Glacier Detection in the Hindu Kush Himalaya Region

Fundamentals of Data Science 2022
Sapienza Università di Roma
https://github.com/jonasbarth/fds-2022-final-project

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November 2022

Abstract

Monitoring glaciers is important to understand and track the effects of climate change. Automated recognition of glaciers in satellite images would speed up the work of scientists and help to tackle climate change. The project's inspiration is drawn from the paper[1] that focuses on pixel-wise detection of glaciers from Landsat 7 satellite images. We explore an image-wise classification tasks, engineered features using colour and gradient histograms, and compare the performance of K-Nearest Neighbours (KNN), Logistic Regression, Naive Bayes, and Convolutional Neural Network (CNN) classifiers. We find that colour histograms with simple models perform similarly to a fine-tuned VGG16 CNN, whereas gradient of histograms are often just slightly better than random guessing. Finally, we share some ideas for future work.

1 Introduction

Glaciers are a key indicator of past and current climate change. As the global average temperature rises, glaciers melt at faster rates, which contributes to the rising sea levels and threatens their role as a freshwater resource for human consumption and agriculture, among other key activities [15]. Processing and analysing the vast amount of satellite glacier image data is an effortful and lengthy process that would benefit from the use of intelligent systems [10]. Identifying glaciers on image data, would help to monitor their extent, elevation change and velocities, which allows us to understand how they respond to climate change.

2 Related Work

We base our project on a paper where the authors proposed a pixel-wise classification method for Landsat 7 satellite images from the HKH region [1]. As GPU accelerated image classification has been gaining popularity in the last decade, image classification of glaciers also saw more attention. Raza et al. [11] compared object and pixel wise classification methods on Landsat images. Nhijawan, Parg, and Thakur also compared classification methods for multispectral Landsat images [8]. Marochov, Stokes, and Carbonneau used a CNN to classify Sentinel 2 satellite images of glaciers in Greenland. [6]. CNNs are powerful image classification tools, however due to the usual lengthy and expensive training, we will also opt for simpler classifiers that leverage some feature engineering.

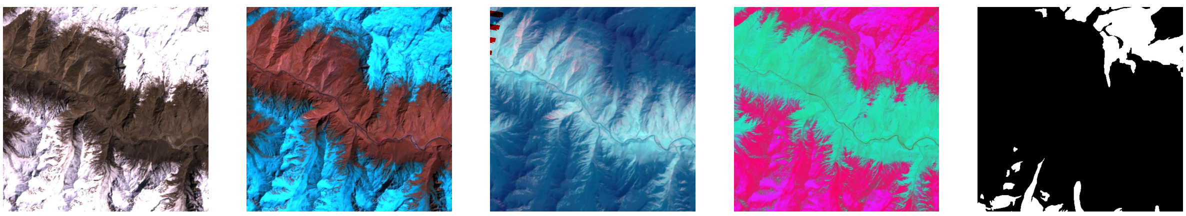
3 Dataset

The data used in the project is based on an existing dataset [7], filtered down to 741 image patches [1] that originate from 35 images taken by Landsat 7 [14] satellites in the HKH region. Each image patch is of size 512×512 and is part of a larger original Landsat image. Using smaller patches instead of the Landsat images, simplifies the data pre-processing, model training, model prediction, and reduces model complexity. The patches have 10 channels coming from Landsat and 5 channels coming from the Shuttle Radar Topography Mission (SRTM) [4], giving a total of 15 channels.

Channel	Name	Description	Resolution
1	LE7 B1	Blue (0.45 - 0.52 µm)	30m
2	LE7 B2	Green (0.52 - 0.60 µm)	30m
3	LE7 B3	Red (0.63 - 0.69 µm)	30m
4	LE7 B4	Near-Infrared (0.77 - 0.90 µm)	30m
5	LE7 B5	Short-wave Infrared 1 (1.55 - 1.75 µm)	30m
6	LE7 B6 VCID 1	Low-gain Thermal Infrared 1 (10.40 - 12.50 µm)	30m
7	LE7 B6 VCID 2	High-gain Thermal Infrared 1 (10.40 - 12.50 µm)	30m
8	LE7 B7	Shot-wave Infrared 2 (2.08 - 2.35 µm)	30m
9	LE7 PAN	Entire visible spectrum (0.4 - 0.7 µm)	30m
10	LE7 BQA	Quality Assessment Band	-
11	NDVI	Vegatation Index	15m
12	NDSI	Snow Index	15m
13	NDWI	Water Index	15m
14	SRTM Elevation	Elevation Index	30m
15	SRTM Slope	Slope Index	30m

Table 1: Channels in each image patch. LE7 indicates Landsat 7.

Each image patch is represented as a 15-dimensional numpy array of shape (512, 512, 15) and is associated with a 2-dimensional binary mask of shape (512, 512, 2). The 2 channels of the mask are: clean glacier, debris-covered glacier, and tell us what kind of glacier each pixel belongs to. In reality, the clean glacier accounts for an overwhelming majority of pixels as there are few debris-covered glaciers.



(a) 1, 2, 3 (b) 2, 4, 5 (c) 6, 7, 8 (d) 11, 12, 13 (e) Mask

Figure 1: The extracted channels of an image and the corresponding mask

This can be used for a pixel-wise classification [1], however for simplicity, we decided to go for image wise classification, i.e. predicting whether an image contains a glacier or not. Image patches that contain $> 5\%$ glacier pixels are labeled as glacier images. Moreover, we doubled the existing dataset with image patches that contain no glacier in order to provide more data variety, with the train, test, validation split shown in Table 2.

Train	Test	Validation
766	220	110

Table 2: The split of the data.

4 Features

4.1 Band Selection

The 15 bands in the image patches might not all be needed for classifying whether an image patch contains a glacier or not. Some channels will be better at capturing important information needed for detecting glaciers than others. Additionally, reducing the number of dimensions will help to alleviate the negative effects brought on by the curse of dimensionality [2]. We slightly modify the band selection findings of [1] and train our models on bands shown in Figure 1.

4.2 Histogram of Oriented Gradients (HOG)

HOGs are feature descriptors that use intensity gradients to describe the shape of an object within an image [3]. We think that finding the shapes of glaciers can help with classification, as the white snow and ice has a definitive border with the the darker mountains. The preprocessing steps were downsampling to (214, 214) and adding gaussian blur to smooth noise. The output histogram is the feature vector $[0, 1]^b$, where b is the number of bins, that will be fed into our chosen models.

(a) Channels 1, 2, 3 (b) HOG Image (c) Histogram

Figure 2: The RGB Histogram of Oriented Gradients.

4.3 Histogram of Colours (HOC)

HOCs are feature descriptors that use the distribution of colors (or multi-spectral colors) to describe the object within the image [9]. This makes them robust to shape and spatial information changes and effective for detecting objects which share some distinctive colors. For example two very different shapes of the same colours will be encoded in the same way. We think this is useful for the glaciers classification as they are notoriously shapeless, but also intuitively share at least one color, white.

The output is a $[0, 1]^{b \cdot d}$ vector, where d is the number of channels and b is the number of bins for each channel.

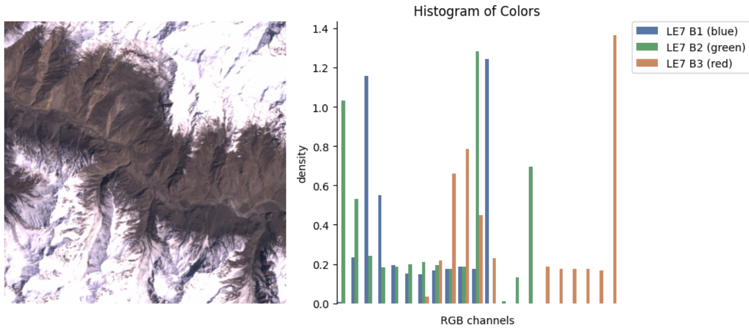


Figure 3: RGB Histogram of Colors

5 Models

We employ and compare a range of feature engineering and image classification methods to determine whether an image contains a glacier or not. For feature engineering we opted for colour histograms [12] and histogram of oriented gradients [3]. We also performed feature selection on the image channels. The classifiers are Logistic Regression, KNN and CNN.

5.1 KNN

The KNN is a non-parametric supervised learning algorithm, after defining a measure of distance between the samples, the algorithm performs classification by assigning it the class of the k nearest neighbours [5].

The KNN performs better when the classes are easily separable, and we wanted to see if this also applied to glacier vs non-glacier images. The KNN is very easy to train and we found the possibility to best tune the hyperparameter k appealing. As inputs we used HOGs and HOCs.

5.2 Logistic Regression

The Logistic Regression Model allowed us to do binary classification among the images, determining whether they contain a glacier or not. Its simplicity in setup and training, made it a very appealing approach to solve our classification problem. We tried with two different inputs: HOGs and HOCs.

5.3 Naive Bayes

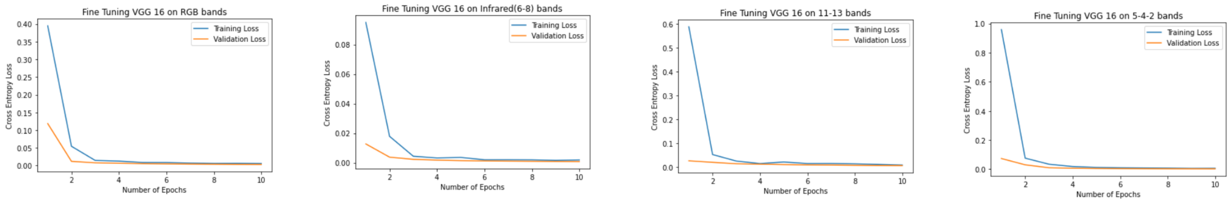
Naive Bayes is a probabilistic machine learning model where we have the independence assumption for the given features in the dataset. In this approach parameters are learnt specific for each of the classes involved. In our case, the independence assumption does not really makes sense, as the features are complementary in nature. But due to its simplicity in implementation and training we went for it to solve our classification problem.

5.4 CNN

Finally, we employed CNN networks for the aforementioned classification task mainly motivated by its abilities of spatial localisation of the object of interest and non-linear transformation of the features. Further, we wanted to see the difference in performance produced by engineered features v/s CNN-learned features.

We chose to use VGG-16 network which was proposed by Karen Simonyan and Andrew Zisserman of the Visual Geometry Group Lab of Oxford University in 2014[13]. Since we are dealing with binary class classification problem we had to reduce the last linear layer from 1000 nodes to 2 nodes. In the pre-processing step we performed Normalisation, Replacement of missing Value and Rescaling to (224, 224) of the dataset before passing them to the network in batches.

The modified VGG-16 network was fine-tuned on the training set (validation set was used as performance monitor) to improve the performance of network. Through fine-tuning we observed improvement of up to 8-10 percent prediction performance.



(a) RGB (b) Infrared(6-8) (c) Index(11-13) (d) 5-4-2

Figure 4: The Loss curves obtained during Fine-tuning VGG-16 on different bands combinations.

6 Benchmark

Since there is no previous work on the exact same task (identifying regions with glaciers, as a first stage for diverse posterior analysis related with glaciers), we use random guessing as a baseline for our models.

7 Results

We evaluated the classifiers on three metrics: **accuracy**, **precision**, and **recall**. The CNN is the overall best performer with near perfect scores for all metrics and for almost all band combinations. The band combination 11-12-13 (snow, water, vegetation indices) performed noticeably worse than any of the other subset of bands. Although this pattern does not hold for the KNN, Logistic Regression, and Naive Bayes models.

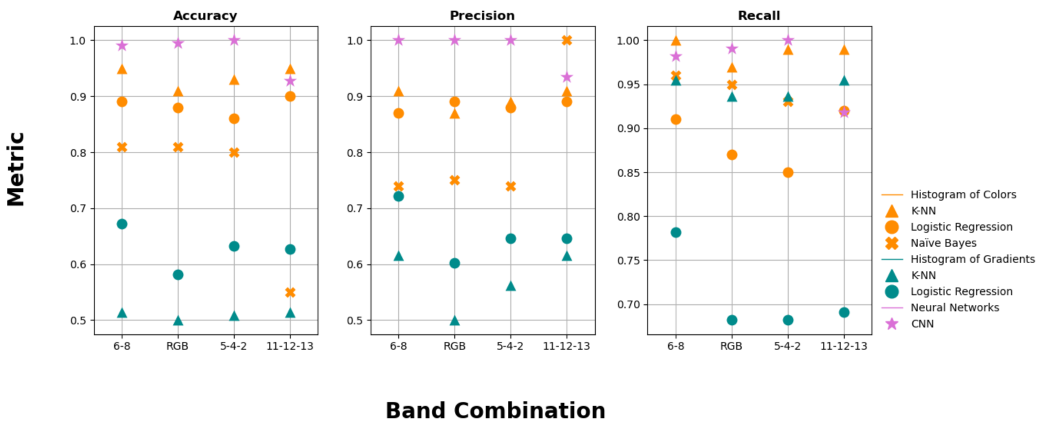


Figure 5: Scores of our models.

The classifiers using HoC as input perform significantly better than those classifiers that used HOG as input for the overwhelming majority of bands across all three scores. Whereas the HoC classifier scores mostly settle between 0.8 and 1.0, the HOG classifier scores mostly hover among 0.5 and 0.7. The accuracy of the KNN with HOGs is essentially no better than random guessing. There are some exceptions, e.g. the accuracy of the Naive Bayes for the band combination 11-12-13 or the recall of the Logistic Regression for the band combination 6-7-8, however the overall picture strongly suggests that HOG classifiers perform worse.

8 Conclusion & Future Work

The better performance of the HoCs over the HOG also hints at the fact that the information about glaciers is actually encoded in the colours and not the gradients and shapes. Intuitively, this makes sense as glacier colours are less varied than the glacier gradients. Glaciers are mostly light and highly reflective, whereas their edges are irregular and likely don't follow a strong enough pattern to warrant using them as a feature inside a machine learning model.

Out of the three scores, we believe **recall** to be the most important, as we want to maximise true positives. The reasoning behind this is that our machine learning program would be part of a more comprehensive framework where it should act as a first filter that has a higher chance of capturing all glaciers for further selection or processing.

We see two areas of future work. The Landsat images in our dataset are all from the same time of the year. To increase the robustness of our models, it would be good to complement the dataset with images taken during other seasons. Instead of using image-wise classification, use pixel-wise classification as it is provides more information about the extent of the glacier.

9 Roles

We split the features analysis in groups of two people and a member entirely dedicated to CNN. Then we all put together our conclusions and benchmark the performance metrics obtained.

- KNN (HOG), Logistic Regression (HOG). Preprocessing, models and visualisations - Javier, Jonas.
- KNN (HOC), Logistic Regression (HOC), Naive Bayes (HOC) and visualizations - Matteo, Mattia.
- CNN: Models, Pre-processing and visualizations - Nemish
- Final score diagram - Mattia.

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