

Multi-Layer U-Net for Kelp Forests Satellite Prediction

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Abstract

Purpose

Kelp canopy serves as the foundation for many coastal marine ecosystems, covering large swaths of ocean coastlines around the world. Kelp is essential for a lot of ecosystems around world because it provides habitat and food for thousands of species.

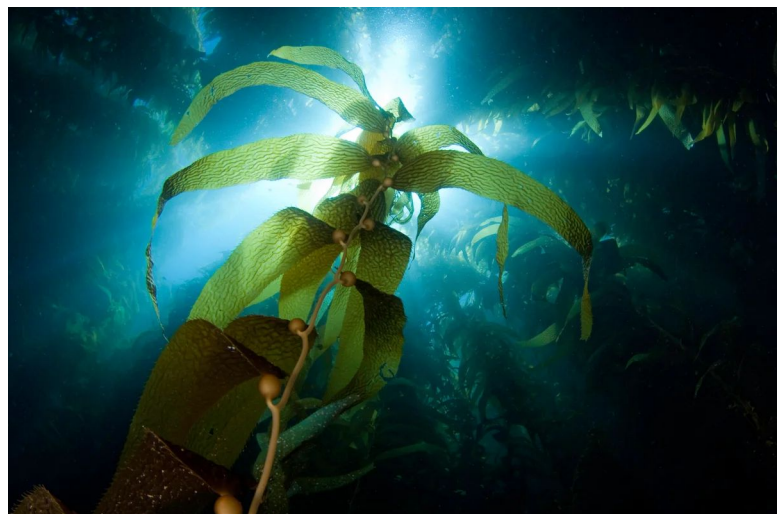
The purpose of this project is to develop an algorithm for binary semantic segmentation of satellite imagery to predict the presence or absence of kelp canopy, and the goal of the project is to leverage machine learning methods to facilitate environmental monitoring and marine conservation efforts.

Methods

We utilized a dataset comprising TIFF image files with seven layers of matrices: Short-wave infrared (SWIR), Near-infrared (NIR), Red, Green, Blue, Cloud Mask, and Digital Elevation Model (DEM). Each layer provides distinct information crucial for segmentation, such as vegetation health, surface reflectance, cloud presence, and elevation. We employed multi-layer U-Net and F-CNN architecture which was trained on the labeled data to learn the mapping between input satellite imagery and corresponding kelp canopy presence/absence masks.

Results

The prediction result is a single-layered, binary mask made up of 0s and 1s with 1s indicating the pixels with the presence of the kelp and vice versa.



Introduction & Significance

Kelp forests play a vital role in marine ecosystems worldwide. These lush habitats, dominated by giant kelp, serve as critical refuges and feeding grounds for myriad marine species, from small invertebrates to large fish and marine mammals. Beyond their ecological significance, kelp forests also hold immense economic value, contributing over US\$500 billion annually through services like fisheries production and tourism.

Despite their importance, kelp forests are facing fatal threats, including climate change-induced disturbances, overfishing, and unsustainable harvesting practices. To safeguard these invaluable ecosystems, there is an urgent need to enhance methods for mapping and monitoring them effectively.

However, the dynamic nature of kelp ecosystems presents a formidable challenge for comprehensive and robust monitoring efforts. Rapid responses to environmental factors such as temperature fluctuations, wave disturbances, and nutrient availability underscore the need for agile and adaptive monitoring techniques.

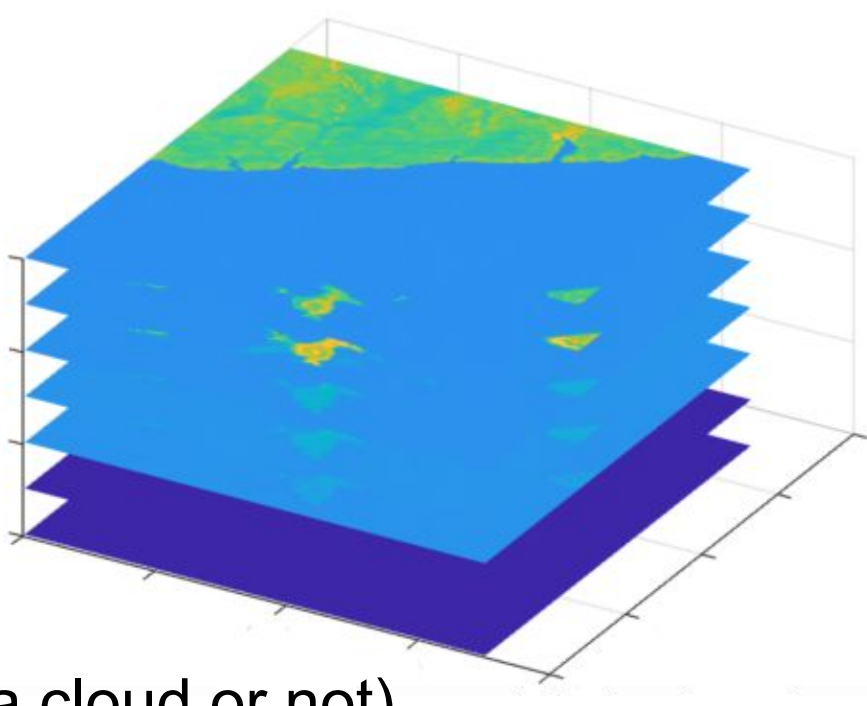
Datasets

- Image data is a (7061, 350, 350, 7) discrete integer set
 - Total of **6 billion** pixels
- Label data is a (7061, 350, 350, 1) binary set
 - Total of **1 billion** pixels

Methods

Training Data

- Short-wave infrared (SWIR)
- Near-infrared (NIR)
- Red
- Green
- Blue
- Cloud Mask (binary – is there a cloud or not)
- Digital Elevation Model (meters above sea level)



U-Net Architecture

We used PyTorch to build a U-Net architecture (Exhibition 2.D. & Exhibition 2.E.) which is a type of convolutional neural network (CNN) commonly used for image segmentation tasks. The U-Net architecture consists of a contracting path (encoder) followed by an expanding path (decoder), which forms a U-shape, hence the name "U-Net".

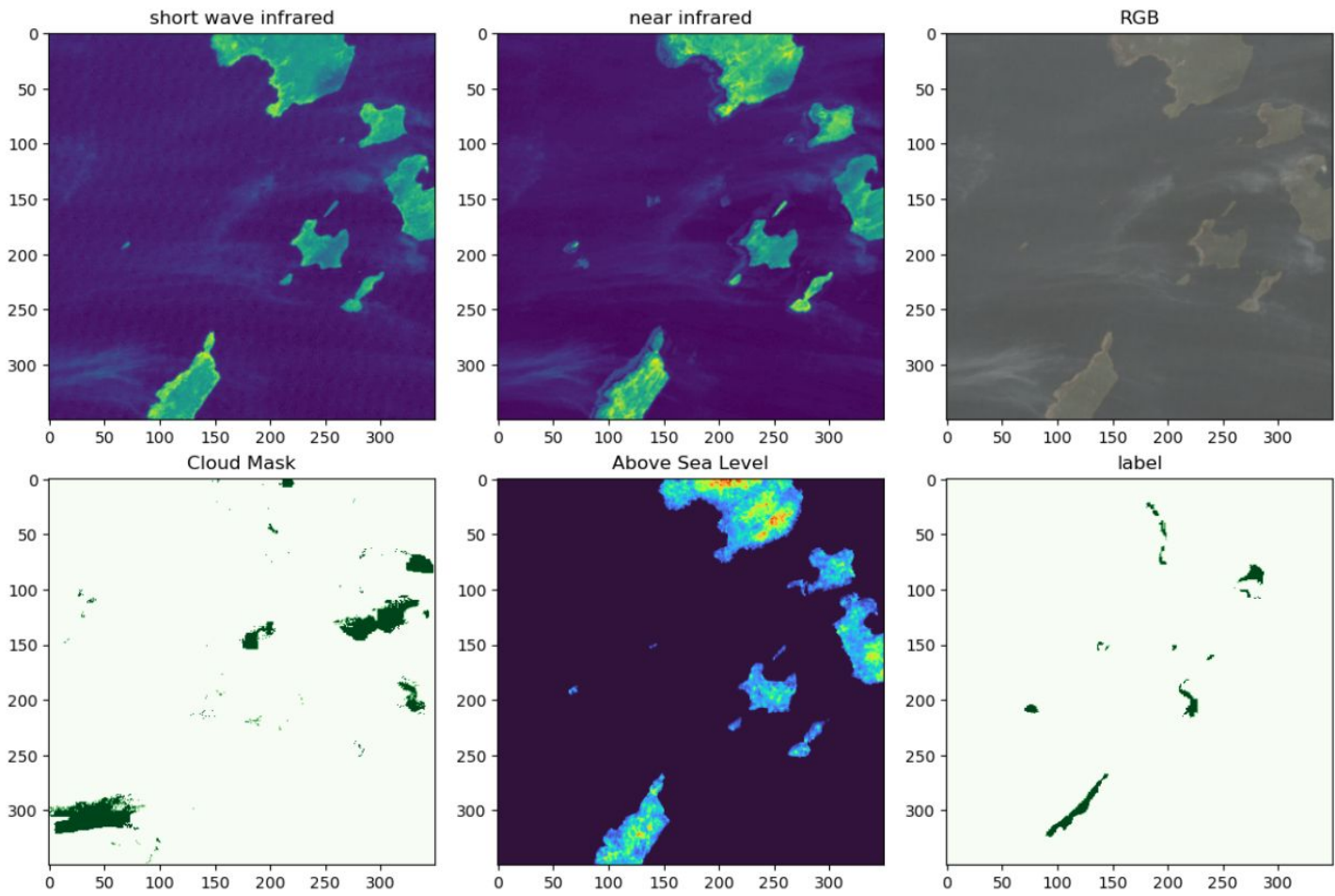
Aggregating

To improve model performance, we also implemented aggregating by training two U-Net on different layers of the satellite images:

- U-Net** model for short wave infrared + near infrared + cloud mask + land elevation, input size : [350, 350, 4] with the output [350, 350, 2]
- U-Net** model for RGB, input size : [350, 350, 3] with the output [350, 350, 2]
- Fully Connected Neural Networks**: Combine the output of the two U-Net models.

Then, we aggregate the prediction result by combining the results of two models pixel by pixel.

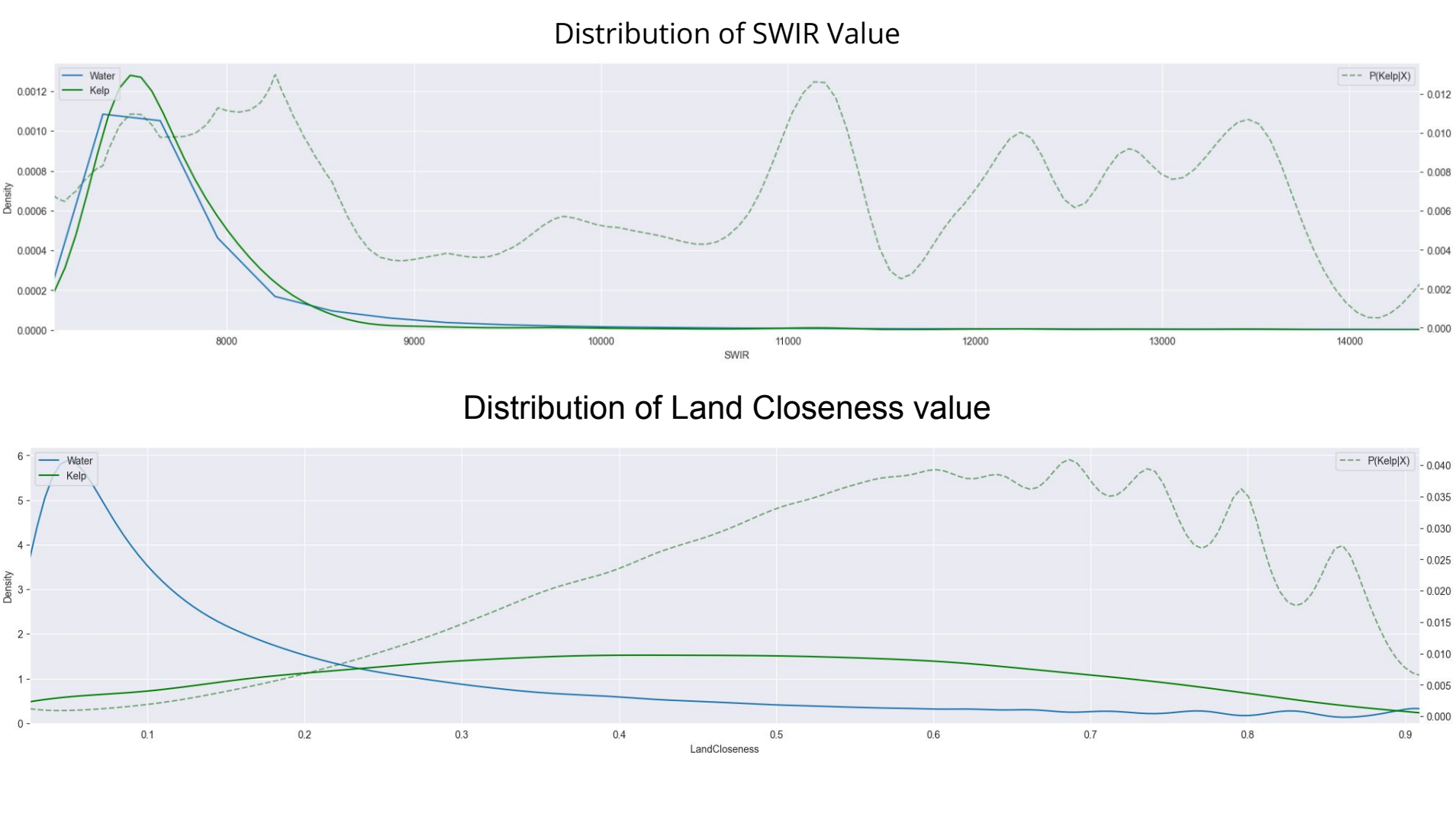
Exhibition 1.A. Visualization of Training Data



Exhibition 1.B. Kelp Location

Factors Supporting Image Segmentation:
In short wave infrared (SWIR) and near-infrared (NIR) images, areas such as **deep water** and **kelp canopy** exhibit absorbs green light. Specifically, the dense structure of kelp canopies enables efficient absorption of green light.

Exhibition 1.C. Band Analysis



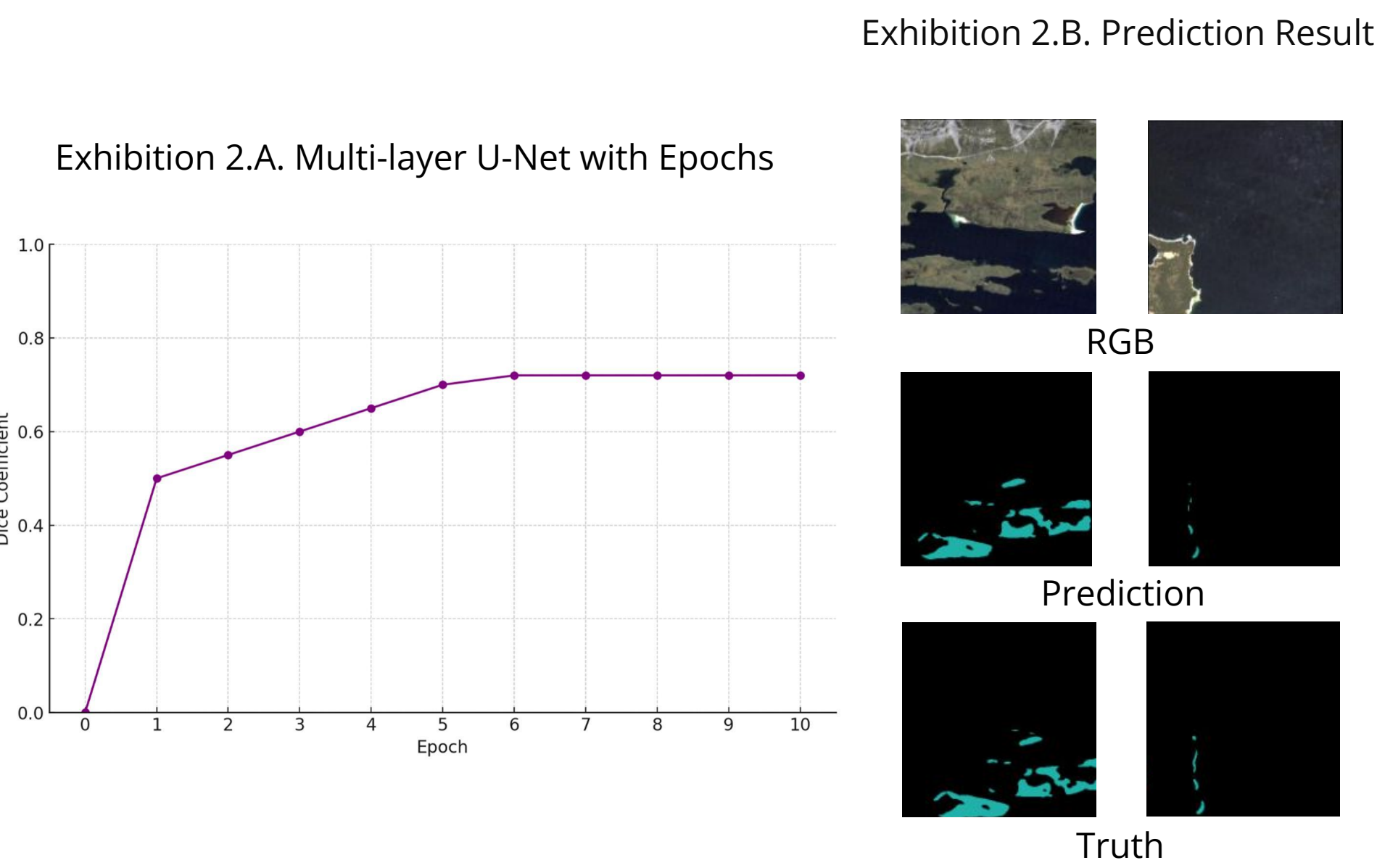
Results

Metrics

The Dice Coefficient is calculated on a per-pixel basis, where our multi-layer TIFF image for a patch is compared to the corresponding pixel in the ground-truth TIFF image for the same patch. This calculation is performed for each image in the test set, and the resulting Dice Coefficients are then averaged to provide an overall assessment of your model's performance.

Performance

Upon analyzing our model performance with the Dice Coefficient, we noted two key trends: a sharp performance boost at epoch 1, quickly elevating segmentation accuracy, followed by a performance plateau starting after epoch 7. This initial surge suggests our models' setup or initial data handling was particularly effective, rapidly enhancing their predictive capabilities. The subsequent flattening of improvements signals reaching an optimization peak, beyond which little gain is achieved, guiding us to an optimal stopping point for training to prevent overfitting and conserve resources.



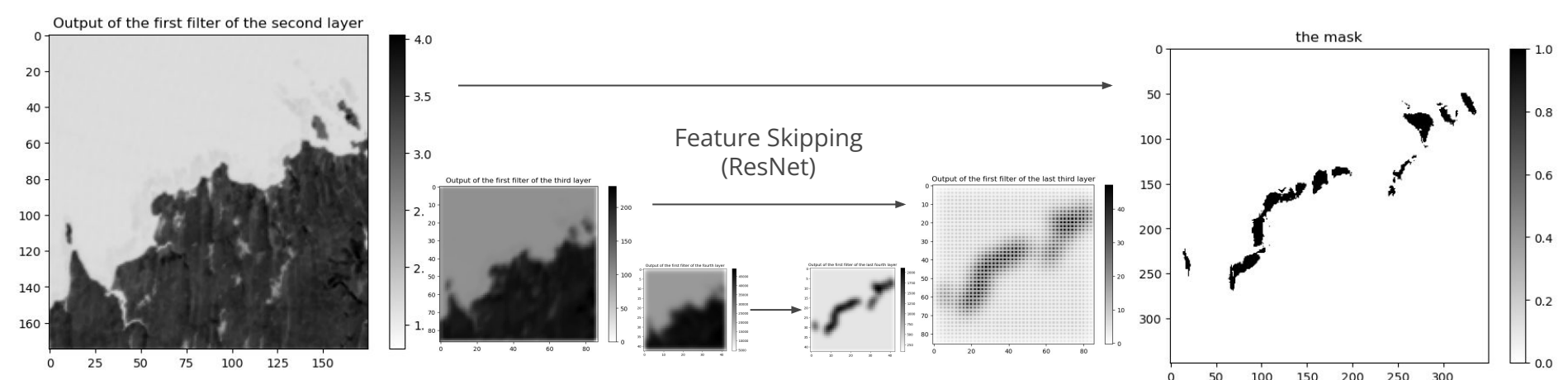
Exhibition 2.C. Dice Coefficient Analysis

$$Dice = \frac{2 \times TP}{(TP + FP) + (TP + FN)}$$

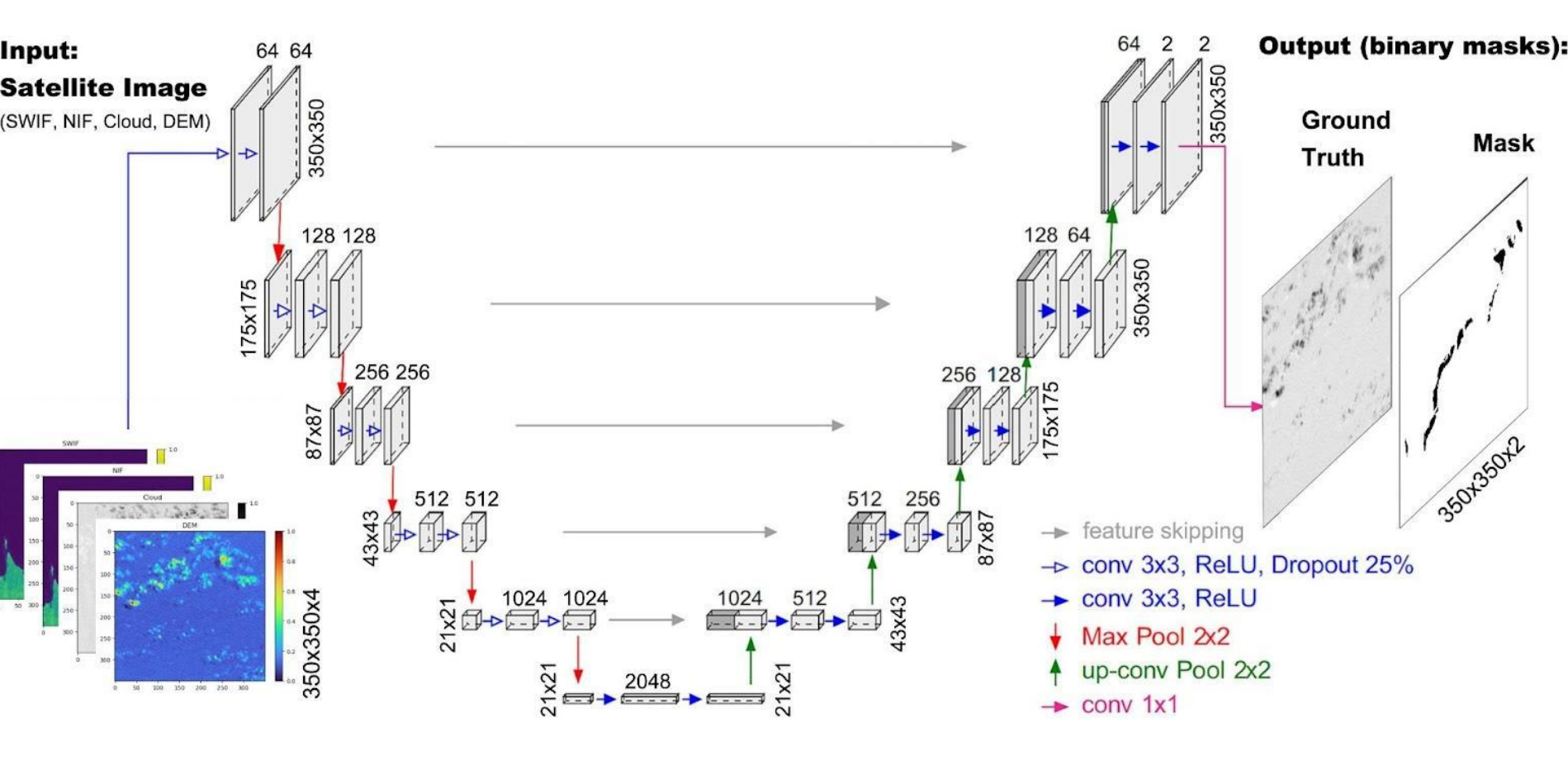
$$Dice\ Score = \frac{2 \times \text{Overlap}}{\text{Algorithm} + \text{GroundTruth}}$$

A Dice Coefficient of 0.6 means that the similarity between the two compared sets is moderate, indicating that there is a significant amount of overlap between the predicted mask and the actual mask.

Exhibition 2.D. Visualization for the U-Net Model



Exhibition 2.E. U-Net (4 layers) Structure



Discussion

Satellite Imagery Breakdown

- SWIR can penetrate through smoke and thin clouds, making it valuable for geological mapping. It is sensitive to moisture content in soil and vegetation, aiding in plant stress analysis and water management
- NIR is highly reflective in healthy vegetation, enabling the discrimination of vegetation types and conditions. NIR can also help in distinguishing between water bodies and land, as water absorbs NIR radiation.
- RGB layers represent the primary colors perceived by the human eye, crucial for creating true-color images.
- Cloud Mask is a binary layer that identifies the presence of clouds in satellite images, allowing for accurate analysis of ground conditions. Filtering out clouds is essential for precise assessment of vegetation, water bodies, and other features, enhancing environmental monitoring and agricultural assessments.
- Digital Elevation Model represents elevation above sea level in meters.

U-Net Architecture

Our model structure is based on the original U-Net architecture introduced by Olaf Ronneberger, Philipp Fischer, and Thomas Brox in their 2015 paper titled "U-Net: Convolutional Networks for Biomedical Image Segmentation". However, there is a difference in the size of the input image tiles. While the original U-Net model's input image size is [224, 224, 3], ours is [350, 350, 7].

Improvement

- Jittering & Image augmentation
Adding more variety to the training data can help the model generalize better, reducing overfitting and improving performance on unseen data.
- More flexibility with model structure
Introduce attention gates in the U-Net to allow the model to focus on relevant features for segmentation.

Conclusion

Despite of its ecological and economic significance, kelp forests has been facing external threats. Therefore, it is important to monitor and preserve kelp forests. However, its dynamic nature of kelp make monitoring efforts challenging, and machine learning is a good alternative methods. The U-Net architecture presents a highly effective and versatile solution for this binary segmentation tasks.

References

Marquez, L., et al. "Artificial intelligence convolutional neural networks map giant kelp forests from satellite imagery." Scientific Reports, vol. 12, no. 1, 23 Dec. 2022, <https://doi.org/10.1038/s41598-022-26439-w>.



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