Grad project

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1. Motivation

Monitoring glaciers are one of the most important tasks in the field of glaciology. We can manually delineate outline of glaciers using GIS software. However, this task requires so much work (Boring!) and time with high accuracy. Therefore, I developed machine learning toolkit which enables us to digitize the calving front positions in satellite images automatically. There are several reports about the detection of glaciers calving fronts using convolutional neural network (Mohajerani et al., 2018, Baumhoer et al., 2019). The figure 1 shows Colombia glacier in Alaska (Red square) taken in 1986 by Landsat. Its terminus has retreated more than 20 km (12 miles) to the north since 1980s. I represent how the frontal position of Colombia glacier changed over the time using convolutional neural network.

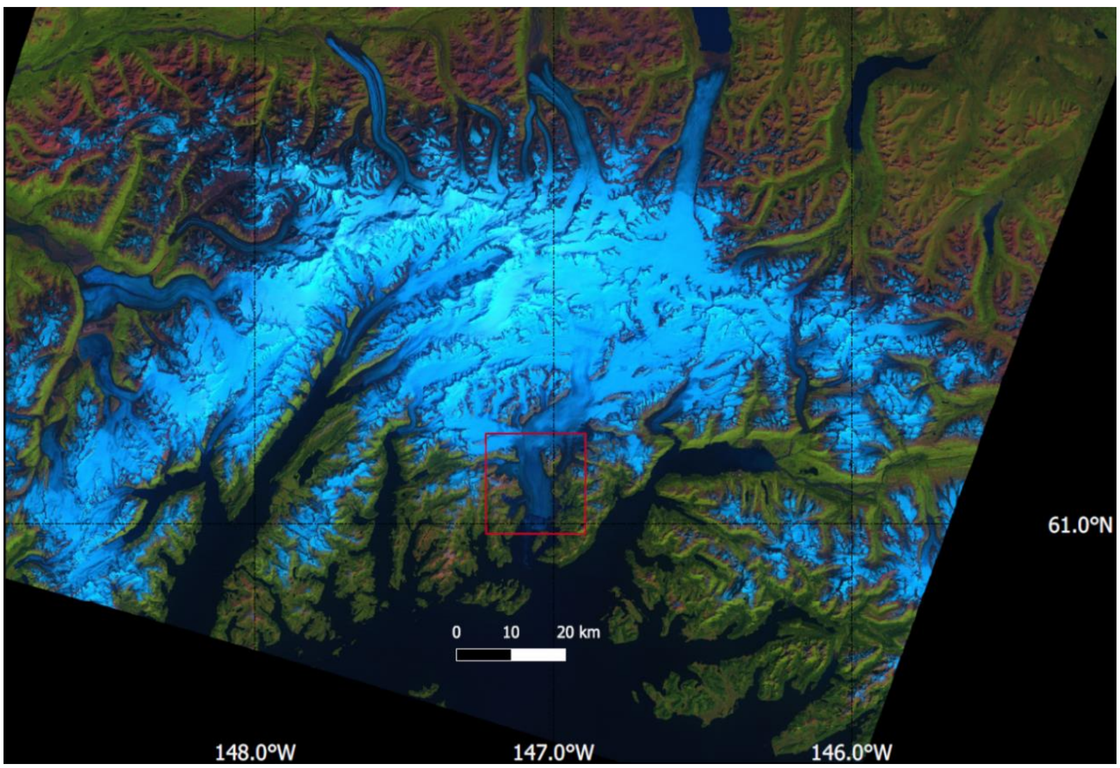


Fig. 1 Location of Columbia glacier in Alaska (Red square)

2. Methods

In this study, 200 Landsat images (Level 1 Landsat Data from the USGS Earth explorer portal for Landsat 5 and 7) were used for preparation of training data. These images were resized to 200 by 200 pixels maintaining the aspect ratio of images in the end. These images were also processed to extract the edge of objects in images using Canny Edge Detection (Fig. 2). Two thresholds are required to detect the outline of objects in an image. Any edges with intensity gradient more than the higher of the two thresholds are sure to be edges and those below the lower of them are sure to be non-edges, so discarded. Those who lie between these two thresholds are classified edges or non-edges based on their connectivity. Each threshold was set up as 30 and 60, respectively. They were further binarized by a predetermined threshold (=128) and end up being labeled as the edge (=1) and other than it (= 0) eventually (Fig. 2).

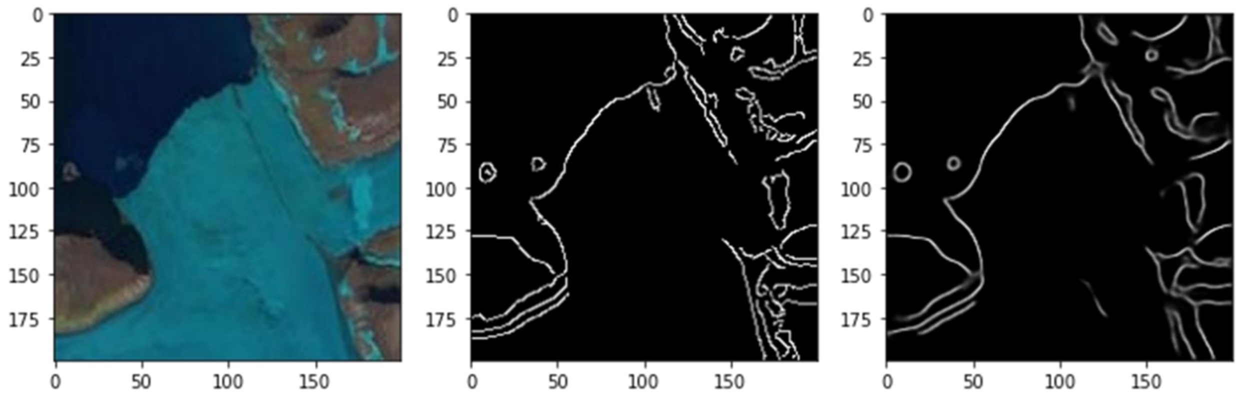


Fig. 2 The Pre-processed image (Input image (left), the edge of glaciers obtained by Canny Edge Detection (center)) and the Post processed image (right).

To extract the border between glaciers and ocean or lake, I developed the autoencoders which are specific type of feedforward neural networks where the size of input is the same as that of the output (Fig.3). They compress input into a lower dimensional code and then reconstruct the output from this representation. I used 200 × 200 pixels tiles with three input channels (R, G and B). To train the neural network (NN), each input tile is convoluted by a 3 × 3 kernel with stride 1. The three input channels are convoluted to 16, 32, 64 and 128 feature maps of the size 25 × 25 pixel exist at the end of the encoding block. Thereafter, the decoder block up-samples this densified information to assign each pixel of the input image to a classification result. The last 16 feature channels are pooled by a 1 × 1 convolution with the Sigmoid activation function to acquire the prediction for each class (outline or not). Finally, the size of output image comes out as same as that of input image. This model ends up being 575,831 training parameters.

I minimize the Mean Square Error (MSE) loss using the Adam optimizer with batches of 10 images at a time. Training the NN for 240 epochs leads to the MSE of 0.00523. the validation loss kept decreasing as opposed to accuracy which resulted in 95.8%. After training the data, I applied to the model for the images which have never been used to make predictions (Fig. 2). They are added to geo-referencing using GIS software to quantify the change of frontal position of glaciers. The errors in the test dataset show the error of the NN. I measure the test error by calculating the averaged width of the enclosed area bounded by the manually delineated and the network-delineated calving fronts (Zhang et al., 2019, Baumhoer et al., 2019). The mean retreat distance was also obtained as the area change divided by the mean glacier width for the period of interest (Moon and Joughin., 2008).

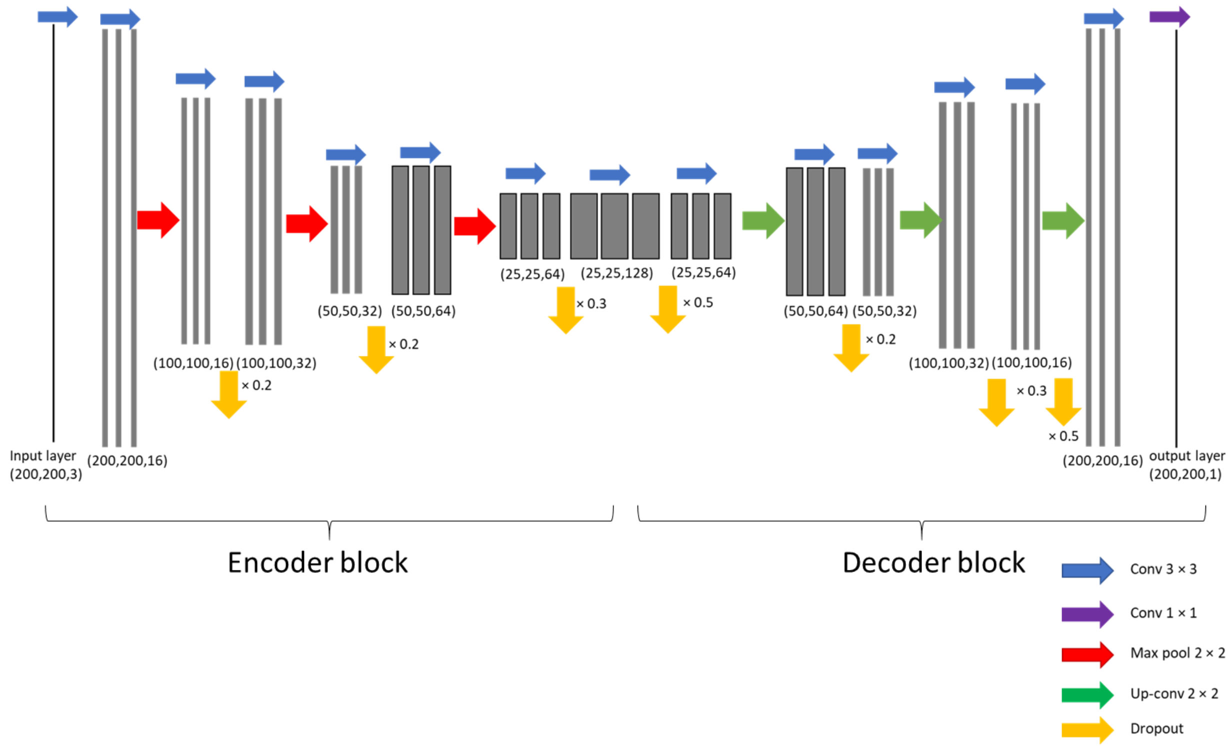
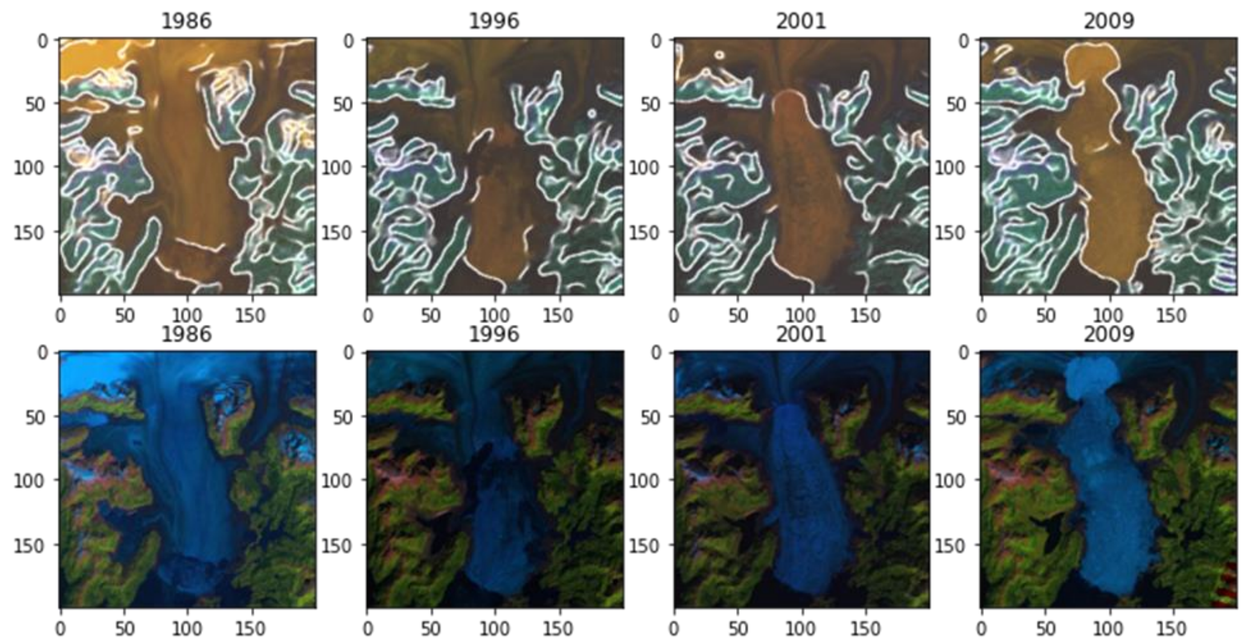


Fig. 3 Architecture of the neutral network (First model).

3. Results

I trained the neural network (NN) on a set of 200 preprocessed 200 × 200 input images from calving glaciers in Greenland, Patagonia, and Alaska. The training was halted when the validation loss started to stay flat owing to overfitting. To confirm how the developed NN works for prediction of calving fronts beyond the training set for different glacier geometries, I tested the trained network on images of Colombia glacier in Alaska, whose geometry is unfamiliar to the NN during training. The figure 4 shows the results of the prediction using the model. This result shows a good agreement with the frontal position of glaciers in the input image in qualitative way. We also measure the test error by calculating the averaged width of the enclosed area bounded by the manually delineated and the network-delineated calving fronts. The error was 30.4 m, which was within 1 pixel (Spatial Resolution = 90 m). In the end, I found the calving fronts retreated by 13. 7 km during 1986-2009.



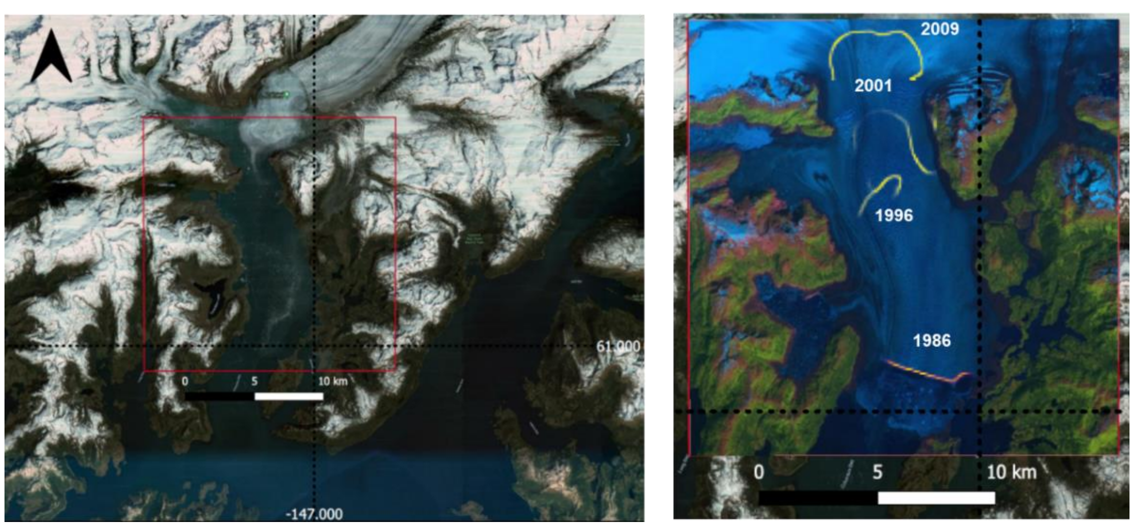


Fig. 4 First row shows the prediction used by my model over the study site and 2nd row shows the raw image. Third row show the location of Colombia glacier (Red square) and its frontal position changes during 1986-2009.

4. Discussions

4. 1. Difficulty in distinguishing iceberg from carving fronts

Fig. 5 shows the model failed to detect the glacier carving front due to low contrast on the mélange or iceberg water, which makes the extraction of the boundary between glacier and ocean challenging task. The mean error in glacier fronts associated with the quality of raw image was 30.4 m, which was similar to Zhang et al., 2019. This small test error suggests that the accuracy of a well-trained network can be close to the human level. To improve detection of glacier carving fronts, it is required to change the threshold on raw images in order to classify the features such as ice, ocean, land, iceberg and mélange clearly. It would be also effective for improvement of my model to select the train data which contains only glaciers with mélange and iceberg. Some train data was not described well in terms of the boundary between calving fronts and melange since the threshold was set to distinguish carving fronts from ocean with no Melange.

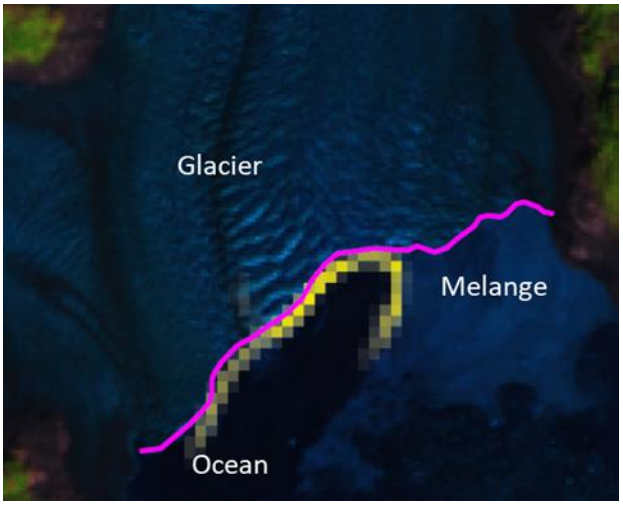


Fig. 5 Comparing manually digitizing (Purple) with automatic mapping (Yellow). Background is a Landsat 5 image acquired in 2001.

4. 2. The Developed model adding the skip architecture

To perform good extraction of coastal areas of Antarctica, Baumber et al., 2019 applied U-net architecture which consists of a fully convolutional network (FCN), which is introduced by Ronneberger et al., 2015. U-net architecture is different from my model (Fig. 3) since there are long skip connection between contracting path and expansive path. In other words, the features from the encoding path at the same stage are cropped and concatenated to the up-sampling feature map. In general, using skip connection combines the coarser depth prediction with local image information to get finer prediction with the smallest loss or highest accuracy. For instance, some information is acquired in the initial layers and is required for reconstruction during the up-sampling done using the FCN layer, which would have lost without the skip architecture due to the depth of the layers. Therefore, an information that we have in the primary layers can be fed explicitly to the later layers using it, which can prevent the vanishing gradients. In addition, the skip connection also promotes to traverse information faster in deep neural networks.

Considering these points, I added the skip connection into my model described in Fig. 2 to improve the prediction of the calving glacier fronts. Additionally, I also changed the channel depth at the first stage of the U-net architecture ranging from 16 to 32 channel (Fig. 6). As a result, the accuracy which calculates how often predictions equal labels improved to 98 % despite the less epoch (160 epochs) compared to the previous model (240 epochs). The developed model makes it improve to describe the edge of glaciers in detail as well as other objects in the image (Fig. 7). Yet, it is still not good enough to delineate the outline in practice using this model. Further investigation is required to detect the carving fronts easily in distinguish from iceberg and mélange.

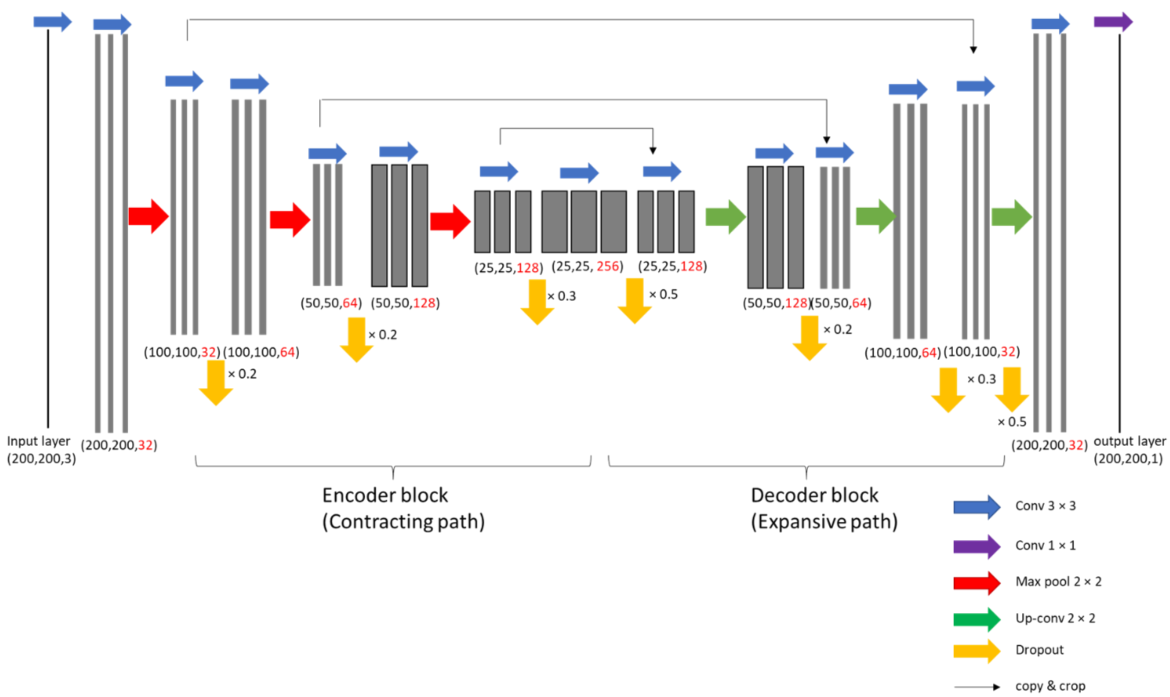


Fig. 6 Architecture of the neutral network after changing the first model described in Fig. 3. The parts written in red are the parts that have been corrected compared to the first model. The skip connections are indicated by black arrows. Black numbers show image size and the number of feature channels.

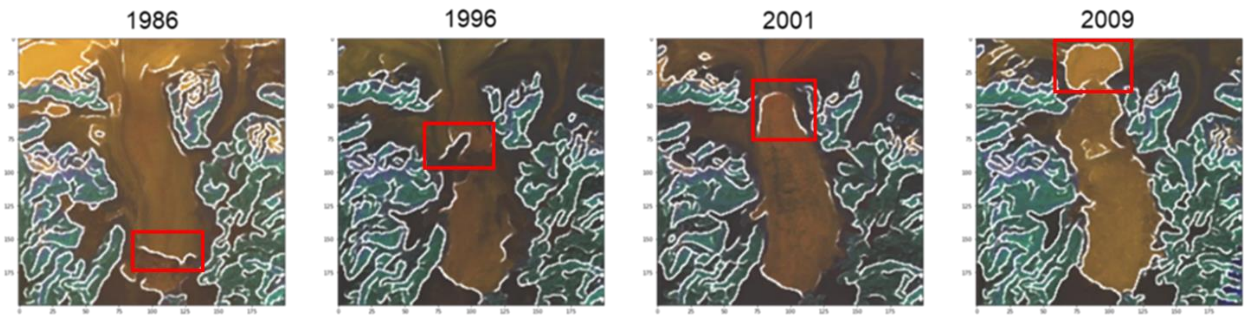


Fig. 7 The predictions using the developed model (second model) (Fig. 6) The red box shows the carving front position.

5. Conclusions

This study represents the detection of the edge of glacier calving fronts automatically using a convolutional neural network. The first model I developed shows a good agreement with the outline of the calving front manually delineated with high accuracy, which is within 30.4 m in terms of uncertainty. Furthermore, the second model added the skip connection, which is called U-net, shows the improvement of the prediction in comparison to the first model. However, the low contrast of images still makes the model challenging to detect the edge of the calving fronts. The prediction by the model strongly depends on the training data. I suggest that the threshold which is the most important to decide the boundary from raw image should be determined separately based on the raw image.

Reference

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