KELP SEGMENTATION

AI 3011: Machine Learning and Pattern Recognition

The Problem

Climate Change Mitigation:
Kelp and other ocean algae generate 50-85% of Earth's oxygen. [2]

Human benefit: Kelp forests generate over US$500 billion annually. [1]

Temperature Sensitivity: Kelp faces critical threats from climate change, overfishing, and unsustainable harvesting practices.

Thus, there is a need to monitor Kelp.

Literature Review: Models Employed

DCGAN + CNN

- **Dataset**: NDAWI values from Sentinel-2 remote sensing images amplified by DCGAN.
- **Optimal Results:**
  Overall accuracy = 94.68%
  kappa = 0.913
- Amplified images classified by UNet, DeepLabv3, and SegNet.
- DCGAN amplification increased OA by 4.43%, kappa by 0.032, and Precision by 4%

$$\text{kappa} = \frac{2*(TP*TN)*(FP*FN)}{(TP+FP)*(FP+TN)*(TP+FN)*(FN+TN)}$$

Zhu H, et al. Remote Sensing Classification of Offshore Seaweed Aquaculture Farms on Sample Dataset Amplification and Semantic Segmentation Model. Remote Sensing. 2023; 15(18):4423. https://doi.org/10.3390/rs15184423

Mask R-CNN

- **Dataset**: Satellite imagery (Landsat Thematic Mapper) with cloud and landmass masks
- **Hyperparameters**: Learning rate and anchor size.
- **Optimal Results**:
  Jaccard's index: 0.87 ± 0.07.
  Dice index: 0.93 ± 0.04
- Cost-efficient and less time-consuming approaches for long-term marine ecological monitoring

Jaccard Index = $A \cap B \,/\, A \cup B$

Marquez, L., Fragkopoulou, E., Cavanaugh, K. C., Houskeeper, H. F., & Assis, J. (2022). Artificial intelligence convolutional neural networks map giant kelp forests from satellite imagery. Scientific reports, 12(1), 22196. https://doi.org/10.1038/s41598-022-26439-w

Literature Review: Why CNNs?

- CNNs can automatically learn and extract relevant features from the image data itself, unlike traditional methods that rely on manually designed feature extractors.

- This makes CNNs well-suited for the complex task of identifying the distinct floating canopy patterns of kelp forests.

- CNNs can leverage data augmentation techniques like rotating, flipping, rescaling images to artificially increase the training data, which the paper shows improves kelp detection performance by reducing overfitting.

- The hierarchical, multi-layer architecture of CNNs makes them highly effective at capturing the complex spatial patterns and shapes characteristic of floating kelp canopy distributions visible in satellite images.

Reference: https://medium.com/codex/what-is-max-polling-in-cnn-is-it-useful-to-use-6f2d6ff44c6

Literature Review: Vegetation Indices

Index	Abbreviation	Formula	Author and Year
Normalized Difference Vegetation Index	NDVI	$\frac{(NIR - R)}{(NIR + R)}$	Rouse et al., 1974
Atmospherically Resistant Vegetation Index	ARVI	$\frac{(NIR - RB)}{(NIR + RB)}$ $RB = R - \gamma(B - R)$	Kaufman and Tanré, 1992
Redness Index	RI	$\frac{(R - G)}{(R + G)}$	Escadafal and Huete, 1991
Transformed Vegetation Index	TVI	$\frac{(NDVI + 0.5)}{\lvert NDVI + 0.5\rvert}\sqrt{\lvert NDVI + 0.5\rvert}$	Perry and Lautenschlager, 1984
Differenced Vegetation Index	DVI	$(NIR - R)$	Clevers, 1986

A. Bannari, D. Morin, F. Bonn, and A. R. Huete, “A review of vegetation indices,” Remote Sensing Reviews, vol. 13, no. 1-2, pp. 95–120, aug 1995.

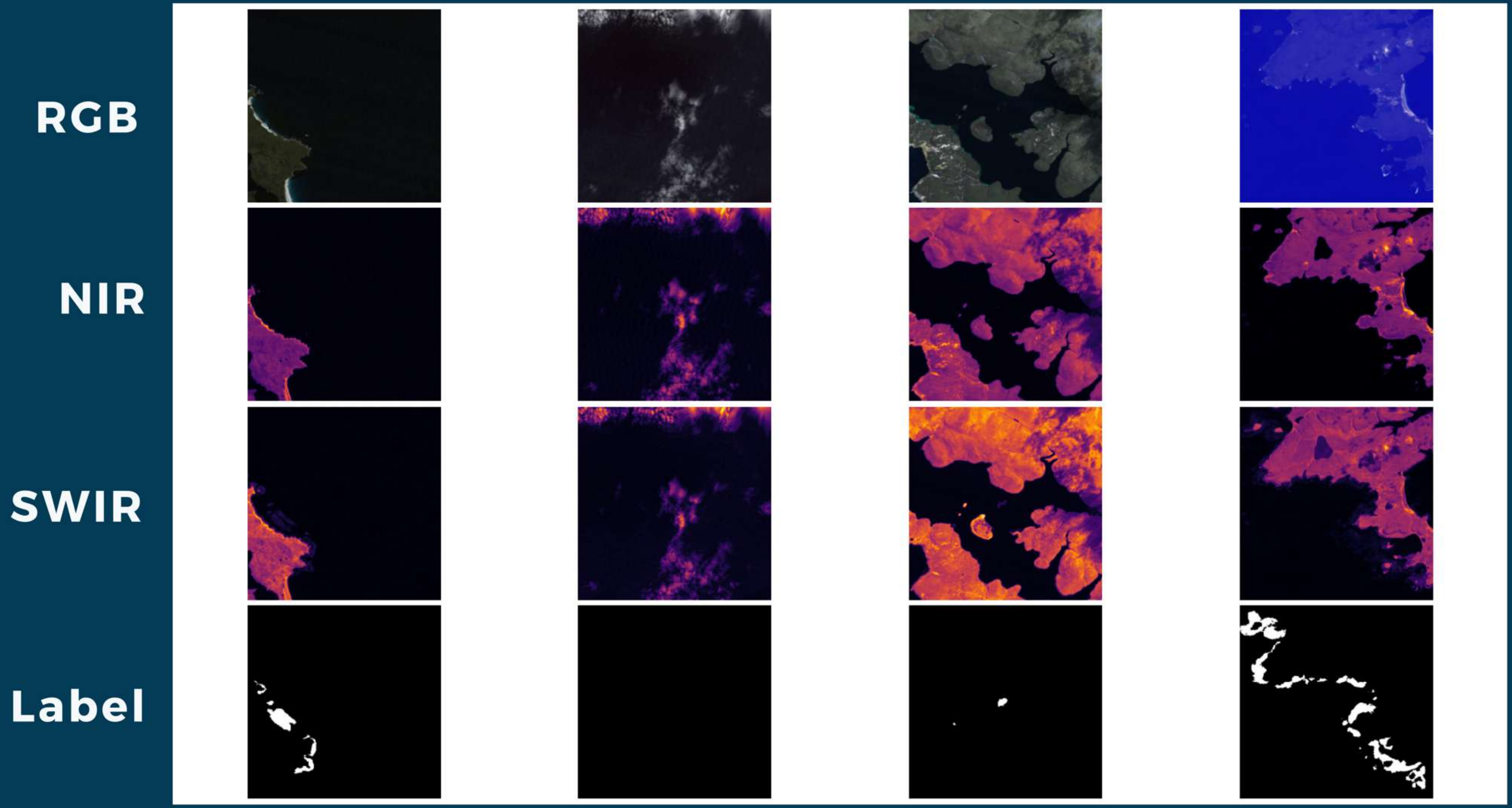
Index	Abbreviation	Formula	Author and Year
Normalised Difference Water Index	NDWI	$\frac{G - NIR}{G + NIR}$	Gao (1996)
Chlorophyll Index	CI	$\frac{G}{R}$	Xu (2006)
Modified Normalized Difference Water Index	MNDWI	$\frac{G - SWIR}{G + SWIR}$	Abrams (1998)

DATASET

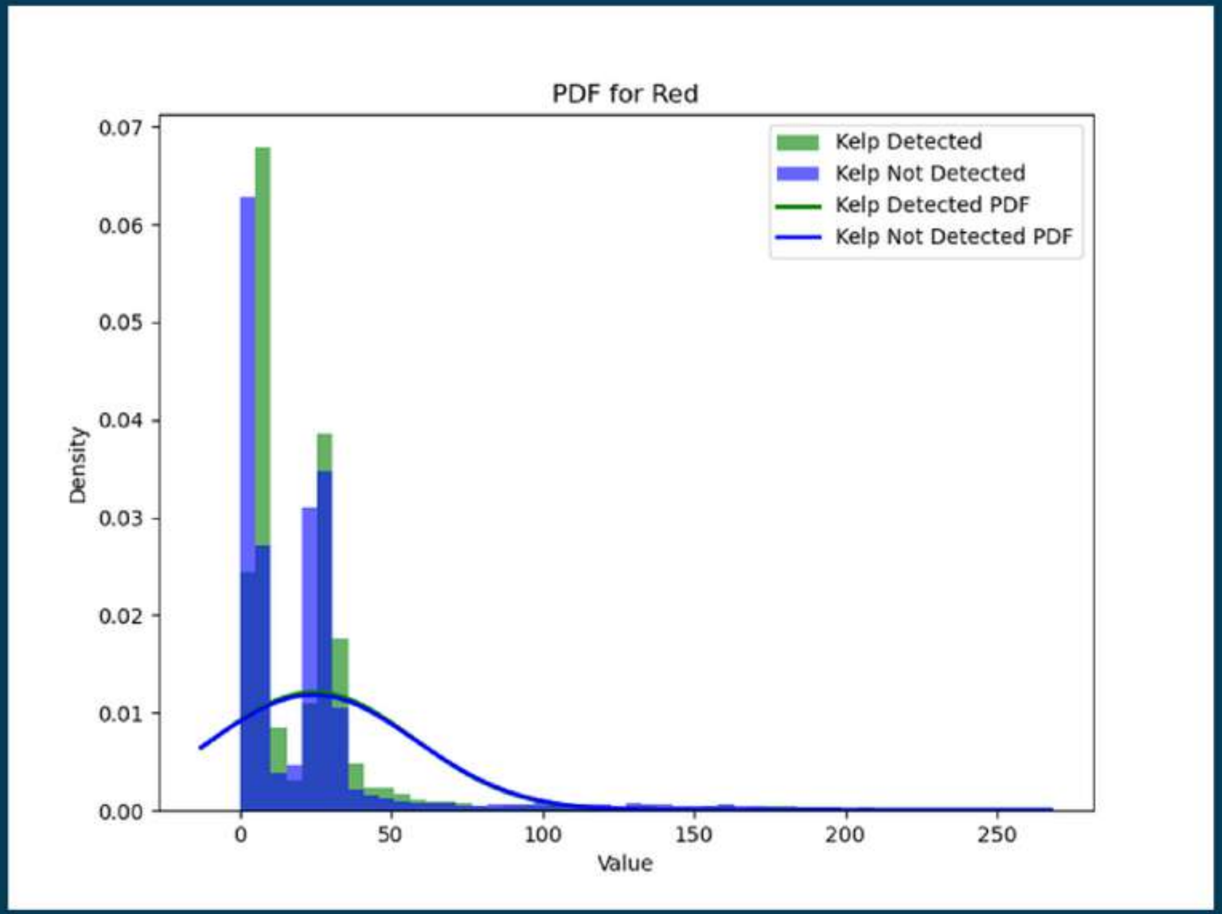
Image Format: (350x350) px, TIFF, 30m resolution

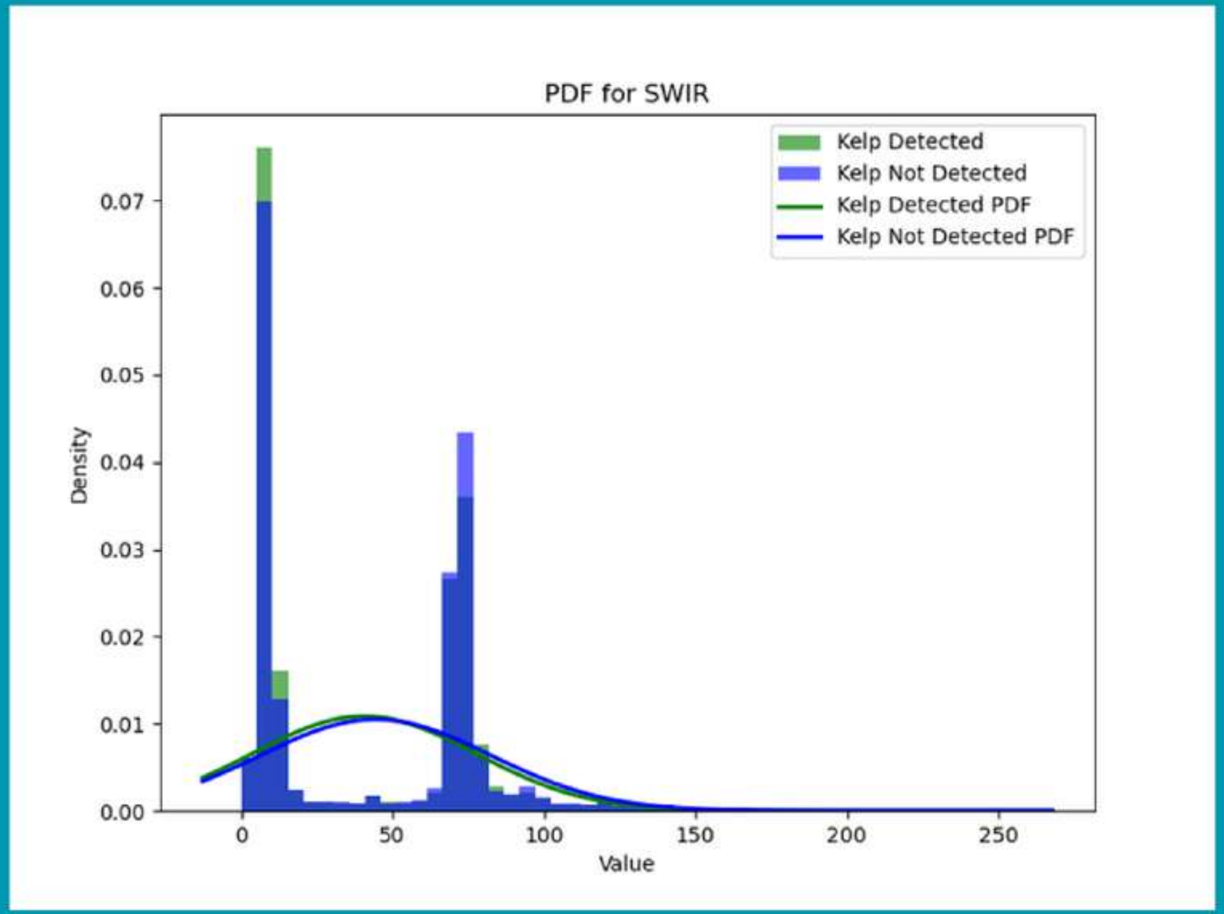
RED	GREEN	BLUE	NEAR INFRARED (NIR)
SHORTWAVE INFRARED	CLOUD MASK	DIGITAL ELEVATION MAP	PIXEL-WISE LABEL

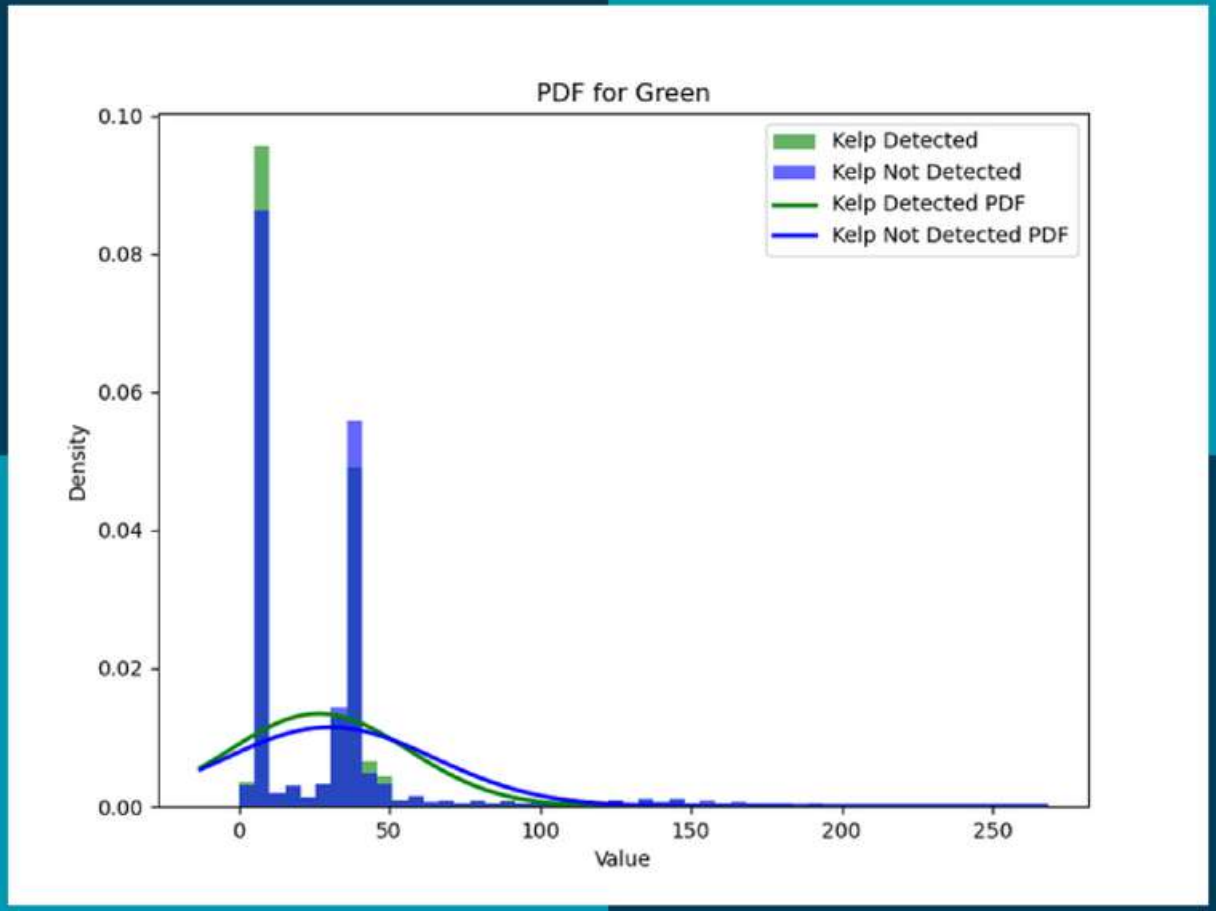
Dataset Sample

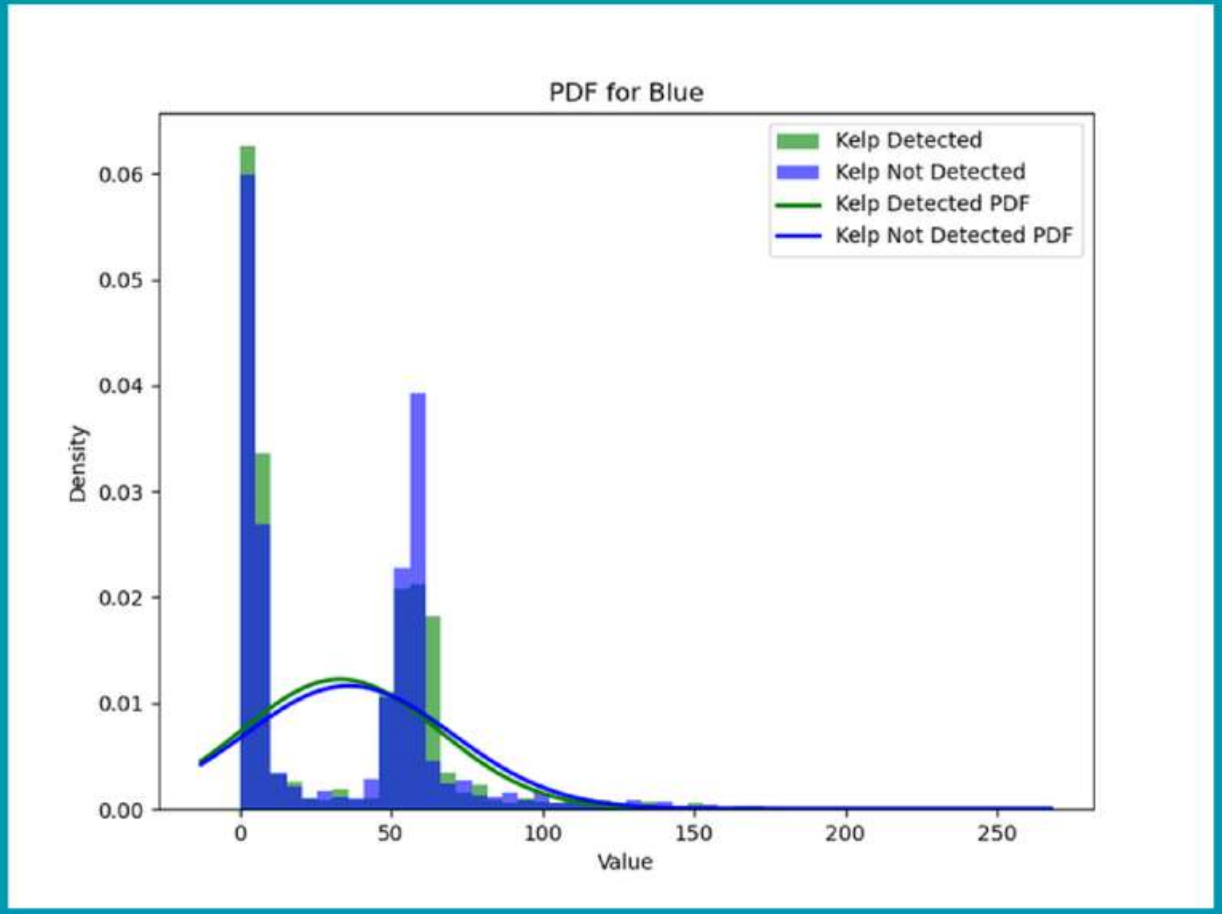


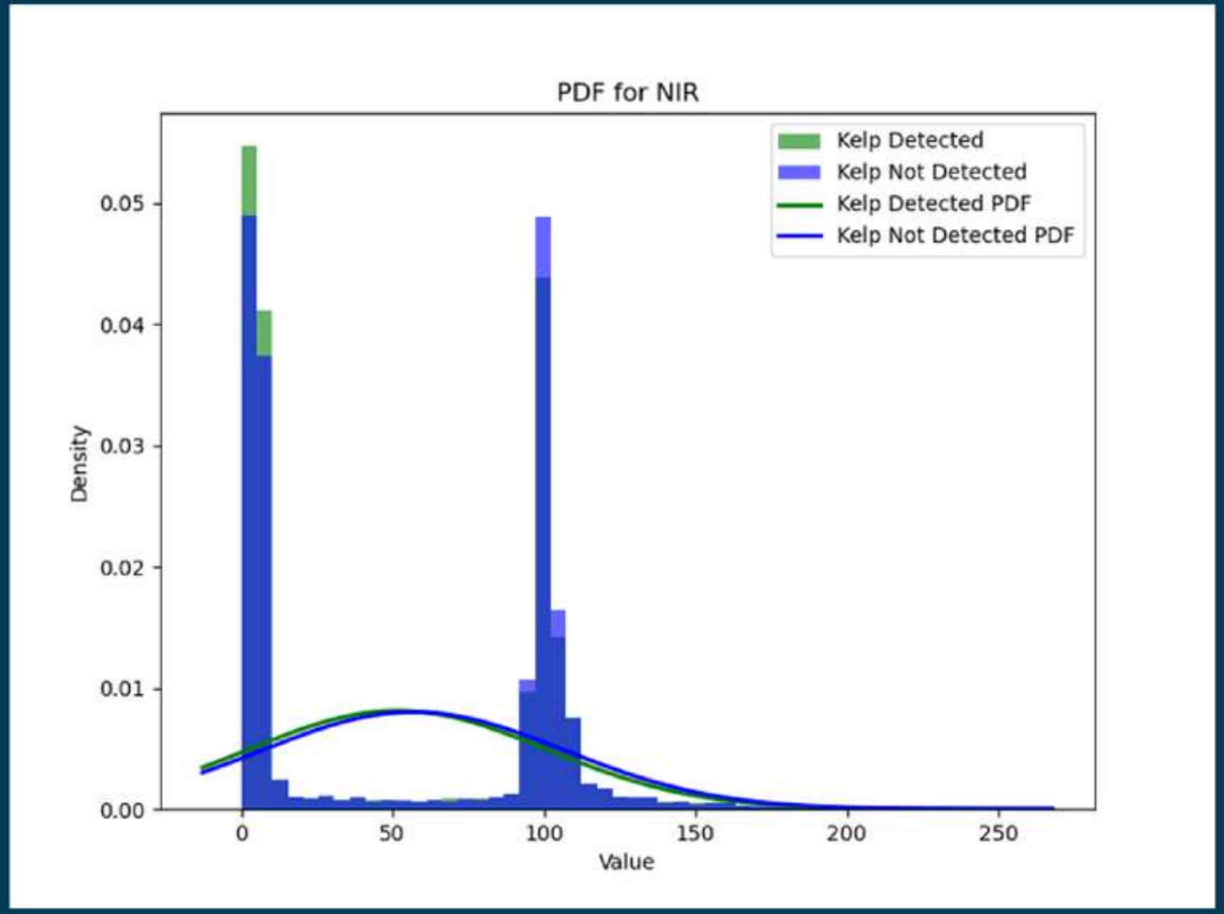
Probability density functions of absence and prescence of Kelp





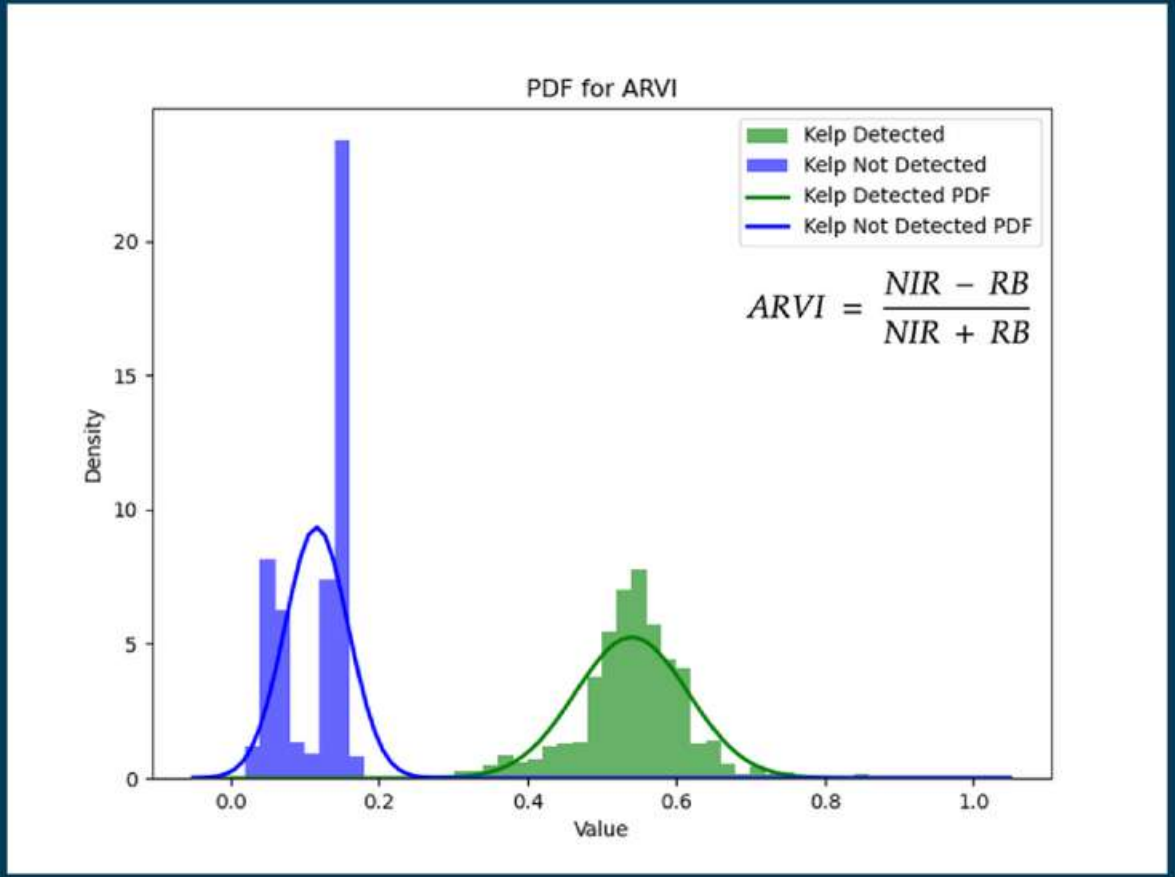


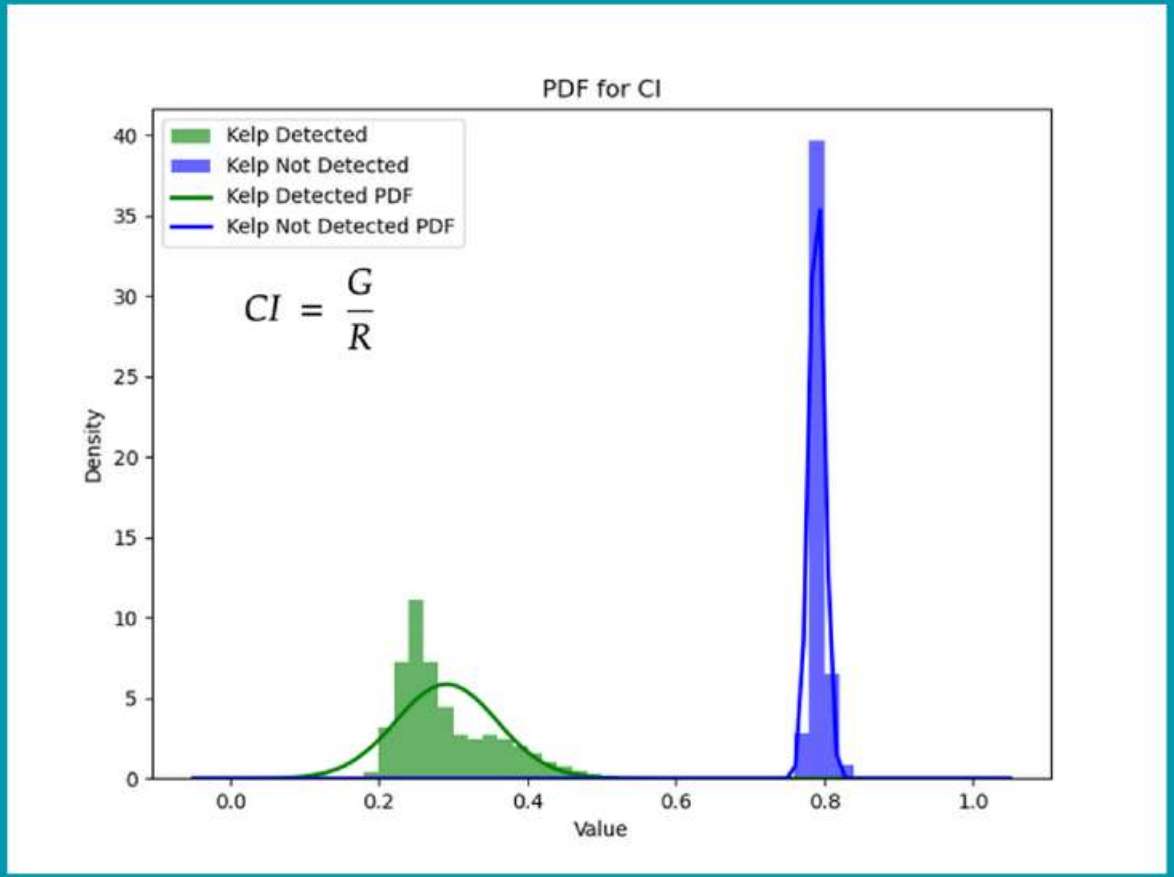


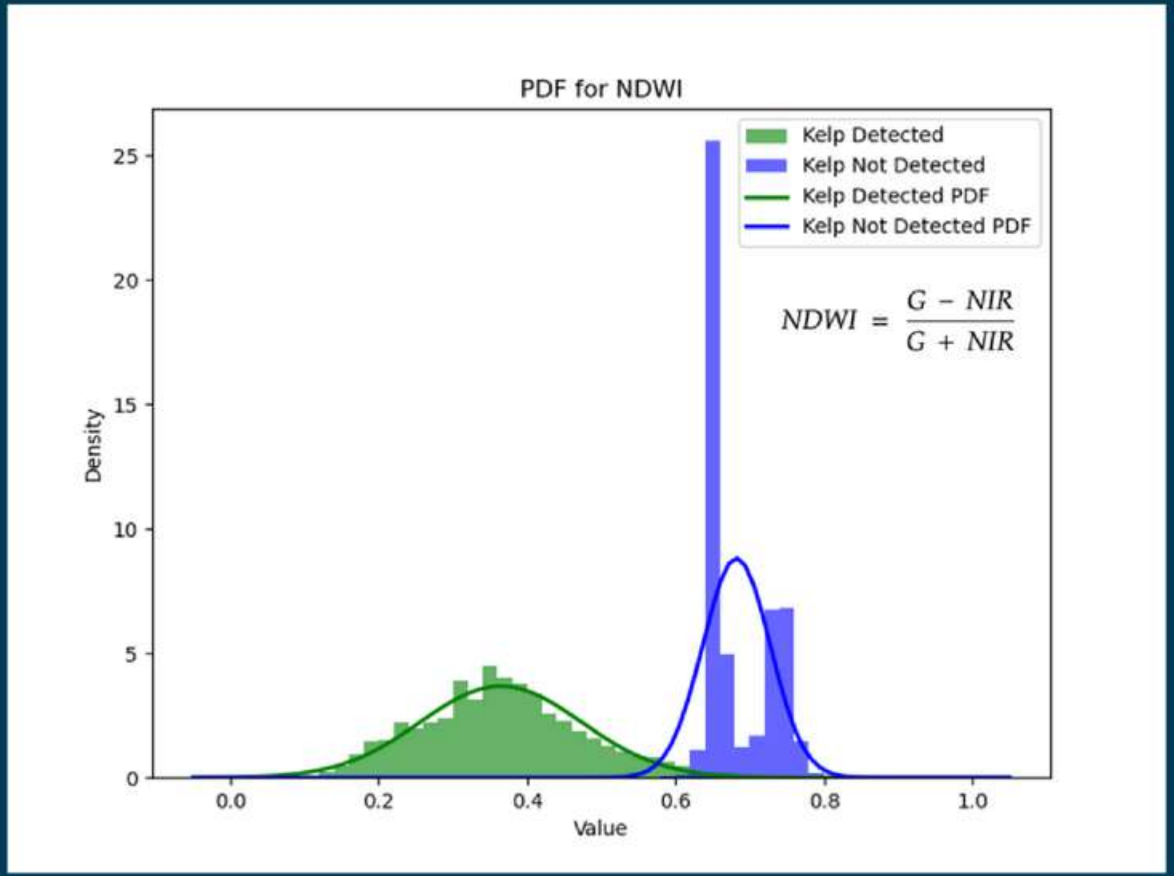


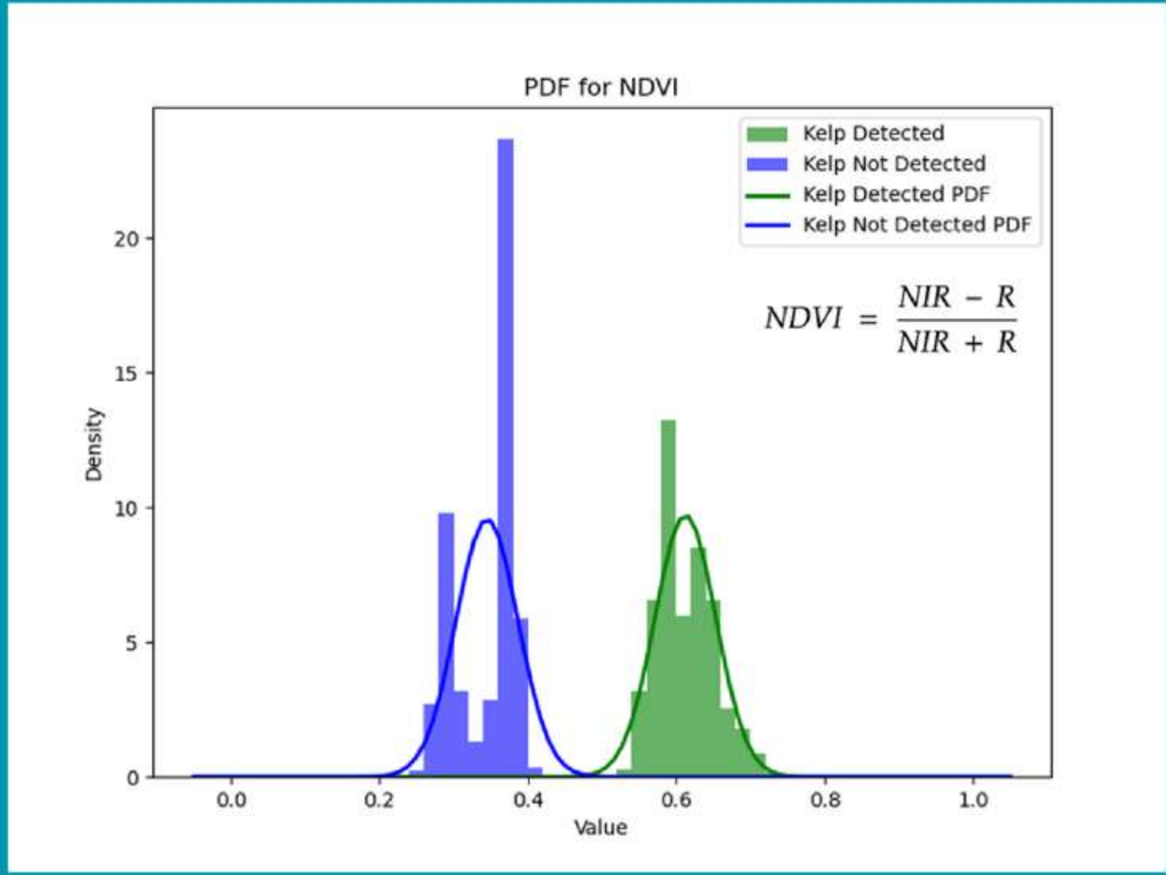
FEATURES EXTRACTED

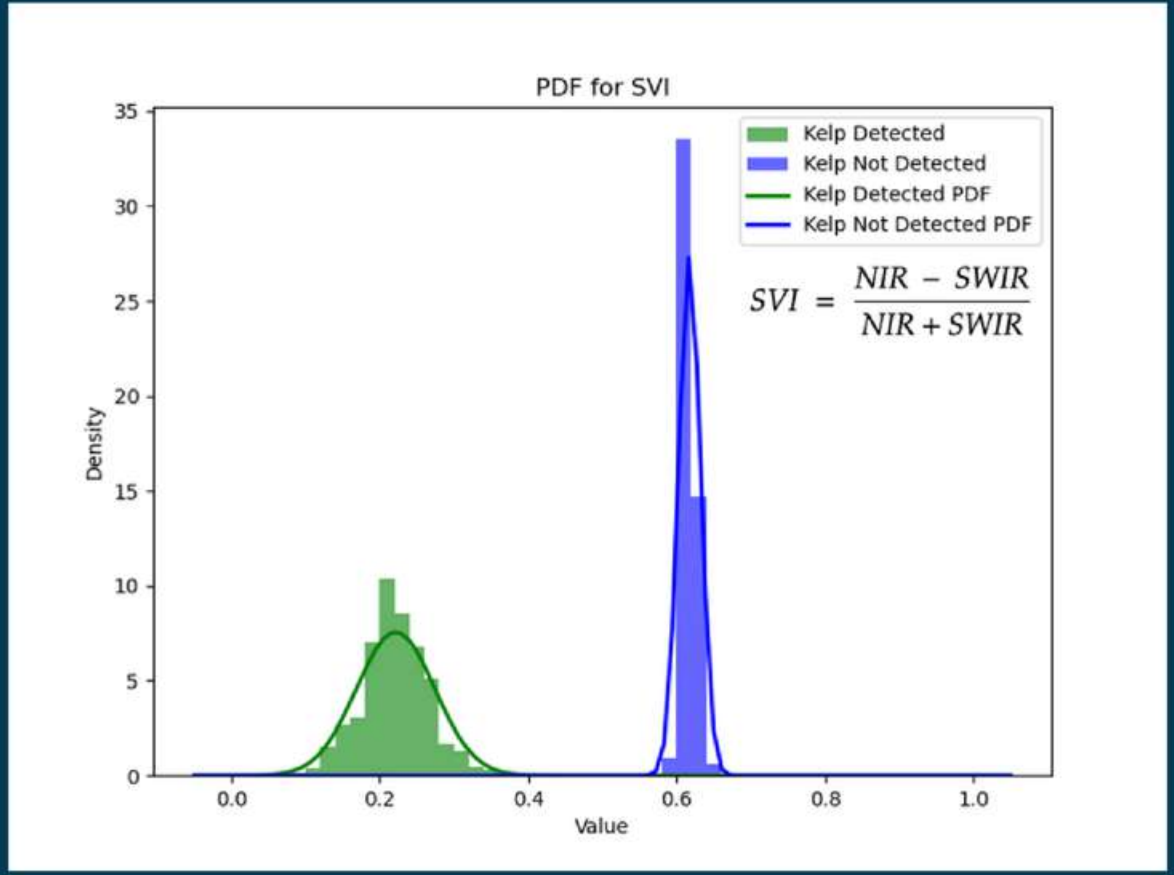
- Atmospherically Resistant Vegetation Index (ARVI)
- Chlorophyll Index (CI)
- Spectral Vegetation Index (SVI)
- Modified Normalized Difference Water Index (MNDWI)
- Normalized Difference Water Index (NDWI)
- Normalized Difference Vegetation Index (NDVI)

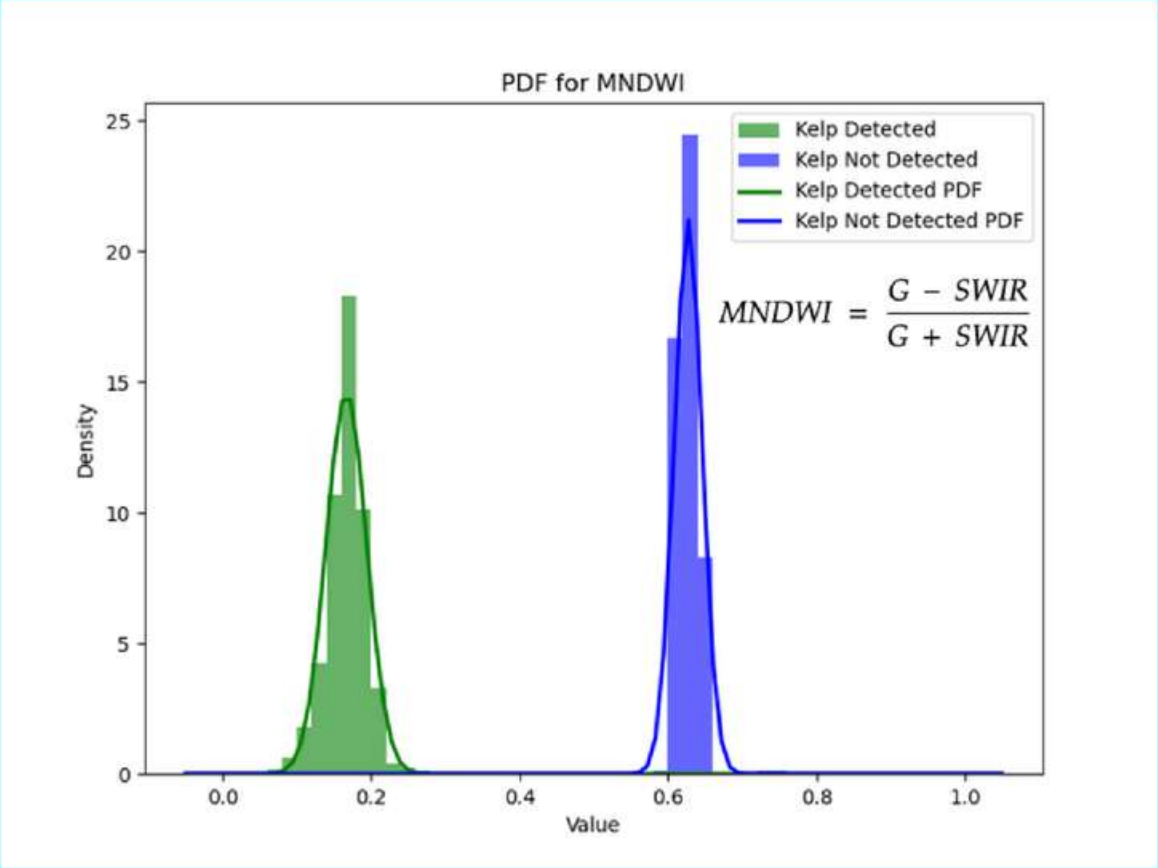

PDF for ARVI
Kelp Detected
Kelp Not Detected
Kelp Detected PDF
Kelp Not Detected PDF
$ARVI = \frac{NIR - RB}{NIR + RB}$
Density
Value


PDF for CI
Kelp Detected
Kelp Not Detected
Kelp Detected PDF
Kelp Not Detected PDF
$CI = \frac{G}{R}$
Density
Value


PDF for NDWI
Kelp Detected
Kelp Not Detected
Kelp Detected PDF
Kelp Not Detected PDF
$NDWI = \frac{G - NIR}{G + NIR}$
Density
Value


PDF for NDVI
Kelp Detected
Kelp Not Detected
Kelp Detected PDF
Kelp Not Detected PDF
$NDVI = \frac{NIR - R}{NIR + R}$
Density
Value


PDF for SVI
Kelp Detected
Kelp Not Detected
Kelp Detected PDF
Kelp Not Detected PDF
$SVI = \frac{NIR - SWIR}{NIR + SWIR}$
Density
Value


PDF for MNDWI
Kelp Detected
Kelp Not Detected
Kelp Detected PDF
Kelp Not Detected PDF
$MNDWI = \frac{G - SWIR}{G + SWIR}$
Density
Value

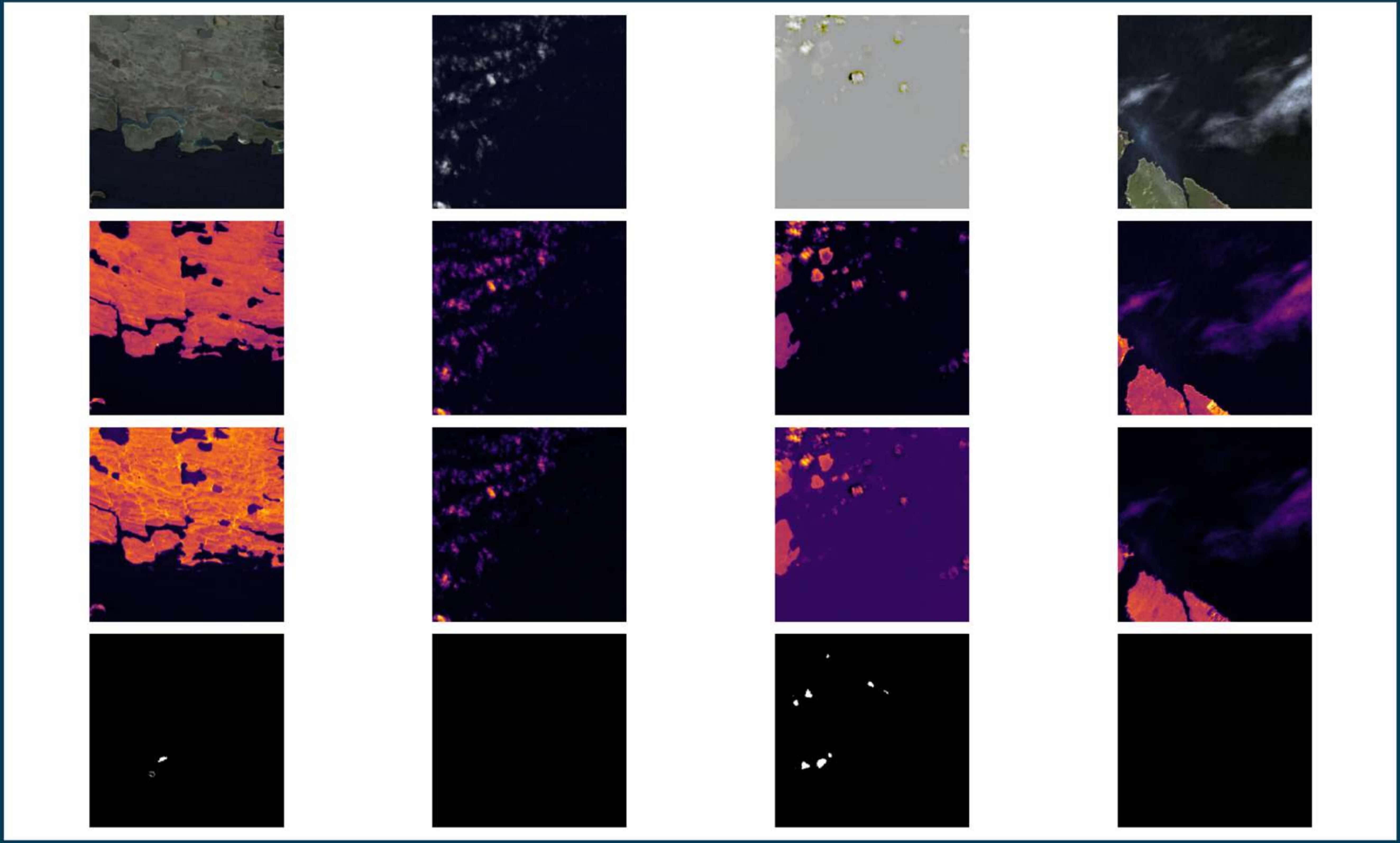
Pre-Processed Images

RGB

NDVI

NDWI

Label



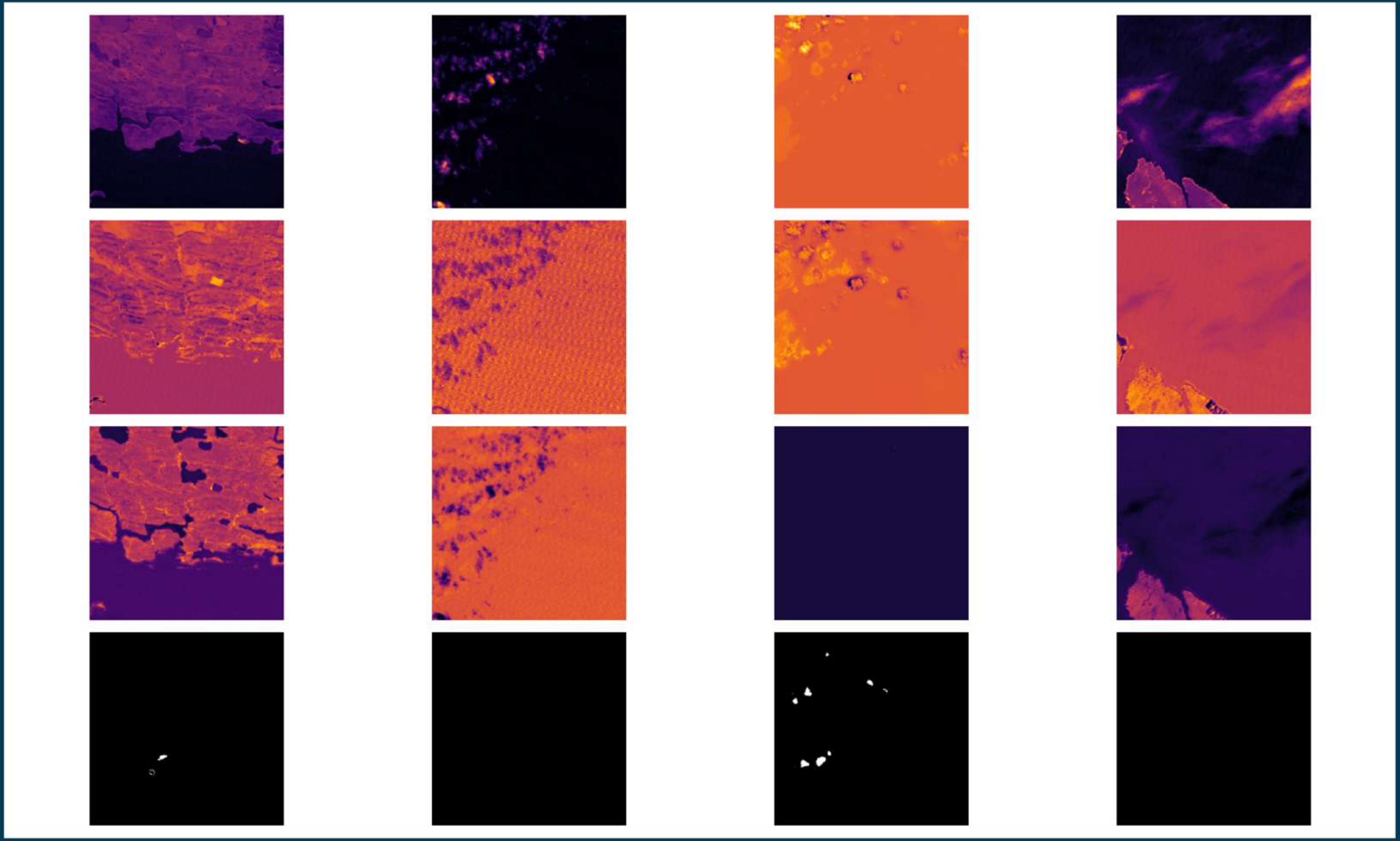
Pre-Processed Images

MNDWI

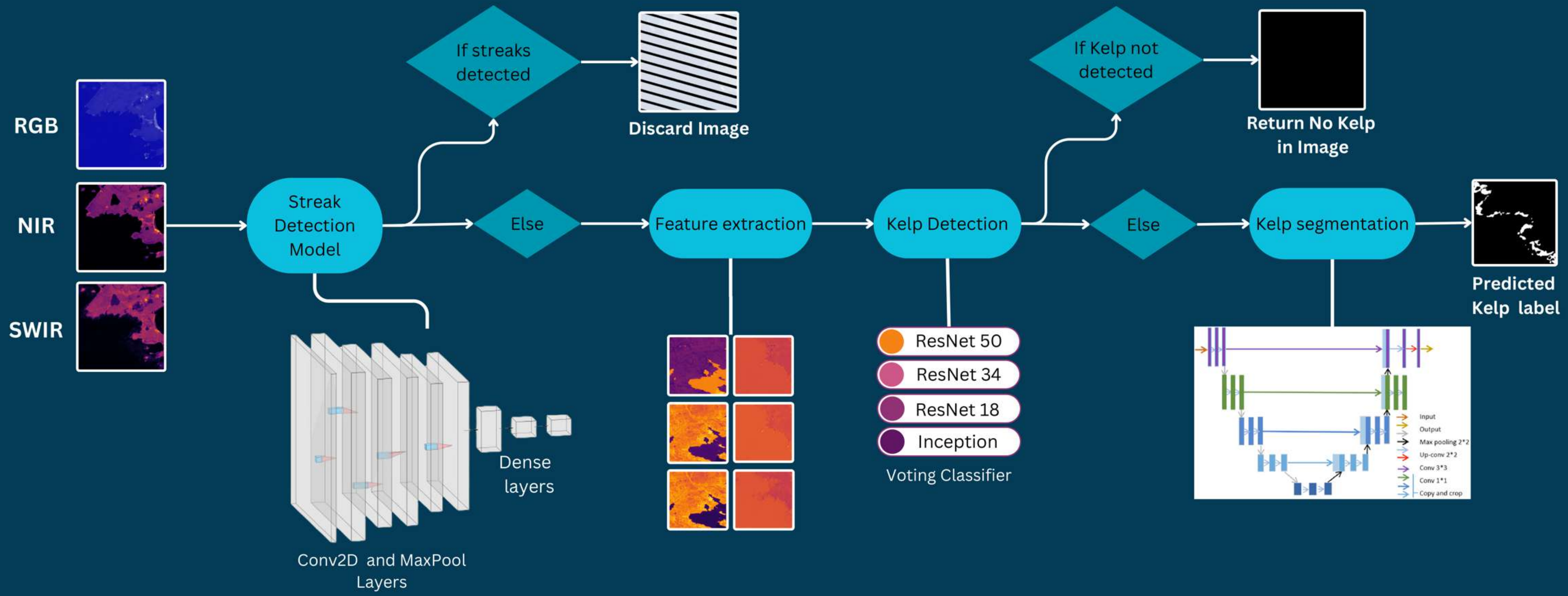
SVI

ARVI

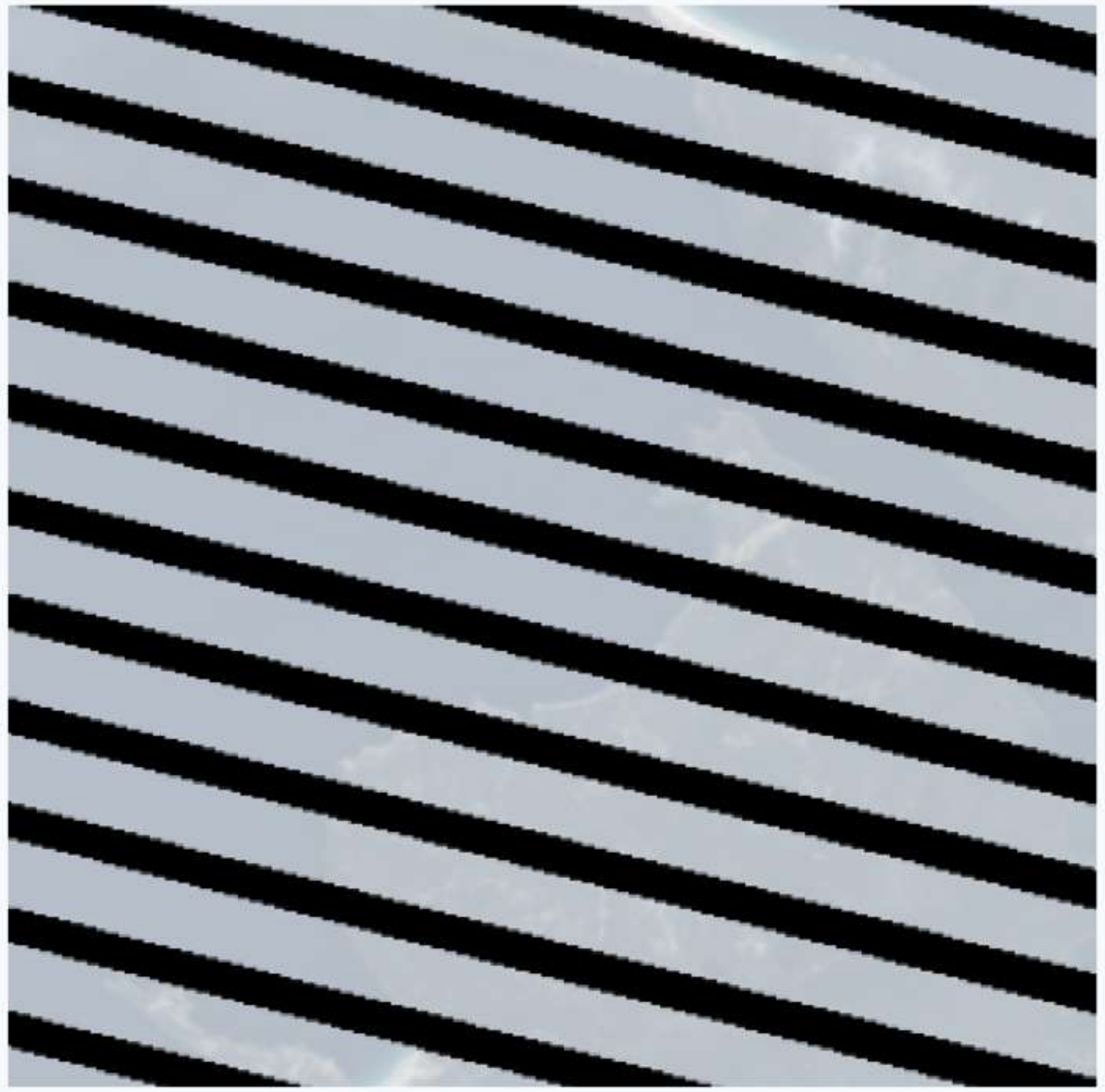
Label

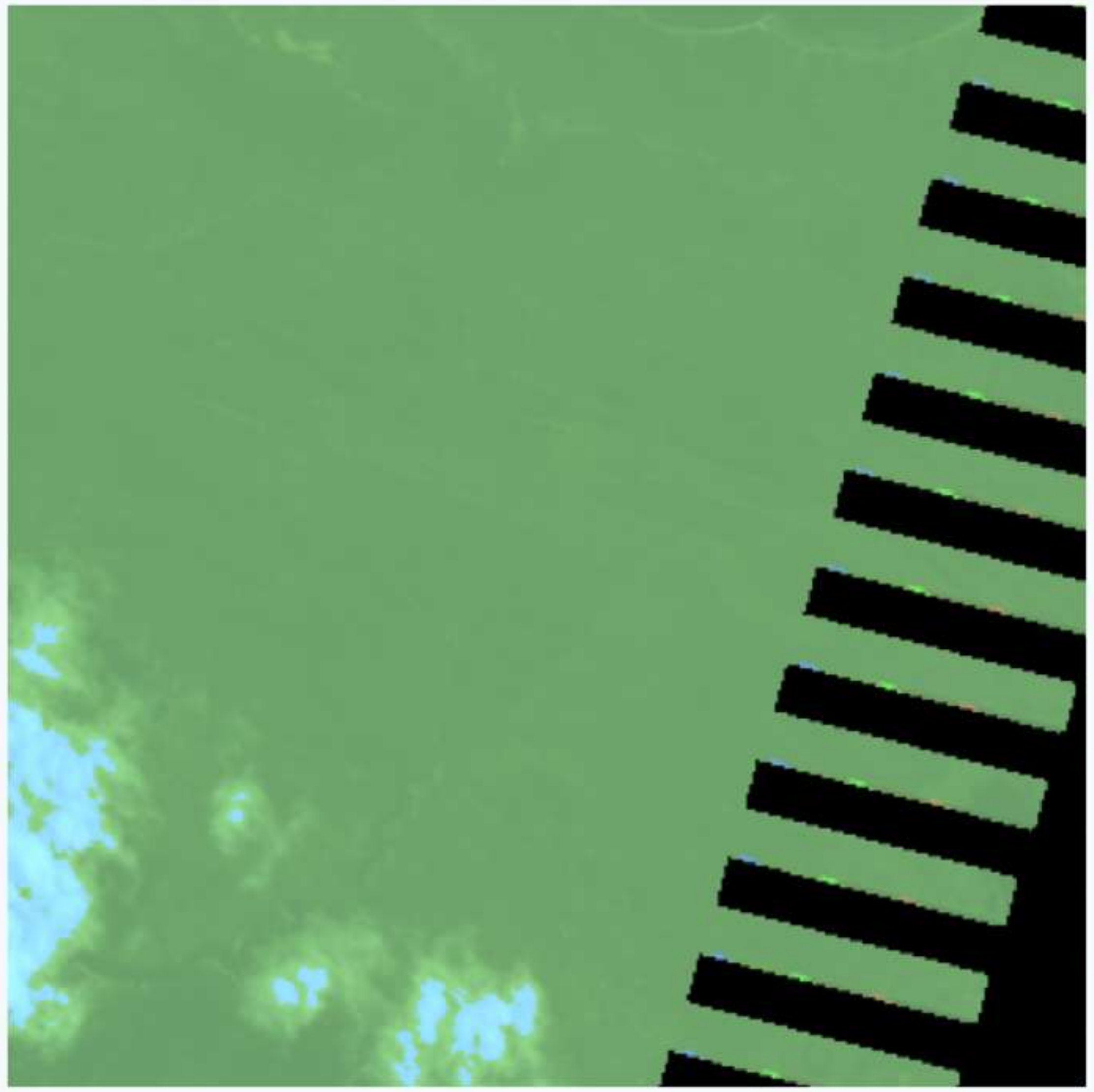


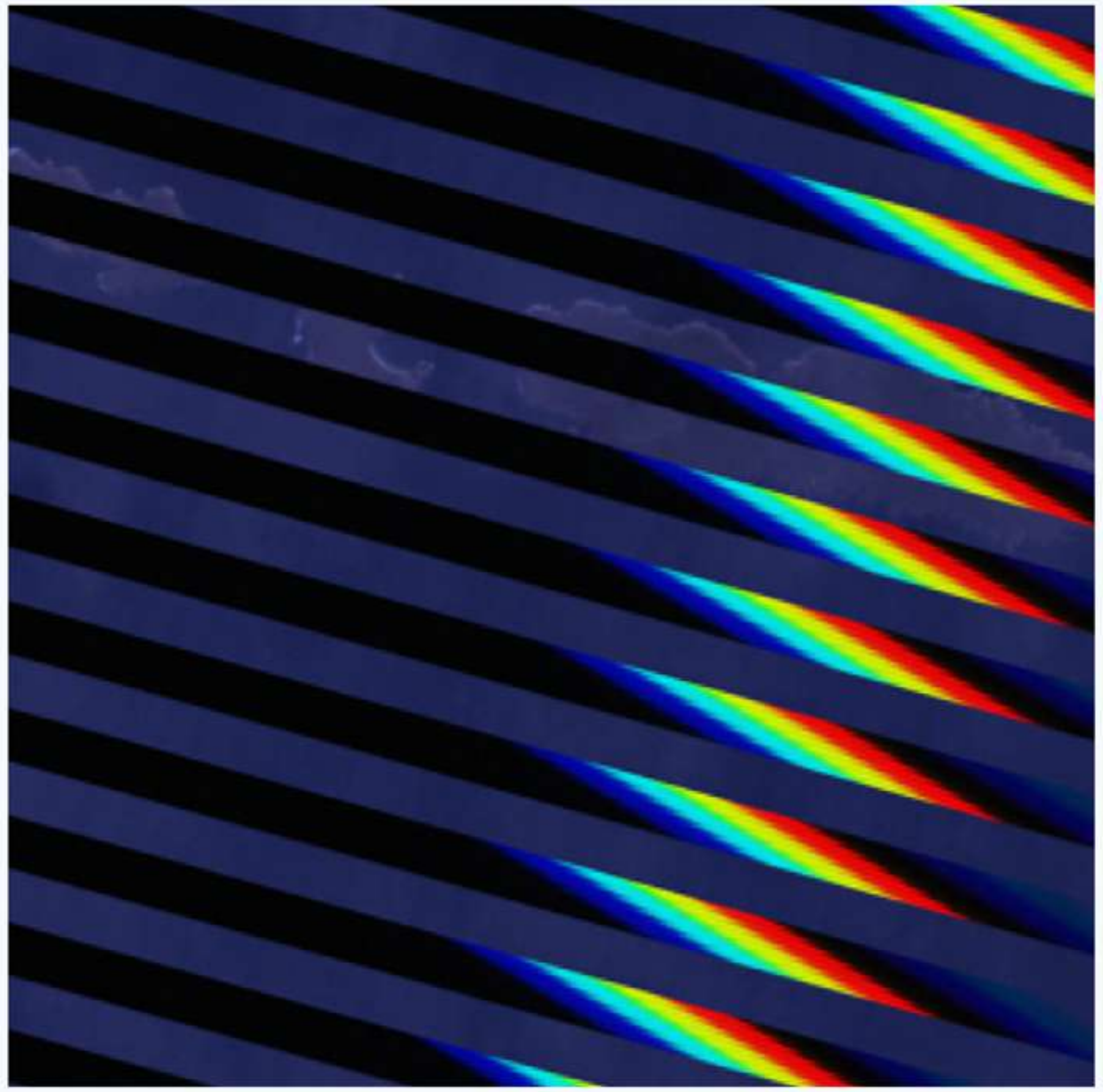
Model Pipeline



Images with Streaks







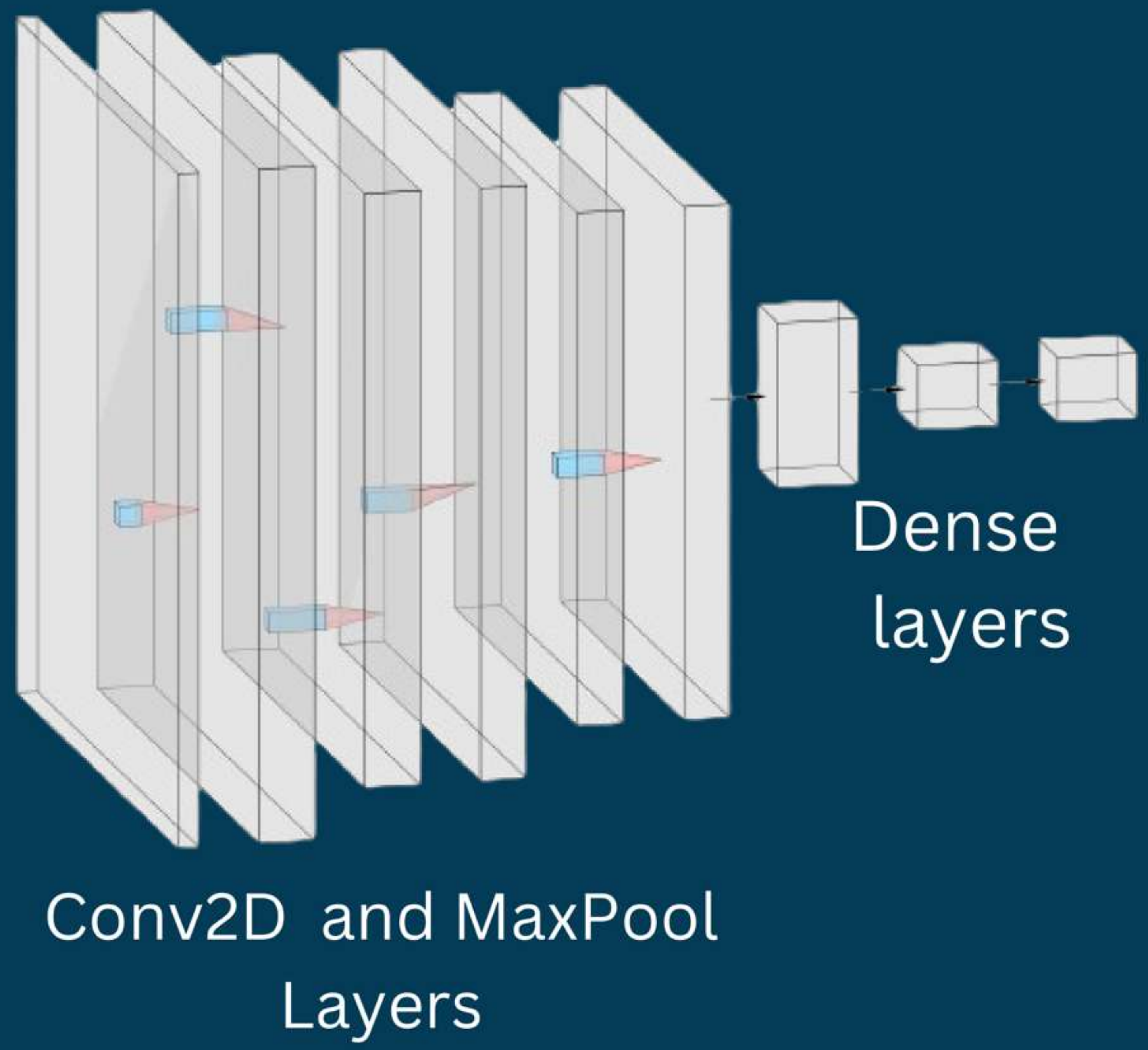
Streak Finder Model

Dataset Statistics:

- **Number of Images with Streaks:** 848
- **Number of Images without Streaks:** 4787
- **Ratio:** 0.1505

Performance Metrics:

- **F1 Score:** 0.952
- **Balanced Accuracy:** 0.954



Detection Models

Model Architecture	Accuracy	F1 score
ResNet50	0.7734	0.7531
ResNet34	0.7713	0.7593
ResNet18	0.7129	0.6913
Inception	0.716	0.6732
Voting Classifier	0.7812	0.8387

Segmentation Model

Model: UNet

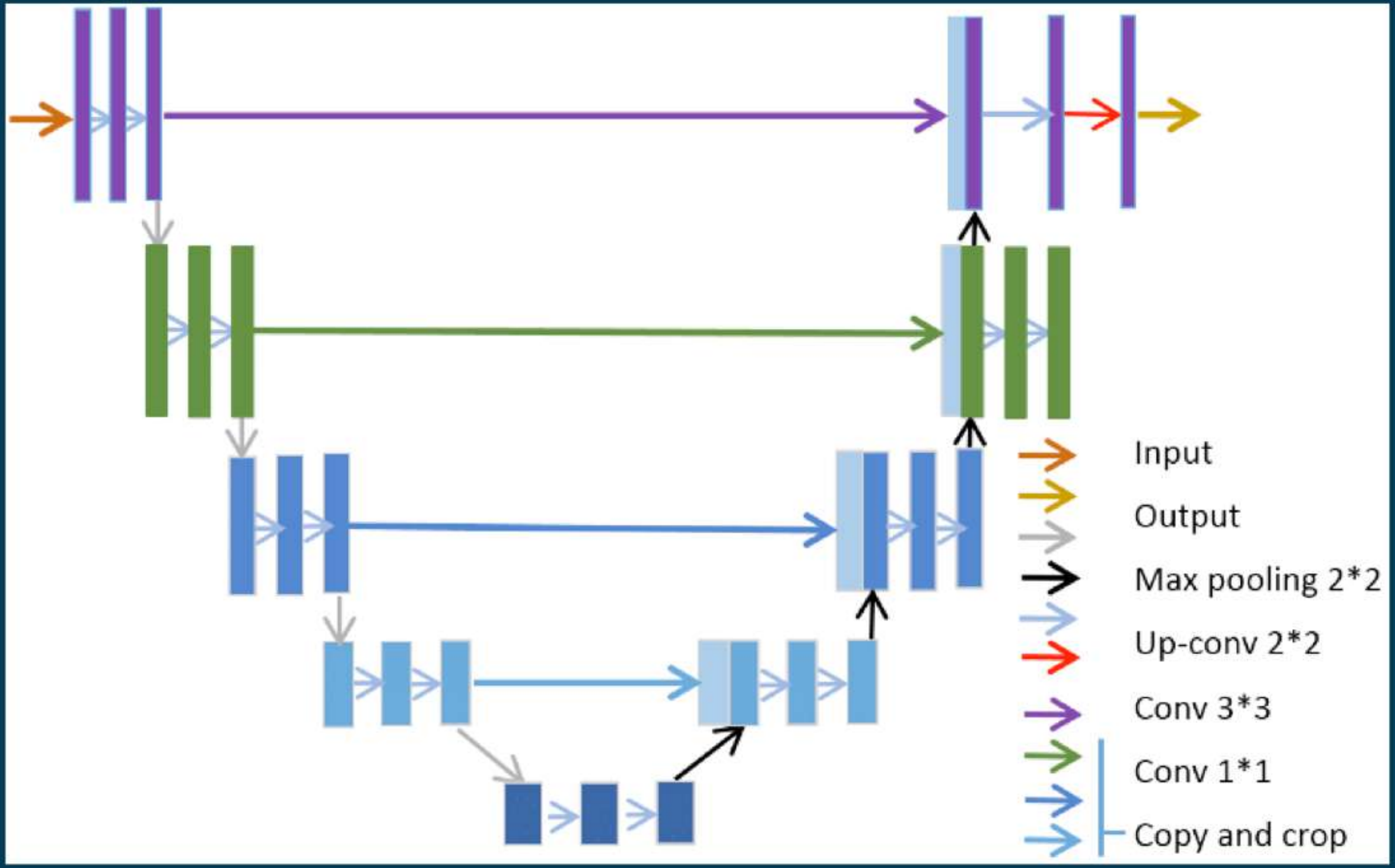
Index: MNDWI

(Modified Normalized Difference Water Index)

Average dice Coefficient: 0.553

$$\text{Dice coefficient} = \frac{2 * |X \cap Y|}{|X| + |Y|}$$

Model Architecture:



Graphic Courtesy: Y Ding, F Chen, Y Zhao, Z Wu "A Stacked Multi-Connection Simple Reducing Net for Brain Tumor Segmentation" IEEE Access, vol. 7, pp 99 5, 2019. [Online]. Available: 10.1109/ACCESS.2019.2926448.

Segmentation Model Output

IMAGE GROUND TRUTH MODEL OUTPUT

DataDriven Competition Leaderboard

1st Place: Epoch IV

- **Model Used**: A mixed ensemble of models trained on different feature sets, including UNets with VGG encoders, SwinTransformers and a ConvNext model.

- **Results:**
  Dice Coefficient: 0.7332

- Gradient boosting decision tree was also used with the already trained models.

Reference: https://github.com/TeamEpochGithub/iv-q2-detect-kelp

2nd Place: xultaeculcis

- **Model Used:** The model was a UNet with EfficientNet-B5 encoder pretrained on ImageNet.

- **Results**:
  Dice Coefficient: 0.7318

- They even tried XGBoost and SAHI(Slicing Aided Hyper Inference) as alternate pretrained model options that gave them Dice Coefficients of 0.5125 and 0.6848 respectively.

Reference: https://github.com/xultaeculcis/kelp-wanted-competition

Sources

[1] Eger, A.M., Marzinelli, E.M., Beas-Luna, R. et al. The value of ecosystem services in global marine kelp forests. Nat Commun 14, 1894 (2023). https://doi.org/10.1038/s41467-023-37385-0

[2] National Oceanic and Atmospheric Administration. (n.d.). Ocean oxygen. NOAA's National Ocean Service. Retrieved from https://oceanservice.noaa.gov/facts/ocean-oxygen.html


THANK YOU