OPTICAL MONITORING OF AVALANCHE REALEASE ZONES IN BESSANS, HAUTE MAURIENNE VALLEY, FRANCE, WITH A REMOTE AND ENERGY SELF-SUFFICIENT CAMERA SYSTEM

Ishak Barkat[1], Christophe Lin-Kwong-Chon[1], Alain Duclos[2,*], Maxence Carrel[3], Severin Staehly[3], Cédric Périllat[2], Gaëlle Bourgeois[4], Anne Lescurier[4], Roger Fiandino[5], Argheesh Bhanot[1], Frédéric Pourraz[1]

[1]LISTIC, Université Savoie Mont-Blanc, Annecy, France
[2]ALEA SARL, Aussois, France
[3]Geoprevent, Zurich, Switzerland
[4]Departmental Council of Savoie, Chambéry, France
[5]Municipality of Bessans, Bessans, France

ABSTRACT: The slopes between the Pointes du Châtelard and the Pointe de Claret in the Vanoise National Park, Haute-Maurienne in France are located right above the village of Bessans, its main access road and ski lifts. In recent years, several significant avalanches came down these slopes, potentially threatening the village. Notably, several bungalows of the local camping ground were partially destroyed by a large powder avalanche impact in 2004. Avalanche safety in the valley is managed by a committee consisting of road authorities, local officials, and independent avalanche experts. Due to the topography, most slopes are not visible from the valley, hence limited information about snow coverage and the avalanche situation of the upper part of the slopes is available. This causes a major challenge for the decision-makers who take actions such as avalanche control or road closing. Being the only access road to the valley, minimizing road closure is critical for its 6000 inhabitants. To address this challenge, an energy self-sufficient camera system was installed at almost 3000 masl on a ridge on the opposite side of the valley, to automatically take photographs of the avalanche slopes. The camera was modified to enhance contrast of the snow cover and avoid pixel saturation due to high snow albedo. Photographs can be recorded every 15 minutes at 42 MP resolution and in a high dynamic range. A specific high dynamic range mode was developed for night conditions so that valuable information is available 24/7 for the avalanche safety committee. Preliminary results of image analysis tests performed using both digital image correlation and deep learning algorithms demonstrate the potential of this quantitative method to support decision-making. Digital image correlation is used to measure local accelerations in the snow cover that could potentially lead to glide-snow avalanches, while deep learning algorithms classify events. During the first winter of application, the 2023/2024 season, camera images played a crucial part in the decision-making process of the avalanche safety committee and can be used by the avalanche experts to further evaluate critical remote locations of the region known to be prone to similar conditions and where no data is available until now.

Keywords: Avalanche monitoring, energy self-sufficient camera system, image processing, digital image correlation, deep learning.

1. INTRODUCTION

The Departmental Council of Savoie is responsible for avalanche risk management on its road network, including access to many of the major ski resorts in the French Alps (Tignes, Val d'Isère, Val-Thorens, Courchevel, etc.). Since 1998, the Departmental Council has been working with a team of snow and avalanche experts (ALEA SARL) and have acquired specific equipment, notably for snow-meteorological measurements (ISAW) and automatic avalanche detection. Although automatic snow and weather measurements now provide satisfactory data, both in quantity and quality, data on actual avalanche activity is still too scarce; many avalanches go undetected (at night or in bad weather), and when traces of them are discovered, it is no longer possible to date them accurately. It is therefore difficult to develop and validate forecasting models (Bourgeois et al., 2013).

To progress, as early as 1999, a prototype of infra-sound avalanche detection system (Arfang, IAV, (Chritin et al., 1996)) had been developed and tested in Bonneval-sur-Arc (Haute-Maurienne-Vanoise/Savoie) to protect the departmental road RD902, with the aim to be put into use quickly to manage avalanche risk (Duclos et al., 2001). Nevertheless, it was moved a few years later to a site with less at stake, due to errors deemed prohibitive by the Department. Geophones (SLF) had also been implanted, but without results, due to some technical problems. The RD902 has since been secured by more than 25 remote avalanche control systems. However, a section of this same road remains exposed to very large avalanches between

*Corresponding author address:
Alain Duclos, email: duclos.alea@gmail.com

the villages of Lanslevillard and Bessans. Installations similar to those installed at Bonneval-sur-Arc have been requested by the commune of Bessans (altitude 1700m), but the scale of the threatening slopes (1700 m vertical drop) and the potential damage to buildings led the department to choose, in a first step, a more cautious and observationary approach. Indeed, in the past (1935), the chimneys of the village school have already been destroyed by avalanche powder clouds. More recently (2004), the roof of a building not used in winter has been torn off before crossing the RD902, several days after a crisis period that had caused the temporary preventive closure of the road. On each occasion, the avalanche starting zones were indeterminate, often in high altitude areas that were difficult to see from the valley, even in clear weather conditions.

Recent developments in automatic image capture and processing induced the Departmental Council to choose an approach built on camera-based observations (Stähly et al., 2023) as at least a partial response to the need for a better understanding of avalanche activity. A new project was launched in 2022, to test the automatic capture of high-resolution images to be assessed visually by avalanche experts, with the aim of developing an automatic image-processing based analysis in the near future. In addition to the institution (Department and Commune de Bessans), snow Experts (ALEA Sarl) and suppliers (Geoprevent), academics are also involved in the project (University Savoie Mont-Blanc, LISTIC laboratories). On the one hand, the aim is to help local decision-making in real-time, both by the communal safety commission and by the Departmental Council (preventive closures, reopenings, activation of preventive avalanche control from helicopters); on the other hand, to highlight a particular situation that could affect other sites in the Department; and finally, to build up a database to refine the environment-surrounded learning. For the time being, the Departmental Council prioritized a camera-based approach over other automatic detection systems such as Doppler radar (Meier et al., 2016), due to the large amount of information, sometimes unexpected, that is provided by the images. This includes information relative to the distribution of snow cover in high-altitude areas, determined as much by precipitation as by the effect of wind or avalanches that have already occurred. During this first 2023-2024 season, the exploitation of the photos was exclusively human, but already very rewarding. Nevertheless, the aim was to create an initial working basis for automatic avalanche recognition, first using an approach based on well-known digital image correlation algorithms and then using more recent deep learning algorithms.

Digital image correlation algorithms have been widely applied to different research fields for several decades to measure deformations and displacement. These algorithms have also already been applied to the avalanche field (Feick et al., 2012; van Herwijnen et al., 2013). Thereby, the focus of the authors was mainly on the detection of glide cracks and the measurement of their expension as well as the monitoring of cornice dynamics (Vogel et al., 2012). About deep learning method, a recent ground-based photographic method proposed by Fox et al. (2024) is developed with an objective of real-time avalanches classification. Conjointly, the UIBK dataset with 4090 ground-based photographs containing 7228 avalanches labeled by experts is presented. Localisation with bounding boxes, avalanches classification and avalanches segmentation are encoded in this dataset. The deep vision approach relies on two sequential models, a ResNet152 for avalanche predetection and a YOLOv3-SP for avalanche localisation and classification. The paper proposes a live hybride AI framework to monitoring webcams and present potentially alarming images to experts for validation. In this same way, another recent paper by Hafner et al. (2024) proposes an interactive avalanche segmentation to support avalanche mapping in webcam imagery. The study focused on the Dischma Valley in the town of Davos, and covered 14 cameras in 6 different locations. The SLF dataset presented in this paper is based on image acquisition every 30 minutes during the day, and contains 400 annotations. Segmentation of avalanches are performed in this study with a pixel-wise deep model. The interactive function is achieved by the intervention of an expert who places positive clicks on the avalanche, and negative clicks on the background. These clicks are ingested by the model, enabling it to improve classification and segmentation results.

Deep learning methods, while advanced, face challenges in reliability due to variable environmental conditions and data quality, leading to issues like false alarms and missed detection. To address these, expert validation and adjustments are crucial for improving accuracy. This paper presents the results from the first season of avalanche monitoring in the Maurienne valley using a camera-based system, detailing the difficulties encountered, benefits obtained, and future outlook. It also analyzes the effectiveness and reliability of deformation algorithms and deep learning detection methods for identifying and monitoring avalanche events, based on observations from the 2023-2024 season. Following this introduction, a presentation of the site is given in section 2. along with a presentation of the energy-efficient acquisition equipment and the database produced. Section 3. presents the methodology employed, featuring both a classical approach and a deep learning approach. The results and limitations of the methodology are presented in section

4.. Section 5. discusses the season's operational results, contributions to decision-making, and future directions. The article concludes with a final summary.

2. EXPERIMENTAL SETUP

2.1 Bessans site

The camera system was installed at ca. 2950 m on a ridge close to the Pointe de Soliet in Bessans. The location of the system was choosen carefully in order to provide an optimal view of the avalanche release zones located at ca. 4.5 km on the other side of the valley.

2.2 Camera acquisition system

A robust steal pole with a foot allowing versatile positioning angles was used to optimally cope with the alpine terrain. A picture of the system is displayed on Figure 1. The camera system is installed in a weather-proof housing and contains the camera itself, as well as data transmission and power management units. The camera is equipped with an optical filter that improves the quality of the snow cover images and reduces the pixel saturation due to the brightness of sunlight reflections on the snow cover. A consequence of the implementation of this filter is the reduced range exhibited by the images in RGB, so that the images appear to be in greyscale. The system is equipped

Figure 1: The camera monitoring system installed close to the Pointe du Soliet in Bessans, France, with the avalanche release zones of interest close to the Pointes du Châtelard and Pointe de Claret in the background.

with an anti-snow system continuously removing the snow that could cover the camera lens during important snow-fall. Due to the remoteness of the system's location, the power supply of the camera and of the data transmission unit is covered with an energy self-sufficient system consisting of batteries and a 200 W solar panel. The different electronic components and the power supply system were designed to operate normally for two weeks under adverse weather conditions and with limited solar output.

2.3 Bessans-Alps dataset

The camera system records several high-resolution (42 MP) images up to every 15 minutes that are combined to generate high-dynamic range (HDR) images exhibiting an improved contrast both for visual inspection and automatic feature detection. A dedicated HDR algorithm was developed for night images, allowing to partially overcome the lower light intensity and providing usable images. More than 4000 images were acquired during the first avalanche season (2023 - 2024).

3. METHODOLOGY

3.1 Overall methodology

Overall methodology for monitoring and detection is presented in Figure 2. The method uses two distinct approaches: digital image correlation for detecting snow pack surface deformations, and deep learning for classifying avalanche events.

3.1.1 Data preprocessing

Clear sky filtering. Images containing clouds provide no information on the surface of the mountain other than overcast conditions. Weather and nivological stations are located in the town of Bessans and in the nearby ski resort of Bonneval-sur-Arc. However, it does not offer a good representation of mountain whole visibility. In order to perform imagery algorithm and to exclude images containing clouds, we apply filtering according to the combination of brightness measurement and edge detection with trial-and-error thresholding. The edge detection is implemented with Canny (1986) algorithm.

Co-registration. The camera system is subject to wind and temperature-induced material expansion. To ensure spatio-temporal coherence, images are registered to the clear, cloud-free image batch using the scale invariant feature transform method developed by Lowe (2004). Affine co-registration is then applied using a moving reference image. Whenever the coherence of the time series becomes compromised, the reference image is replaced, ensuring that the registration process continuously adapts to changes in acquisition conditions.

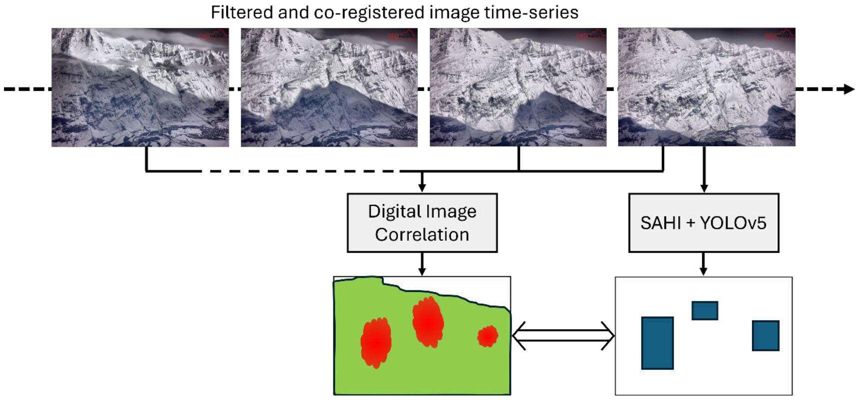

Figure 2: Overall methodology implemented for avalanche monitoring and detection.

3.1.2 Digital image correlation

The digital image cross-correlation is performed on the time-series that successfully passed the clear sky filtering and co-registration steps. This technique is used to reveal surface displacements and deformations, which could indicate stress accumulation or instability, potentially leading to cracking and sliding of the snow pack. We use a time series of several days as input, analyzing deformations for each hourly pair to minimize the impact of shadows cast by the opposing cliff. In order to ensure consistency in deformation estimation despite changes in image acquisition rates, we skip any 24-hour image pairs where an image is missing, such as due to cloud cover. When too many images are missing, we apply temporal weighting to the available data. This involves adjusting the importance of the available image pairs based on the time intervals covered, thereby maintaining a balanced contribution to the deformation analysis.

3.1.3 Deep learning model

Based on the work of Fox et al. (2024), we trained a deep learning model on their ground image UIBK avalanche database and inferenced it to Bessans-Alps time-series. Since generating a Bessans-Alps annotations base would be too tedious, we experimented deep learning by using transfer learning. In order to adapt to larger images and variable size objects, we used the Slicing Aided Hyper Inference (SAHI) algorithm developed by Akyon et al. (2022) to perform detection with sliding and overlapping windows. We implemented YOLOv5 Ultralytics (2021) bounding boxes and segmentation models by training from scratch. To obtain comparable results, we used the same dataset splitting as in Fox et al. (2024), with 3,612 images for the training set and 478 for the validation set. A total of 10% of the images in the training set are dedicated to the validation set. Selection of the validation set is based on three different randomized experiments to obtain the standard deviation of model test set performance.

For inference stage, the detection threshold is set at 0.25 to retain the maximum number of detection, as the transfer learning approach can result in low confidence scores. Then, two post deep-inference filters are added to improve the raw results by removing simple false positives. Firstly, the snow-covered canopy of the woods or the city can lead to miss-classifications. A binary mask overlaying the mountain, which acts as a spatial filter is used to delimit the study area. Secondly, hallucinations in saturated or low-light conditions are addressed with an additional filter based on detection count and its derivative.

4. RESULTS

4.1 High Dynamic Range images

Two examples of images acquired by the system are displayed on Figure 3, where the upper image was taken at 3 AM and the lower one at 5 PM. The high contrast and clear visibility of the image acquired at night (top) is made possible by the application of high exposure time and the customized night HDR algorithm.

4.2 Digital image correlation

The results obtained with the cross-correlation algorithm are shown in Figure 4. The inner displacement field is color-coded with the magnitude of the displacement intensity and allows to visually detect zones with important displacement (possible avalanche precursory signs like glide cracks or local displacements due to settlements). In case of avalanche events or cornice collapse, no displacement are measured because it is not possible to compute the correlation between the images compared. In such cases, such as visible in the inset of Figure 4, correlation losses can be used to directly identify zones with important changes.

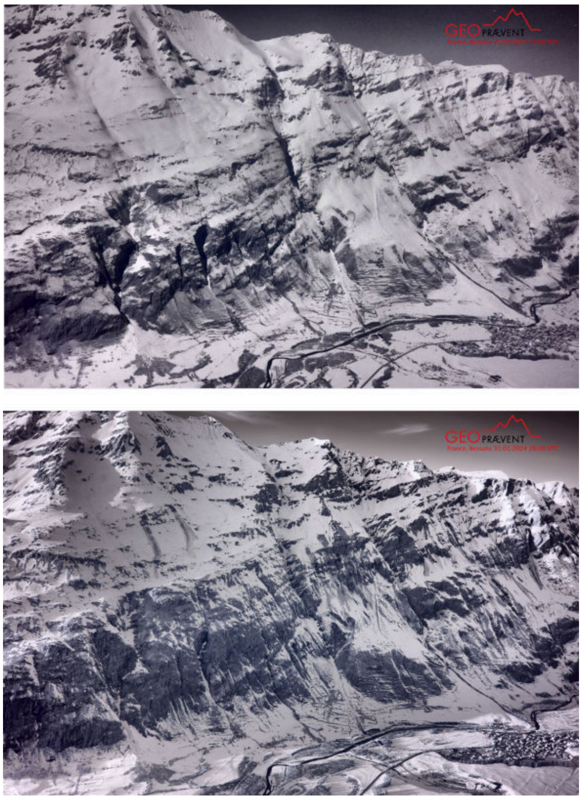

Figure 3: Images acquired with the camera system, under night conditions on February 25th 2024 at 3 AM (top) and on January 31st at 5 PM (bottom).

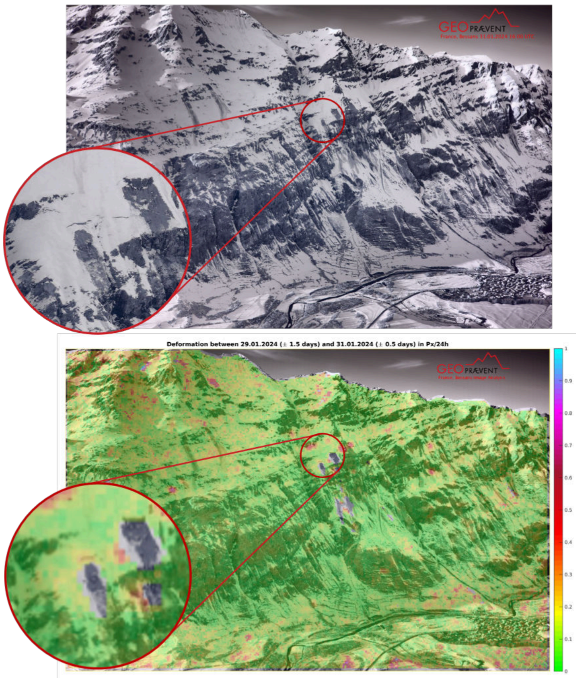

Figure 4: Deformation between 2024-01-29 (± 1.5 days) and 2024-01-31 (± 0.5 day) in Px/24h.

4.3 Deep learning model

4.3.1 Classification and localisation

Training and time execution. Deep learning training and inference are performed on a workstation equipped with dual NVLink RTX6000 GPUs. The two YOLOv5 models were trained for 180 epochs, with an early stopping criterion set to 25 epochs if neither loss nor accuracy improved. The models' architecture accepts an input size of 896, with an initial learning rate of 0.01, adjusted to a final learning rate of 0.1 using the OneCycleLR scheduler. During training, an Intersection over Union (IoU) threshold of 0.20 was applied, and a confidence threshold of 0.25 was used for detection. We conducted multiple validation tests on different input sizes (640, 672, and 896), and varied the IoU thresholds and confidence levels. Model training was completed in 3 hours on the UIBK dataset, with the multiclass annotations and 3 different validation seeds. On the test set, the bounding boxes model achieved an F1 score of 45.6±2.3%, with a precision of 61.6±6.8% and a recall of 37±5.7%. And the segmentation model achieved a higher F1 score of 49±2.4%, with a precision of 53.8±5.6% and a recall of 43.6±3.9%. Each SAHI inference is performed in under 30 seconds with these 7952×5304 pixel images.

Inference validation. Inference is performed on the period from November 2023 to January 2024. A dozen of major events are validated by experts during this period. Deep learning succeeds in detecting all of the cataloged events and detects more small size avalanches. The set of inference validations is limited in number but shows some preliminary practical results, which are presented below. The bounding box detection and segmentation models are labeled differently, with different colors also used to clearly distinguish between them.
Two significant slab were referenced at the top of the massif. Figure 5 shows the results of these detection. The two events were detected with a confidence of 32% and 66% respectively. Another unexpected slab was detected inside the left coombe. The boundary with the snow cover is not quite clear, which could explain the lower confidence index of 26%. The segmentation model also detects the same slab avalanches with equivalent coefficients. The loose class is correctly detected in Figure 6 with values of 52%, 35% and 55%. Moreover, a glide avalanche is correctly identified although not catalogued with the bounding boxes model and a confidence value of 27%. The segmentation model detects only two loose avalanches here, with confidence of 28% and a high value of 71%. Both the bounding box and segmentation methods effectively identified the loose avalanches. These methods complement each other in this context, with no false detection observed. The segmentation is precise,

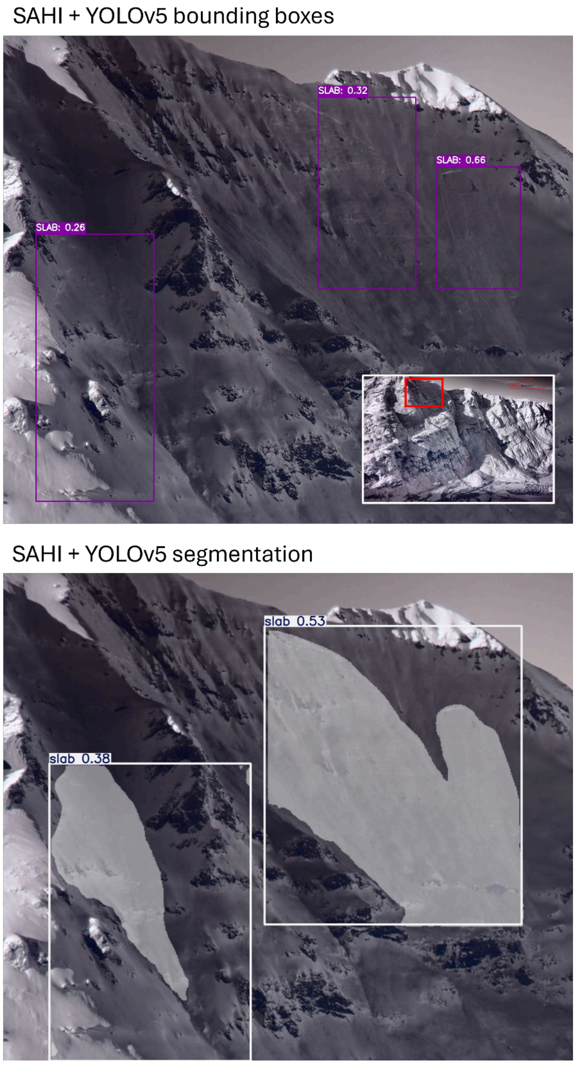

Figure 5: Catalogued slab avalanches (2023-12-03 at 3 PM).

offering a clear delineation of the avalanche zones. However, some avalanche looses are also present on the brightly lit left side, and are not detected by any model.

Deep learning temporal detection. Figure 7 depicts a cataloged glide event over three days. Four key elements are presented: the pixel difference visually highlights daily changes that have occurred, deformation indicates areas of significant correlation loss, corresponding to regions of movement, and finally, detection from both the bounding box model and the segmentation model. Some events may trigger larger avalanches. Detection begins with an initial fracture in the top layer, followed by continuous detection of an increasingly extensive glide with a higher confidence index (from 41% to 74%). Deformation zones become progressively more apparent over time, confirming the event's presence through both method by deep algorithms and correlation loss.
With regard to event precursors, a significant drop

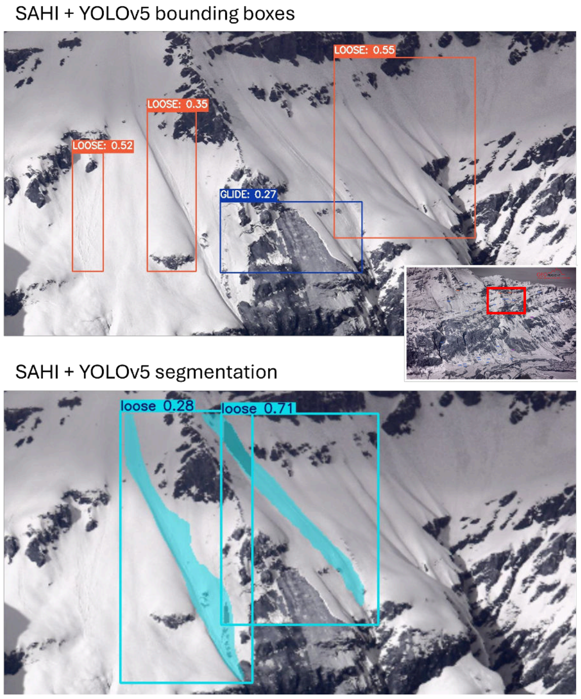

Figure 6: Catalogued loose avalanches (2024-01-29 at 4 PM).

in correlation is observed at 4 PM, followed by initial detection using YOLO bounding boxes, leading up to the glide's collapse at 5 PM.
However, the deep detection model exhibits inconsistencies that may cause confusion. For example, the "loose" class is detected only once, despite the increasing intensity of the avalanche and snow pack fall over time. This inconsistency highlights a classification error, as the observed phenomenon is not simply "loose" snow but rather an accumulation from the underlying slab, representing a specific case of an avalanche interrupted by a rocky barrier. This ongoing glide event merits further analysis and should be included in an extended training dataset. Moreover, the segmentation model shows fewer detection, in fact the glide is detected only once, and the discontinuous snow accumulation is identified only after the event under favorable lighting conditions.

4.3.2 Deep learning limitations

Hallucination. Deep learning models that reproduce results based on annotations, phenomena such as dreams and hallucinations, although not explicitly labeled, may emerge as a result of the model's operation. This is particularly relevant in cases where the model operates under variable lighting conditions. This same limitation has been highlighted by Fox et al. (2024) and Hafner et al. (2024) with unfavorable illumination condition. For illustration, a raw inference result is shown in Figure 8 under the case of poor lightning condition. We observe abnormal slab detection on almost all rocks and some glide on the town, which is entirely incor-

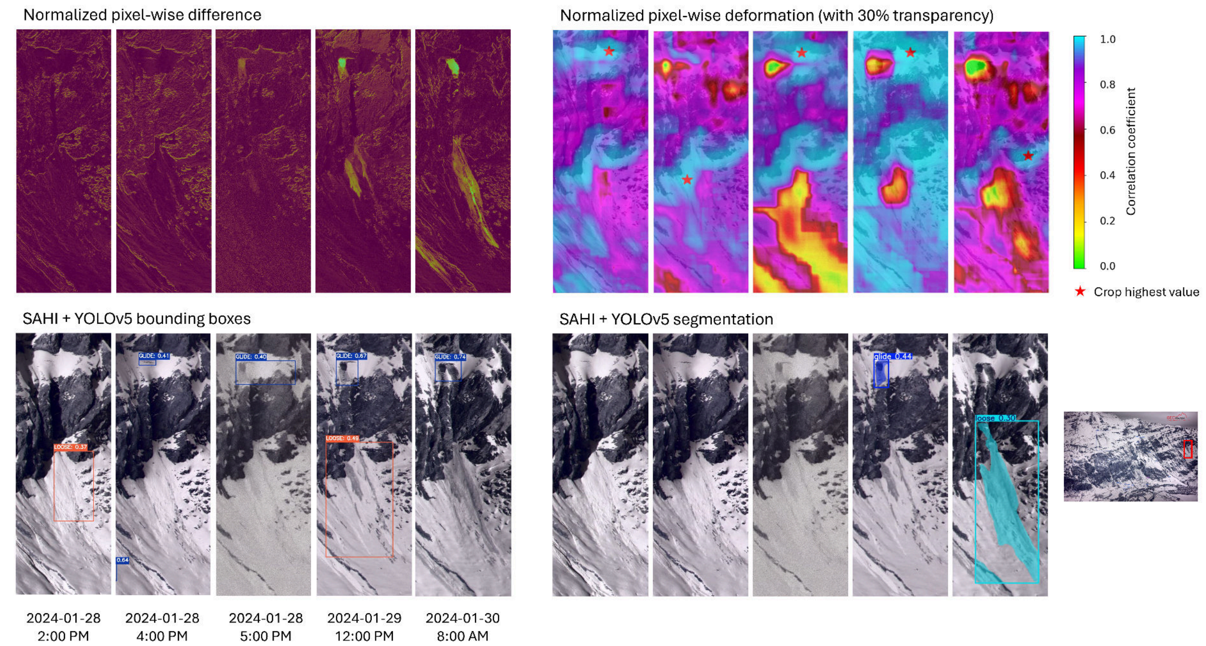

Figure 7: Catalogued glide avalanche detection over time (2024-01-28 to 2024-01-30).

rect. The temporal evolution of raw detection without the use of post-inference filters is given in Figure 9. For this week, the hallucination phenomenon is particularly recurrent in the early evening as the city lights up.

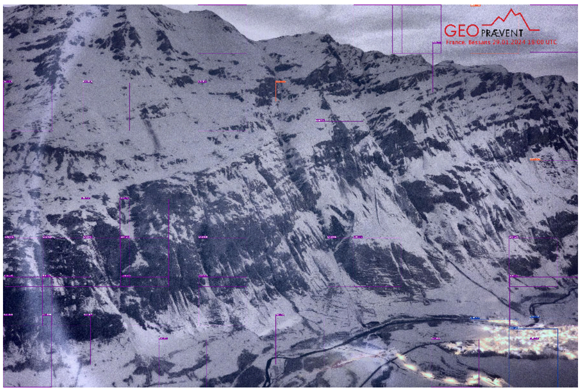

Figure 8: Example of detection overestimation during a model hallucination phase (2024-01-29 at 6pm).

Detection inconsistency. Inconsistency of detection can be noticed both spatially and temporally. Figure 7 shows a discontinuity in detection around the rocks. The same result is denoted all over the massif where glides on top of the rocks are detected, but discontinuous snow accumulation at the base of the rocks remaining undetected. This pattern of detection is consistent across the massif, where similar issues are observed. Additionally, detection varies over time as event are not consistently identified in every frame despite remaining visible throughout. As shown in Figure 9, the number of detection

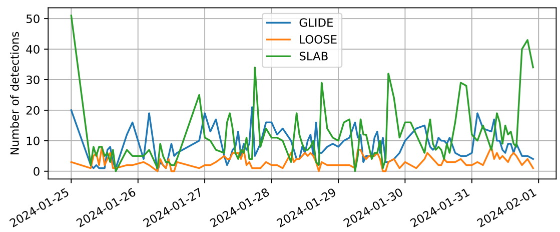

Figure 9: Number of raw detection per class obtained over the last weekend of January 2024.

changes over time. Variations in light and shadow have a huge influence on the detection capability of the deep learning model. If the avalanche is not snow-covered and lighting conditions are favorable, then detection can be carried out on several images, which would validate or invalidate the detection. However, detection cannot be fully ensured, which is why the use of other algorithms, such as motion detection, can provide additional support.

5. DISCUSSION

Both the raw night and day image data provided interesting results helping operators of the system in the visual inspection of the data throughout the season. With the images recorded, it was possible for the operators of the system to remotely evaluate the evolution snow cover conditions in the area, as well as seeing how the avalanche situation evolved. This was even possible in changing visibility conditions (snow, fog), as the relatively high frequency of image recordings (15 minutes) allowed to take advantage of short improvements of the visibility conditions.

The image-processing approach based on the digital image correlation provided a useful visual help to detect changes in the snow cover, potential avalanche precursory signs and avalanche triggering (by correlation loss). However, some further developments would be necessary to automatically detect these changes, or moreover, to be able to automatically detect and classify them. Here, the approach based on deep learning seems more promising. A number of perspectives can be pursued in order to improve the deep learning-based detection models under the constraint of using optical images:

- On image quality pre-processing, one approach might be to analyze avalanches even under low-light conditions, using methods that are not light-dependent. This could include image decomposition techniques to isolate textural information. On the other hand, the use of algorithms to improve image quality would enable a constant level of detection to be maintained, regardless of variations in illumination condition.

- Instead of using a single robust model, we could consider an adaptive model with the use of models specific to each environmental condition. Another way would be to use an adaptive model that adjusts its parameters in real time to changing environmental conditions.

- Transfer learning and domain adaptation can be coupled to deploy the detection tool on multiple sites with limited annotated dataset. Domain adaptation is particularly useful for generalizing models to different environments or to data from different sources.

- Finally, the time-series imagery provides dynamic information that can be leveraged by deep learning to detect events. This information can be used as input for a model, from detecting avalanches in individual images at time t to identifying their emergence over a time-series of images. Temporal information can also be integrated externally via a quantitative and qualitative snow pack deformation analysis.

6. CONCLUSIONS

This paper introduces an optical monitoring system installed in Bessans, Haute-Maurienne, France, that was used by local avalanche authorities and experts to visually inspect avalanche slopes above the main access road of the region. Image-processing analyses based on digital image correlation and more sophisticated deep-learning algorithms for avalanche detection show that these technologies have a potential to help experts in their monitoring and forecasting tasks. Further developments should focus on increasing the reliability of the detection algorithms, their speed and aim at automating the algorithms. Moreover, the possibility of adding another camera to the monitoring concept to gain some additional information is under evaluation.

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