A deep learning approach to map shoreline structures with high-resolution imagery and convolutional neural networks

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Introduction

The traditional approach to collecting and mapping shoreline structures consists of a GPS field survey to collect coordinates and attribute information of coastal structures, and then manually delineating the structures and extracting basic feature information (e.g., type, material, and length) from remotely sensed data or other available digital images. These processes are time and resource intensive, and require in-situ surveys and well-trained technicians to carry them out. In this study, we explore the effectiveness of a deep learning approach to map shoreline armoring structures from remotely sensed high-resolution imagery, mainly focused on riprap, bulkhead, breakwater, and groins – the four major shoreline stabilization structures constructed in coastal Virginia. We further present pyShore on ArcGIS pro, an implementation of this deep learning algorithm made available for human coders to apply as a part of a semi-automated workflow.

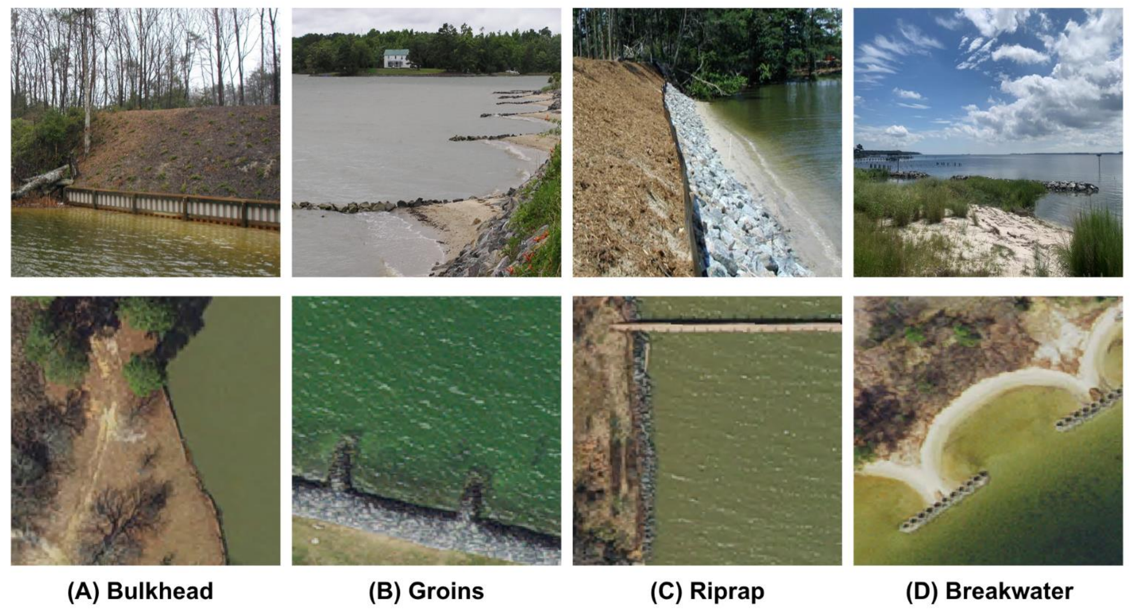
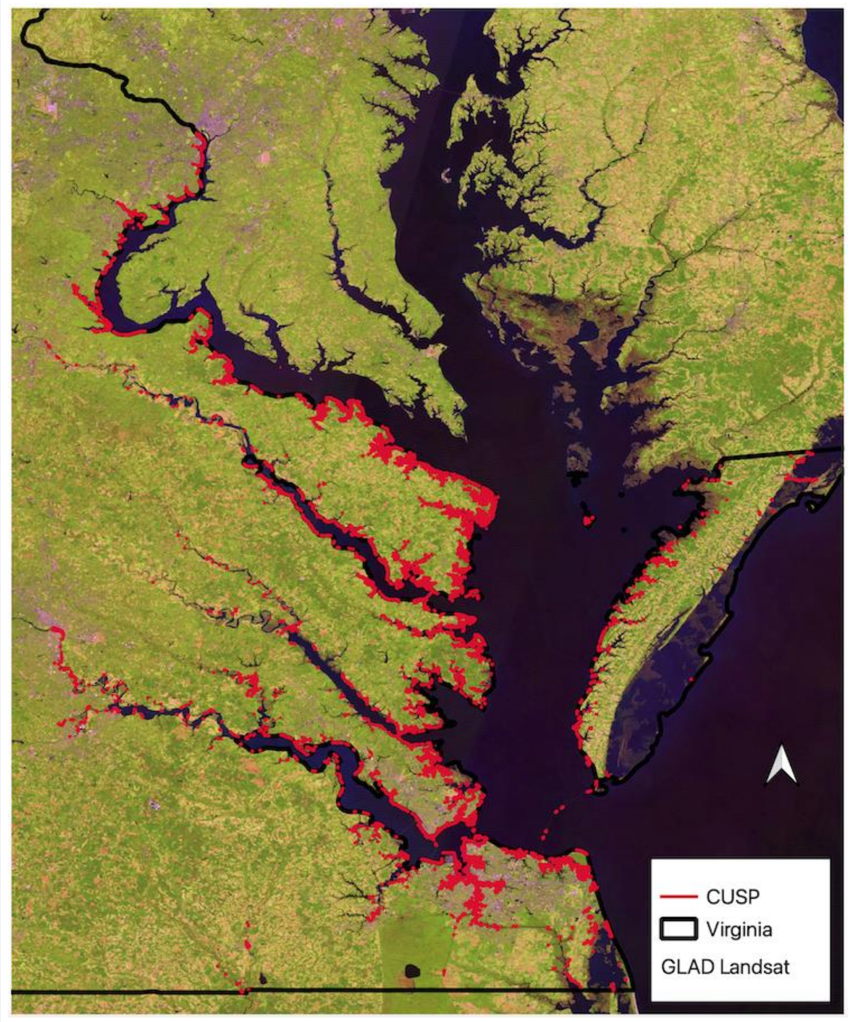


Figure 1. A visualization of the four shoreline armoring techniques we focus on in this study. The upper four images are taken on-site, and the lower four images are from VA orthoimagery. (Lv et al., 2023)

Study Area & Data



In this study, we focus on 17,239 kilometers of shoreline located in the state of Virginia in the United States. The majority of this shoreline surrounds the Chesapeake Bay, a protected estuary responsible for over a hundred billion US dollars of economic output every year, predominantly related to commercial fishing, tourism, recreation, and timber (Phillips and McGee, 2014).

Data Imagery:

- National Agricultural Imagery Program (NAIP)
- Virginia Base Mapping Program (VBMP)

Data Annotation:

- NOAA Continually Updated Shoreline Product (CUSP)

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Methodology

The U-Net is a well-established, relatively light weight (under 10 million parameters and forward-pass timings of less than a second for 256 × 256 images) deep learning algorithm for semantic segmentation based on convolutional network architectures (Ronneberger et al., 2015). The algorithm's architecture includes two parts: down-sampling and up-sampling, also called the encoder and decoder. The encoder extracts varying resolution feature maps through a series of convolutional, rectified linear units (ReLU), and max-pooling layers. The decoder stage contains and combines (a) each feature map from the down-sampling process, and (b) spatial information through an up-sampling and concatenation process (Fig. 3). This data flow of down-sampling and up-sampling constructs a U-shape of architecture, thus the output layer maintains the same resolution as the input layers. One key benefit of using this learning architecture is that it has been shown to be effective in cases with few training images, while still retaining high levels of segmentation accuracy (Ronneberger et al., 2015). Two additional semantic segmentation algorithms – DeeplabV3 (Chen et al., 2016) and Pyramid Attention Networks (PANs) (Li et al., 2018) – are also explored and tested in this study.

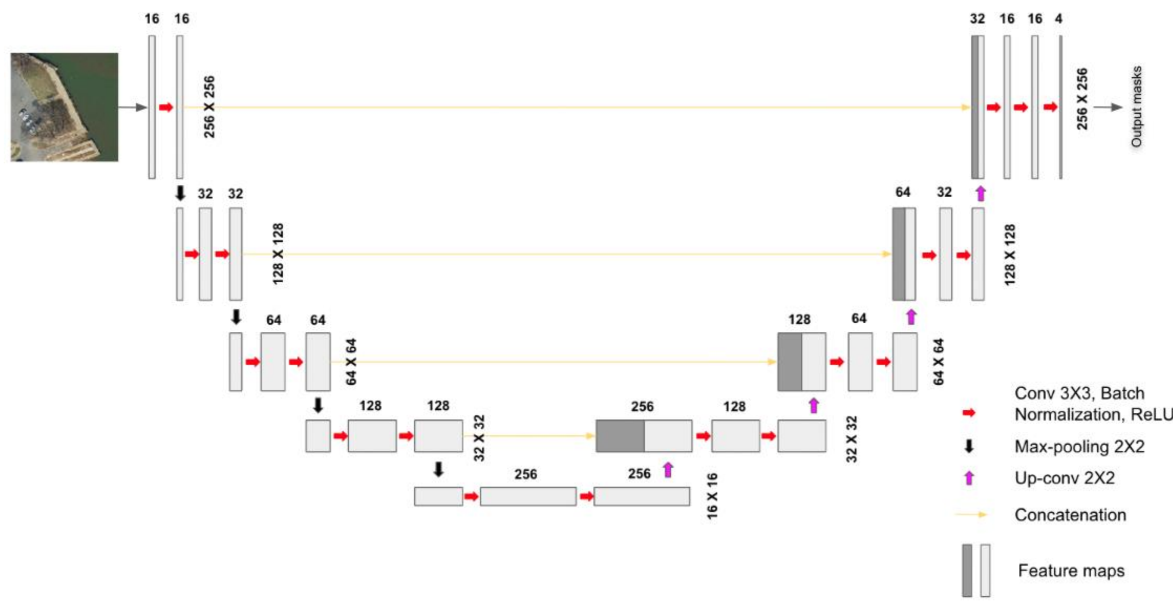

Figure 3. The U-Net architecture (Example of a 3-band input image with 256 × 256 pixel-size). The boxes indicate the feature maps at each layer, and the number on the top of each feature map shows the depth of feature map (channel). Numbers on the right side of each feature map are image/feature maps dimension.

Results

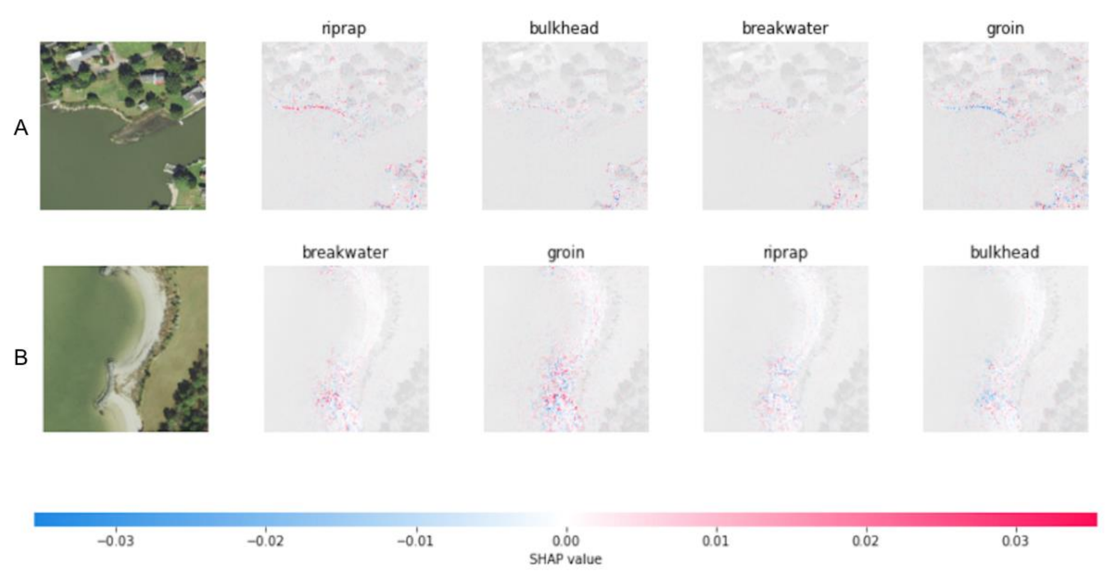

Figure 4. The above shows two random correctly classified test images in the first column. The second, third, fourth, and fifth columns show the pixels/features that contributed against and in favor of prediction for each of the four classes. For example, the upper-left image is a riprap structure that was predicted by the model most likely to be a riprap, then bulkhead, breakwater, and groin. Blue pixels represent areas that work against classification in a given class and the red pixels represent areas that work for classification (Lv et al., 2023)

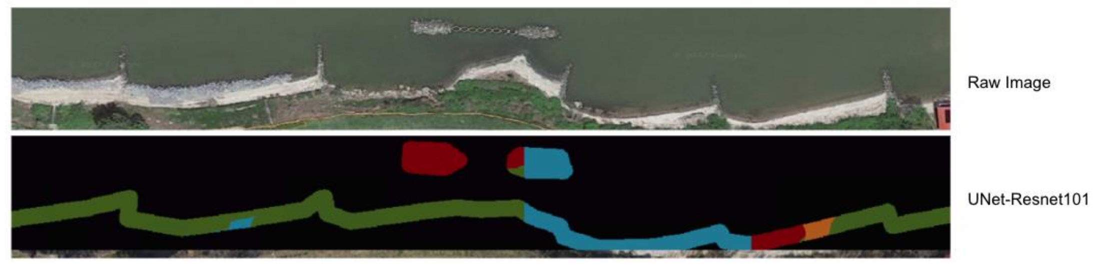

Figure 6. Result visualization predicted by Unet-resnet 101 trained on VBMP 3-band imagery (Lv et al., 2023)

- Our findings suggest that relatively less complex networks are some of the strongest performers for the task of shoreline feature detection.
- Inclusion of near-infrared band provides 1% - 2% overall accuracy improvements over 3-band optical approaches depending on various models.
- A semi-automated toolkit ArcGIS – pyShore - for shoreline structure classification was presented.

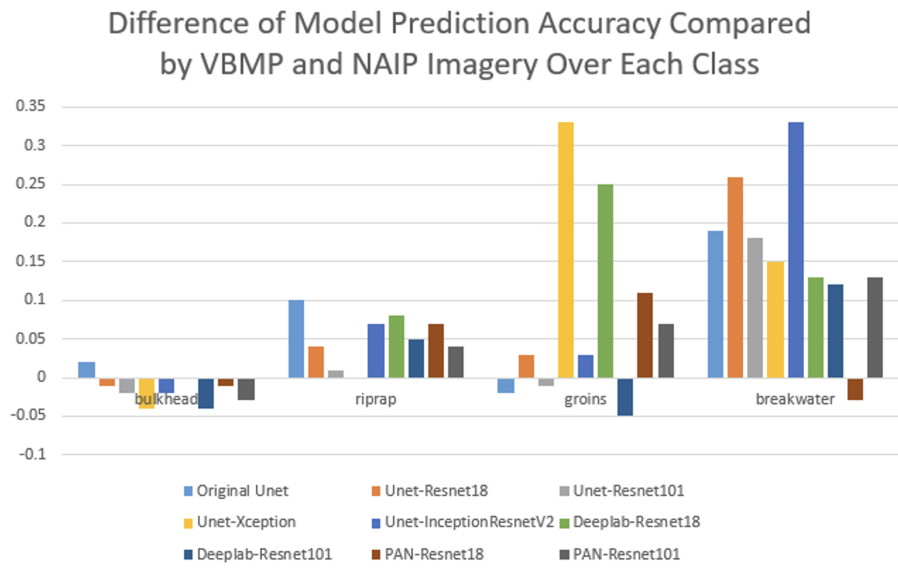

Figure 5. Precision improvement for each class when contrasting models fit in Virginia using the VBMP orthoimagery and NAIP imagery(Lv et al., 2023).

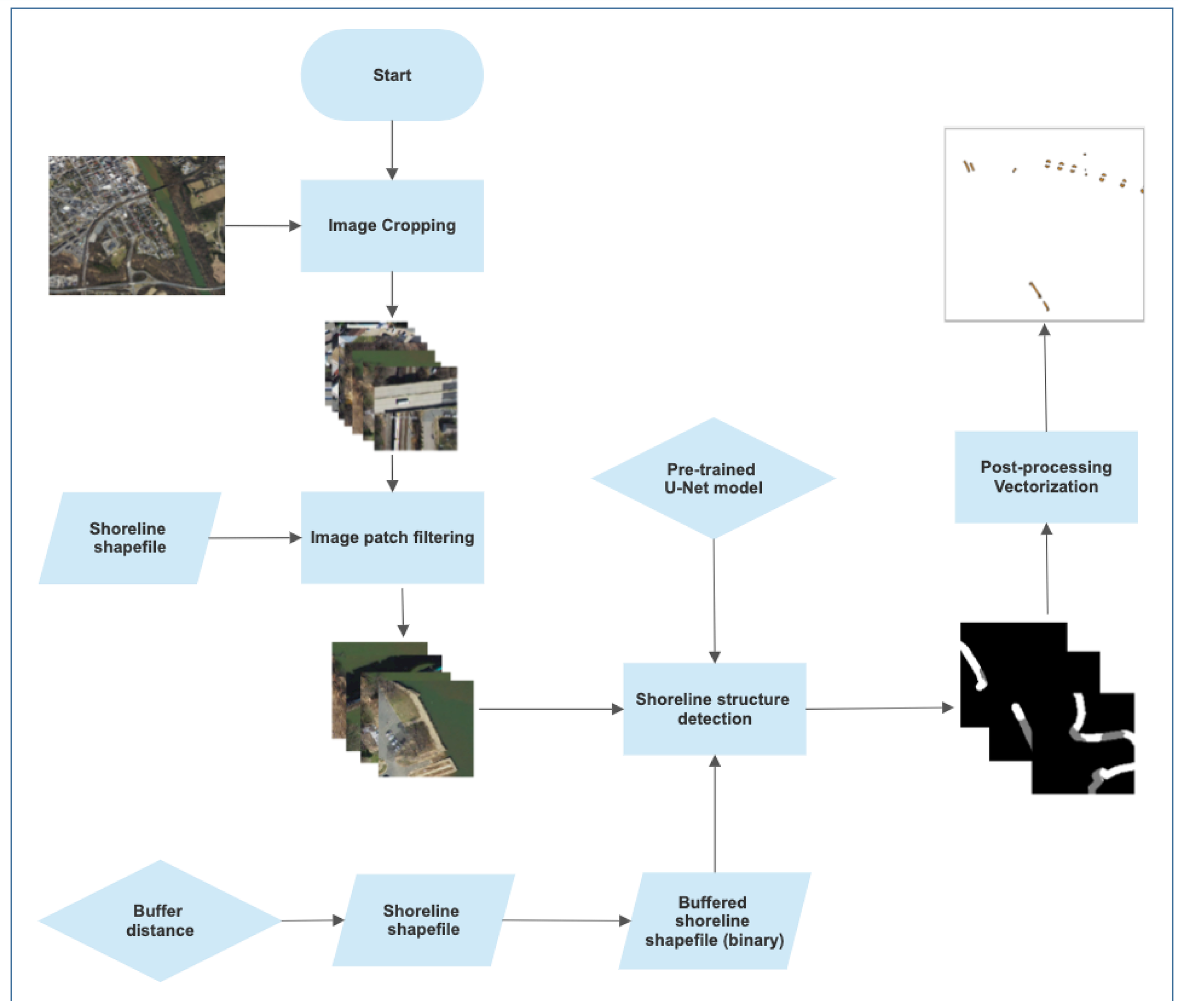

Figure 7. Workflow of shoreline structure detection using the pyShore ArcGIS Pro toolkit (Lv et al., 2023).

Conclusions

In this project, we sought to explore the capability of convolutional neural network architectures to identify shoreline structures from remotely sensed imagery. This study provides (1) an initial benchmark accuracy (72%) for deep learning-based shoreline structure localization in Virginia , and (2) a computationally efficient semi-automatic toolkit that can be deployed in desktop environments which harnesses the proposed method for applied use. These findings, and the related toolkit provide a new method for local and state governments in the US to generate shoreline inventories, and improve the management of coastal resources and infrastructure.

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