SnowBall Project: Remote sensing, model and in-situ data fusion for snowpack parameters and related hazards in a climate change perspective (2014 – 2016)

AVALANCHE DETECTION IN VERY HIGH RESOLUTION OPTICAL SATELLITE IMAGES

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- NR – Norwegian Computing Center
- WUT – West University of Timisoara

Detection of avalanches in remote sensing images

Satellites has a great potential for mapping of avalanches since it makes it possible to monitor large areas **fast** and **efficient**. We may:

- Monitor size and the frequency of avalanches in areas without settlements
- Provide an independent assessment of the risk of avalanches in areas of special interest
- Create statistics on where avalanches most likely occur, how large they are, and under which weather conditions they are triggered
    - Important in future planning of infrastructure

The Snowball project aims to develop algorithms for automated detection of avalanches in very high resolution (VHR) optical satellite images

Objectives

Main objective

Develop methodology supporting a future service providing hind-cast and real-time snow and avalanche information retrieved from earth observation data.

Sub-objectives

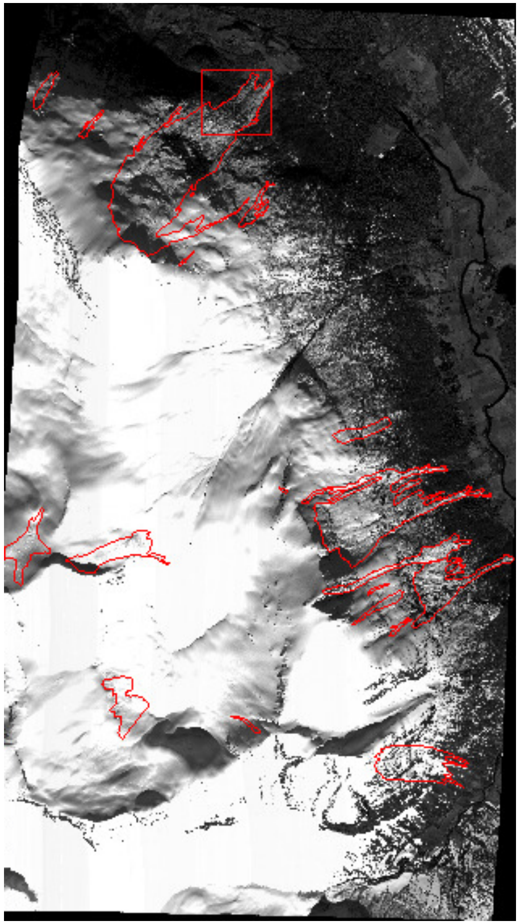
- Develop robust pattern recognition techniques to detect and map the outline of avalanches in VHR optical satellite data.
- Develop robust change-detection algorithms to detect changes in land and snow cover caused by avalanches in High Resolution (HR) satellite data.
- Create the avalanche inventory and the associated geodatabase regarding morphometric parameters and snow characteristics.
- Perform simulation of avalanche trajectories based on DEM's, release areas and friction parameters.
- Develop improved avalanche hazard assessment.

Optical image dataset

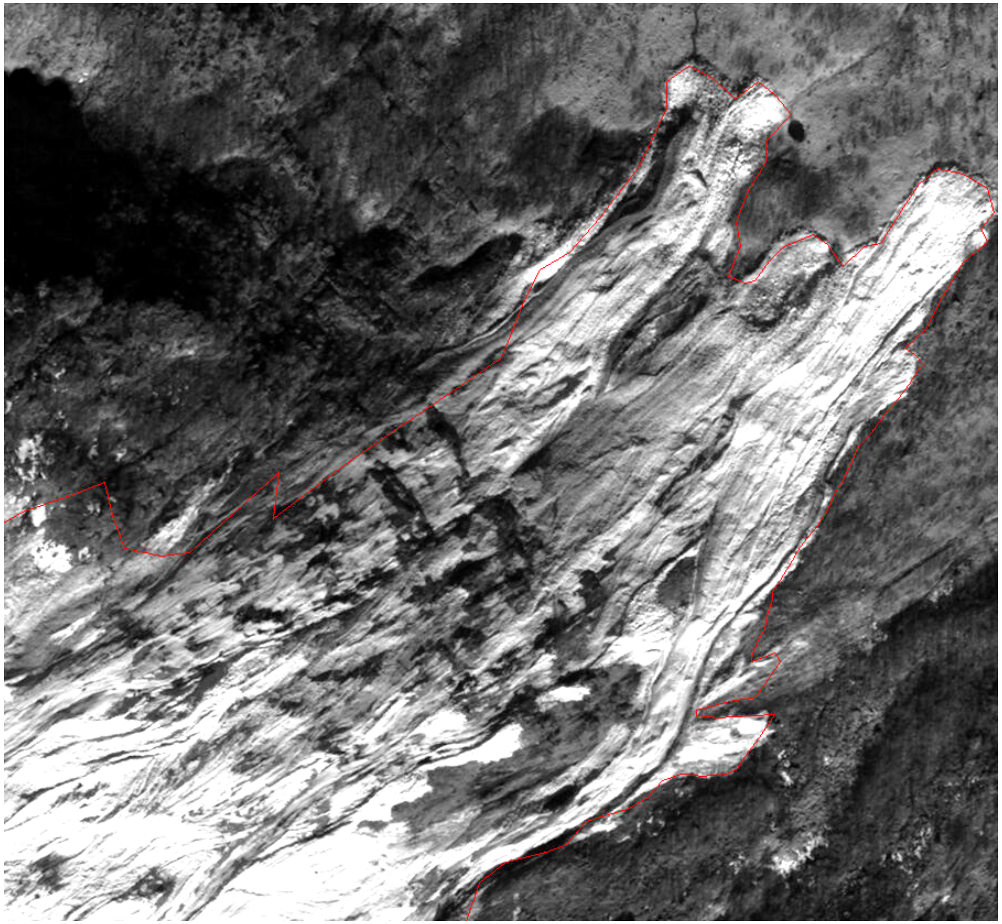
	Location	Sensor	Acquisition date	Spatial resolution
Training	Hellesylt (NOR)	QuickBird	April 16, 2005	0.6m
	Loen (NOR)	WorldView-1	April 12, 2010	0.5m
	High Tatra (SLO) (lower right)	WorldView-1	April 2, 2009	0.5m
Testing	Dalsfjorden (NOR)	QuickBird	April 3, 2005	0.6m
	Eikesdal(NOR)	QuickBird	April 13, 2011	0.6m
	High Tatra (rest)	WorldView-1	April 2, 2009	0.5m
	Stjernøya (NOR)	WorldView-1	April 17, 2013	0.5m
	Fagaras (RO)	GeoEye	April 11, 2012	0.5m

Avalanche examples – Hellesylt, Norway, 2005

6946m



3888m

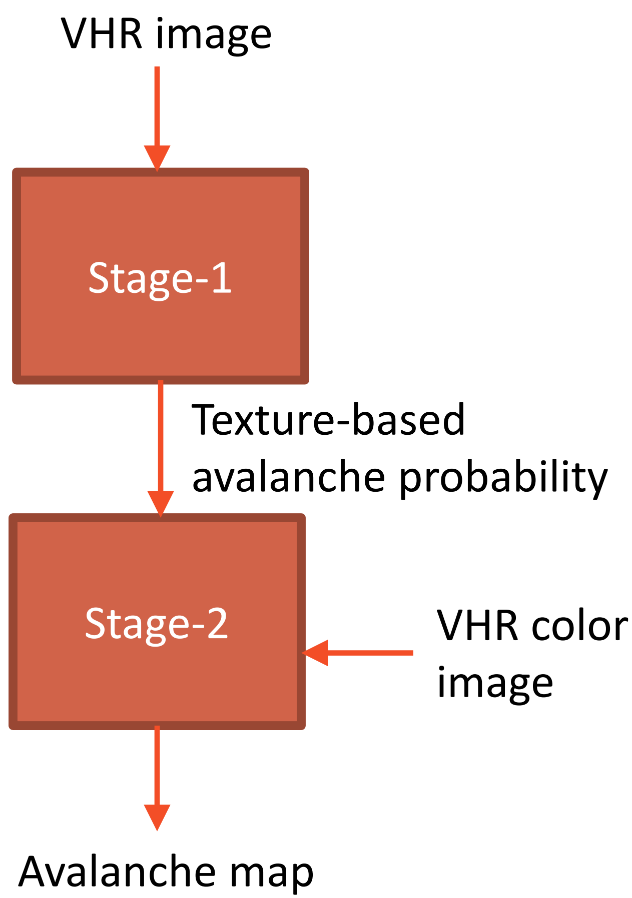


Avalanche detection

The avalanche detection algorithm consists of two stages:

Stage-1: A superpixel based texture classification stage that is based on the learned feature representation approach and a random forest classifier.

Stage-2: A post-classification stage that also consists of a random forest classifier, but uses the probability output of Stage-1, the panchromatic values and the NDI-values as features.



Superpixel-based learning feature representation algorithm

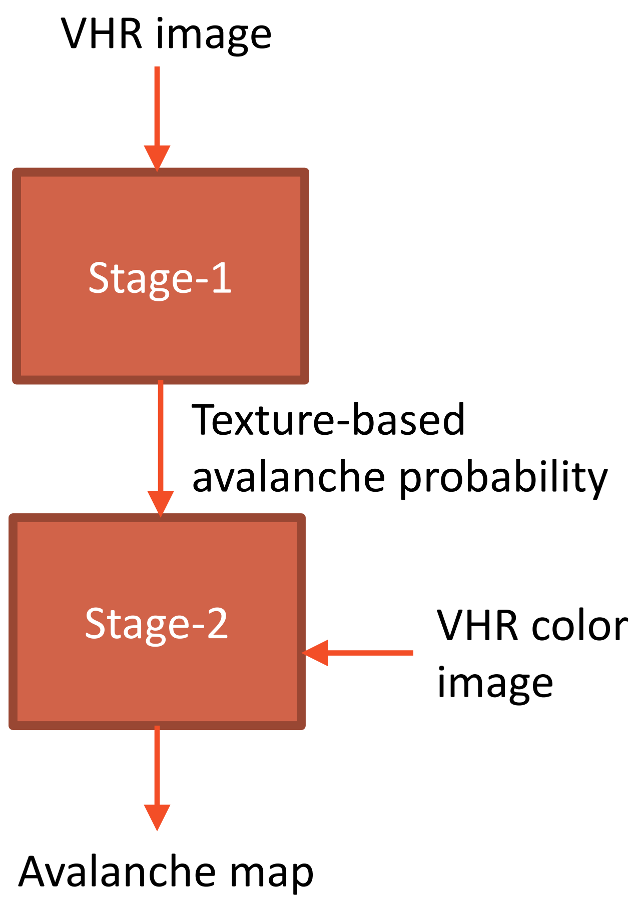
Algorithm

Stage-1

1. Learn a representation (dictionary) of the data
2. Enhance (filter) the image using the learned dictionary
3. Aggregate the filter responses into superpixels
4. Estimate the avalanche probability

Stage-2

5. Extract color features
6. Classify each superpixel as avalanche or non-avalanche



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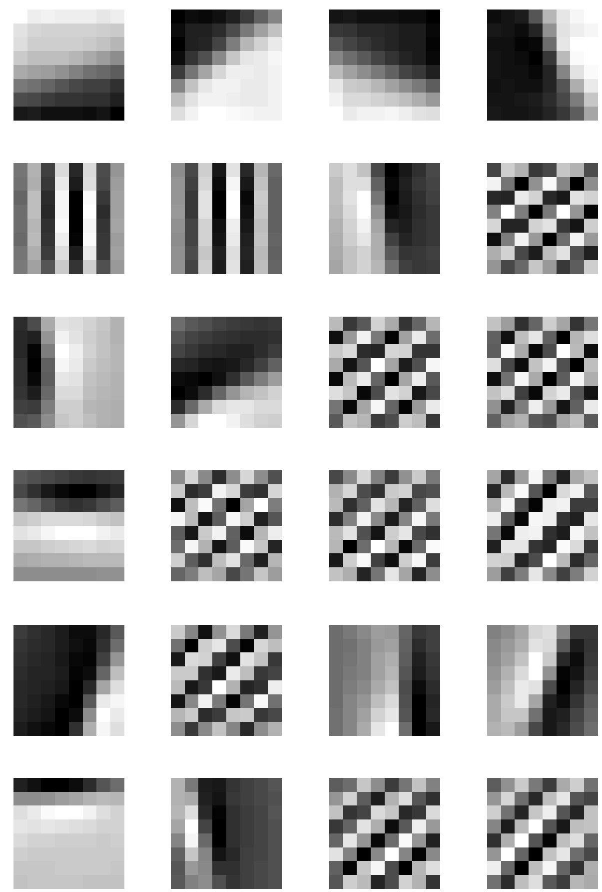
Dictionary consists of 300 atoms.
Learned using the spherical K-means



24 of 300 atoms

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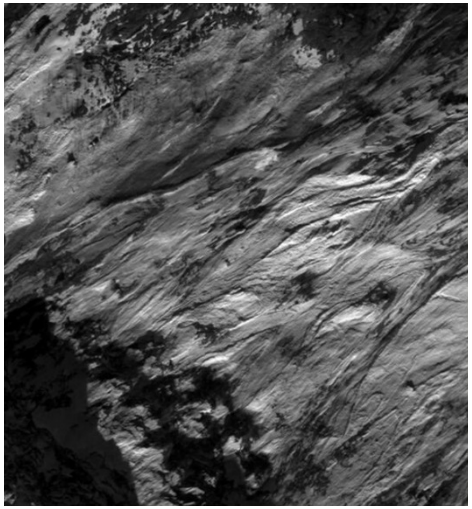

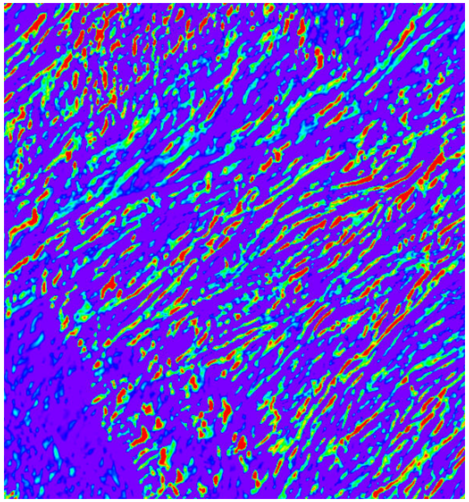

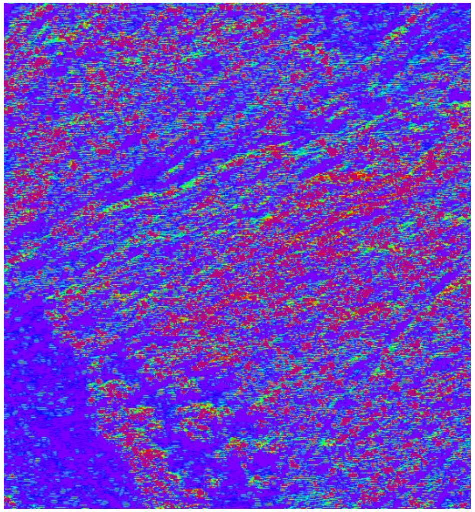

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Superpixel algorithms group pixels into perceptually meaningful atomic regions

- capture image redundancy
- provide a convenient primitive from which to compute image features
- greatly reduce the complexity of subsequent image processing tasks

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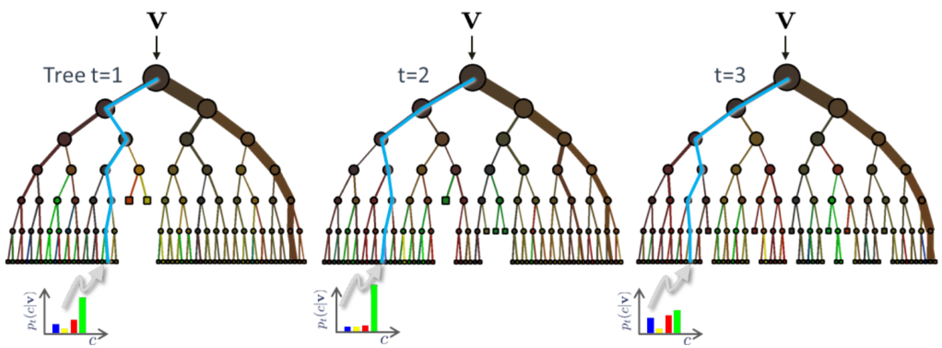
Random forest classifiers operate by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes of the individual trees



Features applied:

- 300 filter responses

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Normalized difference index

$$NDI = \frac{IR - RED}{IR + RED}$$

Panchromatic value (gray level intensity)

$$PAN$$

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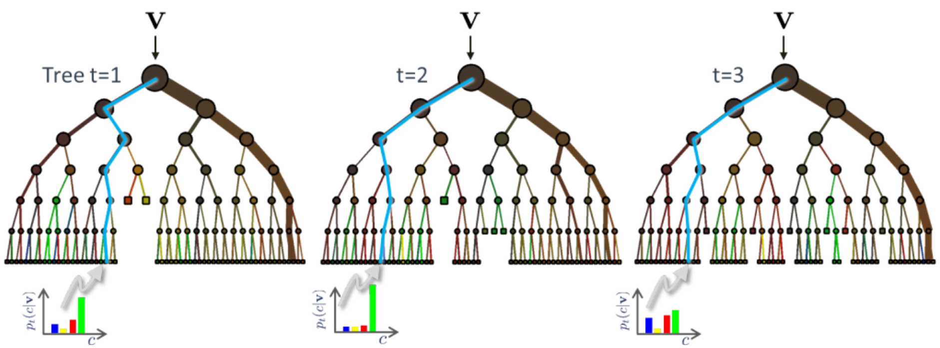
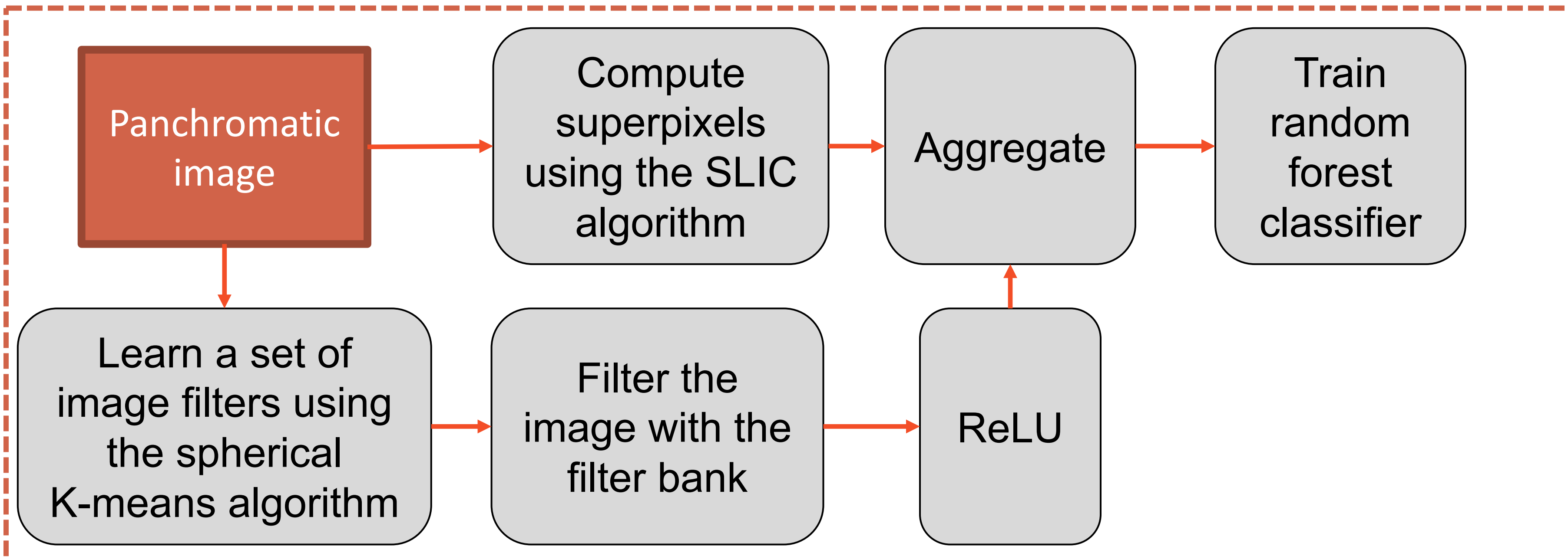


Features applied:

- Texture-based avalanche probability
- NDI
- PAN

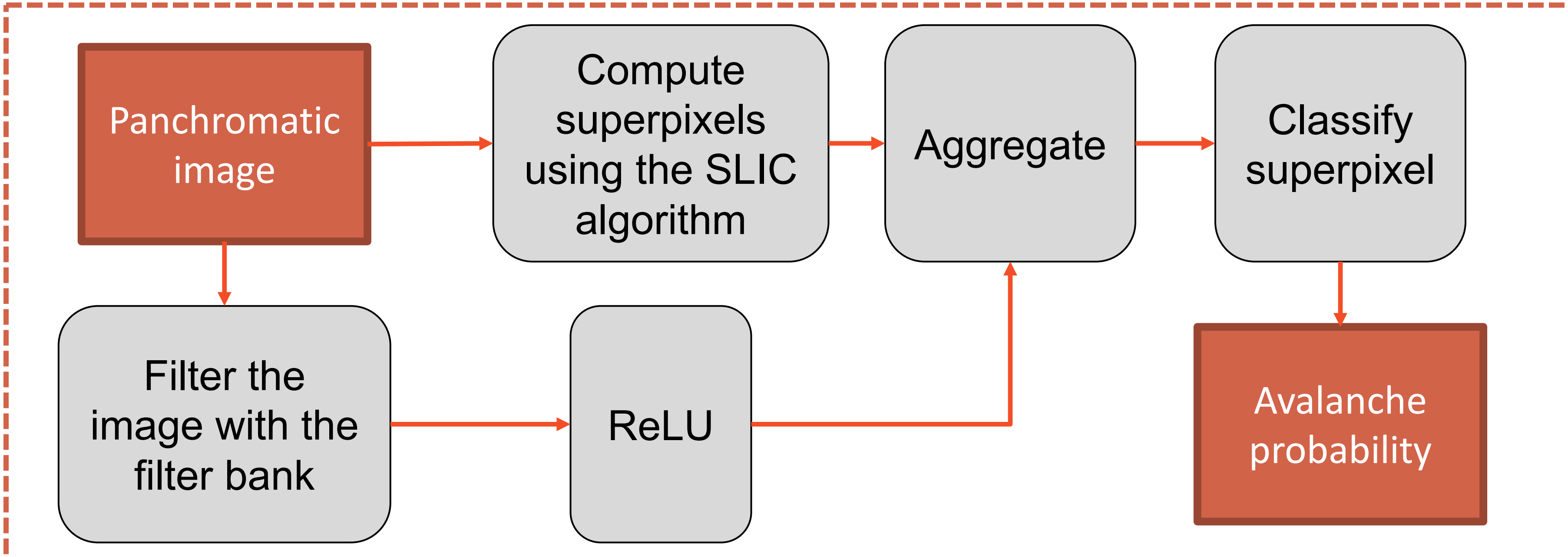
Training chain

Stage-1



Execution chain

Stage-1



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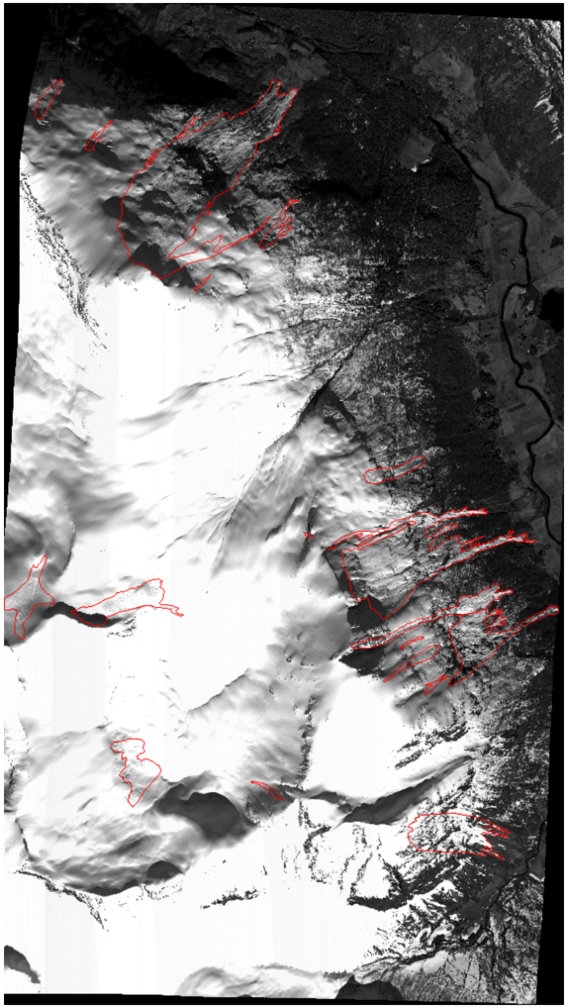
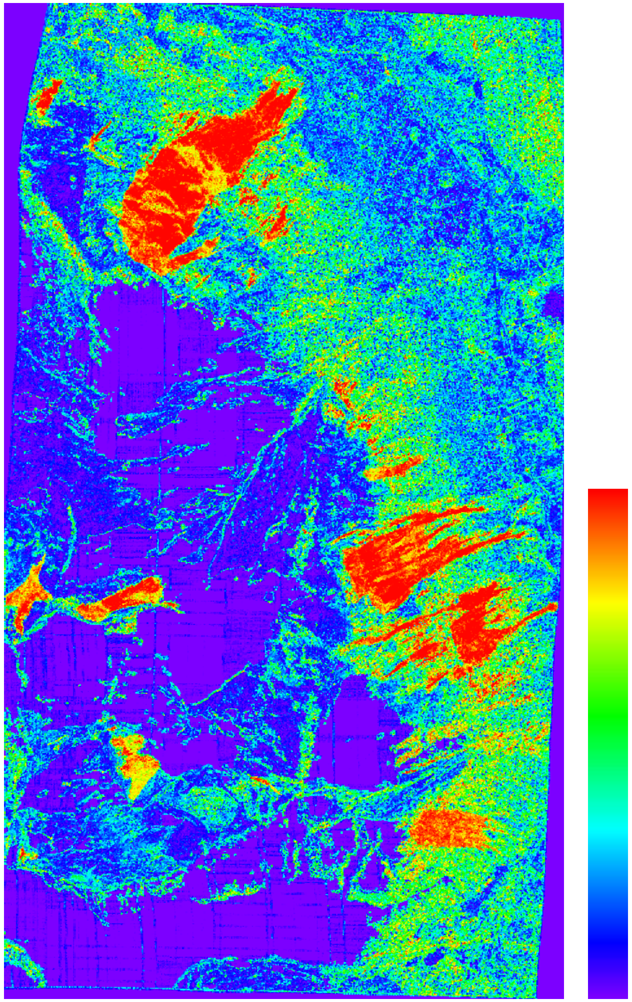
Texture-based probability of avalanche, Hellesylt, Norway (training image)





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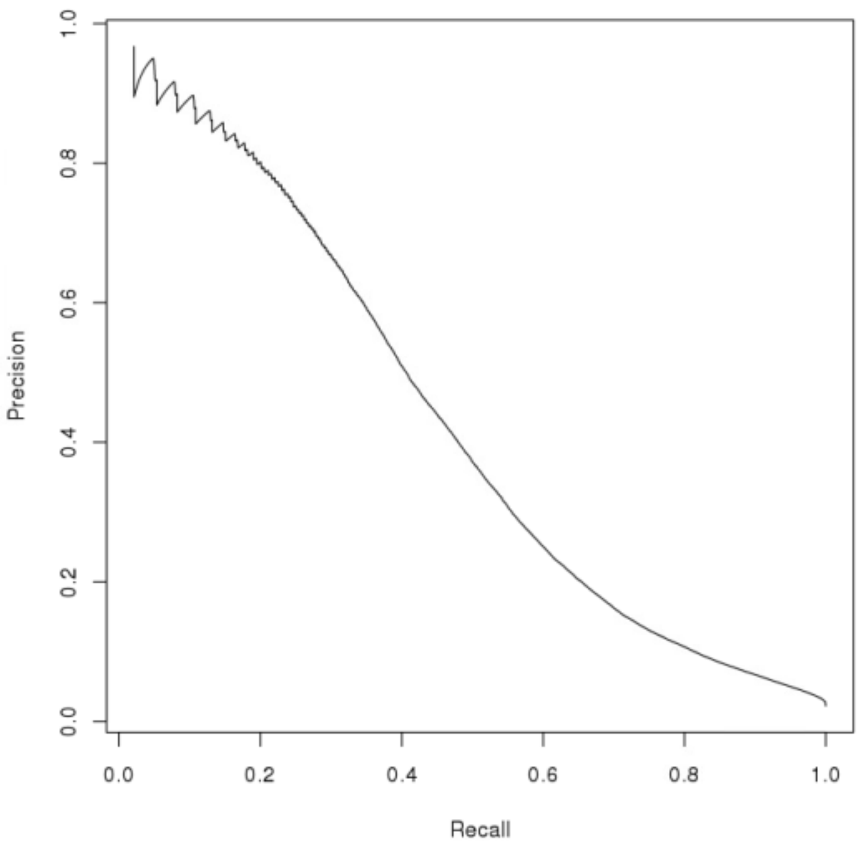
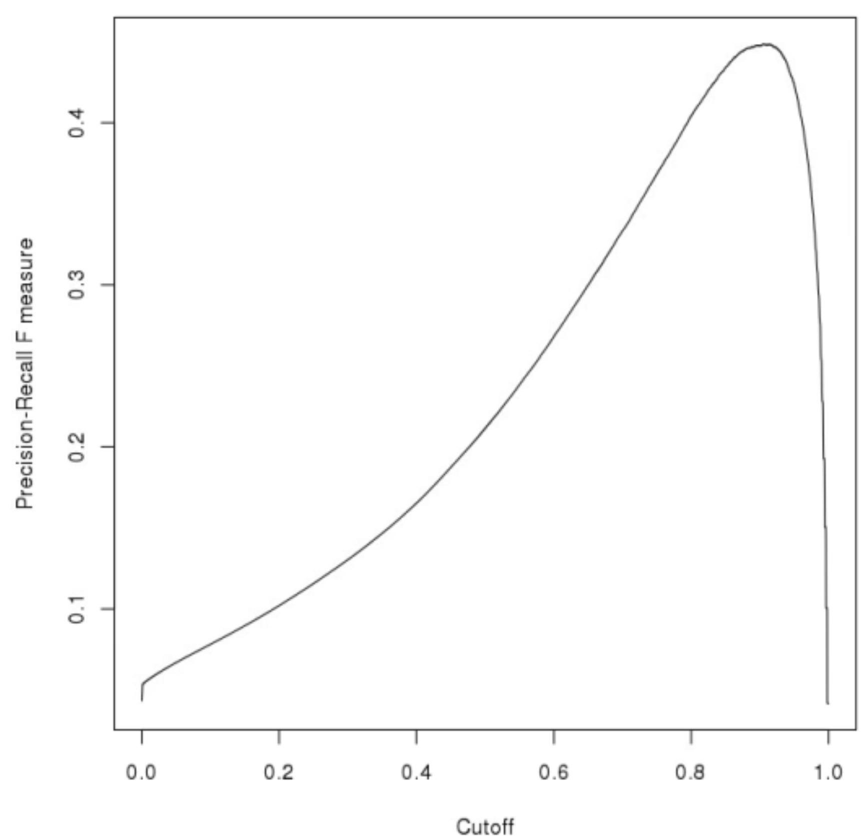
Precision-recall analysis





Precision: no. true positives / (no. true positives + no. false positives)
Recall: no. true positives / (no. true positives + no. false negatives)

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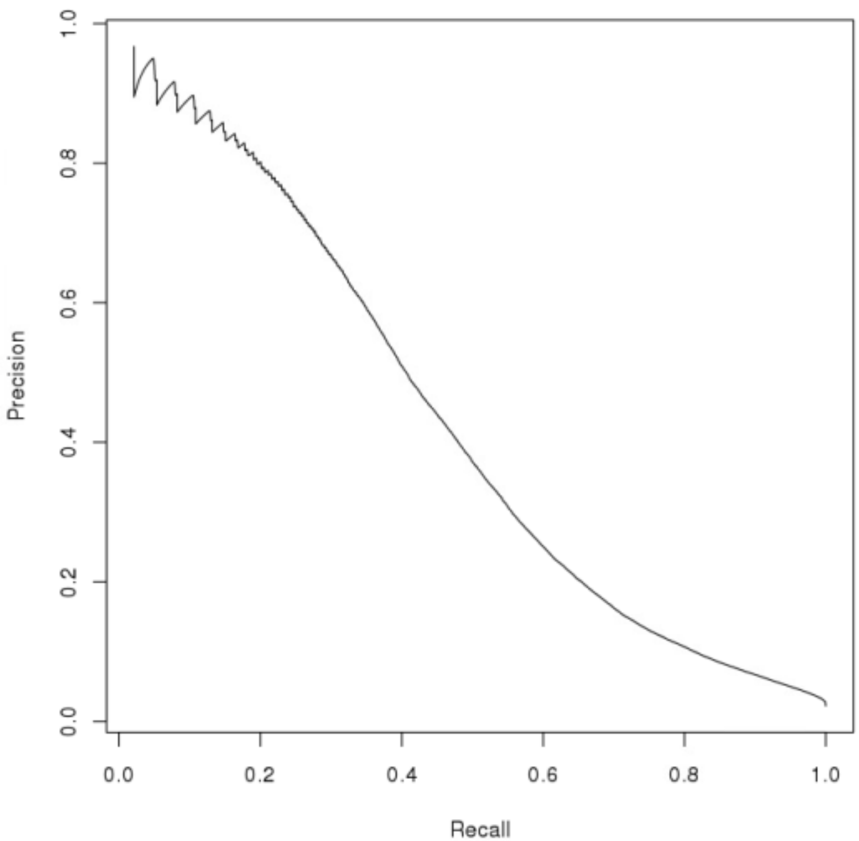
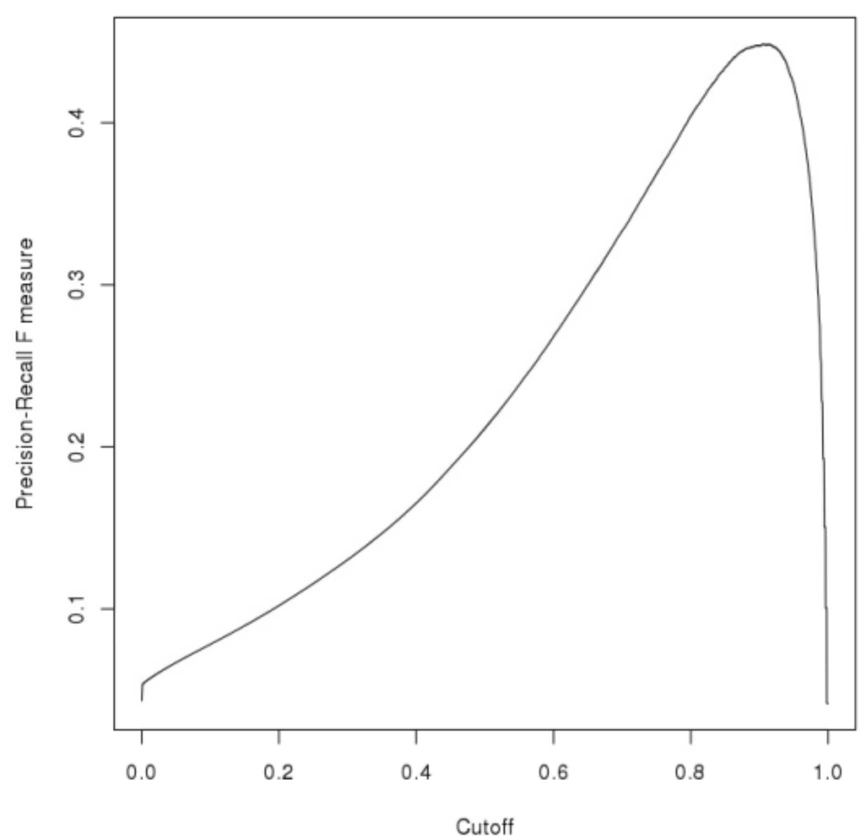
Precision-recall analysis





Precision: How many selected elements are relevant?
Recall: How many relevant elements are selected?

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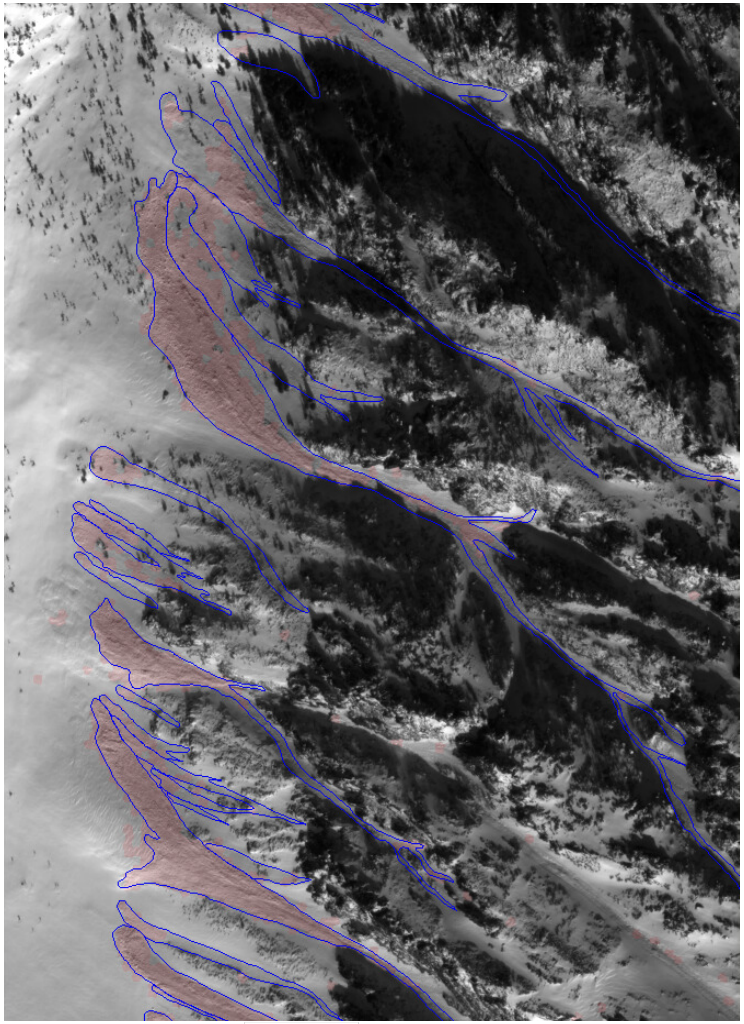
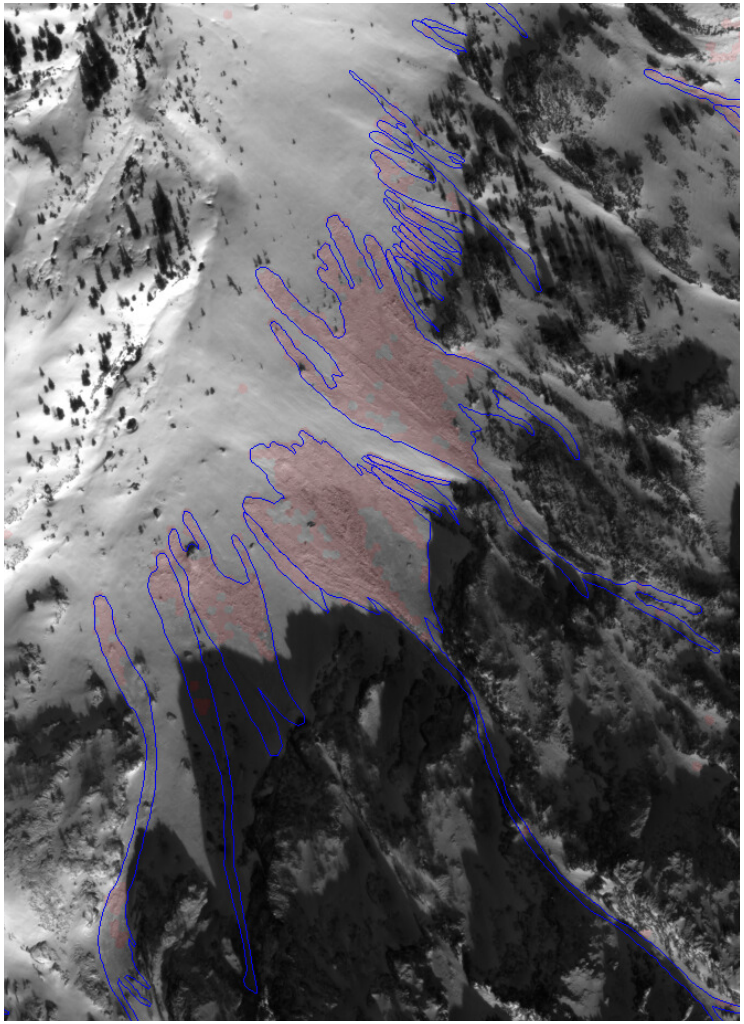
Successful avalanche detections, Fagaras, Romania





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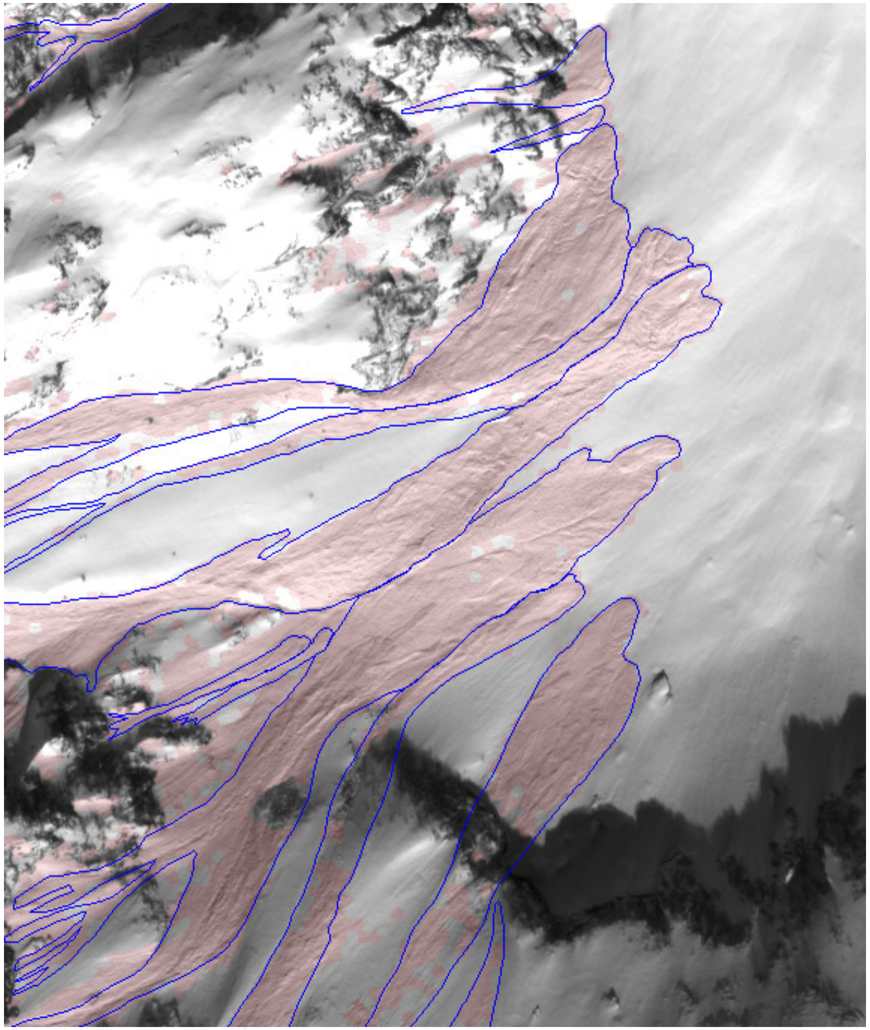

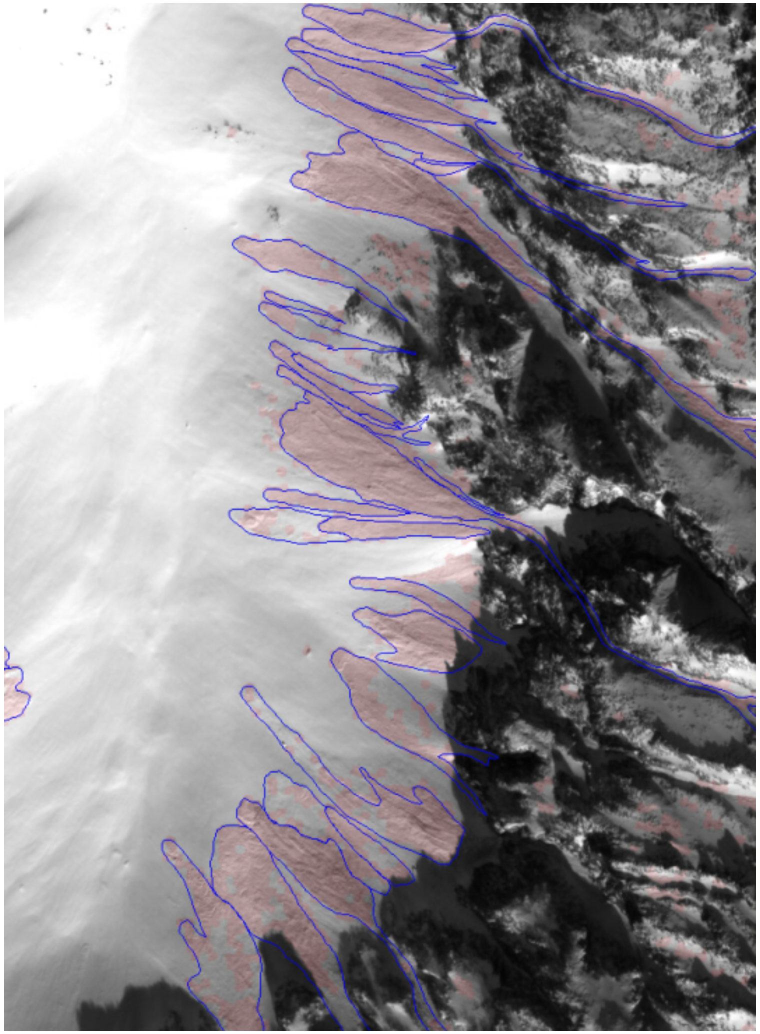

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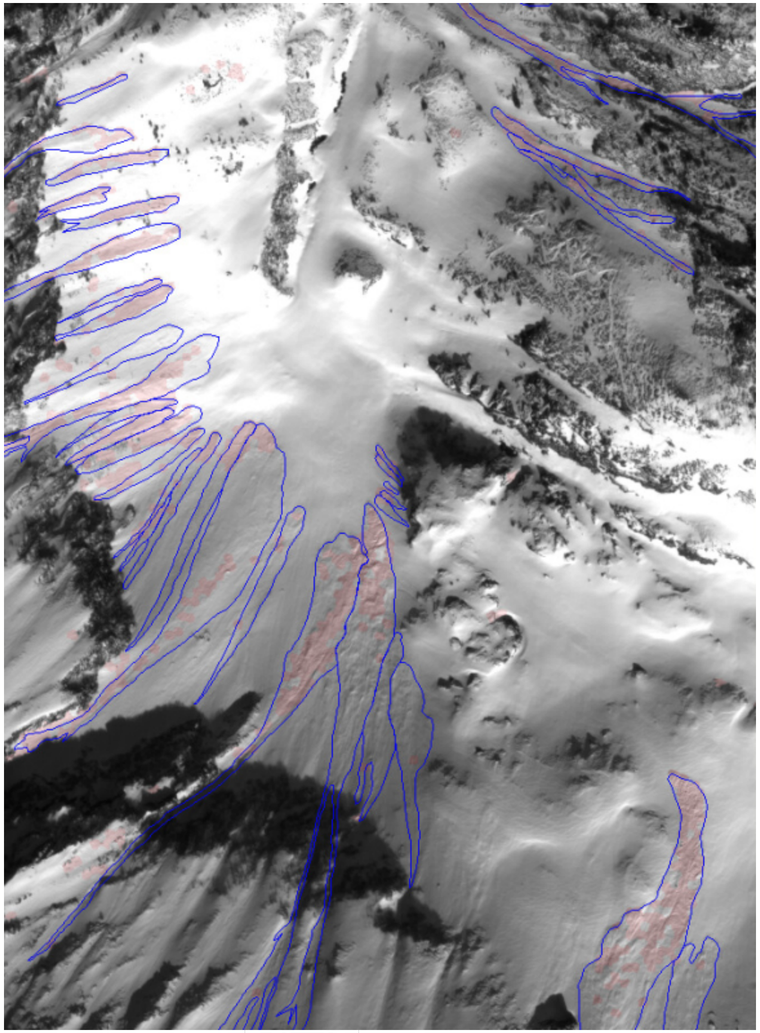
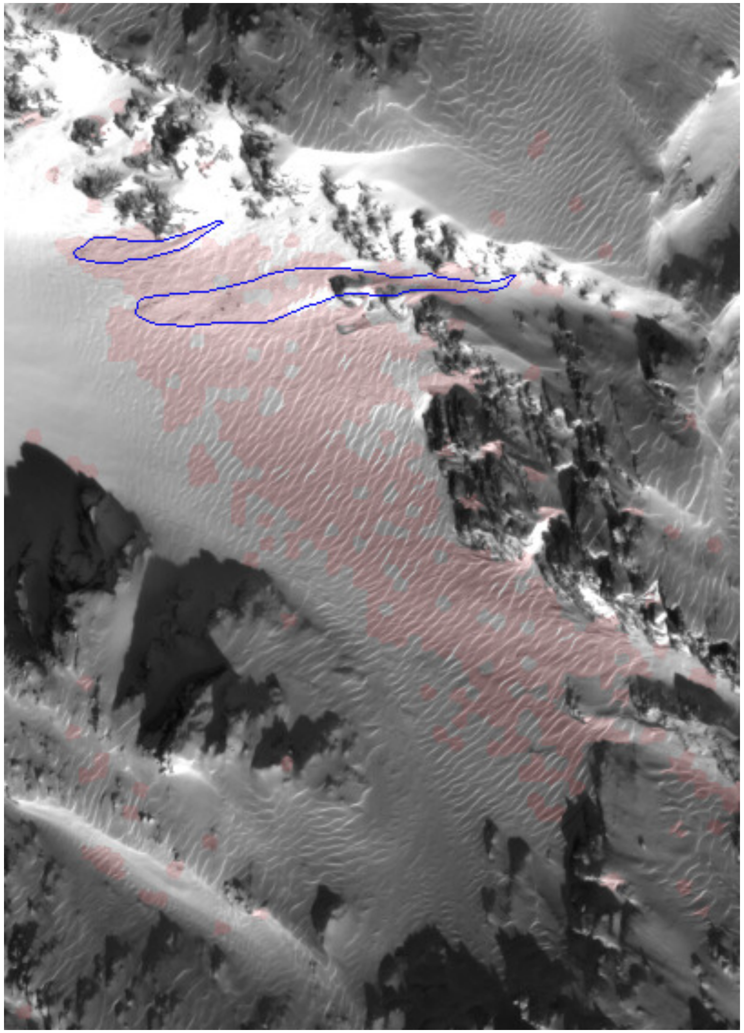
Challenging cases, Fagaras, Romania





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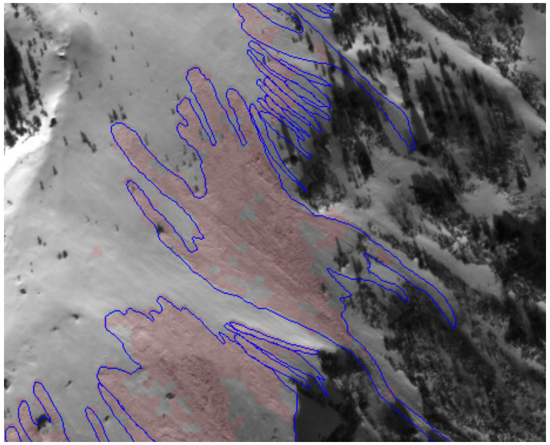
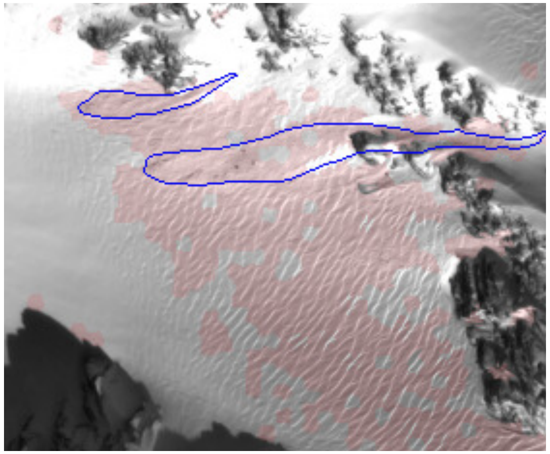
Conclusions



The methods are able to automatically identify clearly visible, new, avalanches.

Sometimes difficult to distinguish avalanches from rugged snow patterns caused by wind.



We also suggest applying some sort of merging algorithm in order to connect avalanche objects that belong to the same avalanche path.

Deep learning has caused a revolution in computer vision the last years, and approaches based on deep neural network may provide improved results for avalanche detection.

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