
Automated Glacier Boundary Delineation and Change Detection Using U-Net and CNN on Sentinel-1 SAR Imagery

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Abstract.

In worldwide effect of climate change roughly indicated by Glaciers. So it is most important that, accurate mapping of their boundaries are essential for to measure environment impact. The proposed research work on Deep Learning (DL) based framework for automated glacier detection using optical satellite images and corresponding ground-truth. The work is divided into two semantic segmentation models, first model depends upon classical U-Net architecture with an Encoder/Decoder structure with skip connections and second model a custom Convolutional Neural Network (CNN) designed to feature extraction was developed and evaluated. All the models are trained using Glacier-Lake PNG data-set. Overall Experimental results clearly indicates that, the U-Net model outperforms the CNN, achieving 97.74% test accuracy, along with higher overlap metrics, Dice coefficient and Intersection over Union (IoU). Final visual analysis of predicted segmentation masks further demonstrates that, improved boundary delineation capability of U-Net, in complex regions containing debris and shadows. Finally, the proposed framework demonstrates an efficient and scalable approach for glacier monitoring and it will support large-scale climate change studies.

Keywords. Glacier Mapping, Sentinel-1 SAR, Semantic segmentation

1. INTRODUCTION

Glaciers are the prime indicators of climate change, some are the common indicators are sea-level rise, water resource variability, and hazards like glacial lake outburst floods. Traditional method of manual mapping glaciers from satellite imagery is very time consuming [1], subjective, and difficult in complex terrains. Limitation of remote sensing offers large-scale monitoring, but distinguishing glacier ice from debris and snow remains challenging. The proposed research offers Deep Learning (DL) model like semantic segmentation models like CNNs and U-Net, has improved automated glacier detection. Mainly here it compares U-Net with a baseline CNN [2] using optical satellite images and binary masks, aiming to enhance segmentation accuracy and enable multi-temporal glacier change analysis.

2. BACKGROUND AND RELATED WORK

Nowadays, glacier monitoring is increasingly important due to climate change and its impacts on global sea levels, water resources, and surrounding ecosystems. Traditional satellite remote sensing [3], particularly Landsat and Sentinel imagery, provides valuable high-resolution observations for monitoring glacier dynamics over large areas. However, accurately delineating glacier boundaries remains challenging because of complex mountainous terrain and varying environmental conditions [4]. Glacier mapping using the Normalized Difference Snow Index (NDSI) combined with digitization techniques [5] can provide reliable results under favorable conditions but performs poorly in areas with debris-covered ice, shadows, and seasonal snow. Moreover, manual mapping over large regions is labor-intensive and time-consuming. To address these limitations, deep learning (DL) techniques have demonstrated strong potential for remote sensing applications, particularly semantic segmentation [6]. Convolutional neural networks (CNNs) and architectures such as U-Net can learn complex spatial patterns directly from imagery, enabling automated and accurate glacier boundary extraction. These capabilities offer improved efficiency and reliability for glacier monitoring systems [7].

3. METHODOLOGY

The proposed framework employs a deep semantic segmentation pipeline for automatic glacier detection from optical satellite imagery using an improved U-Net with a customized CNN. U-Net adopts an encoder-decoder architecture [8] to learn hierarchical features while preserving spatial information through skip connections. Multi-Head Self-Attention (MHSA) is incorporated at the bottleneck to capture long-range dependencies [9] between glacier regions and visually similar backgrounds, including snow, rocks, and clouds.

3.1. U-Net Architecture

The segmentation pipeline, illustrated in Figure 2, uses a symmetric encoder-decoder structure with skip connections [10]. The encoder processes $256 \times 256 \times 3$ RGB images using 3×3 convolutions, ReLU, batch normalization, dropout, and max-pooling. The decoder uses transposed convolutions and skip connections to restore spatial resolution, followed by 1×1 convolution and SoftMax activation for binary glacier-background segmentation.

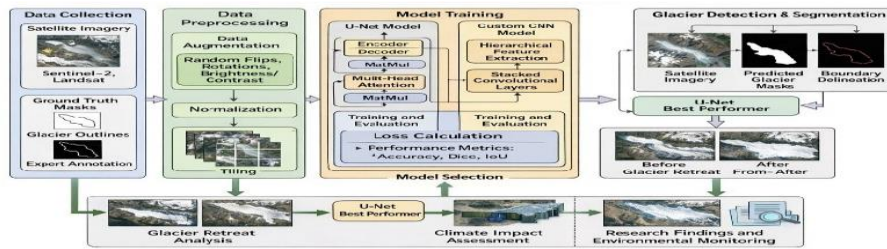


Figure 3.1.1 Glacier Segmentation Architecture

3.2. Custom CNN Architecture

The baseline CNN utilize the sequential convolutional layer for feature extraction, along with down sampling and up sampling for segmentation output. The details customized CNN U-Net architecture shown in figure 3.

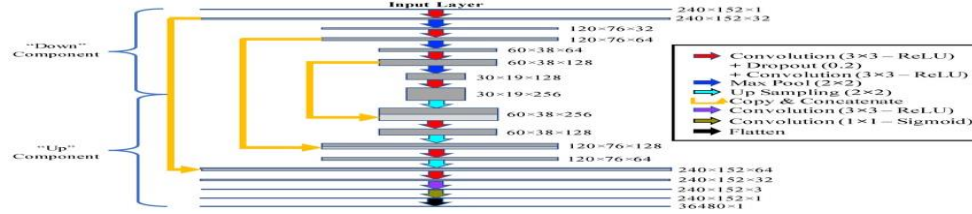


Figure 3.2.1. U-Net Architecture with down sampling, up sampling, skip connections, and convolutions for precise image segmentation.

3.3. System evaluation parameters

Input optical satellite image $I \in \mathbb{R}^{H \times W \times 3}$ (height H , width W , 3 RGB channels) predict a binary segmentation mask $M \in \{0,1\}^{H \times W}$. The deep learning model f_θ approximates a mapping: $I \in \mathbb{R}^{H \times W \times 3}$. The segmentation model f_θ (U-Net or CNN) learns a mapping from the input image to a pixel-wise probability map for two classes: glacier and background. The predicted binary segmentation mask is obtained by assigning each pixel to the class having the highest probability:

$$\hat{M} = \arg \max_c \hat{Y}_{(:,c)} \quad (1)$$

The training is done through the categorical cross-entropy loss over N training samples:

$$L(\theta) = -\frac{1}{N} \sum_{i=1}^N \sum_{h,w,c} Y_i^{(h,w,c)} \log(\hat{Y}_i^{(h,w,c)}) \quad (2)$$

Where Y_i denotes the one-hot encoded ground-truth mask corresponding to glacier and background classes. To improve generalization, increase the variety of training samples, several augmentation techniques were applied during training. Brightness augmentation is applied as

$$I' = I + \delta_b, \delta_b \sim U(-0.1, 0.1) \quad (3)$$

while contrast adjustment is defined as

$$I' = (I - 0.5)\alpha + 0.5 \quad (4)$$

where $\alpha \sim U(0.8, 1.2)$. Pixel values are clipped to ensure that $I' \in [0, 1]$. For multi-temporal glacier analysis, segmentation masks are generated independently for satellite images acquired at times t_1 and t_2 :

$$\hat{M}_{t_1} = f_\theta(I_{t_1}), \hat{M}_{t_2} = f_\theta(I_{t_2}) \quad (5)$$

A change map is computed using binary differencing:

$$\Delta M = \hat{M}_{t_2} \oplus \hat{M}_{t_1} \quad (6)$$

where $\oplus$ denotes the XOR operation that highlights pixels whose class label has changed. The glacier area change is denoted as ΔA where A_p indicates the ground area represented by every pixel. The proposed approach enables quantitative assessment of glacier retreat.

$$\Delta A = A_p(\sum \hat{M}_{t_1} - \sum \hat{M}_{t_2}) \quad (10)$$

4. EXPERIMENT RESULTS

Both models were trained for 50 epochs using batch size 8, Adam optimizer, and categorical cross-entropy (Table 1). Data were divided into training (70%), validation (20%), and testing (10%). U-Net outperformed Custom CNN, achieving 97.74% accuracy, 96.8% Dice, and 93.8% IoU, indicating superior glacier-region overlap and boundary accuracy.

Table 1: Comparative chart of U-Net and Custom CNN on Test Set

Model	Accuracy (%)	Dice Coefficient	IoU	Precision (Glacier)	Recall (Glacier)
Custom CNN	93.24	0.912	0.838	0.895	0.931
U-Net	97.74	0.968	0.938	0.976	0.961

5. CONCLUSIONS

Finally, in proposed work, two segmentation models were tested and indicate that, U-Net outperformed the CNN, by achieving highest accuracy, Dice score and IoU over the custom CNN. This result is achieved by utilizing its encoder decoder design and connections that preserve spatial details. The pipeline contains pre-processing, data augmentation, training and enabling reliable tracking of the glaciers. Overall this scheme offers reliable solution over the traditional system to identify glacier retreats.

6. REFERENCES

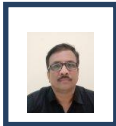
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Biographies



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