Impact of Image Patchification on the Segmentation Performance of Deep Learning Methods with Applications to Mountain Glacier Area Segmentation

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01

Introduction

Why are glaciers important?

Glaciers are an essential part of life

- Supports over 1 billion people
  - Resources
  - Economic Benefits
  - Socio-political Impacts
- Maintains biodiversity

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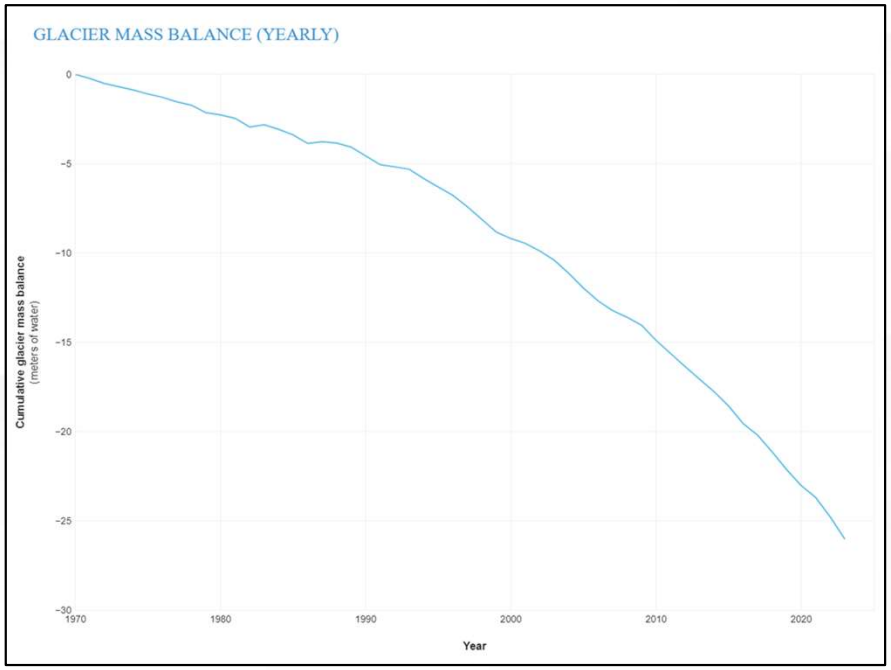
Glaciers and Climate Change



(Lindsey, 2024)

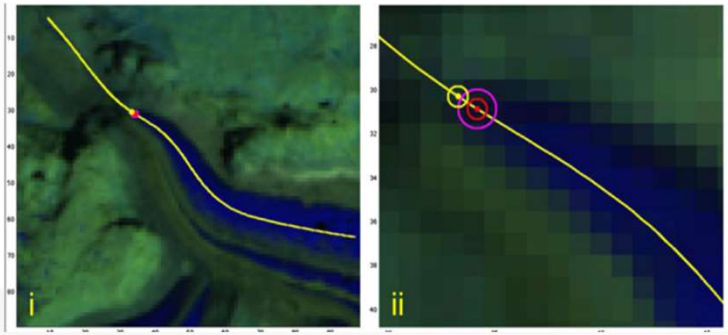
It is important to measure glaciers and their change over time.

02

Previous Work

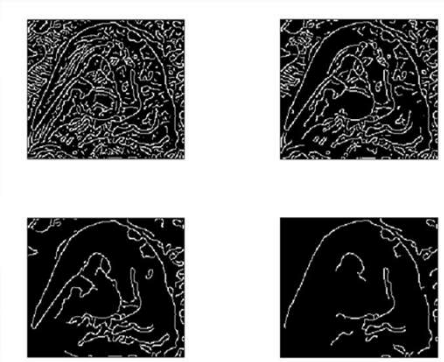
What has been done already?

Terminus Localization



(Kachouie et al., 2013)

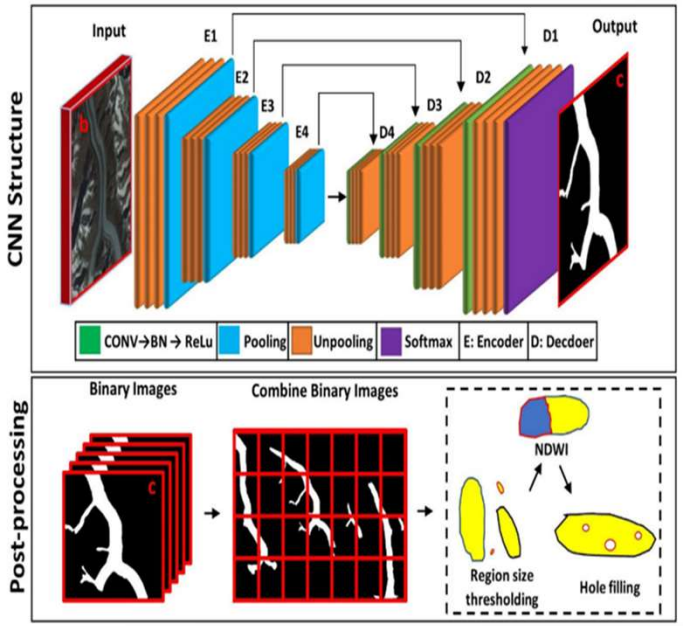
Edge Detection



Region Growing

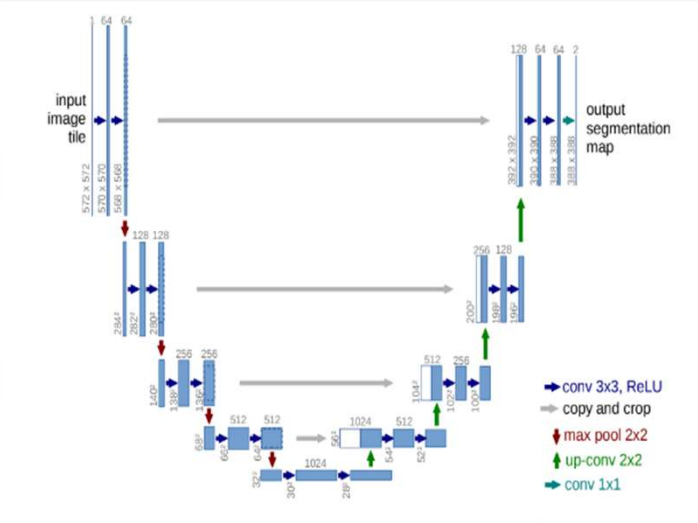
Neural Network

GlacierNet



(Xie et al., 2020)

U-Net

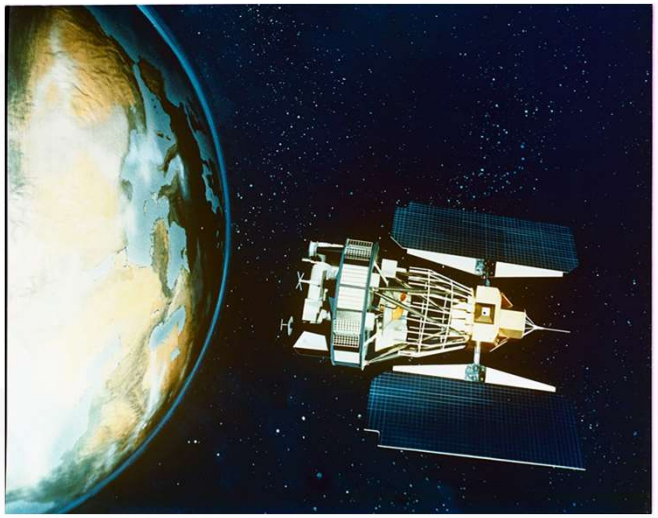


(Ronneberger et al., 2015)

03

Datasets

What is the data?



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Remote Sensing

- The process of detecting and monitoring physical characteristics of an area by measuring it's reflected and emitted radiation from a distance

Uses:

- Cameras on satellites and airplanes
- Sonar systems on ships

Landsat Satellite Imagery

- NASA database of satellite images
- Crosses every point in the world every 16 days
- 1,500 scenes a day jointly from Landsat 8 and Landsat 9

Franz Josef Glacier

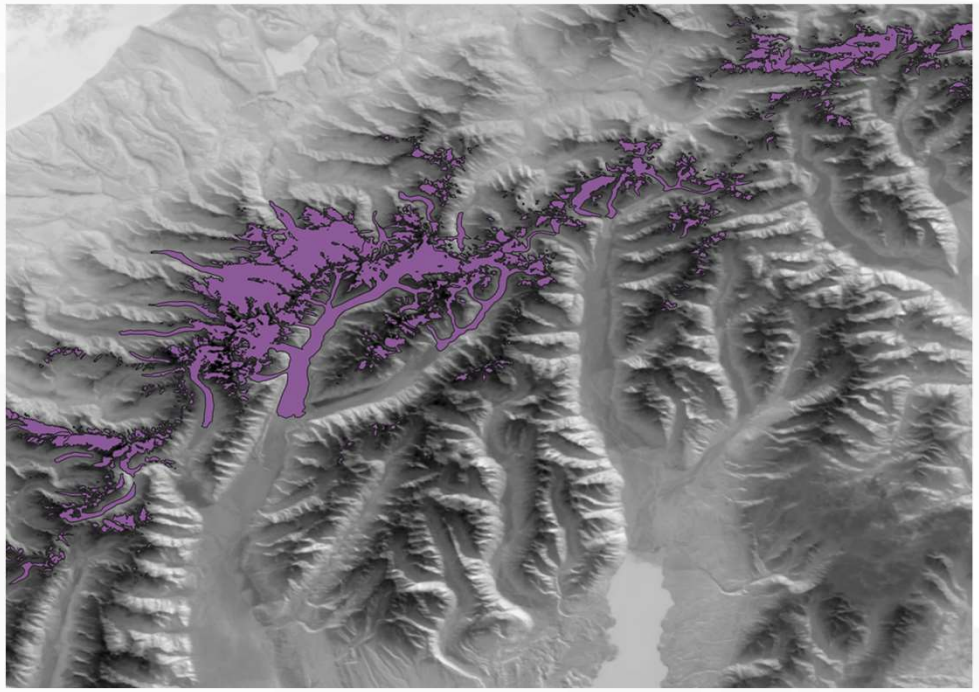
- Southern Alps of New Zealand
- 12 kilometers long
- Good for hiking

1

Labelled Data

Global Land Ice Measurements From Space (GLIMS)

- From the National Aeronautics and Space Administration
- International project to inventory the world's estimated 200,000 glaciers
- Uses data collected from satellites
- Binary
  - Glacier
  - Not Glacier



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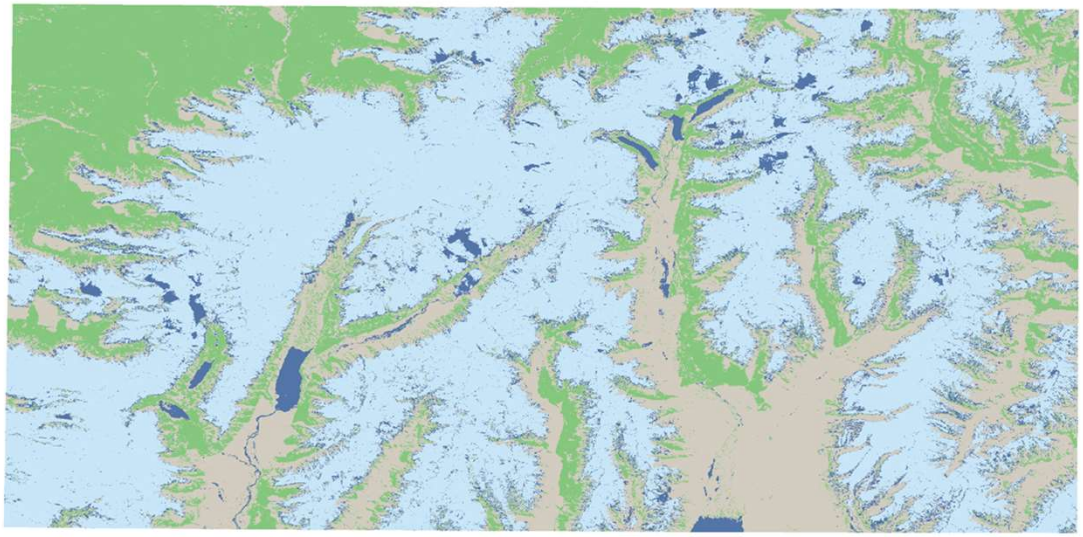
1 find resolutions of each

Joy Gao, 6/27/2024

Labelled Data

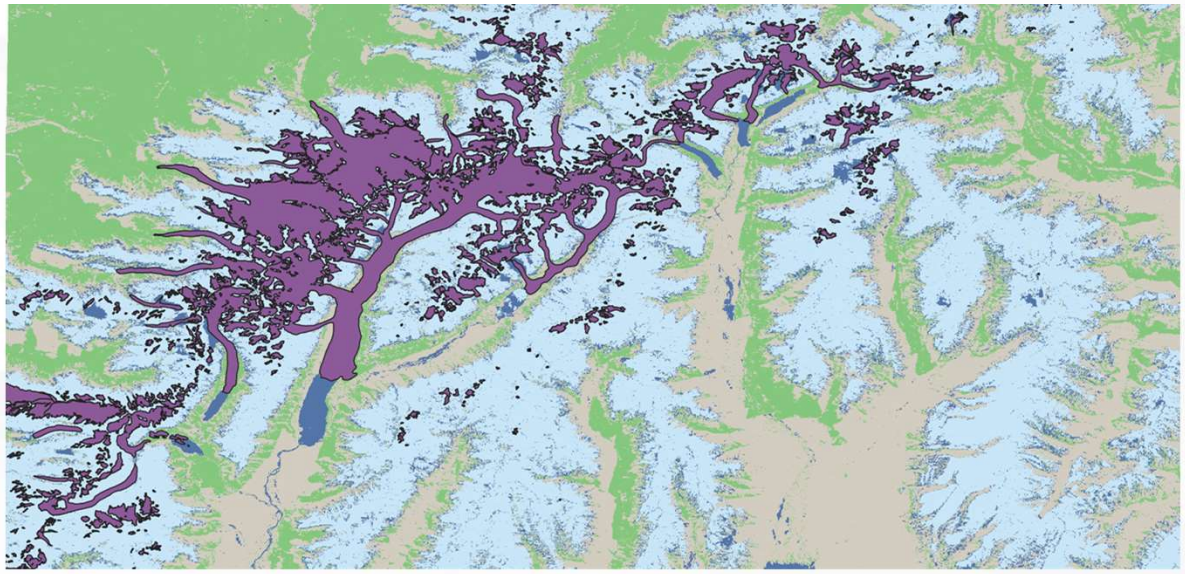
New Zealand Land Cover Database

- Multi-temporal, thematic classification of New Zealand's land cover
- Multi-Class:
  - Permanent Ice and Snow
  - Water
  - Vegetation
  - Barren Land
  - Unlabelled



2 find resolutions of each

Joy Gao, 6/27/2024



3

Discrepancies Between GLIMS and New Zealand Land Cover

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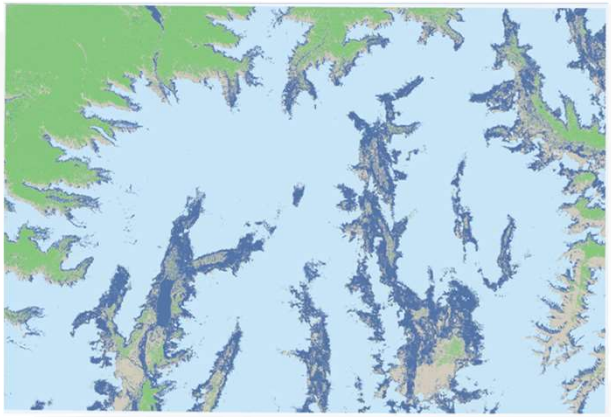
3

permanent ice and snow --> includes glaciers, not all glacier tho

new zealand bases their stuff on their classification system through satellite photos
--> not specifically mapping glaciers

GLIMS specifically maps glaciers
Joy Gao, 6/28/2024



Current Dataset

- 18 Landsat Images
- 18 matching masks from the New Zealand Land Cover Database

Landsat/Mask Image Size: 2048x3072
Over 6.2 million pixels

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Methods

What have I done?

Research Question

4

What is the impact of image patchification on the segmentation performance of deep learning methods with applications to mountain glacier image segmentations?

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4 fix

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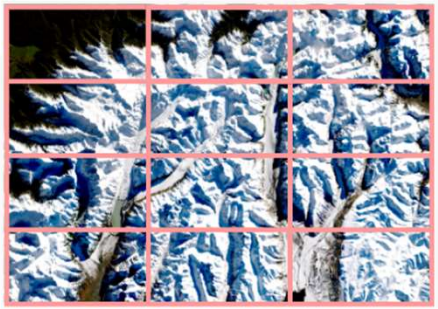
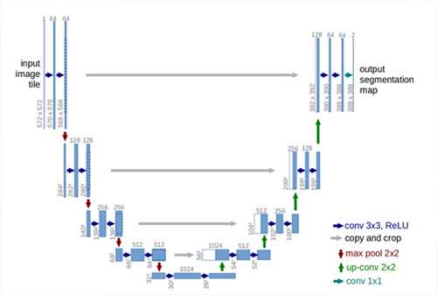
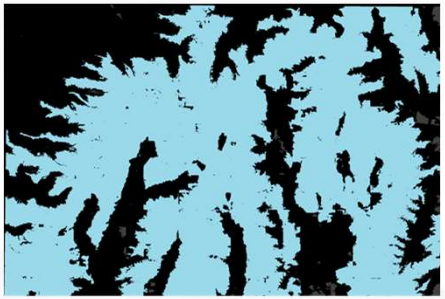
Schematics

Cropping Landsat Scenes → Patchify → Neural Network → Unpatchify and Filtering







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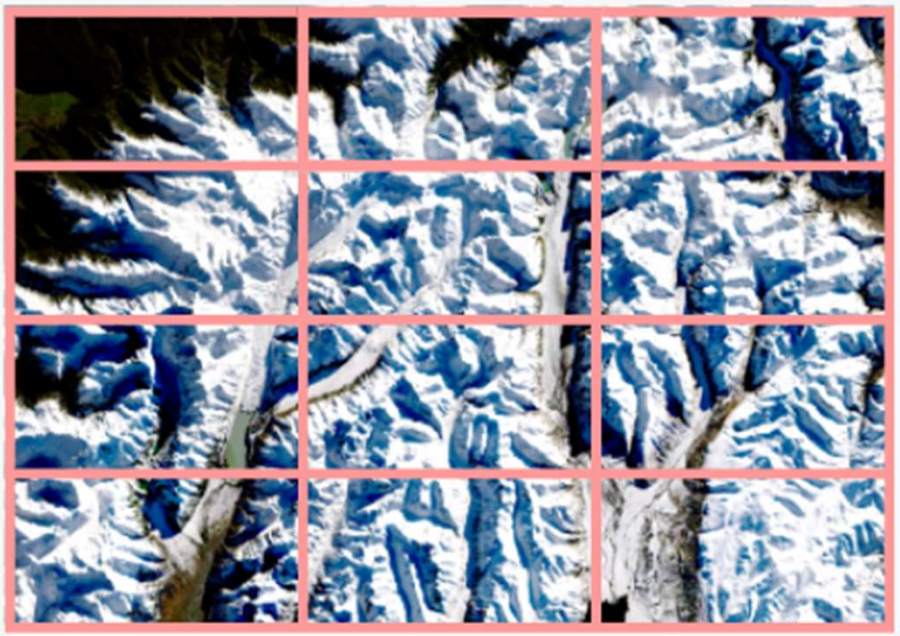
Patchify

What is the need for patchifying the image?

- The image is too big
  - Over 6.2 million pixels

What is the optimal patch size?

- Larger patches → extremely complex neural network
- Smaller patches → problems after segmentation



5 can i say that the patches are processed independently?
Joy Gao, 7/1/2024

6 network is not keeping track of what patch goes where --> considering each patch as its own separate image
Joy Gao, 7/1/2024

Image Segmentation

Image classification vs object detection vs semantic segmentation (credit: codebasics)

Current Architecture: U-Net

9 convolution blocks

Block Structure:

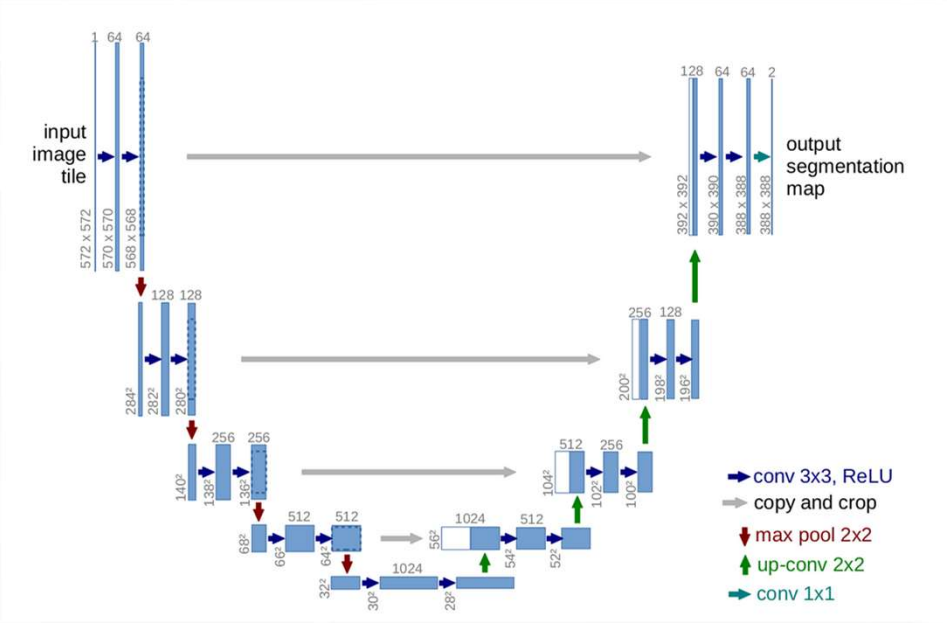
1. 3x3 Convolution
2. Rectified Linear Unit Activation
3. 0.2 Dropout
4. 3x3 Convolution
5. Rectified Linear Unit Activation

Encoder:

- Ends with 2x2 Maxpooling

Decoder:

- Starts with 2x2 Transposed Convolution and Skip Connection



Optimizations

Original Encoder Convolution Block Structure

1. 3x3 Convolution
2. Rectified Linear Unit Activation
3. 0.2 Dropout
4. 3x3 Convolution
5. Rectified Linear Unit Activation
6. 2x2 Max Pooling

Optimized Encoder Convolution Block Structure

1. 3x3 Convolution
2. Rectified Linear Unit Activation
3. 2x2 Max Pooling

Changed the dropout in the last convolution block of the encoder from 0.3 → 0.2

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Comparing U-Net Patch Sizes

Patch Size	Snow(T), Snow(P)	Not Snow(T), Not Snow(P)	Not Snow(T), Snow(P)	Snow(T), Not Snow(P)
64	0.94	0.97	0.03	0.061
128	0.97	0.96	0.039	0.031
256	0.97	0.96	0.03	0.044
512	0.97	0.95	0.046	0.025

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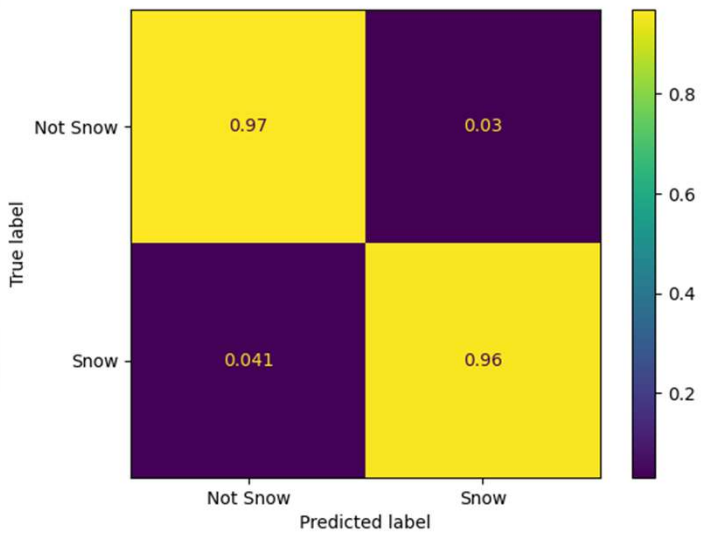
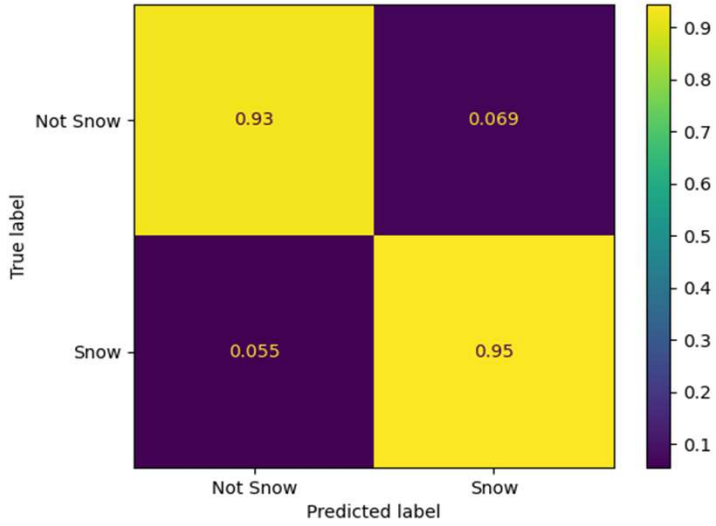
GlacierNet and U-Net Comparison: 256x256



U-Net



GlacierNet

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7

1. talk about the axes
2. talk about the boxes/compare the two --> based on pixels classified into this set, turned into percentage

Joy Gao, 6/28/2024

Unpatchify

- Stitching the patches back together after going through the neural network
- Discrepancies at the borders between patches

Methods Tested

1. Median Filtering
2. Mean Filtering
3. Mode Filtering
4. Gaussian Blur
5. Bilateral Filtering
6. Morphological Operations
    - Opening
    - Closing
    - Dilation
    - Erosion
    - Black Hat
    - Top Hat
    - Morphological Gradient

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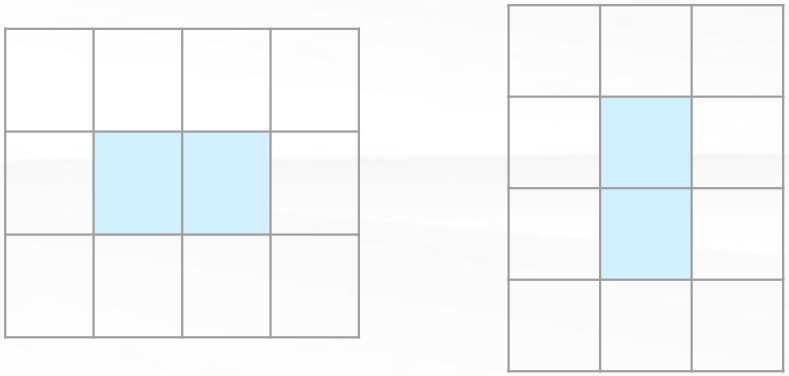
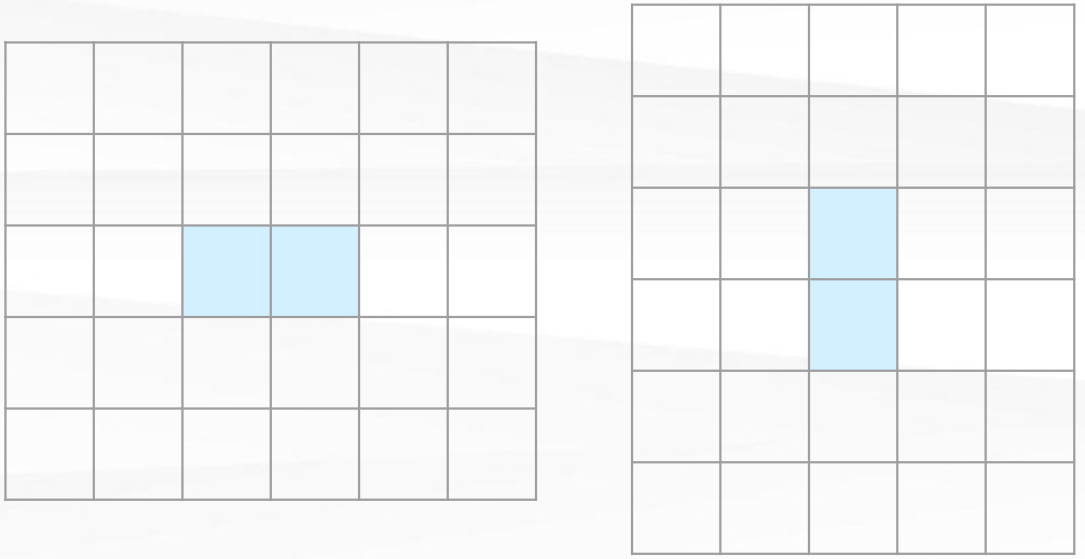
Filter Size: 4x3, 3x4



Filter Size: 6x5, 5x6



Mode Filtering: replacing pixel value with mode of the neighborhood

Median Filtering: replacing pixel value with median of the neighborhood

Patch Sizes: 128, 256

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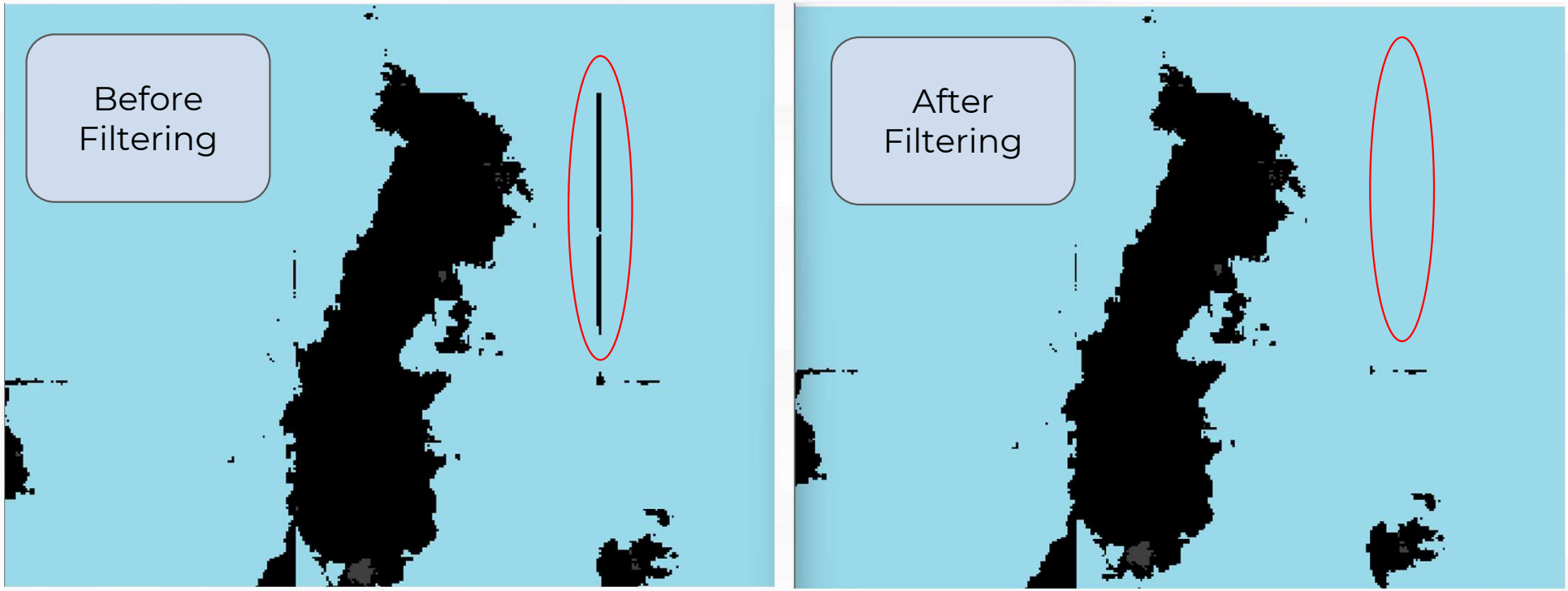
Mode Filtering:



36.487% Positive Increase in Changed Border Pixels

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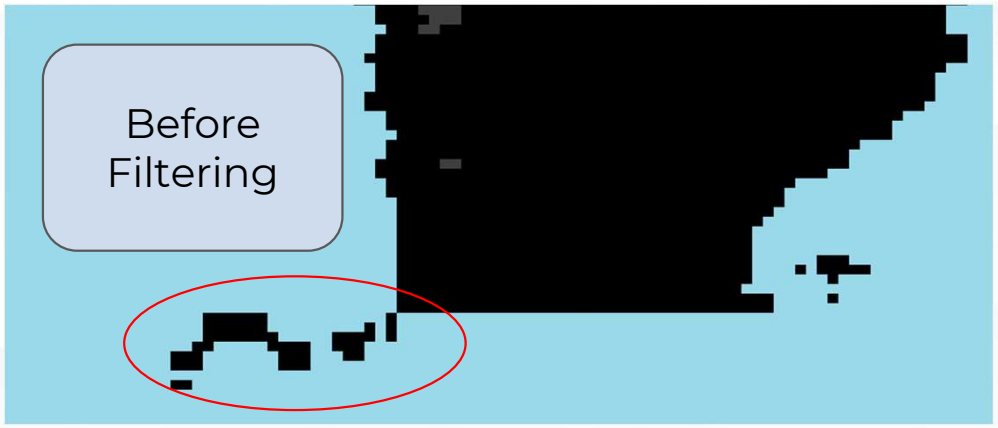
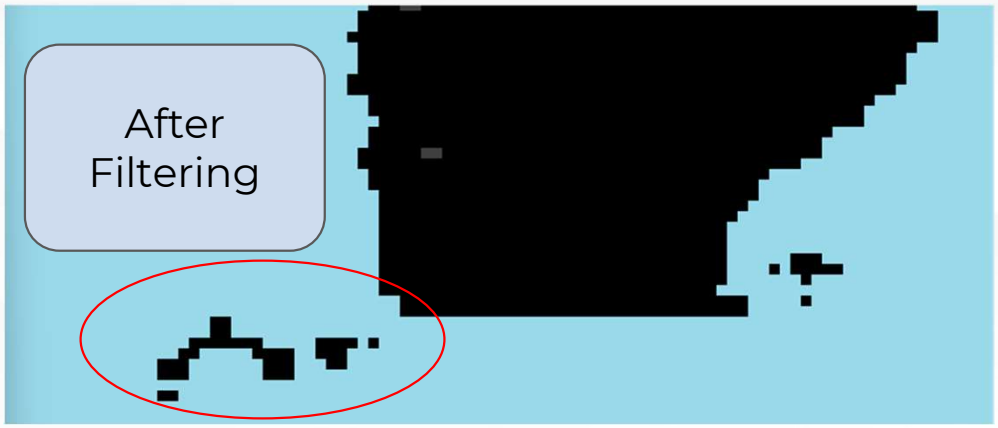
Median Filtering





34.681% Positive Increase in Changed Border Pixels

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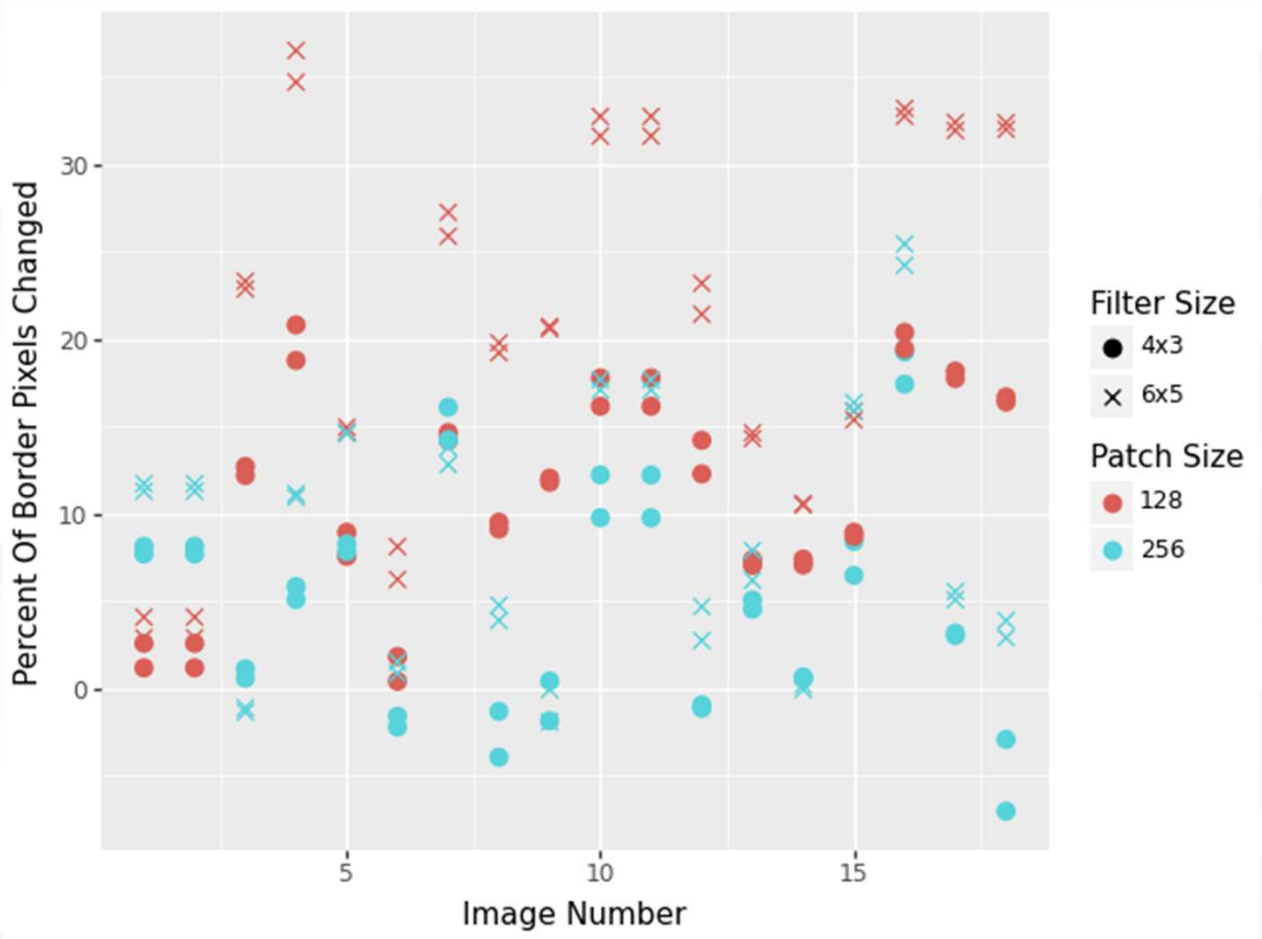

Patch Size and Filter Size Comparison

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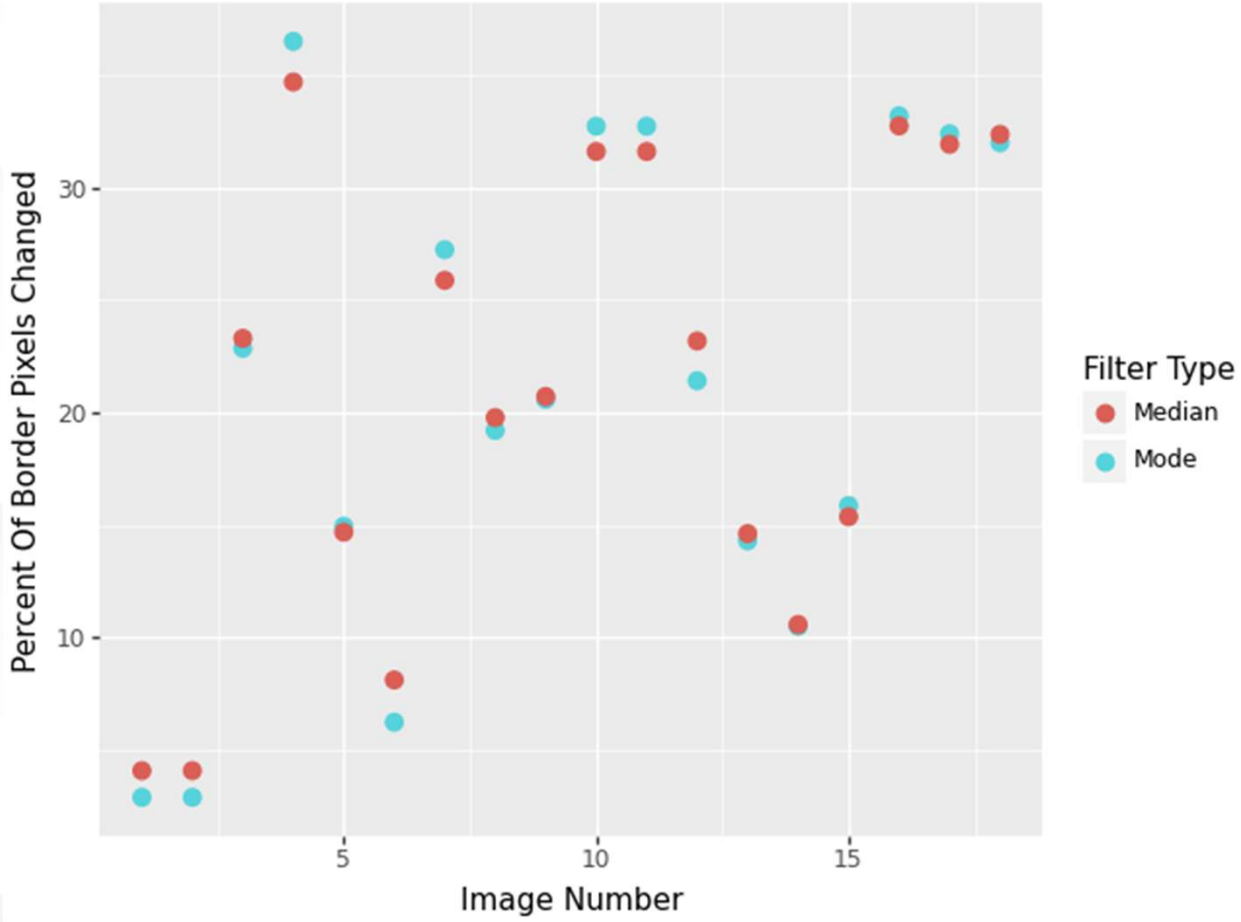
Patch Size: 128x128, Filter Size: 6x5, 5x6



Median Filtering vs. Mode Filtering

Average Percent of Border Pixels Changed

Median Filter: 21.060%
Mode Filter: 21.013%

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Discussion

Neural Networks:

- U-Net outperforms GlacierNet (with caveats)
- Best Performing Patch Sizes: 128, 256

Border Discrepancies:

- Best Performing Patch Size: 128
- Best Performing Filter Size: 6x5, 5x6
- Mode and median filtering perform very comparably

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05

Future Work

What can be done now?

Improve Filtering

- Using more complex and sophisticated filtering methods
- Expanding to more glaciers over longer periods of time
- Using different bands to make the Landsat images
- Differences between GLIMS and New Zealand Land Cover Database
- Trying different architecture for the neural network

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Thank you

Questions?

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06

Supplementary

Extra Clarification and Detail

Bands

Landsat 8-9 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS)

Bands	Wavelength (micrometers)	Resolution (meters)
Band 1 - Coastal aerosol	0.43-0.45	30
Band 2 - Blue	0.45-0.51	30
Band 3 - Green	0.53-0.59	30
Band 4 - Red	0.64-0.67	30
Band 5 - Near Infrared (NIR)	0.85-0.88	30
Band 6 - Shortwave Infrared (SWIR) 1	1.57-1.65	30
Band 7 - Shortwave Infrared (SWIR) 2	2.11-2.29	30
Band 8 - Panchromatic	0.50-0.68	15
Band 9 - Cirrus	1.36-1.38	30
Band 10 - Thermal Infrared (TIRS) 1	10.6-11.19	100 (resampled to 30)
Band 11 - Thermal Infrared (TIRS) 2	11.50-12.51	100 (resampled to 30)

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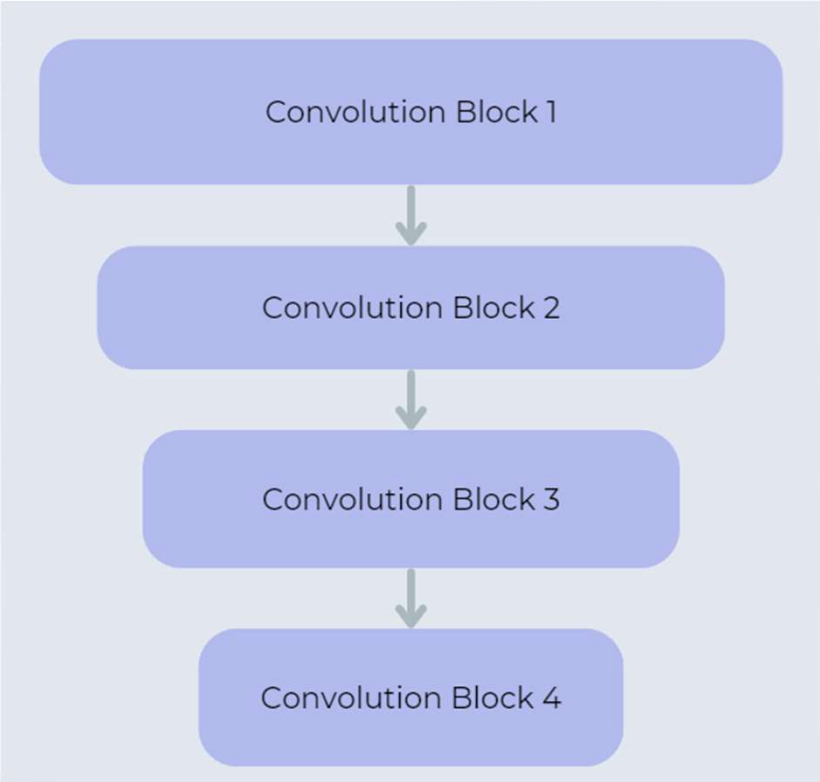
GlacierNet Encoder



CONVOLUTION BLOCK STRUCTURE

2D Convolution Layer: 32 filters, 5x5 filter
Batch Normalization
Rectified Linear Unit Activation

2D Convolution Layer: 32 filters, 5x5 filter
Batch Normalization
Rectified Linear Unit Activation

2D Convolution Layer: 32 filters, 5x5 filter
Batch Normalization
Rectified Linear Unit Activation

Max Pooling: 2x2 filter

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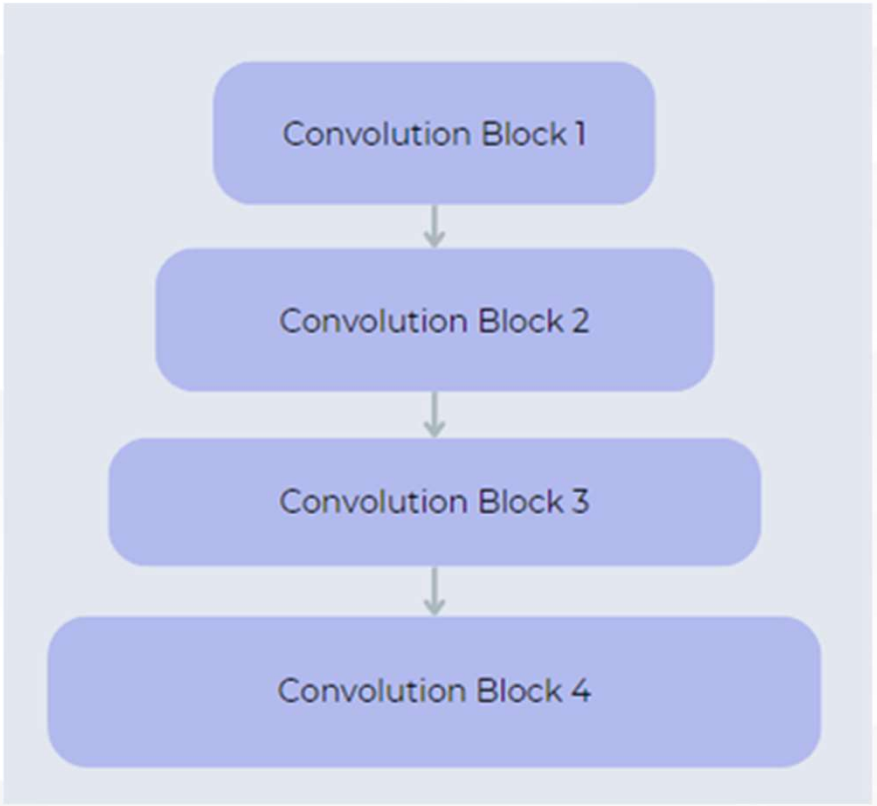
GlacierNet Decoder



CONVOLUTION BLOCK STRUCTURE

Up Sampling: 2x2 filter

2D Convolution Layer: 32 filters, 5x5 filter
Batch Normalization
Rectified Linear Unit Activation

2D Convolution Layer: 32 filters, 5x5 filter
Batch Normalization
Rectified Linear Unit Activation

2D Convolution Layer: 32 filters, 5x5 filter
Batch Normalization
Rectified Linear Unit Activation

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Process

PROCESS

1. Make a binary mask from the multi-class mask
2. Filter along all the internal borders of the fully unpatchified Landsat scene
3. Compute the pixel-wise error between the binary mask and the filtered scene

808 internal borders = 206,848 pixels

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