AVALANCHE FORECASTING IN THE PEJO SKI AREA: A DATA-DRIVEN APPROACH USING A SUPPORT VECTOR MACHINE

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ABSTRACT: Snow avalanches pose a major hazard in alpine ski areas, where reliable local forecasts are essential for operational decisions such as ski slope opening, avalanche control, and staff deployment. However, this kind of forecasting still relies heavily on expert judgment, making the integration of heterogeneous nivo-meteorological observations challenging and potentially subjective. This study presents an interpretable machine learning framework for supporting local avalanche forecasting in the Pejo ski area (Italian Alps), using a 45-year dataset of weather, snow, and avalanche observations. We developed a Support Vector Machine (SVM) classifier to discriminate between days with and without avalanches. The model was trained using historical nivo-meteorological predictors and avalanche records and then independently validated. The optimised model achieved good predictive performance (F1 = 0.83; ROC–AUC = 0.88) in distinguishing avalanche from non-avalanche days. Model interpretability was addressed using SHAP (SHapley Additive exPlanations), which identified cumulative snowfall, snow depth, temperature trends, and seasonal snowpack evolution as the dominant drivers of avalanche occurrence, consistent with established avalanche processes. To support operational forecasting, the model was integrated into a prototype Telegram-based decision-support system that automatically retrieves real-time observations, generates daily avalanche forecasts, provides SHAP-based explanations for individual predictions, and includes an experimental scenario-analysis module to evaluate alternative meteorological conditions. Operational deployment showed good agreement with field observations. The proposed approach combines predictive performance, physical interpretability, and operational integration, providing a transparent decision-support tool that complements expert judgment in local avalanche forecasting.

KEYWORDS: Artificial Intelligence, Avalanche Forecasting, Decision Making, Quantitative Forecasting, Ski Resort Management, Local Forecasting.

1. INTRODUCTION

Avalanche forecasting requires integrating meteorological, snowpack, terrain, and human factors (McClung, 2023; Schweizer et al., 2003). This task is particularly challenging at the local scale, such as in ski areas, where reliable forecasts are essential for slope opening, avalanche control, and staff deployment. The challenge stems from limited data availability, strong spatial variability, and site-specific topographic features. Consequently, integrating heterogeneous nivo-meteorological observations into a consistent hazard assessment often relies heavily on expert judgment, introducing subjectivity into operational decision-making (Schweizer et al., 2003).

Machine learning offers an opportunity to systematically integrate multiple environmental variables and capture complex, non-linear relationships associated with avalanche occurrence. Although its application to avalanche forecasting has increased in recent years, most studies have focused on regional-scale prediction, with comparatively few tackling site-specific operational forecasting (Bellaire et al., 2011; Hendrikx et al., 2014).

The main goal of this study is to bridge that gap by developing an interpretable classifier based on the Support Vector Machine (SVM) technique (Cortes and Vapnik, 1995) to predict avalanche days in the Pejo ski area (Trentino, northern Italy). Second, to provide a decision-support system capable of delivering real-time forecasts, explanatory outputs, and scenario analysis.

2. STUDY AREA AND DATA

2.1 <u>Study Area</u>

The study area is the Pejo ski area, located in the Italian Alps (Trentino). It spans from approximately 1400 to 3600 m a.s.l. and is characterised by different avalanche problems depending on elevation, slope exposure, and season.

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The main avalanche site considered in this study is the Val de la Mite area, where several avalanche paths directly intersect ski slopes on the valley floor, posing a significant operational hazard to the ski resort. Most of them are located on south-facing slopes, while a smaller number occur on north-facing aspects.

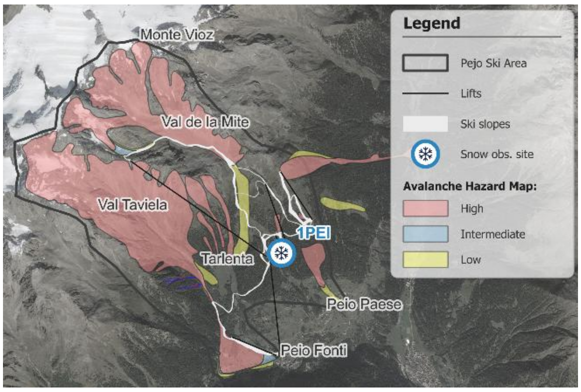

Figure 1: The Pejo ski area with ski slopes, avalanche hazard map, and the location of the daily snow and weather observation site.

Average seasonal snowfall at 2000 m a.s.l. is approximately 260 cm, with high interannual variability typical of inner Alpine regions. The predominant avalanche problems, according to the EAWS (2022) classification, are new snow and wet snow, while wind slabs are less common.

This complex avalanche regime makes Pejo a representative testbed for local forecasting models (Schweizer et al., 2003; McClung, 2023).

2.2 Dataset

The dataset combines long-term meteorological, snowpack, and avalanche observations spanning the 1980–81 to 2023–24 winter seasons. Snowpack observations include standard daily measurements describing snow depth, snow stratigraphy, snow temperature, and snow mechanical properties. The corresponding weather and snowpack data were collected at the Pejo Tarlenta snow observation site (1PEI), located at approximately 2000 m a.s.l., following standardised daily procedures including meteorological measurements, snowpack observations, and documentation of avalanche activity (AINEVA, 2013).

Avalanche occurrence data were obtained from daily observations at Pejo Tarlenta and from the internal Pejo Funivie avalanche database, which contains georeferenced avalanche events, field observations, and photographic documentation. Since 2021, the database has been substantially expanded through systematic field mapping.

Data from Automatic Weather Stations (AWSs) were initially considered but subsequently excluded due to their limited temporal coverage and lack of homogeneity with the long-term observation series.

The complete database comprised 5,038 observation days, of which 668 had documented avalanche activity.

3. METHODS

The overall workflow adopted for developing the avalanche forecasting model is summarised in Figure 2, which provides an overview of the proposed machine learning framework, including dataset construction, SVM model development, model training, performance evaluation, explainability analysis, and operational deployment.

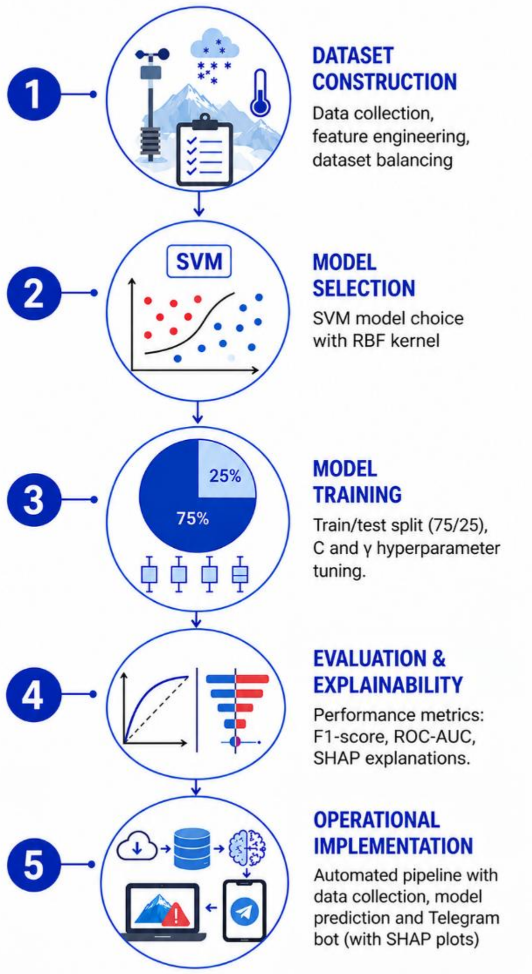

Figure 2: Workflow of the proposed machine-learning framework, from dataset construction to operational implementation.

3.1 Dataset construction

The dataset was constructed through a preprocessing workflow comprising quality control, avalanche event selection, and feature engineering (combining raw observations into physically meaningful predictor variables), informed by a physical understanding of avalanche processes and operational forecasting expertise.

Nivo-meteorological observations underwent quality control to remove obvious measurement errors, physically unrealistic values, and inconsistencies within the time series. We filled short gaps only when no significant meteorological changes occurred; longer or uncertain gaps were rare and excluded from the analysis.

Feature engineering transforms raw data into input variables that better represent the underlying physical processes and provide the model with information relevant to avalanche occurrence. It was applied to characterise both the daily snowpack state and its temporal evolution, since avalanche occurrence depends on these conditions. Cumulative and trend-based predictors (input variables used by the model) were derived using different temporal windows (1, 2, 3, and 5 days). The resulting engineered predictors described both the current snowpack conditions and their recent evolution and included:

- daily meteorological and snowpack variables (e.g., air temperature, snow depth, new snow, and snow temperature);
- cumulative snowfall and precipitation over multiple time windows;
- short-term changes in snow depth;
- temperature trends, amplitudes, and gradients;
- indicators describing wet snow conditions and snowpack evolution.

We removed redundant and highly correlated predictors. The resulting feature set comprises both short-term meteorological variability and the cumulative evolution of snowpack conditions influencing avalanche occurrence.

Avalanche forecasting was formulated as a binary classification problem. Each day was labelled as either an avalanche day or a non-avalanche day based on observed activity. Snow and meteorological observations were paired with corresponding avalanche records. Of the 668 avalanche days in the original database, only medium- to large-sized new-snow and wet-snow events relevant to ski slope management were retained. We excluded small avalanches and wind-driven events due to their localised nature and the need for site-specific wind measurements. We also removed days with incomplete meteorological data over the preceding five-day period.

After this filtering procedure, 175 avalanche days were available for model development. To obtain a balanced dataset, an equal number of non-avalanche days was selected through random undersampling, resulting in a final dataset of 350 labelled observations (175 avalanche and 175 non-avalanche days).

3.2 Model selection

Among the available machine learning algorithms, we selected a Support Vector Machine (SVM) classifier for its effectiveness in binary classification problems involving relatively small datasets and high-dimensional feature spaces. SVMs are particularly well suited to avalanche forecasting because they can model complex relationships among predictor variables while maintaining strong generalisation performance (Cortes and Vapnik, 1995). Moreover, we employed the Radial Basis Function (RBF) kernel because it captures non-linear relationships between meteorological and snowpack predictor variables and avalanche occurrence, enabling the identification of complex decision boundaries without requiring explicit assumptions about the underlying functional relationships.

3.3 Model training

To improve SVM convergence and ensure that all predictor variables contributed equally to the distance calculations, features were standardised to zero mean and unit variance before training.

The final dataset was randomly divided into a training set (75%, n = 262) and an independent test set (25%, n = 88).

The two main SVM hyperparameters controlling model flexibility (C and γ) were determined through a five-fold cross-validation grid search, which repeatedly trains and evaluates the model on different subsets of the training data (Pedregosa et al., 2011). The optimal hyperparameter combination was selected by maximising the mean F1-score, which balances precision and recall and is well-suited to evaluating classifiers trained on balanced datasets (Chicco et al., 2021).

In addition to the binary classification output, the trained SVM model was configured to provide calibrated probability estimates. These probabilities were obtained by applying Platt scaling (Platt, 1999) to the SVM decision function, which represents the distance of each sample from the separating hyperplane. The resulting continuous avalanche probability was used for operational interpretation and temporal analysis, while binary avalanche/non-avalanche predictions were obtained by applying a 0.5 probability threshold.

3.4 Model evaluation and explainability

Model performance was evaluated on the independent test set using the F1-score (Chicco,

2021) and the receiver operating characteristic area under the curve (ROC–AUC), which measures the model's ability to distinguish avalanche from non-avalanche days across different classification thresholds. The F1-score was prioritised because it balances precision (the proportion of predicted avalanche days correctly classified) and recall (the proportion of observed avalanche days correctly identified), making it particularly suitable for avalanche classification. In this context, recall is especially critical because missed avalanche events (false negatives) represent the most severe operational error, while precision helps limit excessive false alarms.

Model robustness was further assessed using five-fold cross-validation (Kohavi, 1995). This resampling procedure evaluates model consistency across different subsets of the training data. It uses bootstrap resampling (Efron and Tibshirani, 1993), which repeatedly retrains the model on randomly resampled datasets to assess model stability. Fifty bootstrap resamples were generated across a range of hyperparameter configurations around the optimal solution. The low variability in both the F1-score and the Matthews Correlation Coefficient (MCC) (Chicco, 2021), a balanced performance metric that accounts for all outcomes in the confusion matrix, indicated consistent model performance.

To improve transparency for operational applications and overcome the black-box nature of the SVM, model explainability was investigated using the model-agnostic SHAP (SHapley Additive exPlanations) framework (Lundberg and Lee, 2017). Using the training dataset as the background distribution, SHAP quantifies the contribution of each predictor variable to individual model predictions, independently of the internal structure of the machine learning algorithm.

Global SHAP analysis, based on summary and dependence plots generated using the SHAP Python package (Lundberg et al., 2020), was used to assess whether the model captured physically meaningful relationships between predictor variables and avalanche occurrence.

Local SHAP analysis, using force plots (showing how each variable pushes a prediction toward or away from avalanche occurrence) and heatmaps (summarising variable contributions across many predictions), was performed to interpret individual predictions by examining how meteorological and snowpack variables contributed to correct classifications, false alarms, and missed avalanche events.

Together, this multi-scale explainability framework supports the assessment of both the model's physical consistency and its suitability for operational avalanche forecasting.

3.5 Operational Implementation

To bridge the gap between model applications and operational avalanche forecasting, we developed a Telegram-based decision-support tool that couples real-time nivo-meteorological observations with the trained SVM model. Daily data are automatically retrieved from the Meteotrentino Open Data portal, processed into the same engineered predictor variables used during model training, and used to generate same-day avalanche forecasts using the trained SVM model.

The operational workflow also includes SHAP-based interpretability outputs, which provide graphical explanations of the variables contributing to avalanche or non-avalanche predictions (Figure 3). The developed tool enables forecasters to compare model outputs with expert judgment and to better understand the physical drivers underlying predicted risk.

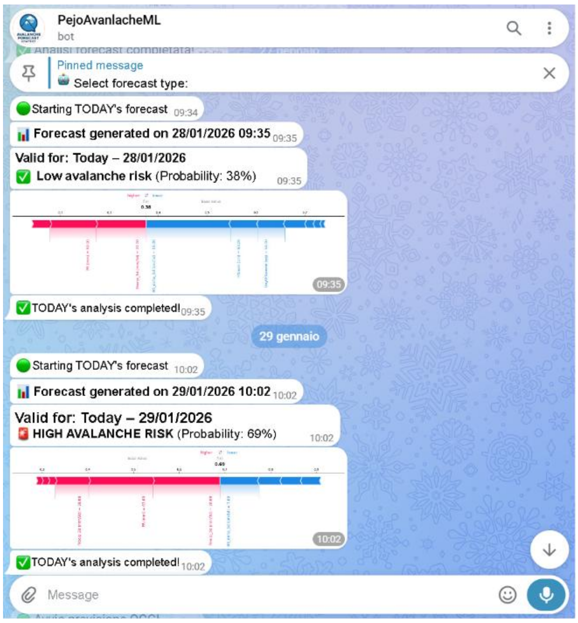

Figure 3: Telegram-based decision-support tool showing daily avalanche probability and SHAP-based explanation of the prediction.

We also developed an experimental scenario-based prediction module to explore next-day avalanche conditions. The module uses the current-day meteorological and snowpack state data as input. Moreover, it allows the user to modify key meteorological variables, such as expected snowfall and temperature changes, for the following day. Based on these user-defined scenarios, updated predictor variables are generated using simplified empirical relationships that describe the expected evolution of snow and meteorological conditions, and the trained SVM model is then used to estimate the corresponding avalanche occurrence probability.

The framework enables rapid evaluation of alternative meteorological scenarios to support operational decision-making.

4. RESULTS

4.1 Model Performance

The confusion matrix (Table 1) shows that the model correctly classified the majority of avalanche and non-avalanche days, with a limited number of false positives and false negatives.

The optimised model achieved an F1-score of 0.83 and a ROC–AUC of 0.88 (Figure 4), indicating good discrimination between avalanche and non-avalanche days while maintaining a balanced trade-off between precision and recall, meaning that the model simultaneously limits both missed avalanche events and unnecessary false alarms.

Table 1: Confusion matrix of 88 test samples.

	Observed Avalanche	***Observed Non-Avalanche***
Predicted Avalanche	31	5
Predicted Non-Avalanche	10	42

The model correctly identified 31 out of 41 avalanche days, while 10 avalanche events were missed (false negatives). The relatively low number of false negatives highlights the potential of the proposed approach to support operational avalanche forecasting and ski-area management, where missed avalanche activity represents a critical error.

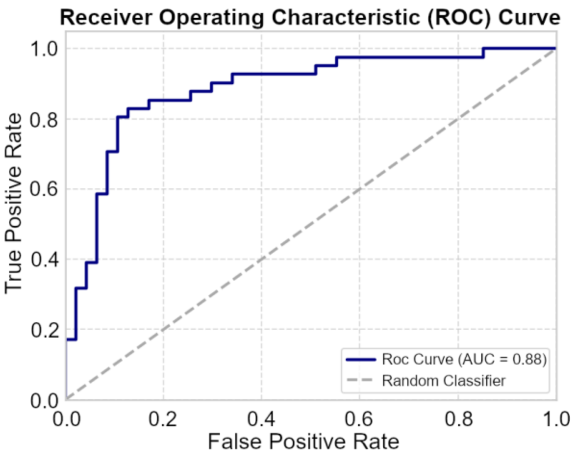

Figure 4: ROC curve and AUC of the SVM model.

Performance evaluation on the independent test set showed results consistent with the model optimisation phase, suggesting good generalisation capability and limited evidence of overfitting. Bootstrap resampling further confirmed model robustness, with low variability in both the F1-score and the Matthews Correlation Coefficient across neighbouring hyperparameter configurations around the optimal solution.

4.2 Model Interpretation Using SHAP

Global SHAP analysis identified the most influential predictors (Figure 5). The six dominant variables were DayOfSeason, representing seasonal effects and associated changes in solar radiation; snow depth (HSnum); cumulative precipitation over the previous three days (Precip_3d); ram penetration (PR), an index describing the hardness of the upper snow layers; snow temperature at 10 cm depth (TH01G); and daily snow settlement, expressed as the change in snow depth (HS_delta_1d). Other variables, including additional temperature-related predictors, also contributed to the model, but only the six most influential predictors are discussed here.

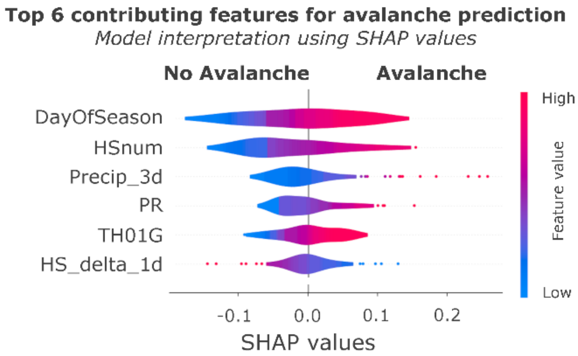

Figure 5: SHAP summary plot showing the global importance of the six most influential predictors.

Results suggest that higher avalanche probabilities were mainly associated with late-winter conditions, when increased solar radiation promotes snowpack moistening, with a deep snowpack, which reduces terrain roughness and can lead to larger avalanches, with recent heavy snowfall, which increases snowpack loading, with the presence of a deep surface soft layer, indicating the potential for large volumes of snow to be mobilised, and with warm snowpack conditions and rapid snowpack compaction. Overall, warming conditions were consistently associated with higher avalanche probabilities. In contrast, stable weather conditions, limited precipitation, a shallow snowpack, and a cold snowpack contributed to lower predicted probabilities.

Local SHAP graphical analysis shows how each variable contributes to a specific prediction, with red and blue bars indicating contributions toward avalanche and non-avalanche outcomes, respectively. Each explanation starts from the SHAP base value, corresponding to the average avalanche probability of the training dataset, and ends at the final model output (f(x)), representing the predicted avalanche probability for the analysed day. To improve readability, only the most influential variables are shown individually, while the remaining positive and negative contributions are grouped as “Other features”.

Figure 6 shows two examples of graphical analysis. The top plot shows the results of a correctly predicted avalanche day. The main drivers are: high precipitation (Precip_3d, Precip_2D), a thick snowpack (HSnum), and a thick, soft surface layer (PR). The bottom plot shows a correctly predicted non-avalanche day. In this case, the main drivers are early-season conditions (DayOfSeason) and a shallow snowpack (HSnum).

This event-scale interpretation allows for comparison with expert knowledge of avalanche forecasting.

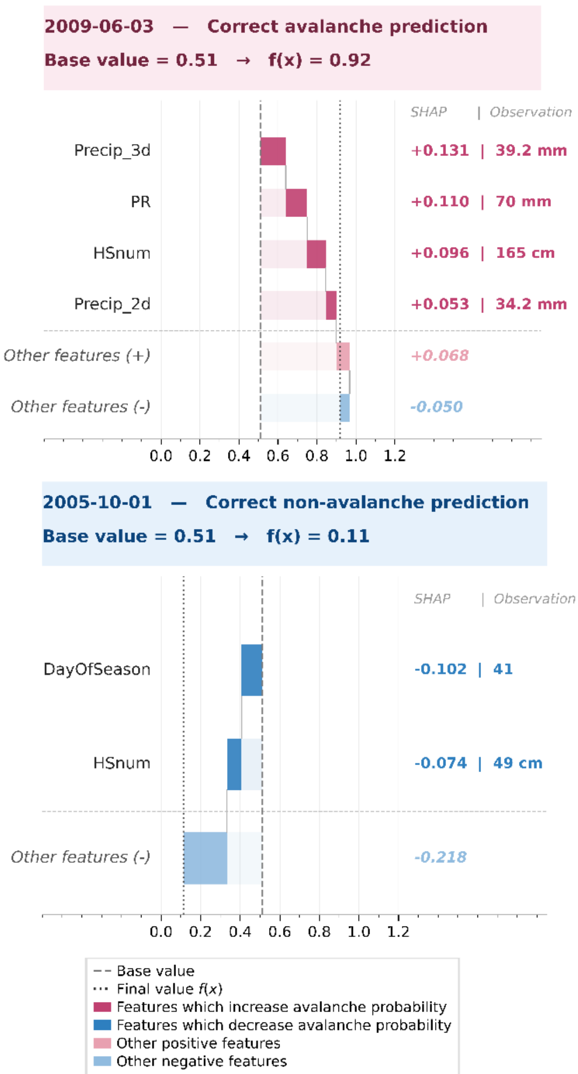

Figure 6: Local SHAP analysis for correctly predicted avalanche (top) and non-avalanche (bottom) days.

4.3 Operational Validation

To evaluate model performance under conditions closer to operational application, the winter season 2024–2025 was used as an independent validation period characterised by unseen meteorological conditions and snowpack states.

Figure 7 shows the calibrated avalanche probability produced by the optimised SVM model compared with observed avalanche activity. Overall, the model reproduced the main temporal evolution of avalanche activity, with higher predicted probabilities occurring during periods characterised by observed avalanche releases. Although model performance was evaluated using a binary avalanche/non-avalanche classification, the continuous probability output was retained for operational analysis because it provides additional information on the temporal evolution of avalanche likelihood beyond the final classification.

Several specific cases provide insight into the model’s behaviour. The first case (1) corresponds to missed small avalanches, which were outside the target avalanche class considered during model development. The second case (2) concerns a period classified as non-avalanche by the model, during which medium-to-large, mainly wind-induced avalanches occurred. These avalanche types were not represented in the training dataset because wind-driven events were excluded from the analysis. The third case (3) highlights periods of false-positive classifications following previous avalanche activity. These cases may be related to the post-release clean-out effect: previous avalanches can remove part of the unstable snowpack, reduce snow loading, and eliminate weak layers, thereby reducing subsequent avalanche activity even when meteorological conditions remain favourable for instability.

The operational Telegram bot developed in this study was subsequently deployed during the 2025–2026 winter season as a prototype decision-support tool for local forecasters. This phase focused on operational use and qualitative feedback rather than quantitative evaluation.

Despite the limited number of avalanche days during the season, operators reported general agreement between model outputs and field assessments, meaning that the model generally highlighted the same critical avalanche periods identified by experienced forecasters. Correct predictions were observed, particularly for wet-snow and new-snow avalanche situations. Conversely, some overestimation of avalanche probability occurred towards the end of the season, likely due to progressive snowpack stabilisation and the effects of repeated minor avalanche activity.

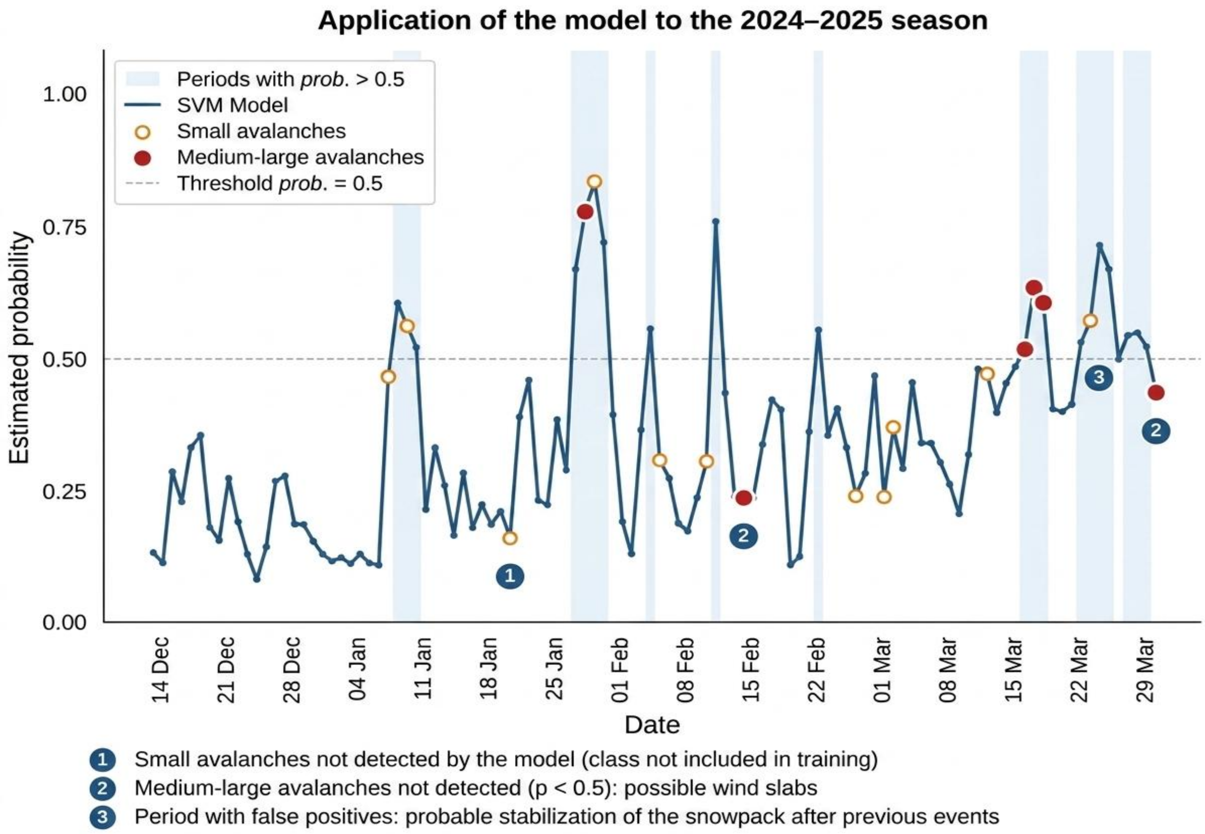

Figure 7: Independent validation of the SVM model during the 2024–2025 winter season. Predicted avalanche probability (blue line) is compared with periods of observed avalanche activity (light blue shading). Numbered cases are discussed in the text.

5. DISCUSSION

The results demonstrate that machine learning can effectively support local avalanche forecasting when long-term, high-quality observational datasets are available, with the SVM classifier capturing relevant relationships between meteorological conditions, snowpack characteristics, and avalanche occurrence (Pozdnoukhov et al., 2008; Pérez-Guillén et al., 2022).

As shown in Section 4.2, the dominant SHAP predictors align with established avalanche formation processes, indicating that the model captures physically meaningful relationships rather than purely statistical correlations.

Operational validation during the independent 2024–2025 winter season and prototype deployment in 2025–2026 provided encouraging evidence of practical applicability. Although the number of avalanche days during operational testing was limited, predictions generally agreed with field observations, particularly during new-snow and wet-snow cycles, indicating robustness across different seasonal conditions and supporting the potential use of this approach in operational avalanche forecasting.

The tendency to overestimate avalanche conditions at the end of the season may be related to progressive snowpack stabilisation and a reduction in the amount of available unstable snow following repeated natural releases.

The site-specific nature of the model is an intentional design choice because avalanche release depends strongly on local terrain, snow climate, and operational practices that vary between ski areas. While the trained model is specific to Pejo, the underlying workflow can potentially be transferred to other ski areas with comparable long-term observational datasets. Several limitations remain. The binary classification approach does not provide information on avalanche size, type, or hazard level, and performance depends on the quality and consistency of available observations. Rare mechanisms, such as persistent weak-layer avalanches, remain difficult to represent due to a limited number of examples. At the same time, wind-related processes cannot be addressed due to the lack of high-resolution wind measurements near release areas.

6. CONCLUSIONS

This study presented an interpretable machine learning framework for local-scale avalanche forecasting in the Pejo ski area (Italian Alps), based on a 45-year dataset of nivo-meteorological observations and avalanche records. The

SVM classifier achieved strong predictive performance (F1 = 0.83; ROC–AUC = 0.88), while SHAP analysis revealed the meteorological and snowpack variables driving the predictions. This combination of predictive capability and interpretability supports the use of machine learning as a decision-support tool for operational avalanche forecasting.

The prototype Telegram-based system enables automated forecasting and visualisation of avalanche drivers within operational workflows. Independent validation during the 2024–2025 winter season showed encouraging agreement between predictions and field observations, particularly during new-snow and wet-snow avalanche cycles.

Although developed for Pejo, the proposed workflow can be adapted to other alpine environments with long-term observational datasets. Remaining limitations include the binary formulation of the target variable, which does not account for avalanche size, frequency, or activity level. Further limitations include the limited representation of specific avalanche mechanisms, particularly wind-driven processes, due to the lack of high-resolution wind measurements, and the dependence on manual observations.

Future developments should focus on expanding validation across different alpine regions and integrating additional data sources, including automatic weather stations, snowpack models, remote sensing products, and Numerical Weather Prediction forecasts. Future work should also explore ensemble, deep learning, and hybrid approaches while preserving interpretability and operational usability.

Overall, this study demonstrates that interpretable machine learning combined with long-term operational observations can provide an effective decision-support framework for local avalanche forecasting, complementing expert assessment with transparent, data-driven insights.

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