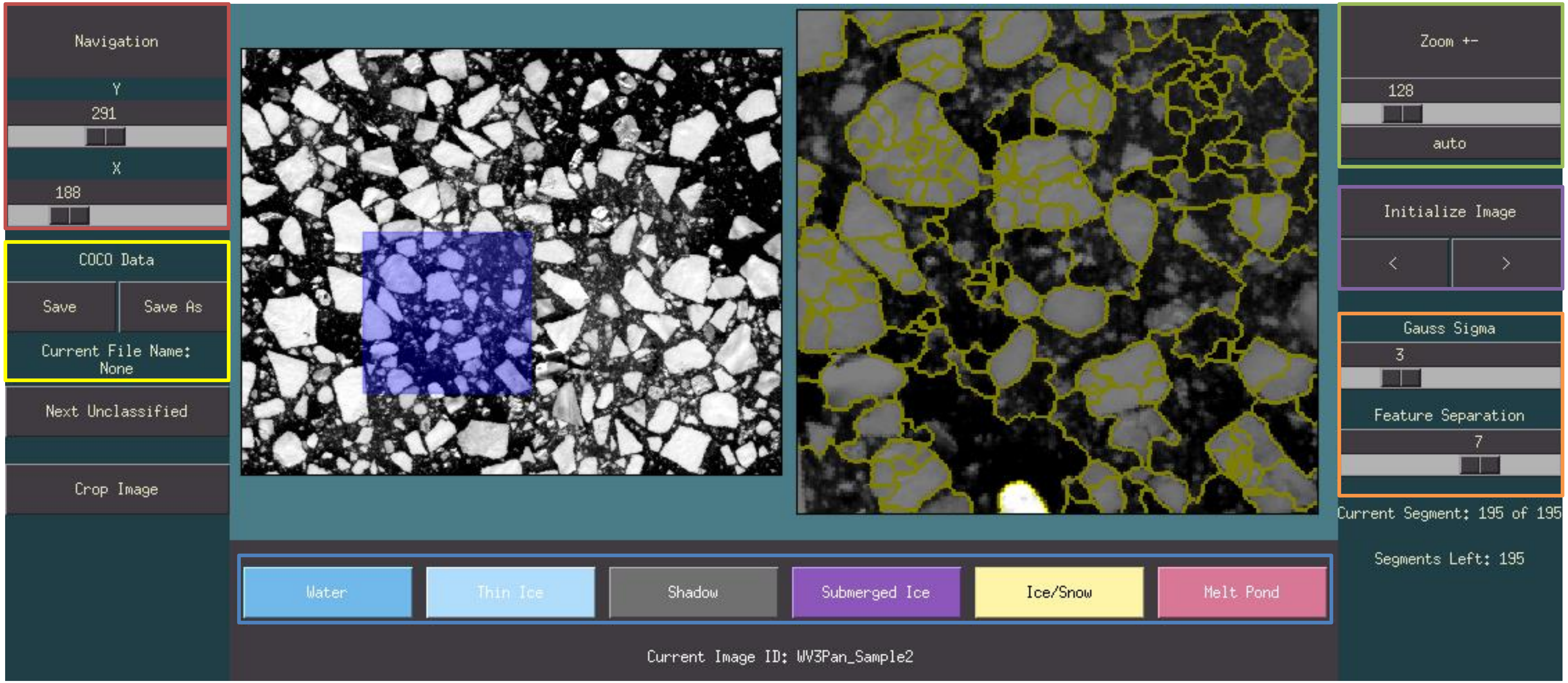
Overview of Methods

1) Create software to enhance data collection
2) Use software to create datasets
   A. Crop Images to normalize input data
   B. Classify Images to create training data
   C. Save and collect Data
3) Examine integrity and quality of data
4) Apply data in a training scenario

Arc-CI Training GUI



Our Process

We divide data collection into two phases:

Cropping Phase

- We want images of the same size (256x256)
- We can create multiple images from one large image

1) Upload large images to the GUI
2) Use the auto button to set the crop size to 256x256
3) Collect as many samples as possible
4) Repeat

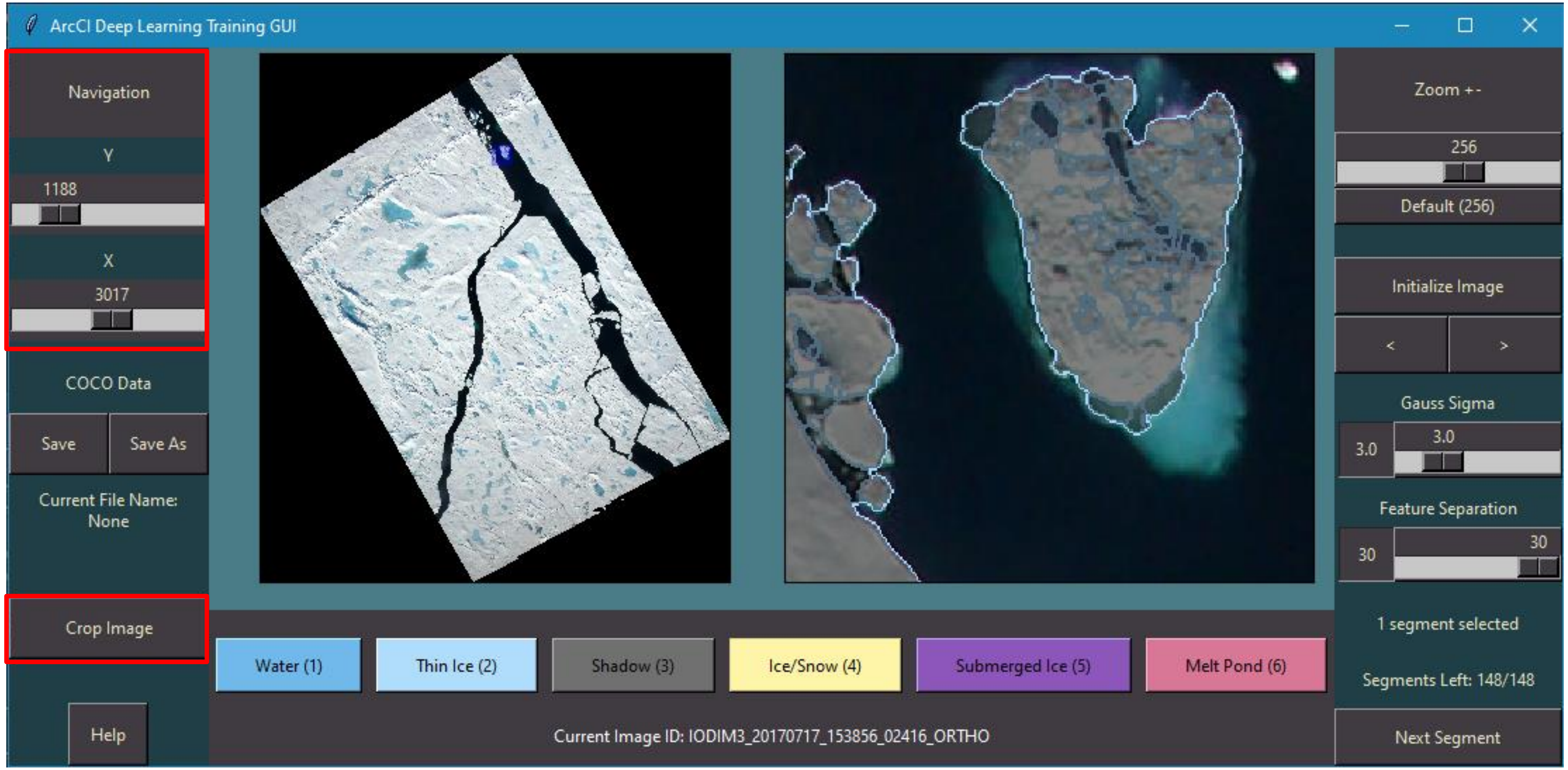
Classification Phase

- We will classify the 256x256 images we created in the cropping phase

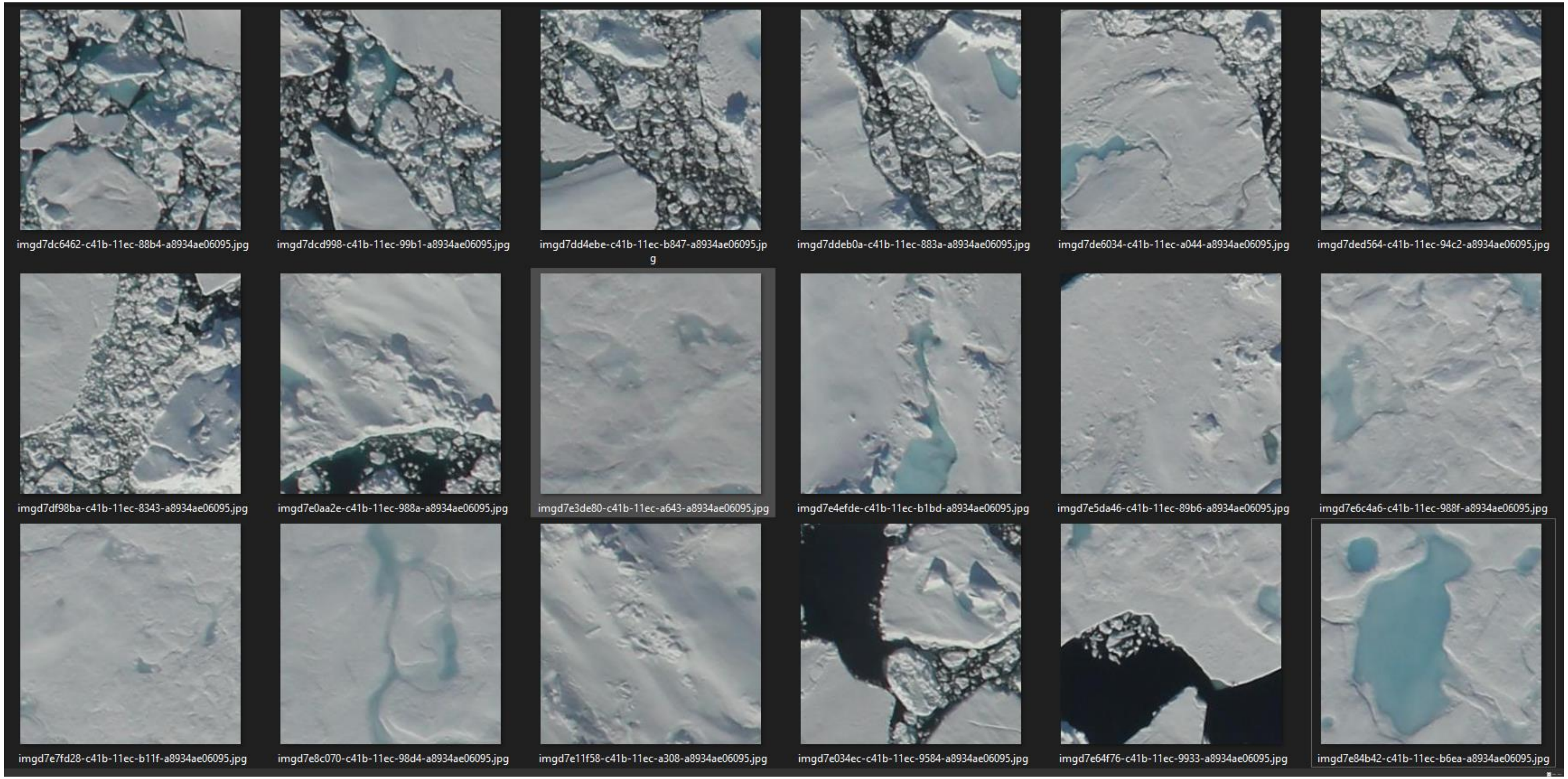
1) Use segmentation parameter sliders to find an accurate segmentation map
2) Classify segments
3) Save dataset after finished classifying

Cropping Phase – Adjusting the Zoom Window

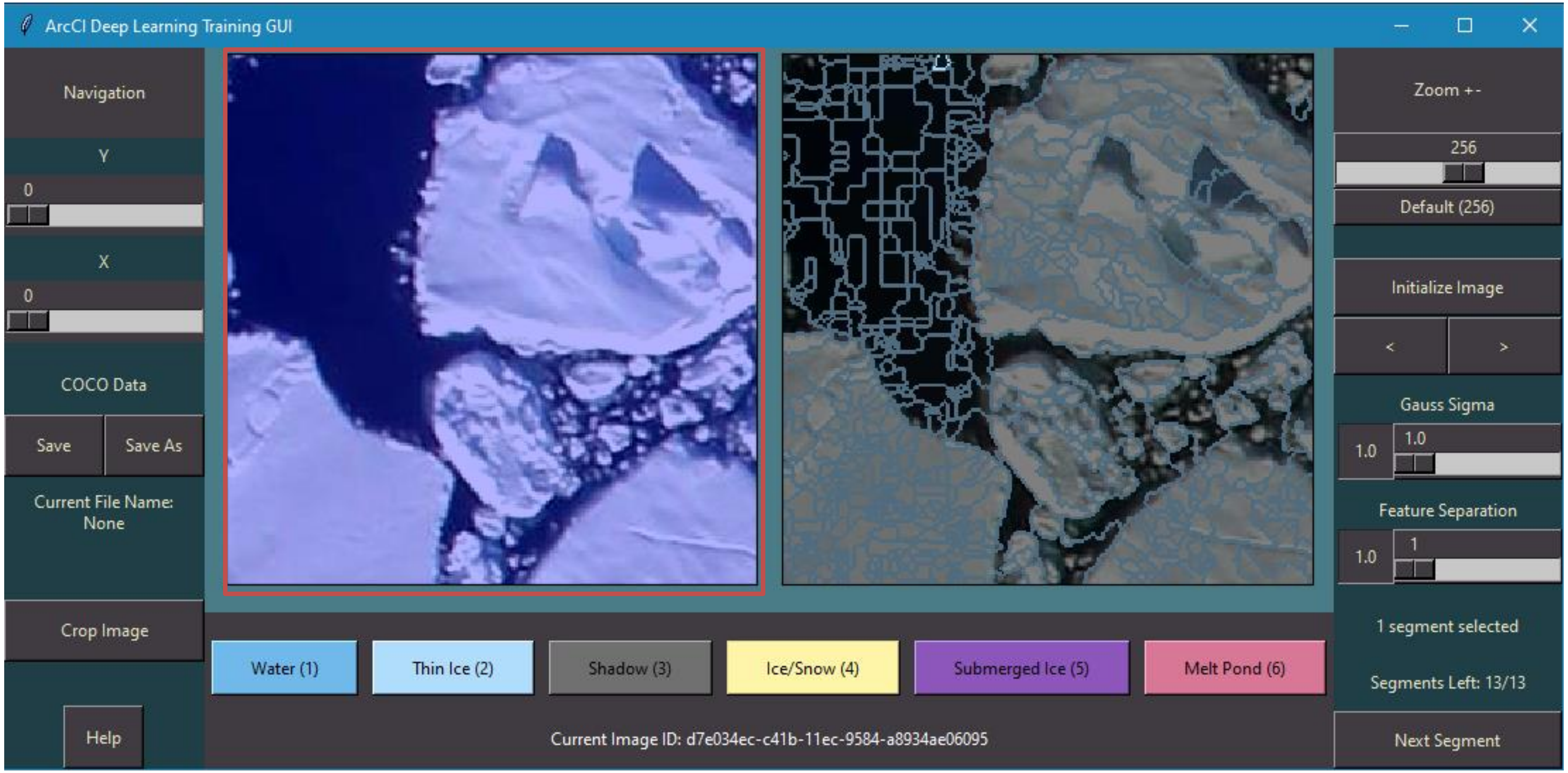
Cropping Phase – Normalized Input Collection



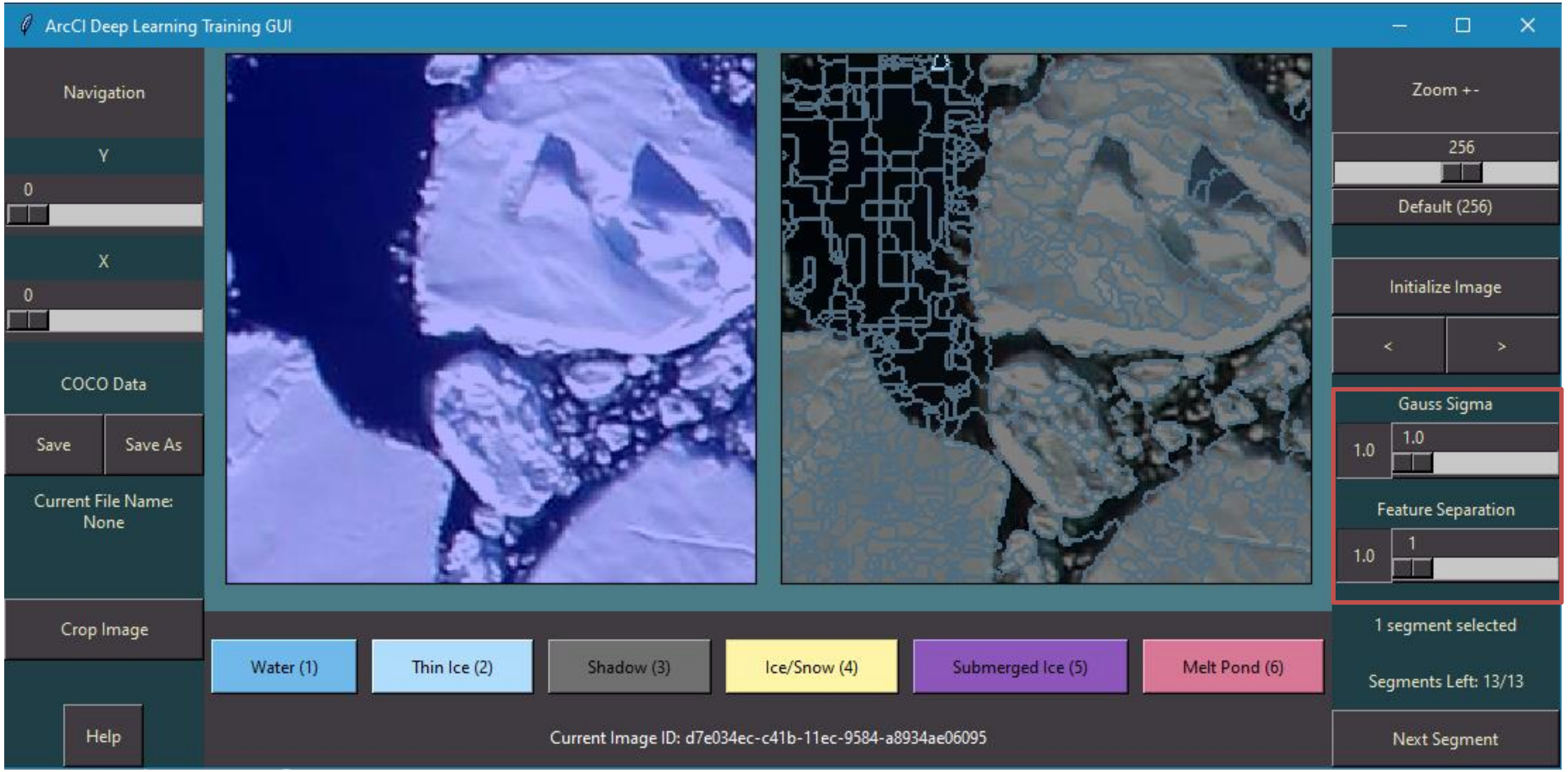
Transition – Change GUI Read Target



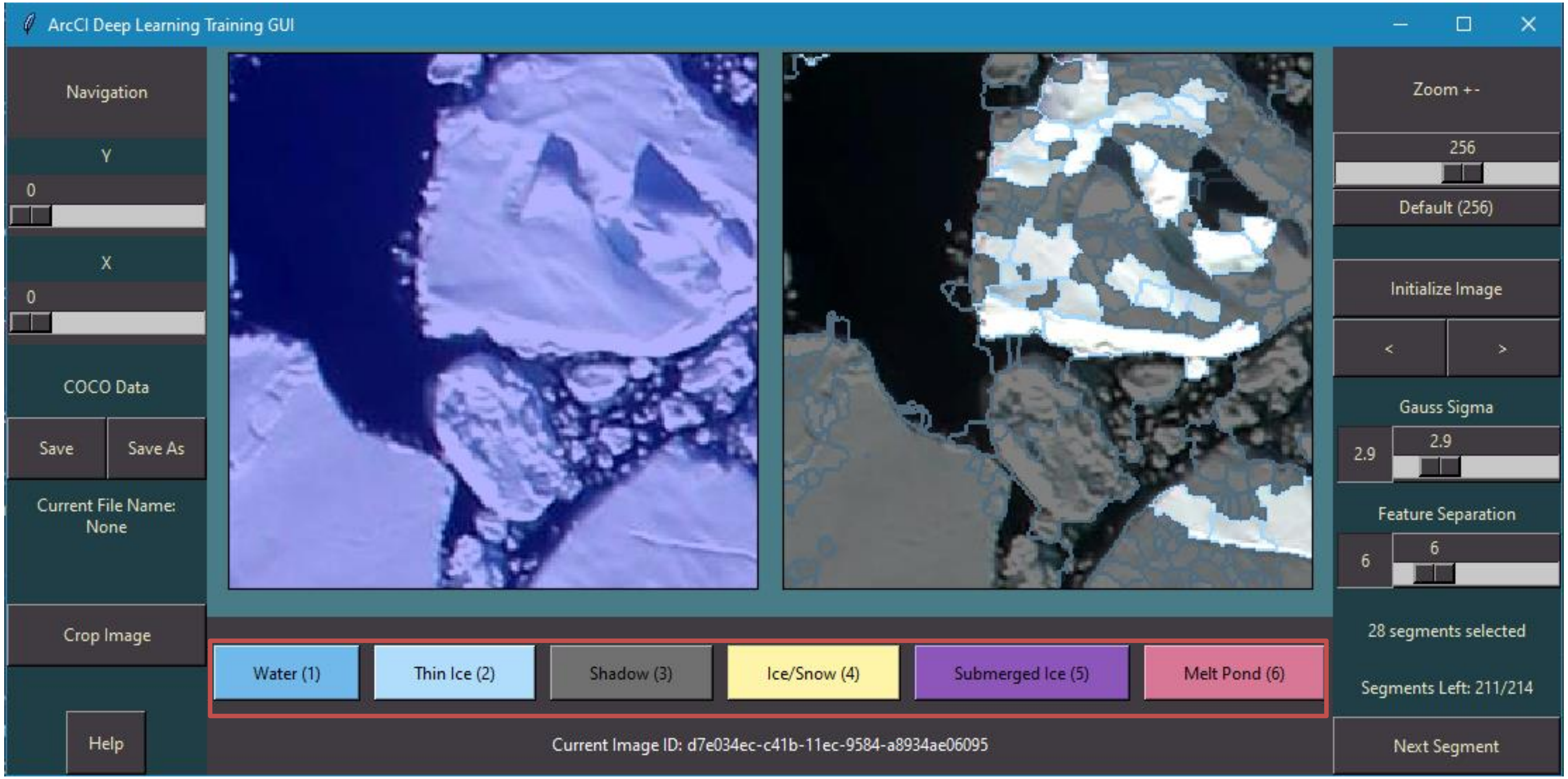
Classification Phase – Ensuring Normalized Input



Classification Phase – Redrawing Segments



Classification Phase – Passing Labels

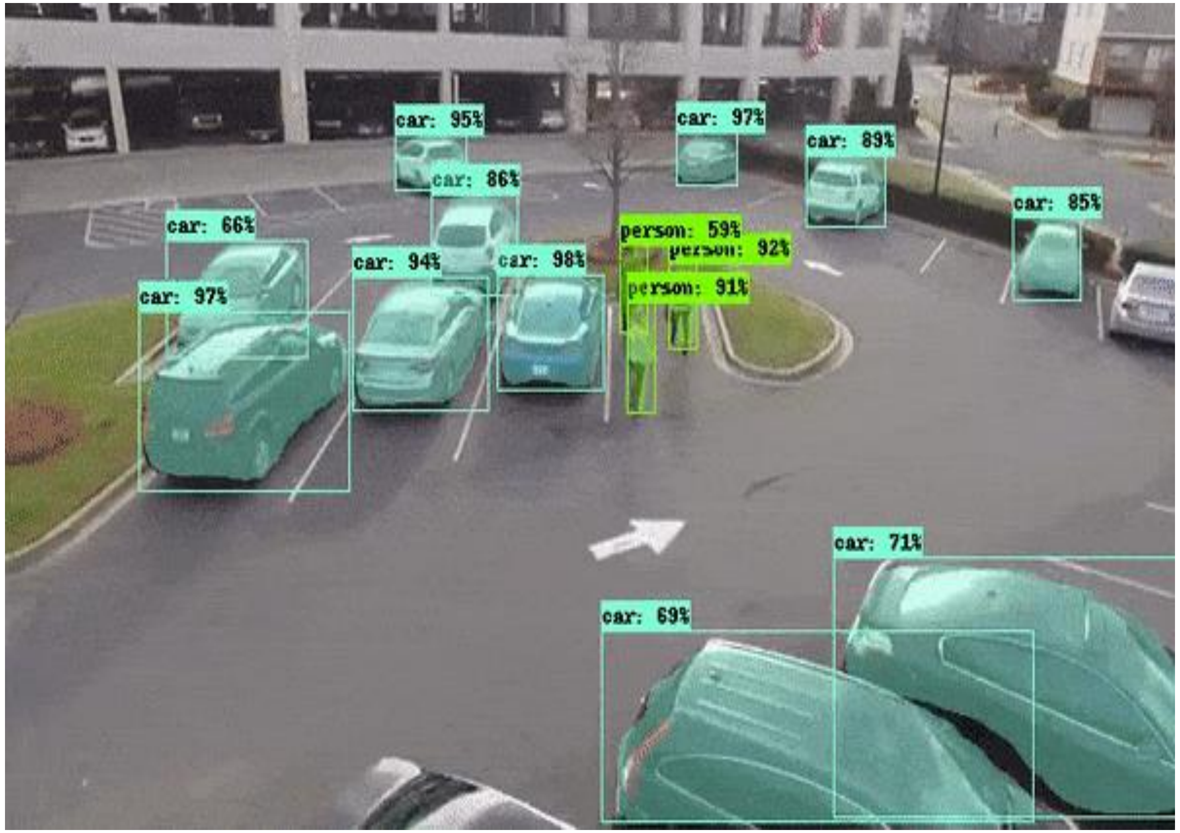


COCO Naming Conventions

Microsoft Common Objects in Context (COCO) is a massive dataset of common objects.

It is known as one of the most difficult to tackle computer vision datasets, and therefore has garnered popularity for its naming conventions – which we use.

The broader Arc-CI project aims to create an expansive collection of computer vison datasets like COCO for sea ice[1].



[1]Dexuan Sha, Xin Miao, Mengchao Xu, Chaowei Yang, Hongjie Xie, Alberto M. Mestas-Nuñez, Yun Li, Qian Liu and Jingchao Yang, "An On-Demand Service for Managing and AnalyzingArctic Sea Ice High Spatial Resolution Imagery", Data, 5:39, 2020. doi:10.3390/

COCO Naming Conventions

```
"annotation": [
    {
        "id": 1,
        "image_id": "731aad0a-3e66-11ec-98c4-2f44a69d5f32",
        "category_id": 0,
        "segmentation": {
            "size": [
                256,
                256
            ],
            "counts": [⋯
            ]
        },
        "iscrowd": 1
    },
```

Data is stored in a dictionary using the .JSON file type. Annotation: (labels and classifications)

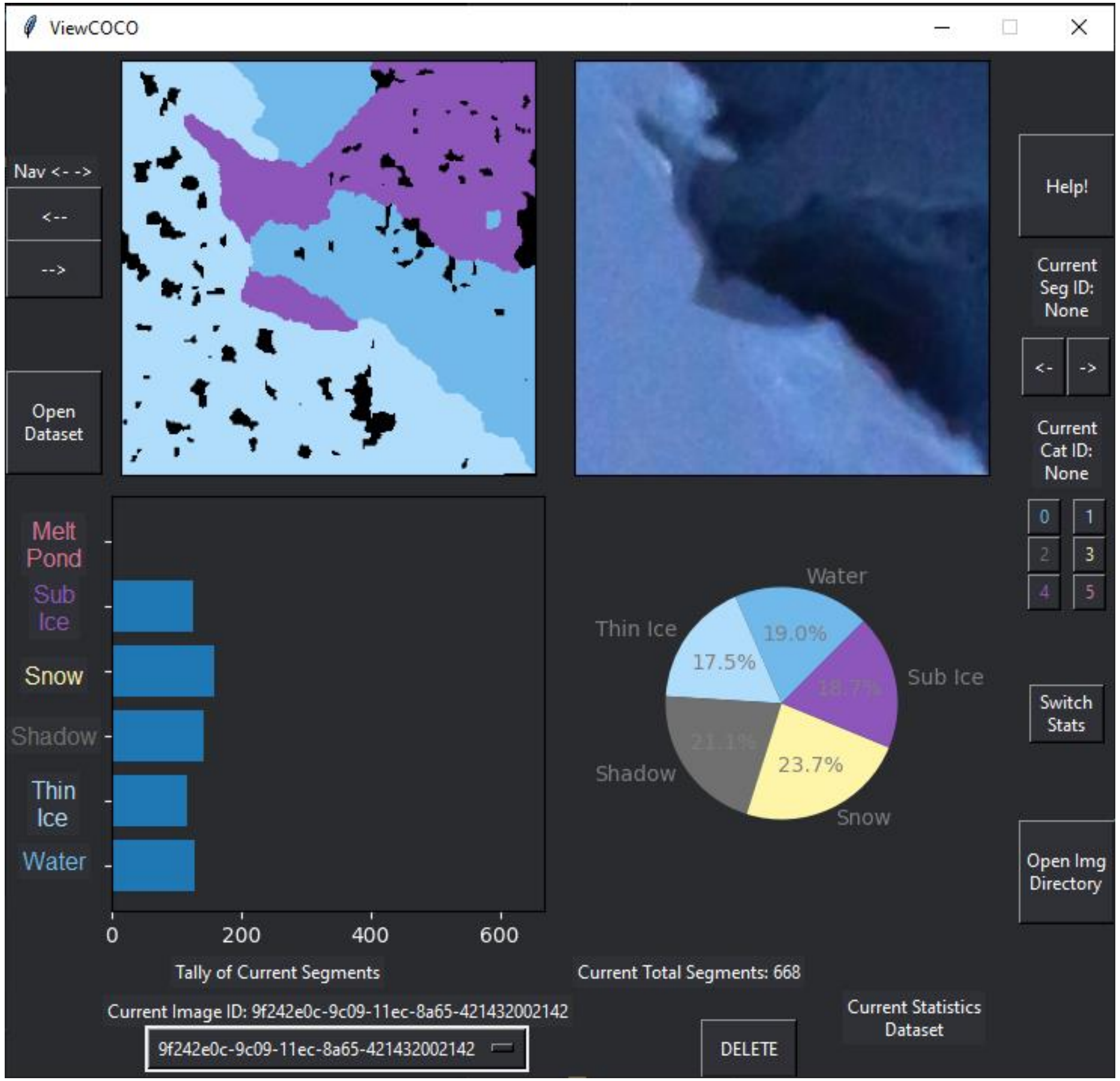
id - id of segment
image_id – image UUID
category_id – classification
Segmentation – location and size of segment (RLE)

Analyzing Data

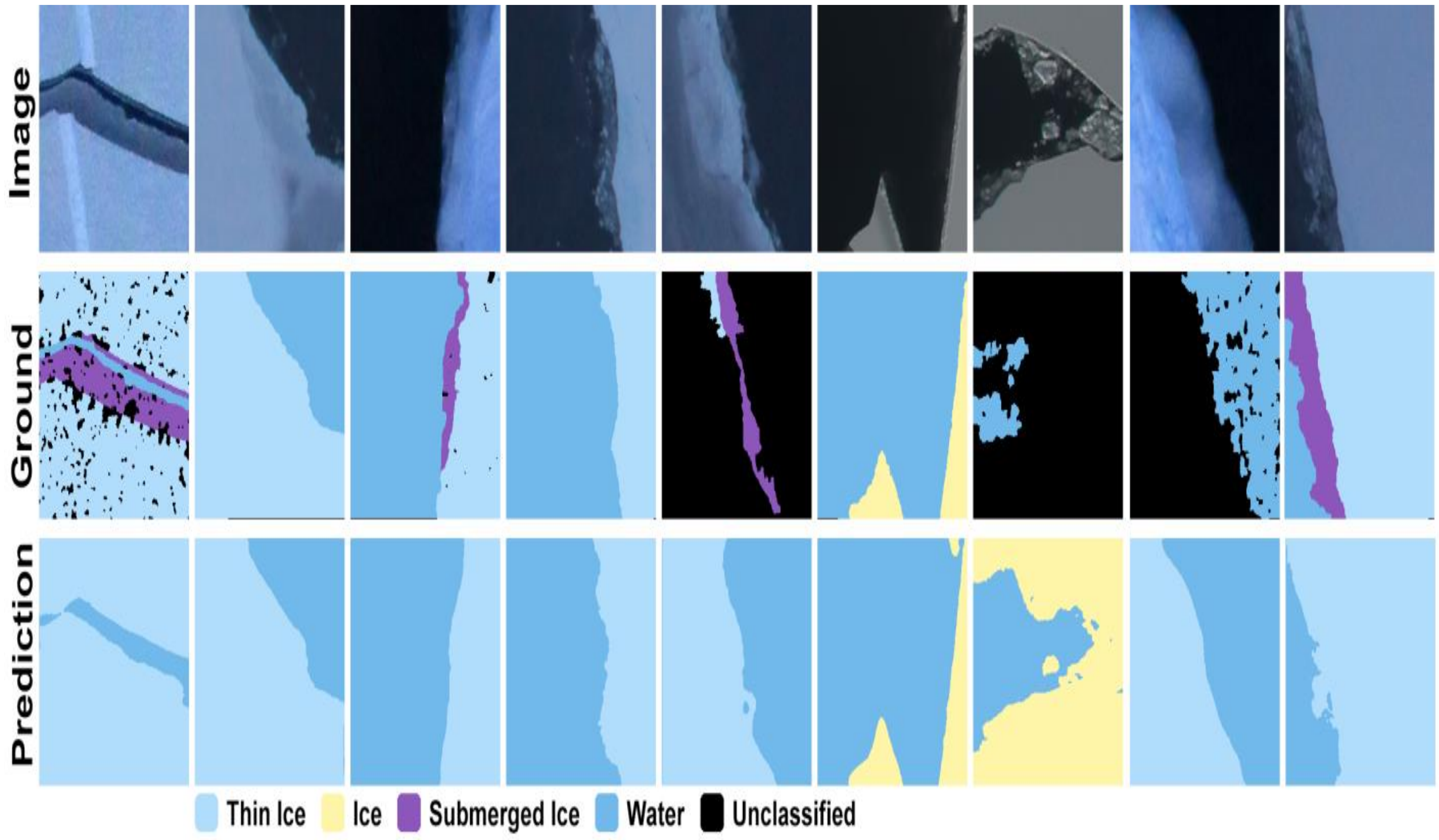
The viewCOCO module allows users to check images and masks side by side to ensure accuracy.

Users can reclassify segments

The module maps basic statistics automatically, and can toggle between a single image or a whole dataset



Results



We find that just with a small dataset of around 30 images we can illicit some significant feature detection on a custom Fully Convolutional Network (FCN)

This dataset is very small compared to most comprehensive computer vision datasets, and the accurate feature predictions from trained models proves our effectiveness in conveying feature data with few samples necessary.

Conclusions

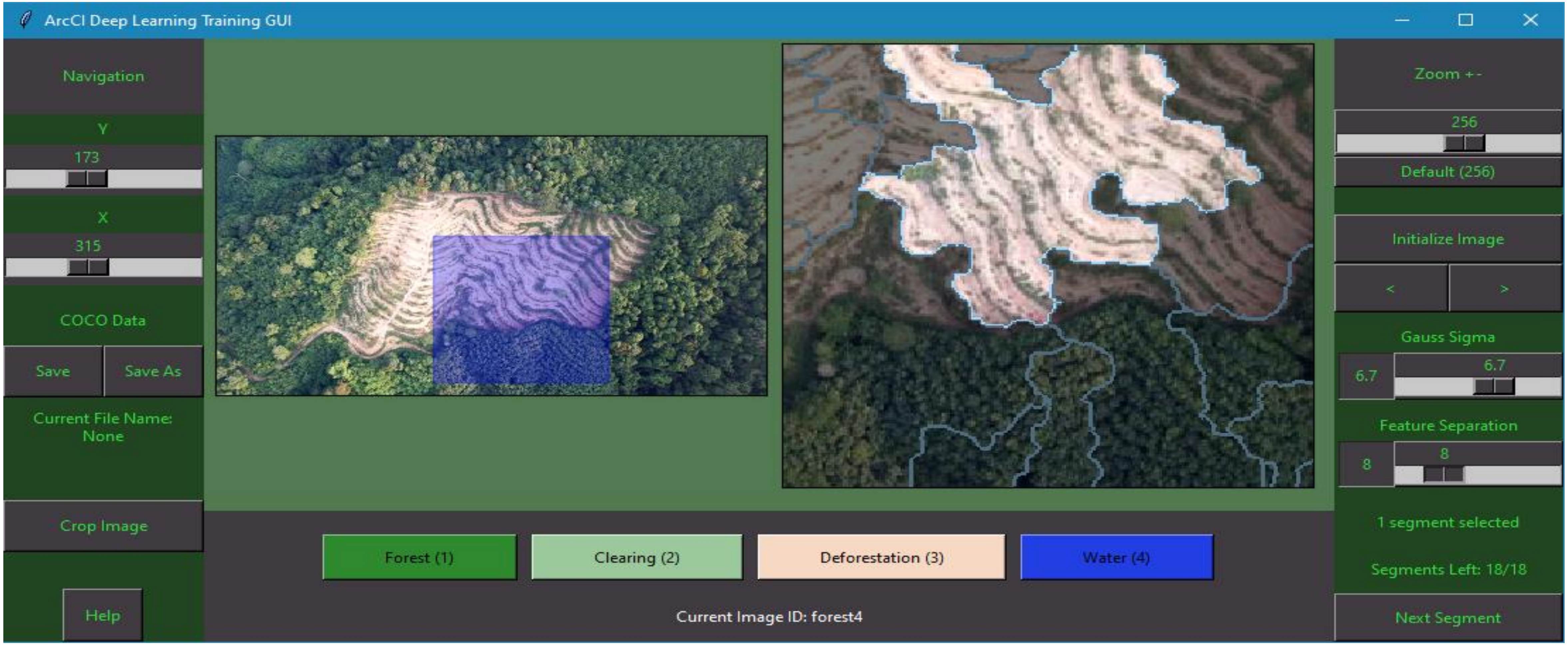
- Our methods of reducing the time-cost of training dataset creation in the context of HSR images of Artic sea ice are effective.

- We allow domain professionals the ability to collaborate to create large amounts of data using an intuitive system of tightly integrated tools.

- The data that these tools produce is sufficient in providing an intelligent DL model with enough information to learn about the given image’s feature similarities, meaning this project can be adapted to classify any ontology of objects.

- Training data can be of other geospatial phenomena, or can be of something else entirely (medical imagery, traffic, facial detection, etc.

Possible Adapdations - Deforestation Detection



References

[1] Dexuan Sha, Xin Miao, Mengchao Xu, Chaowei Yang, Hongjie Xie, Alberto M. Mestas-Nuñez, Yun Li, Qian Liu and Jingchao Yang, "An On-Demand Service for Managing and AnalyzingArctic Sea Ice High Spatial Resolution Imagery", Data, 5:39, 2020. doi:10.3390/

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