INTEGRATING AUTOMATED AVALANCHE DETECTIONS FOR VALIDATING AND EXPLAINING AVALANCHE FORECASTING MODELS

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ABSTRACT: Snow avalanches are the deadliest natural hazards in Switzerland and cause significant economic losses annually. Therefore, avalanche detection and prediction are crucial in ensuring safety and mobility in the Swiss Alps. Operationally, avalanche forecasts are issued daily during the winter season to inform the public and local authorities about the avalanche hazard. Whereas traditional avalanche forecasting has been a human-expert decision-making process entirely, machine-learning models have become increasingly used in recent years. In this context, the Swiss avalanche warning service has been at the forefront of using these innovative data-driven tools to supplement current forecasting practices. These data-driven approaches have shown the potential to provide objective decision tools with higher spatiotemporal resolution than human-based forecasts. Nevertheless, the predictions generated by these machine learning models are opaque, usually referred to as 'black boxes', making it challenging for avalanche forecasters to interpret how variables are combined to make predictions. To address this, we employed an explanation method to interpret predictions from a machine learning model developed to predict danger levels for dry snow conditions in Switzerland. Moreover, precise avalanche data collected from an automated seismic detection system at the Vallée de la Sionne test site (Switzerland) are used to validate these danger level forecasts during the winter season 2020-2021. A novelty in future model implementations would be integrating these timely avalanche detections into forecasting models.

Keywords: Avalanche Forecasting, Automatic Avalanche detection, Machine Learning Models

1. INTRODUCTION

Snow avalanches are the deadliest natural hazards in Switzerland and cause significant economic losses annually (Badoux et al., 2016). Therefore, avalanche detection and prediction are crucial to ensure safety and mobility in the Swiss Alps. Operationally, avalanche forecasts are issued daily during the winter season to inform about the avalanche hazard. The severity of expected avalanche conditions is described in public bulletins with a regional danger level summarizing snowpack stability, frequency distribution, and avalanche size (Techel et al., 2020a; EAWS, 2021a). However, current avalanche observations and size estimates still mostly rely on subjective human observations, which are often limited since natural avalanches frequently release under poor visibility conditions (Schweizer et al., 2020).
While traditional avalanche forecasting has been a human-expert decision-making process entirely, machine-learning models have become increasingly used in recent years. In this context, several machine learning approaches have been developed to predict danger levels (Pérez-Guillén et al., 2022; Maissen et al., 2024), assess snowpack stability (Mayer et al., 2022; Herla et al., 2023) and predict avalanche activity (Dkengne Sielenou et al., 2021; Viallon-Galinier et al.; Hendrick et al., 2023; Mayer et al., 2023). These data-driven approaches have shown the potential to provide objective decision tools with higher spatiotemporal resolution than human-based forecasts (Maissen et al., 2024; Pérez-Guillén et al., 2024). Nevertheless, the predictions generated by complex machine learning models are opaque, usually referred to as 'black boxes', making it challenging for avalanche forecasters to interpret how variables are combined to make predictions. Additionally, the accuracy of the existing avalanche prediction models is limited to the quality of data on which they are trained (Hendrick et al., 2023; Mayer et al., 2023). A promising advance involves integrating more precise avalanche data from automated detection systems (Van Herwijnen et al., 2016). Such precise avalanche activity data hold high potential to provide new insight into avalanche formation processes (Van Herwijnen et al., 2016), validate avalanche forecasts in real-time, and develop new forecasting models.

In this study, we combine avalanche data obtained from a detection system installed at the Vallée de la Sionne test site in Switzerland (VdlS) to validate the predictions and explainability of the forecasting model developed by Pérez-Guillén et al. (2022). This model predicts danger levels for dry-snow conditions and was tested operationally by the Swiss

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warning service during the 2020-2021 winter season (Pérez-Guillén et al., 2024). We selected the most active avalanche period of this season to relate avalanche observations with model predictions and forecasts in the public bulletin. Additionally, we applied the SHAP explainability method (Lundberg and Lee, 2017), which quantifies the contribution of each input feature to the model's predictions, in a case study involving a very large powder-snow avalanche released at VdlS.

2. AVALANCHE FORECASTING AND DETECTION IN SWITZERLAND

2.1 Avalanche forecasting

The Swiss avalanche warning service at the WSL Institute for Snow and Avalanche Research SLF (SLF) publishes daily avalanche forecasts throughout the winter season. They are issued at 17:00 local time (LT) and valid until 17:00 LT the following day, with updates provided at 08:00 LT if necessary (SLF, 2023). The key information of the avalanche bulletin is the danger level (Figure 1a), with information on specific locations where the danger level applies, including aspects and elevations (EAWS, 2021b). Each danger region (black polygon boundaries of Figure 1a) of the forecast domain is assigned a danger level based on the European Avalanche Danger Scale (EAWS, 2021a, levels: 1–Low, 2–Moderate, 3–Considerable, 4–High and 5–Very High). Since the 2016-2017 winter season, forecasters have assigned one of three sub-levels to each danger level (except for 1-Low), which are now published in the bulletin since the winter season 2023-2024 (Techel et al., 2020b, 2022; Lucas et al., 2023; SLF, 2023).

Operationally, avalanche conditions are assessed using numerical weather predictions and measurements, snow cover simulations, and avalanche observations made by humans or automatically detected with detection systems (Figure 1b). In Switzerland, weather measurements are provided by a large-scale network (IMIS network; (station network, website)) of automated weather stations (AWS; upward and downward triangles in Figure 1a) distributed throughout the Swiss Alps in high alpine terrain. Driven by these data, the snow-cover model SNOWPACK (Lehning et al., 1999; Morin et al., 2020) simulates the snow stratigraphy for flat terrain and four virtual slopes (North, East, South and West) at the locations of each AWS. Additionally, by extracting input features from these simulations, several machine learning models have recently been developed (Pérez-Guillén et al., 2022; Mayer et al., 2022; Hendrick et al., 2023), providing different outputs consulted for operational avalanche forecasting since the winter season of 2021-2022.

2.2 Avalanche danger model

Pérez-Guillén et al. (2022) developed a random-forest model to predict the avalanche danger level for dry-snow conditions in Switzerland. The input features of the model combine a set of meteorological variables averaged over a 24-hour time window and features extracted from the simulated snow-cover profiles (a detailed description of each variable is available in Pérez-Guillén et al. (2022)). This danger level model has been tested in an operational setting, providing *nowcast* and *24-hour forecast* predictions of the danger levels during the winter season 2020-2021, achieving a ≈70% agreement rate between the model-predicted danger levels and the Swiss avalanche forecast (Pérez-Guillén et al., 2024). Additionally, the continuous expected danger values (E_D in Pérez-Guillén et al. (2024)) showed high correlations (Pearson correlation coefficients of $r_p > 0.8$) with the sub-levels used by the Swiss avalanche warning service.

The model generates danger level predictions every three hours for each AWS for flat terrain and the four virtual slope aspects. For instance, the *nowcast* predictions for the North (upward triangles) and the South (downward triangles) aspects are represented in Figure 1a with the danger levels published in the bulletin on 28 January 2021. The model predicts danger levels from 1-Low to 4-High since 5-Very High was merged into 4-High during model development (Pérez-Guillén et al., 2022). As shown in Figure 1a, the model predicted danger level 4 in the central danger region of the Swiss Alps, which was forecast with danger level 5.

2.3 Automated avalanche detection

The Vallée de la Sionne avalanche test site (Figure 1a), managed by SLF, is a unique location where high-quality avalanche data have been acquired using over 20 active technologies since 1998 (Sovilla B. et al., 2013). The VdlS avalanche database contains more than 1000 avalanches of varying flow types and sizes, both artificially and naturally triggered (Figure 1b). The avalanche starting zone covers 30 ha at elevations from 2200 to 2700 m a.s.l., with mean slopes facing east to southeast, favouring snow accumulation due to prevailing westerly and northwesterly winds. The total avalanche path length is ≈2500 m. Two seismic stations are used to activate the alarm system, which triggers the data acquisition for all measurement devices. These include seismic and infrasound sensors, radars, cameras, and other instruments that provide detailed information on avalanche flow characteristics and dynamics. Moreover, the AWS of Donin du Jour (Figure 1a), which is located at 2385 m a.s.l. and 2 km from the avalanche starting zone of VdlS, transmits real-time weather data to the SLF avalanche warning service. For this study, we used danger level

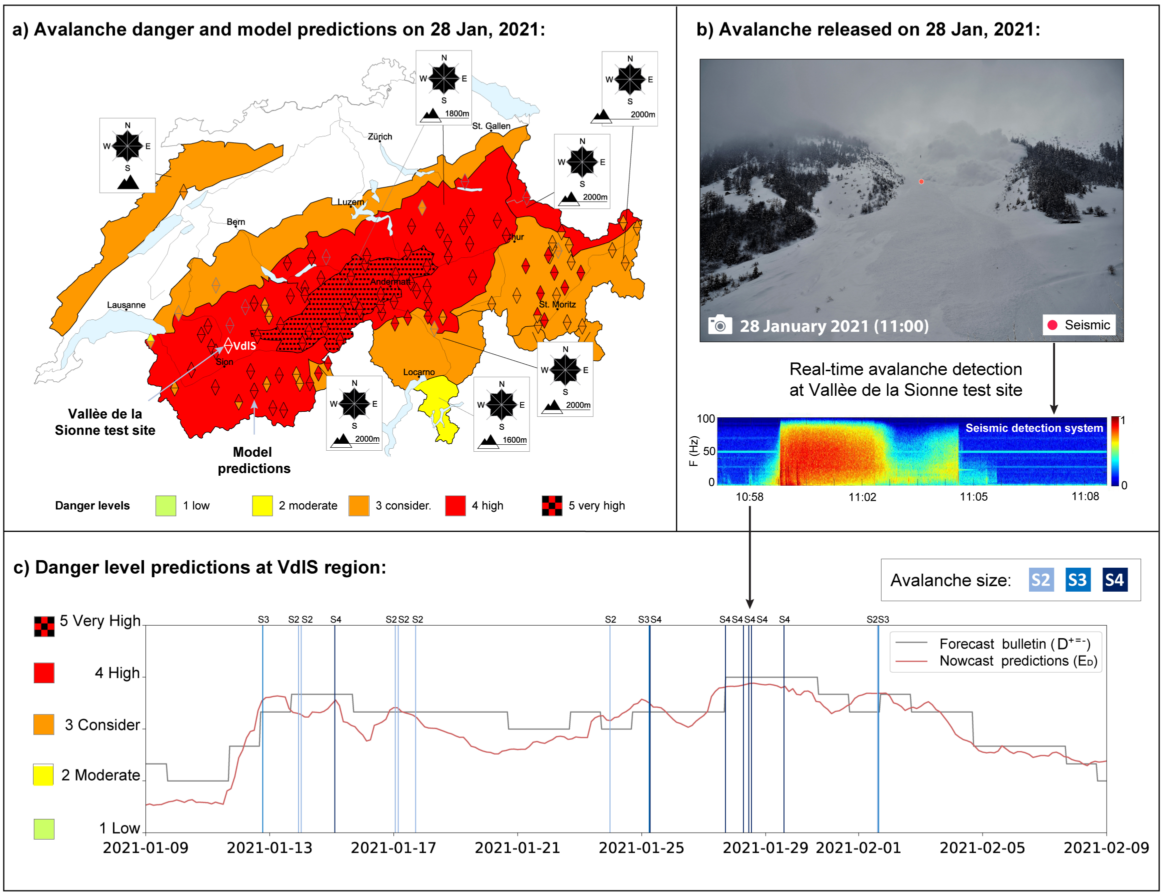

Figure 1: a) Map of Switzerland showing the forecast danger level (background colour) as published in the bulletin issued on 28 January 2021. In addition, the *nowcast* predictions of the danger level model are shown for each weather station, represented by upward triangles for the North (N) and downward for the South (S) aspects, with the colour representing the danger level. Black contoured triangles denote predictions *within* the aspects and elevation as specified in the bulletin, whereas grey triangles represent predictions *outside* of the aspect-elevation zone forecast for each danger region (black contour lines). b) Picture and seismic data of an avalanche detected at VdIS on 28 January 2021 at 10:50 LT. c) Time series of the sub-levels from the public avalanche bulletin (grey), the *nowcast* E_D predictions for the East aspect of the danger level model (red), and the avalanches detected seismically (blue lines) at VdIS during this period. Avalanche sizes range from size 2 (S2) to size 4 (S4).

predictions for the East aspect (main orientation of the VdIS starting zone) from this station during the 2020-2021 winter season, when the model provided real-time forecasts without influencing the danger levels reported in the public avalanche bulletin.

3. RESULTS

3.1 Danger level predictions at VdIS

Overall, the model effectively captured, and even with a higher temporal resolution, the dynamic nature of avalanche forecasting and variations across different slope aspects and elevations. This is shown by the time series of the *nowcast* E_D predictions (East aspect) and the forecast sub-levels during a selected forecasting period in the VdIS region characterized by high danger levels and avalanche activity (Figure 1c). The model increases the danger level predictions during two consecutive snowstorm episodes and decreases them afterwards. Indeed, the E_D values are highly correlated with the forecast sub-levels ($r_p = 0.91$; $p < 0.01$), with mean deviations in model performance mainly concentrated within one sub-level qualifier (Figure 1c).

3.2 Avalanche activity

The detection system at VdIS provides accurate information on the release time of individual avalanches, regardless of weather or visibility conditions. During the winter season of 2020-2021, dry-snow avalanche activity detected at VdIS was high, with 24 natural avalanches ranging in size from 2 to 4 (EAWS, 2021c). Overall, in 24-hour periods with at least one avalanche, the mean E_D was 3.2 ± 0.5 (a high level 3), and when there was no avalanche, it was 1.9 ± 0.8. The distribution of E_D values predicted by the danger level model at the time of avalanche release across different avalanche sizes is shown in Figure 2. The mean E_D range between 3.3 ± 0.5 (Size 2), 3.6 ± 0.1 (Size 3), and 3.8 ± 0.1 (Size 4), indicating that larger avalanches correlate with higher danger level predictions.

The most active avalanche activity period occurred during two snow storms in January, resulting in the

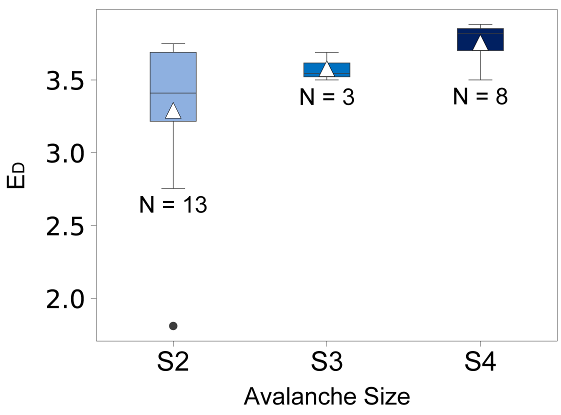

Figure 2: Box plot distributions of the expected danger values predicted by the danger level model at the time of dry-snow avalanche releases (N = number of avalanches) at VdlS during the 2020-2021 winter season, categorized by different avalanche sizes.

release of 17 avalanches: 7 of size 2, 2 of size 3, and 7 of size 4 (Figure 1c). All these avalanche events correlate with the danger level forecast in the bulletin $\geq 3^{+}$. Between 13 and 17 January, two avalanche cycles occurred, which resulted in peaks and increases in model-predicted and forecast danger levels in the bulletin. On 28 January 2021, four very large avalanches released within 24 hours, including one very large powder-snow avalanche detected at 10:58 LT, which reached the bottom of the valley (Figure 1b). This event corresponded to an increase in the predicted danger value to 3.8, with the model indicating a danger level of 4-High (Figure 1c), consistent with the forecasted danger level in the public bulletin for this region (Figure 1a). We focused on this avalanche case study to apply an explainability method and understand why the model predicted this danger level at the exact time of the avalanche release.

3.3 Interpretability of predictions on 28 January

Pérez-Guillén et al. (2024) employed the SHapley Additive exPlanations (SHAP) approach (Lundberg and Lee, 2017) to interpret the driving variables that impacted the model's danger level predictions. SHAP values measure the contribution of each input feature, which can be either positive or negative concerning the predicted value. For our case study on 28 January, we used the Tree SHAP algorithm (Lundberg et al., 2018) to compute SHAP values, using as input the *nowcast* data (averaged weather input features from the previous 24 hours and SNOWPACK-derived features from the East aspect simulations) from VdlS at 12:00 LT, the closest time window to the powder-snow avalanche released at 10:58 (Figure,1b).

Figure 3 shows SHAP force plots for the danger level model, detailing the individual features and their impact for each danger level probability. The final *nowcast* model prediction on 28 January at the time of the avalanche release was 4-High. The predicted probability for danger level 4 is 0.77, whereas the values for the other danger levels are low, almost null for danger levels 1 and 2. The key features driving this avalanche danger prediction are the high amount of new snow accumulated in the previous day (34.2 cm, HN24) and over the past three days (70.2 cm, HN24_3d), with a mean precipitation rate of 3.3 kg/s^2/h (MS_Snow) and a skier penetration depth of 37.2 cm. Additionally, the 7-day sum of new snow (70.2 cm, HN24) and a minimum critical cut length of 0.1 m (min_ccl_pen) also contributed to predicting danger level 4. Conversely, these features negatively impacted the prediction of danger levels 1 and 2, resulting in null output values. The second-highest model output value is for danger level 3, where a structure stability index of 2.1 (S4) and a wind drift accumulation of 76.2 cm (wind_trans24_3d) increased the probability of this level.

4. DISCUSSION

4.1 Automated avalanche detection for forecasting

Real-time avalanche activity data acquired from various detection systems installed in Switzerland is visualized operationally during the preparation of the bulletin. This data is crucial for validating past forecasts and enhancing the accuracy of new ones. For instance, the avalanche activity recorded at VdlS is directly transmitted to the avalanche warning service. We observed that high avalanche activity correlates with periods of danger levels exceeding 3 (Figures 1c and 2), as shown in previous studies (Schweizer et al., 2020). Due to the higher temporal resolution of the model's predictions, maximum values in E_D predictions coincide with (or occur shortly after) precise avalanche release times (Figure 1c). Therefore, using this precise avalanche activity data to develop new forecasting models will improve the quality of the data currently used in avalanche prediction models (Hendrick et al., 2023; Viallon-Galinier et al.; Mayer et al., 2023), despite the challenge of reducing the dataset size.

4.2 Explainability of predictions

As demonstrated by Pérez-Guillén et al. (2024) in a test with a larger dataset, the SHAP approach provides a comprehensive visualization and quantification of how different features influence the predicted avalanche danger levels. By examining these plots, forecasters can interpret which features impact individual predictions across different danger levels. For instance, in the case study of the very large powder-snow avalanche released on 28 January, new snow accumulations, precipitation rate, skier penetration depth, and critical cut length were

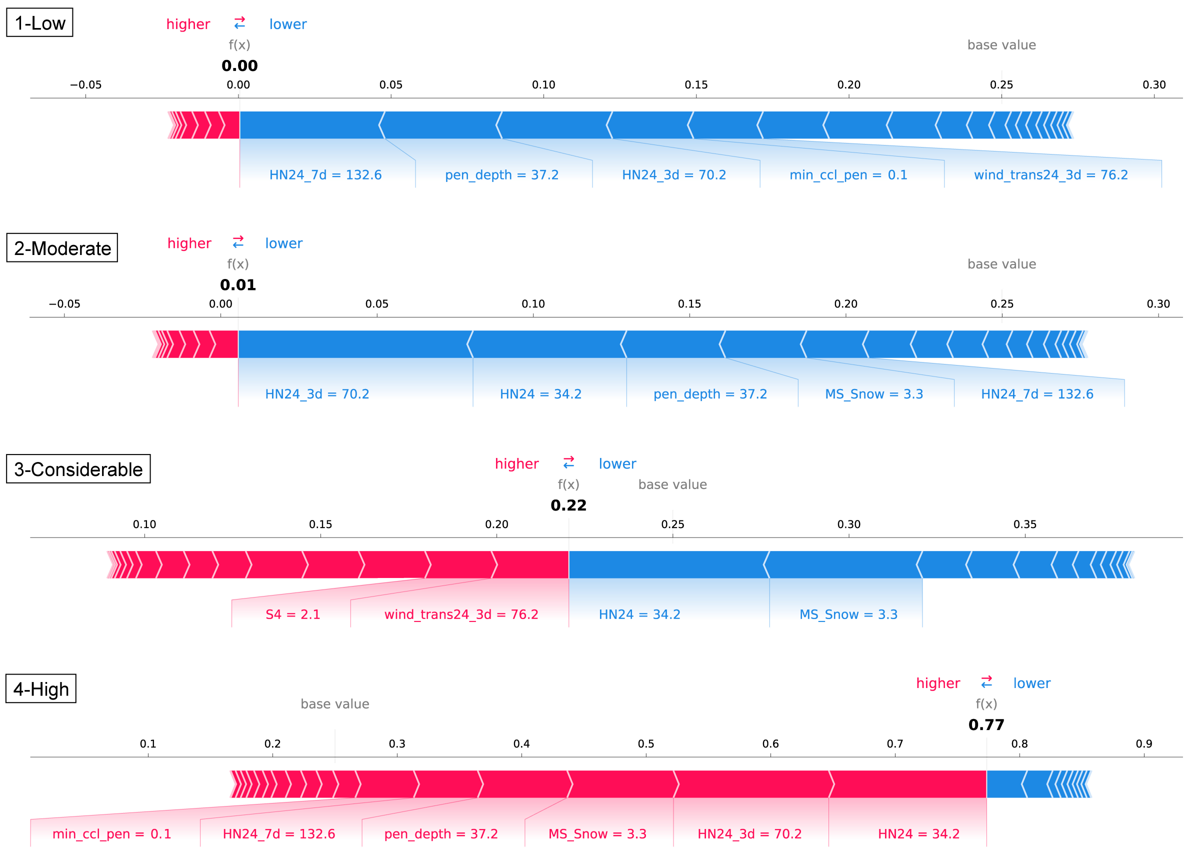

Figure 3: SHAP force plots for *nowcast* danger level predictions (East aspect) on 28 January 2021 at 12:00 LT, which is the closest time window to the avalanche release (Figure 1b). Each force plot shows the model output probability for each danger level (1-Low, 2-Moderate, 3-Considerable, 4-High) and the most important features that contribute to this prediction. Blue arrows show features that decrease the predicted probability per class, i.e. danger level (negative SHAP values), while red ones represent features that increase it (positive SHAP values).

identified as the most crucial variables driving predictions to danger level 4 (Figure 3). These variables are also usually correlated with dry avalanche activity (Schweizer et al., 2009; Mayer et al., 2023). However, it should be highlighted that the driving parameters of the model are measured and modelled at the closest AWS station installed near the avalanche starting zone, which in this case was 2 km away and at a lower elevation than the avalanche release area. A potential improvement would be to use data from the avalanche starting zone and, therefore, consider variations in snow depth due to previous avalanche activity.

5. CONCLUSIONS

This study highlights the potential of combining automated avalanche detection systems with a machine learning model developed to predict danger levels for validating its predictions. We compared the model's predictions with precise avalanche data collected from the Vallée de la Sionne test site, showing that high E_D values in model-predicted danger levels temporally matched with avalanche releases during the high avalanche activity period analysed in this study. Additionally, an increase in danger level predictions correlates with an increase in avalanche size. Applied to a case study of the release of a very large powder-snow avalanche, SHAP explainability provided valuable insights into the key variables influencing the model's predictions, thereby addressing the opacity associated with this type of machine learning model. Integrating automated detection systems and explainable machine learning models is a promising step forward in developing new avalanche forecasting models.

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