

Autoencoder-based feature extraction for the automatic detection of snow avalanches in seismic data

Andri Simeon¹, Cristina Pérez Guillén¹, Michele Volpi², Christine Seupel¹, and Alec van Herwijnen¹

¹WSL Institute for Snow and Avalanche Research SLF

²Swiss Data Science Center, ETH Zurich and EPFL, Switzerland

Correspondence: Andri Simeon (andri.simeon@slf.ch)

Abstract. Monitoring snow avalanche activity is essential for operational avalanche forecasting and the successful implementation of mitigation measures to ensure safety in mountain regions. To facilitate and automate the monitoring process, avalanche detection systems equipped with seismic sensors can provide a cost-effective solution. Still, automatically ~~differentiating~~ distinguishing avalanche signals from other sources in seismic data remains challenging. ~~This is~~ This is mainly due to the complexity of seismic signals generated by avalanches, the complex signal transmission through the ground, the relatively rare occurrence of avalanches, and the presence of multiple sources in ~~the continuous~~ seismic data. ~~One~~ Therefore, we compiled a dataset of seismograms recorded with an array of five seismometers installed in an avalanche study site above Davos, Switzerland. For the winter seasons of 2020-2021 and 2021-2022, this dataset comprised 84 avalanches and 828 noise (unrelated to avalanches) events. An approach to automate ~~avalanche detection~~ the detection of avalanches in seismic data is by applying machine learning methods. So far, research in this area has mainly focused on extracting ~~standard~~ domain-specific signal attributes ~~in the time and frequency domains~~ as input features for statistical models. In ~~this study~~ contrast, we propose a novel application of ~~deep learning autoencoder models for the automatic and unsupervised extraction of features from seismic recordings. These new features are then fed into classifiers for discriminating representation learning from seismograms using autoencoder models to automatically extract features from 10-second seismic signals of~~ snow avalanches. ~~To this end, we trained three Random forest classifiers based on different feature extraction approaches. The first set of 32 features was automatically extracted from the time-series signals by an autoencoder consisting of convolutional layers and a recurrent long short-term memory unit. The second autoencoder applies a series of fully connected layers to extract 16 features from the spectrum of the signals. As a benchmark, a third random forest was trained with typical waveform, spectral and spectrogram attributes used to discriminate seismic events. We extracted all these features from 10-second windows of the seismograms recorded with an array of five seismometers installed in an avalanche test site located above Davos, Switzerland. The database used to train and test the models contained 84 avalanches and 828 noise (unrelated to avalanches) events recorded during the winter seasons of 2020-2021 and 2021-2022. Finally, we assessed the performance of each classifier, compared the results, and proposed different aggregation methods to improve the predictive performance of the developed seismic detection algorithms.~~ On top of that, we applied random forest classifiers to evaluate whether these features facilitate the detection of avalanches. Concretely, we trained one random forest classifier each on a set of expert-engineered seismic attributes (baseline), temporal autoencoder features and spectral autoencoder features. The classifiers achieved an avalanche ~~f1-score of 0.61 (seismic attributes), 0.49~~

recall of 0.67 (± 0.00) (baseline), 0.71 (± 0.02) (temporal autoencoder) and 0.60-0.70 (± 0.01) (spectral autoencoder) and avalanche recall of 0.68, 0.71 and 0.71, respectively. Overall, the macro f1-score ranged from macro average f1-scores of 0.78 (± 0.00) (baseline), 0.70 (± 0.01) (temporal autoencoder) to 0.78 (seismic attributes). After applying a post-processing step to event-based predictions, the avalanche recall of the three models significantly increased, reaching values between 0.82 and 0.91-0.77 (± 0.01) (spectral autoencoder). The developed approach could be potentially used as an operational, near-real-time avalanche detection system. Yet, the relatively high number of false alarms still needs further implementation of the current automated seismic classification algorithms to be used as unique methods to detect avalanches effectively for effective avalanche detection.

1 Introduction

Every winter, snow-covered mountainous regions worldwide are exposed to the destructive potential of snow avalanches, causing fatalities and damage to infrastructure. On average in Switzerland, 25 avalanche fatalities occur every winter (Techel et al., 2016). The catastrophic winter of 1999 resulted in infrastructural damage costing several hundred million Swiss francs (Bründl et al., 2004). Such periods underscored the need for ongoing investments in avalanche prevention measures and providing accurate avalanche forecasts. Avalanche forecasting is mainly driven by analysing weather measurements and forecasts in combination with snowpack and avalanche observations (Schweizer et al., 2020). Detailed information on the location and timing of avalanche occurrences is indispensable for validating avalanche forecasts (e.g. van Herwijnen et al., 2016; Bühler et al., 2022) (van Herwijnen et al., 2016; Bühler et al., 2022), effectively implementing mitigation measures (e.g. McClung and Schaerer, 2006; van Herwijnen et al., 2018), hazard mapping (e.g. Bühler et al., 2022) (Bühler et al., 2022) and the development of statistical approaches to predict natural avalanche release (Sielenou et al., 2021; Hendrick et al., 2023; Mayer et al., 2023). However, avalanche activity data are still mainly obtained through human field observations, which are especially incomplete and uncertain in. Consequently, the poor visibility conditions during storms snow storms, when avalanche activity is usually high (Schweizer et al., 2020) particularly high (Schweizer et al., 2020), lead to incomplete and uncertain avalanche observations. Hence, there is a growing demand for automated avalanche detection systems that provide reliable and continuous avalanche activity data on avalanche activity.

Since avalanches are extended moving sources of seismic energy, seismic monitoring systems can be used to detect natural avalanches in large areas within a radius of several kilometres (Hammer et al., 2017; Pérez-Guillén et al., 2019; Heck et al., 2019), regardless of the weather and visibility conditions. Seismic avalanche detection systems have been employed for several decades to monitor and characterise avalanches (Suriñach et al., 2001; Biescas et al., 2003; van Herwijnen and Schweizer, 2011), assess the source location (Lacroix et al., 2012; Pérez-Guillén et al., 2019; Heck et al., 2018b) and infer flow properties (Vilajosana et al., 2007; Lacroix et al., 2012; Pérez-Guillén et al., 2016). Avalanches generate spindle-shaped, high-frequency signals similar to other types of mass movements (Suriñach et al., 2005), such as landslides, debris flows, and lahars. These patterns have frequently been used to discriminate avalanche signals from other seismic sources. Nevertheless, detect and identify avalanche signals. Although seismic detection systems would provide a cost-effective and large-scale alternative to

60 ~~other systems, such as radars, they~~ have not yet reached the same level of reliability ~~compared to other systems, such as radars,~~
~~when it comes to regarding~~ the automatic detection of avalanches (Schimmel et al., 2017). This limitation is partly due to the
complex signal transmission from the source (i.e., the avalanche) to the receiver and multiple sources of environmental noise
(e.g., earthquakes, aeroplanes, etc.).

~~The~~ As a solution, conventional machine learning methods have been studied and developed over the past decade to
65 automatically classify seismic signals generated by different types of mass movements based on Hidden Markov Models
(Hammer et al., 2013; Dammeier et al., 2016), fuzzy logic (Hibert et al., 2014) and random forest algorithms (Provost et al., 2017)
. For avalanches, the first attempt to automatically distinguish ~~avalanches them~~ from other sources based on seismic features
~~observed-extracted~~ in the time-frequency domain and combined with fuzzy logic was conducted by Leprettre et al. (1996).
Afterwards, Besson et al. (2007) developed a nearest-neighbour approach that successfully detected 65% of previously con-
70 firmed avalanche events. Later, Rubin et al. (2012) divided a seismic data stream into 5 s time windows and extracted 10 spectral
features by applying a ~~Fast Fourier Transform (FFT). Several fast Fourier transform. They tested several~~ machine-learning clas-
sifiers ~~were tested~~ using these input features, such as random forest algorithms, support vector machines, and artificial neural
networks. ~~The~~ Among them, their decision stump classifier reached the highest precision of ~~43.2%~~ 0.13, indicating many false
alarms, on manually identified avalanches, ~~while~~. At the same time, they reported a recall of ~~89.5%~~ 0.90 and an accuracy of
75 ~~93.0%~~ 0.93. More recently, Hammer et al. (2017) and Heck et al. (2018a) applied hidden Markov models (HMMs) to learn class
characteristic patterns based on extracted spectral features for automatic avalanche classification. Extending on this approach,
Heck et al. (2018b) trained an HMM-based method to detect avalanches in continuous seismic data. So far, these approaches
relied on a careful and time-consuming selection of features derived from processing signals in the time and frequency domain.

80 In recent years, the emergence of deep learning algorithms and the extensive growth of collected data ~~and the emergence~~
~~of machine learning algorithms~~ have opened up new perspectives for efficient and automated data processing. ~~Machine~~
~~learning models can handle complex data sets~~ A fascinating subfield of deep learning is representation learning, providing
an alternative to the more traditional process of hand-crafting data representations based on specific domain knowledge
(Bengio et al., 2013; Längkvist et al., 2014). These models can process complex datasets and infer representations in a rea-
85 sonable time by reducing the dimensionality of data (Hinton and Salakhutdinov, 2006) and rapidly synthesise data processes,
providing valuable and complementary insights ~~into data (Mousavi and Beroza, 2022). Over the past decade, statistical and~~
~~machine learning methods have been developed for automatically classifying seismic signals generated by different types of~~
~~slope failures based on Hidden Markov Models (Hammer et al., 2013; Dammeier et al., 2016), fuzzy logic (Hibert et al., 2014)~~
~~and Random Forest algorithms (Provost et al., 2017). So far, these approaches relied on carefully engineered features derived~~
90 ~~from processing signals in the time and frequency domains~~. In contrast, we explored a novel approach to automatic feature
extraction by developing two unsupervised autoencoders for learning temporal and spectral signals. Autoencoders, introduced
by Rumelhart et al. (1986), are neural networks specialised in extracting relevant features from the data, relying on unsupervised
learning. They can be directly trained on raw input signals and thus are not dependent on labels or expert-based tuning of
specialised feature extractors. The architecture traditionally consists of an encoder and decoder, where the former embeds an

95 input signal to a bottleneck layer, i.e. the latent space, where relevant information is stored. This low-dimensional embedding is designed and trained to include all the relevant information of a given signal in a feature vector of lower dimensionality than the input. For example, Mousavi et al. (2019) used an autoencoder to ~~However, these novel deep learning approaches have not yet been explored for seismic avalanche signals, although they have been applied successfully in related domains (Seydoux et al., 2020; Mousavi and Beroza, 2022). For instance, Mousavi et al. (2019) trained feature extractors to cluster seismic signals of an earthquake catalogue and showed comparable precision to supervised methods. Kong et al. (2021) evaluated different autoencoder architectures~~ In contrast, Kong et al. (2021) evaluated similar methods for seismic event discrimination and phase picking. These studies have proven that unsupervised feature extractors can keep up with state-of-the-art models, mitigating the time-consuming and expensive data labelling.

In this study, we ~~explored the autoencoder model for automatic feature extraction from seismic signals generated by avalanches and other sources. First, we~~ , therefore, leveraged the potential of unsupervised representation learning methods by applying the autoencoder model introduced by Rumelhart et al. (1986) for the first time to seismic avalanche signals to automatically extract discriminative features. Moreover, we benchmarked these novel features against our baseline, a set of expert-engineered seismic attributes, by evaluating them on an avalanche classification task using random forest models. With this approach, we aim to advance and automate avalanche detection using seismic monitoring systems. For this, we first compiled a catalogue
105 ~~of seismic events recorded at our~~ 84 avalanches and 828 unrelated noise events recorded with an array of five seismic sensors at a study site above Davos (Sect. 2), Switzerland, throughout the winter seasons of 2020-2021 and 2021-2022. In Sect. 3, we described the foundation of ~~this the training~~ dataset, which is ~~one of the most critical parts of any machine learning model development. Similar to previous studies, we~~ built upon manually picking event onset and end, using each sensor separately and applying a windowing algorithm of 10 s with 50% overlap. We then extracted features from ~~these~~ 10 s seismic time windows
115 and trained classifiers based on these features. In the feature extraction process, ~~we implemented a baseline method (Sect. ??), we implemented two new~~ 4.1), which is a set of engineered seismic attributes. Moreover, we developed two methods based on autoencoders , automatically tuned to extract 32 and 16 input features , and compared them against a set of 57 standard expert-based seismic attributes. The routines to optimize and train the autoencoder models is shown in Sect. ??. Using the ~~different~~ (Sect. 4.2), which learned to automatically extract features from the signal's time and frequency domain respectively.
120 Using these three sets of input features, we ~~trained three random forest classifiers optimised and trained one random forest classifier per set,~~ to automatically distinguish the avalanche signals from other seismic events (Sect. 4.3). ~~We analyzed and~~ Further, we defined two post-processing techniques on the single-sensor predictions to reach sensor array-based predictions through multiple-sensor aggregation, and event-based predictions (Sect. 4.0.1). In Sect. 5 we analysed and compared the performance of the models in Sect. 5. Finally, a discussion of the main results and conclusions is presented a single-sensor,
125 array-based and event-based setting. Finally, in Sect. 6 and 7 we discuss the main results and the potential of applying these methods to avalanche activity monitoring, automatic dataset labelling and early warning in the future and present conclusions.

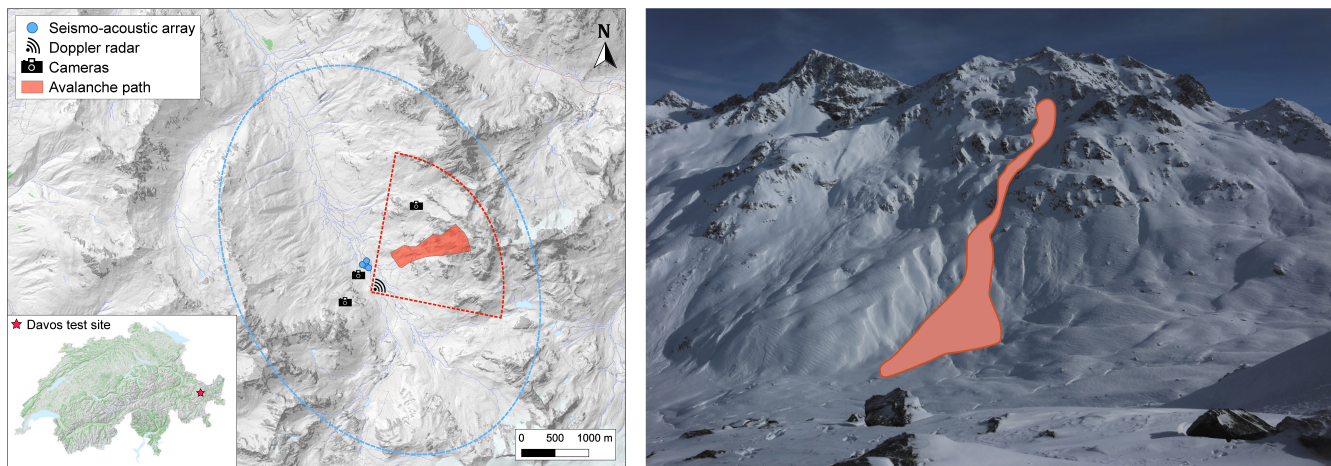


Figure 1. ~~Right~~Left: Map and location of the Dischma study site. The instrumentation consisted of a seismo-acoustic sensor array (blue dots), three cameras and a Doppler radar(~~red-triangle~~). The approximate area where avalanches ~~can-could~~ be detected is shown for the seismo-acoustic sensor array (blue ellipse) and the radar (red cone). Moreover, ~~an-the red-shaded area highlights the same~~ avalanche path is highlighted-with-as in the red-shaded-area photo on the right. ~~Left~~Right: Photo taken by an automatic camera at the Dischma-study site, showing the georeferenced path of a dry-snow avalanche released on 2 February 2022 at 02:31.

2 Study ~~Sitesite~~ site and instrumentation

The ~~study-site-avalanche study site~~ 'Dischma' is located at the end of the Dischma Valley, a tributary valley above Davos, Switzerland (Fig. 1). ~~The-seismic-A continuously operating detection system integrating multiple sensor types monitors~~ avalanches flowing down the surrounding slopes. The system was deployed on a flat meadow at about 2000 m a.s.l. (Eastern Swiss Alps; 46.72°N, 9.92°E). The surrounding mountains form a basin of steep slopes reaching up to 3000 m a.s.l. Since the winter season of 2020-2021, ~~approximately-usually~~ from November to May, we installed a seismo-acoustic sensor array of five co-located seismic and infrasound sensors arranged in a star-like pattern. This spatial configuration allows for the localisation of avalanches (Heck et al., 2018b). The seismic sensors were buried into the ground at a depth of approximately 135 50 cm and subsequently covered by snow during winter. A single measuring unit consists of a one-component seismometer Lennartz LE-1D/V (eigenfrequency of 1 Hz and sensitivity of $800 \text{ V m}^{-1} \text{ s}$) and an infrasound sensor Item-prs (frequency response of 0.2-100 Hz and sensitivity of 400 mV Pa^{-1}). The ~~central-seismic-sensor-consisted-of-only~~ exception was the central measuring unit applying a three-component seismometer LE-3Dlite (eigenfrequency of 1 Hz and sensitivity of $800 \text{ V m}^{-1} \text{ s}$), of which we, however, only used the vertical component in this study. The sensors were connected to the same digitizer (Centaur 140 digitizer from Nanometrics), recording continuously with a sampling frequency of 200 Hz. The seismo-acoustic sensor array monitors avalanches released ~~from-all-slopes~~ within a radius of approximately 3 km (blue ellipse in Fig. 1).

Additionally, the site ~~is-was~~ equipped with a Doppler radar and three automatic cameras to obtain independent validation data provided that weather conditions allowed it, including accurate release times and information on the type and size of the

avalanches. The radar emits electromagnetic waves that are reflected by the avalanche flow, providing the location and velocity
145 of the moving avalanche (Meier et al., 2016). Figure 1 shows the location of the radar, which monitors several avalanche
paths exposed to the west-southwest, covering an approximate area of 4 km² (red delineated area in Fig. 1). ~~In this case,~~
~~avalanches can~~. With this radar, avalanches could be detected up to a maximum distance of approximately 2 km. The cameras
automatically ~~photograph every~~ photographed all surrounding slopes every 30 ~~minutes all the surrounding slopes minutes~~ (Fig.
1).

150 In summary, the combination of detection systems installed at the study site allowed us to assess the limitations and
advantages of each system individually, as well as their combined effectiveness for avalanche detection and characterisation. In
this study, we focused exclusively on automatically detecting avalanches using seismic data. In contrast, we used the Doppler
radar, cameras and acoustic systems to validate the detected avalanche events qualitatively.

3 Data

155 ~~We compiled a catalogue of seismic events from~~ From the continuous recordings of the seismic detection system (Sect. 2), we
compiled an event catalogue for the winter seasons 2020-2021 and 2021-2022. ~~Concretely, we manually picked~~ Foremost, we
collected avalanche signals detected by the radar and cameras. Additionally, we manually picked seismic events within periods
of known avalanche activity ~~and pre-processed the seismic signals. Then~~ (Sect 3.1), ensuring to include avalanches that were not
detectable by these other systems. Next, three experts labelled the events ~~, with which we compiled a two-class classification~~
160 ~~dataset.~~ to compile a binary classification dataset (Sect. 3.2). Lastly, we prepared the signals of the event catalogue for model
development (Sect. 3.3).

3.1 Event picking and signal processing

~~Supervised machine-learning models require a definition of events and a subsequent data annotation for training. For the former
requirement~~ To define avalanche events, we selected signals based on the release times provided by the radar and automatic
165 cameras. In addition, we picked ~~events~~ potential avalanche events and other sources from the continuous ~~recordings~~ seismic
recordings that had been missed by the radar and cameras. Typically, the amplitude of seismic signals generated by avalanches
gradually ~~increases~~ emerges (see Fig. 2) since the avalanche approaches the location of the seismic sensors at our study site
(Fig. 1) and ~~larger seismic energy dissipation~~ seismic energy radiates due to snow entertainment and erosion processes within
the flowing avalanche (Pérez-Guillén et al., 2016). ~~As avalanche signals gradually emerge from background noise and initially~~
170 ~~have a low signal-to-noise ratio (Fig. 2a)~~ Therefore, automated picking methods often miss the starting phase of avalanches and
sometimes entire events. To prevent this, we visually inspected the continuous seismic recordings and identified signals that
exhibited a high signal-to-noise ratio, i.e. were not in the order of magnitude of the background noise. ~~We~~ For efficiency, we
limited our search to periods with known avalanche activity ~~for efficiency. This included,~~ such as avalanche cycles during snow
storms, days when avalanches ~~were~~ had already been detected by the radar and periods with observed avalanche deposits in
175 the cameras.

Before ~~For ease of~~ picking the signals in those periods, we transformed the raw seismic signals ~~from the five sensors to~~ ground velocity (meters per second). Additionally, the signals were linearly detrended, tapered with a Hanning window and filtered with a 4th-order Butterworth band-pass filter between 1 and 10 Hz. We found this to be the most energetic frequency band of the avalanche signals recorded at our study site (Fig. 2), considering the typical relative distance between the avalanche and our receivers. ~~Finally, we manually cut the identified signals to~~ ~~To finally~~ compile a clean event catalogue. ~~To manually pick the start, we manually defined the onset~~ and end times ~~, we visually inspected of the identified signals by visually inspecting~~ the seismic signal, the envelope signal and the spectrogram. In ~~summary total~~, we picked 912 ~~non-background noise signals events~~ lasting between 5 and 515 s, which we ~~labeled~~ labelled in the next step.

3.2 Labelling of events Event labelling

~~For the annotation and labelling of~~ Having picked potential events, three experts assigned signals into two classes, avalanches avalanche and non-avalanche events:

Avalanches: Avalanche events were first identified using the radar and camera data (Fig. 1) ~~. We did this by~~ matching seismic signals to ~~the avalanches observed in the radar data~~ avalanches detected by the radar or on images. A second step to collect avalanches missed by these systems was to visually classify signals based on the characteristic seismic signature of avalanches (e.g. non-impulsive onsets, spindle-shaped signals and triangular-shaped spectrograms; left column in Fig. 2a) as proposed by van Herwijnen and Schweizer (2011). Additionally, the output of wave parameters derived from sensor array processing of the seismic and infrasound data was considered, i.e. backazimuth angles and apparent velocity (Marchetti et al., 2015; Heck et al., 2018b).

Noise (non-avalanche events): Earthquakes were the most frequent source of environmental noise at our study site. They were identified by visual inspection of the signals (typical emergent onsets and usually identifiable arrival of the different phases; middle column in Fig. 2b) and comparison of our seismo-acoustic recordings with two nearby seismic stations from the Swiss ~~National Network (e.g. Clinton et al., 2011)~~ national network (Clinton et al., 2011). In addition, online earthquake catalogues were consulted to match our recordings with catalogued events (SED, 2023; EMS, 2023). The remaining portion of seismic events was generated by different sources, including aeroplanes (right column in Fig. 2e), helicopters, explosions in nearby skiing resorts, weather events (e.g. wind), people or animals walking close to the sensors, and many more unknown event sources. We ~~summarized~~ summarised this collection of unrelated events as a “noise” class. In particular, weak signals generated by non-verified small avalanches might also fall into this heterogeneous ~~noise class. Notably~~ class. Moreover, this definition of the noise class barely included low ~~SNR~~ signal-to-noise ratio (SNR) background noise.

~~To label avalanche events, The~~ three experts independently assigned subjective probabilities using either 0 (~~unidentified avalanche~~ non-avalanche), 0.5 (potential avalanche) or 1 (certain avalanche). ~~A signal was labelled positive if the sum of the three expert scores exceeded 1.5.~~ Note that the average rate of agreement in ~~avalanche score~~ expert probabilities on the avalanche signals between the three experts was 58%. This hints at the inevitable expert bias, the inherent subjectivity and the

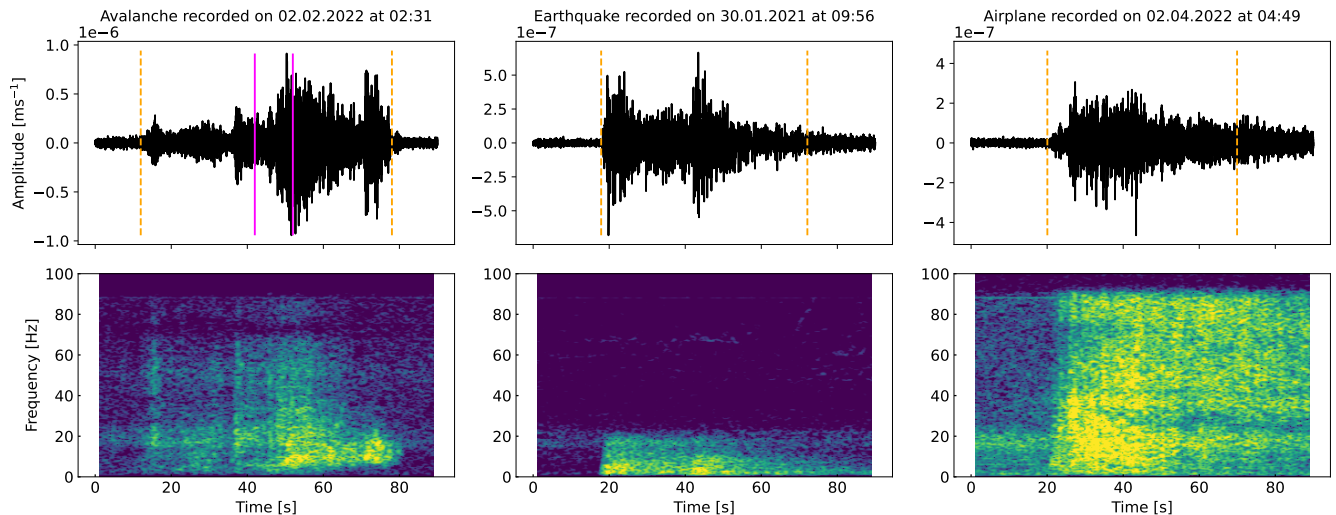


Figure 2. Recordings-Waveform and spectrogram of the avalanche in Fig. 1 (left), an earthquake (middle) and an airplaneaeroplane (right). The dashed orange vertical lines indicate the manual-cuts-of-the-manually defined event catalogue onsets and ends. The pink vertical lines in the avalanche waveform indicate a 10 s seismic snippet extracted by the windowing algorithm. This specific signal window is highlighted later also in Fig. 4 and 10.

complexity of the task. Finally, a signal was labelled positive if the sum of the three expert probabilities was at least 2. In this manner, we compiled an event catalogue with 84 avalanches (31 verified with the radar or camera images) and 828 unrelated noise events from the 2020-2021 and 2021-2022 winter seasons. For completeness but not subject to the binary classification presented in this study, the same labelling process was used for earthquakes, with which we found 183 earthquakes in the noise class. The seismic sensors recorded maximum absolute amplitudes ranging from 3.3×10^{-8} to $4.7 \times 10^{-5} \text{ ms}^{-1}$ for avalanches, 1.3×10^{-8} to $9.7 \times 10^{-6} \text{ ms}^{-1}$ for earthquakes and 1.4×10^{-9} to $5.1 \times 10^{-5} \text{ ms}^{-1}$ for noise signals. Signal duration-durations ranged from 13 to 113 s, 7 to 263 s and 5 to 515 s in each class, respectively. Noteworthy, the amplitude range of the noise class includes the amplitude ranges of both avalanches and earthquakes Notably, the noise class's amplitude range includes the avalanche class's amplitude range, highlighting its heterogeneity.

3.3 Signal windowing, normalisation and dataset splitting

Before training the models Aiming to enlarge the number of samples and develop a model pipeline for real-time detection, we further processed the event data in the catalogue. First, we treated the records of signals of the event catalogue. Therefore, we used each seismic sensor independently yielding a five-fold enlargement's records independently, yielding five times more samples for model training. Second, we applied a 10 s windowing-moving window with 50% overlap to all signals. This windowing resulted in moving window algorithm resulted in again more data samples to train , as the model only received a and ensured fixed-sized input. We note that this strategy might also be inputs for the models. Earlier studies (Lacroix et al., 2012; Hammer et al.,

225 have found the minimum duration of avalanches to be roughly ten seconds. Beyond, this strategy is also beneficial in a poten-
 tial (near) real-time detection system, where 10 s windows are continuously parsed. Lastly, a crucial part when developing
neural networks is input data normalisation (Sola and Sevilla, 1997). By applying the windowing algorithm, we obtained
subsequences of time series. Since waveform characteristics of an upcoming event are not known in advance during inference,
we normalised each window separately by its maximum absolute amplitude instead of using the maximum absolute amplitude
 230 of the entire event to avoid look-ahead normalisation (Rakthanmanon et al., 2012; Lima and Souza, 2023). With this, the la-
 belled data-set-dataset comprised 3'580 avalanche and 37'110 noise (non-avalanche) windows, which include-included 11'575
 earthquake windows. This dataset is at the core of this study and allows us to systematically compare the methods in different
settings.

Lastly, to learn the model Finally, we defined four independent data folds to develop the models and select the best
 235 architectures and optimal architectures and their hyper-parameters , we defined four independent data folds, i.e. three train
folds for cross-validation and a test fold for assessing the error (see Fig. 3). Three folds, comprising 70% of the data samples,
were used for model training and optimisation via 3-fold cross-validation. The test set (top bar in Fig. 3), containing 30% of the
data, was set aside to assess the model performance on an independent inference set. We separated the folds by specific dates to
not induce any correlation between the folds and reduce prevent any correlation and temporal data leakage between the folds.
 240 We chose the dates such that the class distributions across the folds are-even-were approximately balanced (Fig. 3). The first
train fold included dry avalanches exclusively, whereas the second contained a mixture of dry avalanches in the early part of
the period. Additionally, we ensured that the independent test set included both dry and wet avalanchesin the latter. The third
train fold and the fourth test fold spanned the winter season of 2021-2022. Again, the earlier counted towards dry conditions
and the last both wet and dry. This dataset was the foundation of model development and allowed for systematic comparison
 245 of the models in different settings.

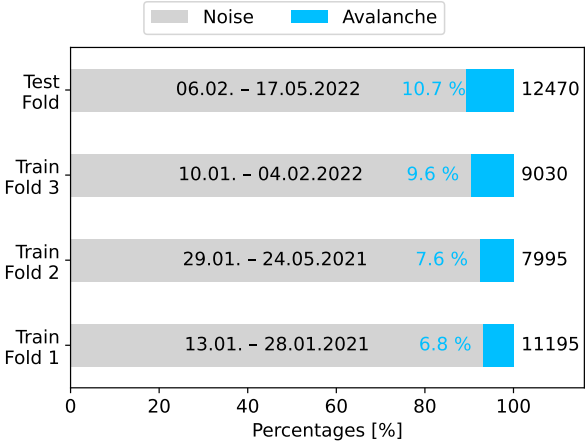


Figure 3. Class distributions and date ranges in the train and test folds. The annotations on-top-at the end of the bars depict-show the total
 number of 10 s seismic windows in each fold. The annotations in blue depict the percentage of avalanche windows.

4 Model development

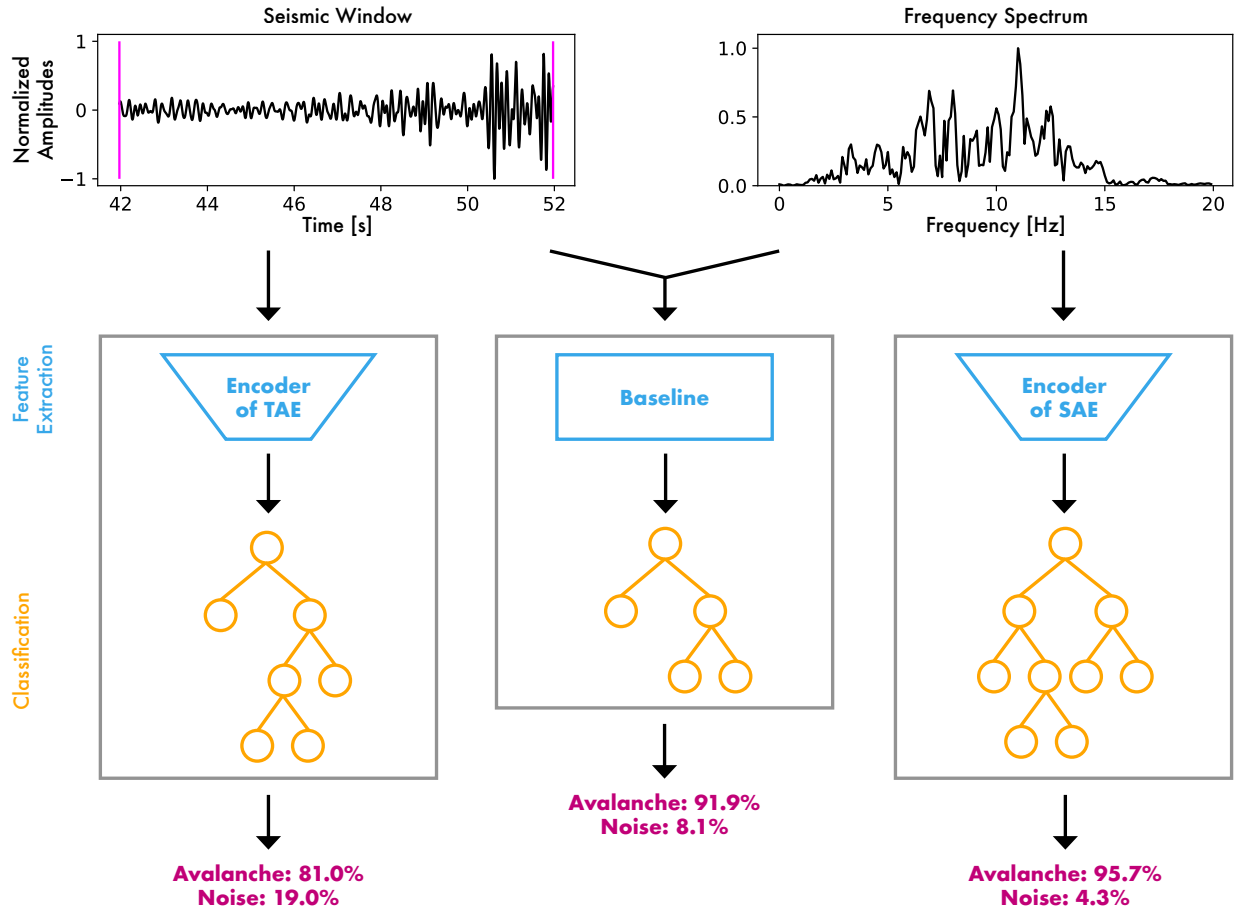


Figure 4. Overview of the three different approaches for methods to infer avalanche classification probabilities. The blue elements depict the feature extraction. During inference, while the decoder of the autoencoders is discarded, and only the encoder is used to extract features. The orange parts show the classification using random forest models. Top The predictions are shown in pink for the given seismic window (blue the same as in the top left of Fig. 2). Left: The temporal autoencoder features (TAE) feature classification; middle: The hand-engineered baseline classification using engineered seismic attributes; bottom right: The spectral autoencoder features (SAE) feature classification.

In order to classify each signal window (Fig. 4), we need to extract features from them (Sect. ??), followed by a classification model learned to discriminate classes of interest (Sect. 4.3). In the former, we used a conventional human-supervised feature-engineering approach (Sect. 4.1 and Appendix B) as a benchmark and two fully unsupervised autoencoders (Sect. ??), which required definitions of the training strategies (Sect. ??). In the latter, we chose and developed binary classifiers for the preceding feature extraction methods (Sect. 4.3).

4.1 Feature-extraction

For the later classification, we first extracted features from the 10 s signal windows (Fig. 4). Feature extraction generally describes the compression of a signal to a lower dimensional embedding ~~while retrieving/preserving to retrieve~~ the signal's most distinctive information. The embedded information (the features) is usually ~~input into~~ ~~used in~~ an upstream classification or regression task. Following this ~~general approach, we explore~~ ~~framework, we explored~~ three methods to extract information from seismic signals either as ~~lower-dimensional-learned~~ feature vectors or domain-specific ~~engineered~~ features, which are then classified as avalanche or noise. ~~Concretely, we implemented a baseline based on a conventional expert-supervised feature engineering approach (Sect. 4.1) and developed two fully unsupervised autoencoders to extract features from temporal and spectral input data, respectively (Sect. 4.2). We then optimised three separate random forest models on top of the preceding feature extraction methods predicting avalanche and noise probabilities (Sect. 4.3).~~

~~In a first attempt, following a~~

4.1 Baseline features

Since representation learning methods are a novel approach in seismic avalanche detection, we sought a baseline against which to benchmark them. Earlier studies on time series classification in general (Ismail Fawaz et al., 2019; Barandas et al., 2020) and on seismic detection of different types of mass movements (Rubin et al., 2012; Provost et al., 2017; Lin et al., 2020; Wenner et al., 2021) developed classification models using traditional feature engineering strategies. Therefore, in the baseline model, we followed a similar approach to Provost et al. (2017), which classified seismic events generated by landslides ~~,we and~~ extracted a set of ~~57 predefined standard seismic attributes~~ (Sect. 4.1). The feature engineering approach is widely used in seismic detection of mass movements (Rubin et al., 2012; Provost et al., 2017; Lin et al., 2020; Wenner et al., 2021; Chmiel et al., 2021) and time series classification in general (Barandas et al., 2020). Additionally, it served as a benchmark for comparing our second approach (Sect. ??), which is to learn the feature extraction completely unsupervised without making any preliminary assumptions about the signals ~~71 expert-engineered seismic attributes~~. Using an unsupervised approach is beneficial when not having ground-truth labels, as in our case. Therefore, we used two autoencoder models to extract features from temporal and spectral input data, respectively (Sect. ??). ~~The autoencoder architecture, which~~ Specifically, we used a subset of 22 waveform, 17 spectral and 18 spectrogram attributes (see Table B1, B2 and B3 for more details). We extracted these from the frequency-filtered (1 to 10 Hz) 10 s seismic signals for all sensors separately. Additionally, we did not include network or polarity-related attributes since we aimed at developing models for a single-sensor setting and our study site was equipped with one-component sensors.

4.2 Autoencoder features

The autoencoder concept was first introduced ~~in Rumelhart et al. (1986)~~ ~~, by Rumelhart et al. (1986)~~ and has since been adapted for various applications (Xugang et al., 2013; Mousavi et al., 2019; Gu et al., 2021). ~~A vanilla autoencoder~~ The architecture consists of an encoder and a decoder. The encoder compresses the input signal to a lower-dimensional embedding, ~~the latent space~~ i.e. the latent (feature) vectors. The decoder ~~transforms feature vectors from this latent space~~ decompresses these feature

vectors to the original input dimension. ~~An Overall, the~~ autoencoder is trained by learning to reconstruct the input signals ~~from the lower-dimensional latent space, which requires the latter to store the most relevant information characterising each piece of the signal. By.~~ Thus, by design, the ~~encoder~~ feature vectors are ~~optimized to carry~~ optimised to preserve the most distinctive information ~~of characterising~~ a given input signal ~~, such so~~ that the decoder can reconstruct it. During inference, ~~the decoder is discarded, and only latent vectors are used as inputs to the classifier, which is trained separately.~~

4.2.1 Seismic attributes

~~In the first approach, we used a set of 22 waveform, 17 spectral and 18 spectrogram attributes (see Table B1, B2 and B3 for more details). These features were extracted from the frequency-filtered (1 given that the autoencoder's purpose is to 10 Hz) and normalized 10 s seismic signals for all sensors separately. Note that we did not include any network or polarity-related attributes. extract features for a classification process on top, the decoder can be discarded. The classifiers, which are trained separately, use solely the feature vectors.~~

4.2.1 Autoencoders

~~Developing neural networks involves optimizing network hyper-parameters and defining a training strategy. Therefore, we used the first three folds in Fig. 3 to run 3-fold cross-validation. We defined a grid of hyper-parameter combinations, iteratively trained the models on two and evaluated them on the left-out fold. We selected the model showing the best average performance on all three folds according to predefined metrics. By definition, the autoencoder performance can be measured with its reconstruction loss. However, given a decent reconstruction, we aimed to find the best input features for classification. Hence, we evaluated the autoencoders based on the avalanche and noise class separation within the latent (feature) space. We calculated the silhouette score (Rousseeuw, 1987) and the Calinski-Harabasz index (Calinski and Harabasz, 1974) for the features and their given expert labels (see Appendix C). The best autoencoder was selected by searching for the highest-ranking combination of silhouette score, Calinski-Harabasz index and the reconstruction mean squared error loss (see Appendix E). Following the model selection, the autoencoders were retrained on the train folds (fold 1, 2 and 3 in Fig. 3), and after, we extracted the autoencoder features from all folds.~~

4.2.1 Architecture

In the ~~first autoencoder, i.e. the~~ temporal autoencoder (TAE) ~~, we considered the seismic time series data, hence the name. It was developed for seismic waveform signals of 10~~ normalised by their maximum absolute amplitude. When dealing with time series data, common choices of computational units are one-dimensional convolutions (Kiranyaz et al., 2021) and recurrent units such as the long short-term memory (LSTM) ~~cells~~ cells (LSTM; (Hochreiter and Schmidhuber, 1997)). Thus, we implemented the encoder as a sequence of 3 ~~convolution~~ convolutional layers and one LSTM cell layer learning temporal dynamics. The best model ~~from the cross-validation procedure (based on the optimisation procedure (Sect. 4.2.3 and Table E2)~~ was composed of convolutions with kernel size 20 (or 0.1 s) and stride 10. This implementation of stride reduces

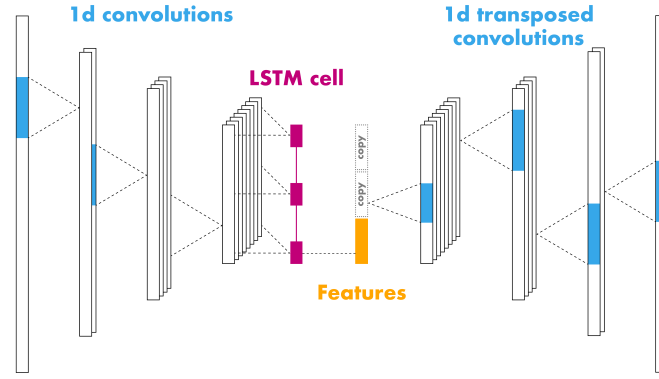


Figure 5. Illustration of the ~~architecture of the~~ temporal autoencoder ~~architecture~~. The encoder comprises one-dimensional convolutional layers (kernels in blue) with leaky ReLU activation and batch normalisation followed by a long short-term memory cell (LSTM, pink). The decoder uses one-dimensional transposed convolutions to decompress the extracted encoder features (highlighted in orange) and reconstruct the input signal.

the initial input length of 2000 samples ($200 \text{ Hz} \times 10 \text{ s}$) to 200, 20, and 2 within each encoder layer. Similarly, ~~we selected~~ ~~the tuning procedure suggested~~ 32 filters in the first convolutional layer ~~and doubled the number~~, which we then doubled in each consecutive layer. In the last encoder layer, the LSTM cell ~~summarizes~~ ~~summarises~~ the output of the convolutions, i.e. two 128-dimensional vectors, to a feature vector of 32 dimensions (32 features). The decoder sequentially repeats this latent vector twice and applies ~~3~~ ~~three~~ transposed convolutions with kernel size 20 and stride 10 to decompress the sequence back to its original length ~~-, i.e. 2000~~. Starting at 128 filters, we halved them in each ~~decoder~~ layer to reach 32 channels. To reduce this number ~~back~~ to the number of input channels, i.e. 1, ~~we applied~~ a convolutional layer with kernel size 3 ~~-, and~~ stride 1 ~~is applied~~ in the decoder output layer.

In addition, we used batch ~~normalization~~ ~~normalisation~~ (BN) (Ioffe and Szegedy, 2015) in all encoder and decoder layers, except for the decoder output layer ~~to stabilize~~, ~~to stabilise~~ and accelerate training. As ~~an~~ activation function, we ~~use~~ ~~used~~ the leaky rectified linear unit (leaky ReLU; (Xu et al., 2015)), ~~which outperformed the tangent hyperbolic function (Tanh) during model optimisation~~. The only exception is again the output layer, where we ~~replace~~ ~~replaced~~ the leaky ReLU with the ~~tangent hyperbolic (Tanh)~~ ~~Tanh~~ function to output values in the same range as the ~~normalized input signals~~ ~~in $[-1, 1]$~~ ~~normalised input signals, which is $[-1, 1]$~~ . In summary, Fig. 5 gives a simplified overview of this architecture comprising 514'337 learnable parameters (226'848 in the encoder). ~~Note that this~~ ~~This~~ architecture is relatively small in the number of trainable parameters ~~;~~ ~~hence and, therefore~~, well adapted to the size of our dataset.

The second autoencoder implementation operates in the spectral domain, ~~henceforth referred to as the~~ ~~hence named~~ spectral autoencoder (SAE). We used the fast Fourier transform (FFT) to convert the filtered 10 s seismic signals into the frequency domain. Thus, the input data to this model ~~contains~~ ~~contained~~ the amplitude spectrum normalised using the min-max ~~normalization~~ ~~normalisation~~. In contrast to the temporal autoencoder, we replaced the aforementioned computational units, i.e.

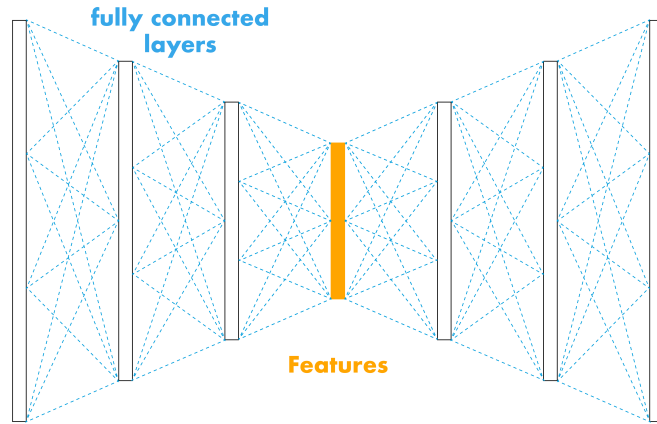


Figure 6. Illustration of the spectral autoencoder architecture. The encoder and decoder are a sequence of compressing and decompressing fully connected linear layers (dashed blue lines). Each layer uses the spectral autoencoder hyperbolic tangent (Tanh) activation function and layer normalisation. The extracted features are shown in orange.

335 convolutions and LSTM cells, with fully connected layers. Through hyper-parameter ~~optimization~~optimisation (Sect. 4.2.3 and Table E4), we designed the encoder and decoder to ~~compose 3~~comprise three fully connected linear layers each. The hidden dimensions in the encoder ~~evolve~~evolved from 200 to 139, 78 and 16 (feature dimension). The decoder ~~is~~was a mirrored version of the encoder. ~~We~~Based on parameter tuning we used the Tanh function as ~~the~~non-linearity of choice in all layers (Table E4). Moreover, we ~~apply layer normalization~~applied layer normalisation (LN) in each layer with the ~~same~~ exception of the output layer. Figure 6 illustrates a simplified version of this architecture summing up to 81'330 learnable weights (40'589 in the encoder). As for the TAE, this architecture is ~~small and even smaller and thus also~~ well adapted to ~~our dataset. the size of the dataset.~~

340

4.3 ~~Autoencoder training~~

~~The training strategy is another main part of model development, which we optimized for the selected autoencoder architectures.~~

345

4.2.1 Training regime

A training step in neural network ~~optimization~~optimisation starts with sampling a batch of predefined size from the dataset. For sampling, given that ~~the data set is our dataset was~~ severely imbalanced (Fig. 3), we ~~implemented the used the so-called~~ weighted random sampler~~(, as implemented in Paszke et al. (2019), see Appendix ??), which samples data points according~~ to user-specified class weights. This allowed us to control the proportion of avalanche ~~PyTorch~~ (Paszke et al., 2019). This sampling method oversamples the minority (avalanche) class and thus prevents the model from biasing towards the majority (noise) class. The sampling process relies on user-defined class weights, which allows the user to control the expected number

350

of minority class (avalanche) samples within each batch. Therefore, we assigned the following relative weight to each sample of the avalanche class (w_{av}), while we assigned the noise samples a weight of one ($w_{no} = 1$). Internally, the sampling method rescales and interprets these weights as probabilities.

$$w_{av} = \frac{N_{no}}{N_{av}} \frac{P_{av}}{1 - P_{av}} \quad (1)$$

P_{av} is the user-defined expected portion of avalanches per batch, e.g. 0.5 for evenly balanced batches. The batch is then passed through the entire network (forward pass) to produce the output (prediction). The output is compared to the target and the ~~reconstruction loss (Mean Squared Error — MSE) is computed~~ mean squared error (MSE) reconstruction loss is computed (see Equation C1). The network weights are then ~~optimized~~ optimised by computing the gradients of the loss function and ~~applying a specified propagating them back through the network~~ (back-propagation algorithm. Within this training procedure, we searched for the optimal number of expected avalanche samples in each batch, the batch size and) using the Adam optimizer (Kingma and Ba, 2014) with a specified learning rate. After, the ~~learning rate to use with the Adam optimizer (Kingma and Ba, 2014).~~ After following next batch is passed to the network repeatedly until all batches in the dataset have been seen once, which defines an epoch. The entire process is then again repeated for a certain number of epochs. Figure E1 in the appendix illustrates the training and validation progress per training epoch for the temporal (TAE) and spectral autoencoder (SAE).

Following our hyper-parameter ~~optimization tuning~~ strategy, we found the temporal autoencoder training optimal with an expected portion of avalanches per batch of ~~0.6~~ $P_{av} = 0.6$, a learning rate of $1e^{-4}$ and a batch size of 128 (Table E3). The model was trained for 120 epochs, i.e. iterations through the entire dataset, with early stopping when the class-separation metrics (Sect. 4.2.2) started decreasing. Additionally, we applied data augmentation by randomly shifting the 10 s window signals by 0 to 1 seconds to either the right or left , to reduce overfitting in the avalanche class and for better generalization generalisation (Zhu et al., 2020). Similarly, in the spectral autoencoder training, we used an expected portion of ~~0.5~~ avalanches $P_{av} = 0.5$ avalanches per batch, a learning rate of $1e^{-4}$ and a batch size of 128 and found 5 (Table E5). Moreover, we found five training epochs to be optimal.

4.2.2 Validation

In addition to the training regime (Sect. 4.2.1), we defined a validation routine for comparing different autoencoder architectures and settings in the model optimisation (Sect. 4.2.3). By definition, the autoencoder performance can be measured with its reconstruction loss. However, given a decent reconstruction, we aimed to find the best input features for the later classification. Hence, we evaluated the autoencoders based on the avalanche and noise class separation within the latent (feature) space. We calculated the silhouette score (Rousseeuw, 1987) and the Calinski-Harabasz index (Caliński and Harabasz, 1974) based on the feature embedding location and their given expert labels (see Appendix C3). We selected the best autoencoder by searching for the highest-ranking combination of silhouette score, Calinski-Harabasz index and the mean squared error loss.

4.2.3 Model selection

385 Developing neural networks involves tuning network hyper-parameters, such as the number of layers, kernel sizes of convolutions or hidden dimensions. Therefore, we used the three train folds in Fig. 3 to run 3-fold cross-validation. Using three folds reduces the impact of data variability and yields more reliable performance estimates. Next, we defined a grid of hyper-parameter combinations (Table D1) and iteratively trained the resulting model configurations on two and evaluated them on the left-out fold. We selected the model showing the best average performance over all three folds according to the predefined validation
390 metrics (Sect. 4.2.2). Besides the internal network parameters, we applied the same procedure to tune the parameters of the training regime (Sect. 4.2.1). Concretely, we searched for the optimal number of expected avalanche samples in each batch (P_{av} in Equation 1), the learning rate and the batch size. Details of this process can be found in the Appendix E.

4.3 Feature classification

~~The motivation for separating the feature extraction and classification processes was manifold. First, the partial uncertainty in the labels led to the conclusion that an unsupervised feature extraction approach is more robust to label noise and therefore preferable, as it could additionally leverage more unlabelled data. In contrast, a fully supervised neural network might suffer from the relatively low number of labels and bias, tending to overfit these expert labels rather than learn avalanche characteristic patterns in seismic signals. In an early stage, we tested this approach and did not observe better results. Thus for better comparability of the features themselves with the benchmark model, i.e. feature engineering, we pursued the unsupervised~~
395 ~~feature extraction approach. Ideally, several classifiers can then be used, combined or ensembled over different feature extraction steps.~~

~~Apart from expert labels, we considered the subjectivity of the manual cuts, the attenuation of avalanche signals with the distance to the sensors and the low initial energy of avalanches, with which we inevitably included 10 s windows from avalanche signals, which rather account towards background noise. This particularly applies to~~ Foremost, this work aims to
405 detect avalanches in seismic recordings. Therefore, ~~the starting and ending sections of a signal (see the upper plot in Fig. 2). Labelling these parts as avalanches (false positives) bears the danger of distracting a fully supervised neural network. Therefore, we decoupled the classification from the unsupervised feature extraction and implemented~~ previous extraction of distinctive features was only an intermediate step. To classify these features, we developed three random forest classifiers ~~for each feature set.~~ one per feature extraction method. We tuned them for the baseline, the temporal and the spectral autoencoder features
410 separately to infer class probabilities (see Fig 4).

4.3.1 Random forest model

The random forest model is a widely used algorithm for classification in general and for seismic event detection (~~e.g. Li et al., 2018; Provost~~ in particular (Provost et al., 2017; Li et al., 2018; Chmiel et al., 2021), as it is favourable when dealing with high-dimensional features and heterogeneous (~~seismic attributes~~ e.g. engineered features) input data ~~and it provides output probabilities estimates.~~

~~The random forest.~~ The algorithm was introduced by Breiman (2001) and belongs to the class of ensemble methods. During training, several decision trees (estimators) are grown. Each tree is grown on a different bootstrap sample of the original dataset, i.e. a random draw with replacement. Instead of using the entire set of features (~~(columns)~~) in the original dataset, a random subset is assigned to each node in the tree individually. The split (branch) is based on a single feature from this random subset, which is optimal under a specified splitting criterion, such as the Gini information criterion (Breiman, 2017) when dealing with categorical (classification) splitting problems. ~~During inference, each tree prediction is aggregated to form a final majority vote, from which it is possible to retrieve class proportions, often interpreted as probabilities.~~

4.3.2 Cross-validation

In search of the best hyper-parameters of this tree-growing algorithm, e.g. the maximal number of estimators (trees), we used a ~~randomized~~ randomised grid search with 3-fold cross-validation. This method evaluates hyper-parameter combinations by iteratively fitting the random forest model to two of the three train folds ~~and testing (Fig. 3)~~ and validating it on the left-out fold. As a scoring function, we chose the avalanche class f1-score to weigh the avalanche precision and recall uniformly. ~~Finally, we averaged the performance and averaged this score~~ across the three folds. This ~~optimization~~ optimisation process was applied with the three feature sets individually, i.e. the ~~seismic attributes and the~~ baseline and autoencoder features, to find the random forests presented in Table D1.

5 Results

~~After completion of the model development, we evaluated the three approaches on the test fold (fold 4 in Fig. 3). First, we summarized the results of the seismic attribute, TAE and SAE feature classification on the windowed~~

4.0.1 Inference and post-processing

During inference, a (test) feature vector is first passed separately to each decision tree in the random forest. Each tree applies its learned sequence of decision rules and classifies the feature vector as either avalanche or noise. Then, each tree's classification is aggregated by computing the mean. For instance, assuming 90 out of 100 trees classified a given feature vector as an avalanche, this sample was assigned an avalanche probability of 0.9, estimated as the fraction of votes within the forest. This process, known as ensembling, is why the random forest algorithm is considered an ensemble method. The only parameter to define was a probability threshold above which, we classified the sample as an avalanche. We used the default threshold of 0.5, which means a sample was classified as an avalanche if at least half of the trees agreed on this classification. Hence, for a single 10 s seismic signals (Sect. 5.1). ~~Further, we s~~ seismic signal, the random forest models provided both a binary classification (avalanche or noise) and the probability for each class.

Then, in the first post-processing step, we leveraged the array of five seismic sensors deployed at our study site and aggregated the ~~predictions by averaging the~~ per-sensor model output probabilities, computing a multi-sensor avalanche probability for each 10 s window window. The array-based avalanche probability was calculated as the mean of the individual probabilities

from each sensor. In the second post-processing step, we revisited the offline avalanche activity monitoring or dataset labelling objective by evaluating the classifiers on entire events rather than single 10 s windows. Therefore, we considered an event an avalanche if at least two (overlapping) consecutive windows (i.e. $2 * 10s - 0.5 * 10s = 15s$ of an event) had been positively predicted. Given that the shortest avalanche in the dataset was 13 s, we considered this boundary feasible. The reason for not aggregating the probabilities over the seismic array (Sect. 5.2). Thus, we gained insights into the predictions of unique event length or similar was that in a continuous application, such as avalanche activity monitoring or labelling of an unannotated dataset, the event length is unknown.

With this post-processing, we could evaluate the performance of the random forest classifiers based on single-sensor, sensor array-based and event-based detections.

5 Results

After model development completion, we evaluated the baseline, the temporal autoencoder (TAE) and the spectral autoencoder (SAE) on the unseen test fold (top bar in Fig. 3). To assess the models' stability, we trained and tested them using 20 different random seeds, i.e. powers of two starting with 2^0 . Therefore, we calculated the mean and standard deviation of all metrics, while for specific result analysis, e.g. Fig. 10, we used the random seed for which a the model showed the highest avalanche f1-score (2^5 for the baseline, 2^{16} for both autoencoders).

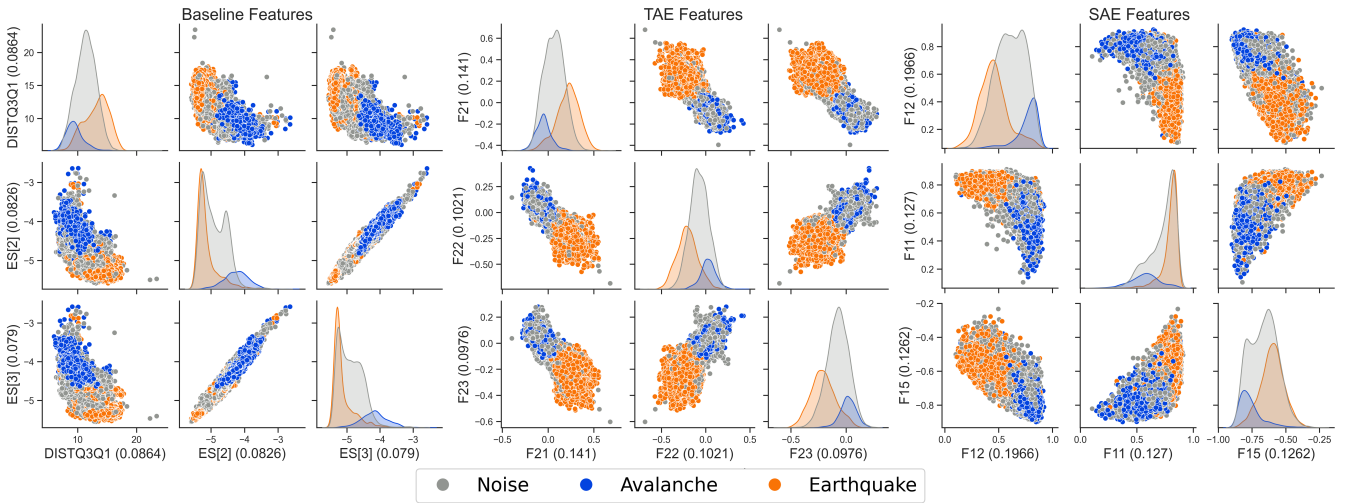


Figure 7. Test set latent space visualisation of the most important features according to the impurity-based feature importance (value in parenthesis) of the random forest models for the baseline (left), the TAE features (middle) and the SAE features (right). In the left plot, DISTQ3Q1 is the mean distance between the 3rd and the 1st quartile of all FFTs as a function of time, ES[2] and ES[3] is the energy in the frequency band [5, 7] Hz and [6, 9] Hz respectively (features 57, 35 and 36 in Table B3 and B2). The axis labels starting with the letter 'F' in the middle and right plot represent a specific autoencoder feature carrying no explicit physical meaning.

5.1 Single-sensor predictions

As a first step, we evaluated the detection performance of each model’s single-sensor predictions on the 10 s signals-at-our study-site.

465 5.2 Single-sensor predictions

seismic signals. The true positive rates (or avalanche recall) were similar across the models (Fig. 8), i.e. between ~~67.3% and 71.2%~~ 67.3% ($\pm 1.4\%$) and 69.8% ($\pm 1.8\%$), indicating that approximately 30% of all avalanche windows were missed. Nevertheless, the avalanche recall was ~~slightly higher for the autoencoder~~ highest for the TAE features classification. Regarding the true negative rates (or specificities), i.e. the probability that an actual noise event will be predicted as noise, we noted that
470 the TAE features classification showed the lowest rate of ~~82.6% and 83.0% ($\pm 1.0\%$)~~ and, therefore also showed the lowest avalanche precision of ~~0.33~~ 0.33 (± 0.01), compared to ~~0.51 for the seismic attributes and 0.45 for the spectral autoencoder features~~ 0.52 (± 0.00) for the baseline and 0.44 (± 0.01) for the SAE (Table 1). Thus, we expect this model to produce comparably more false alarms (false positives) at a rate of 17.0% ($\pm 1.0\%$). Overall, the macro-average f1-score reached values of ~~0.76, 0.67 and 0.74 for the seismic attributes~~ 0.76 (± 0.00), 0.67 (± 0.01) and 0.73 (± 0.00) for the baseline, the TAE features
475 and the SAE ~~features~~ feature classification respectively (Table 1).

Additionally, since the feature extraction and its information content are core concepts of this study, we ~~visualized the~~ visualised part of the latent spaces in Fig. 7. As earthquakes are account for a significant proportion of the noise class (31%) and labels were available ~~, we show anyway, we showed~~ them separately. This ~~visualization~~ visualisation provided some insights into the ~~organization of the autoencoder latent space.~~ organisation of the latent spaces. For instance, all models spatially
480 separated avalanche and earthquake samples.

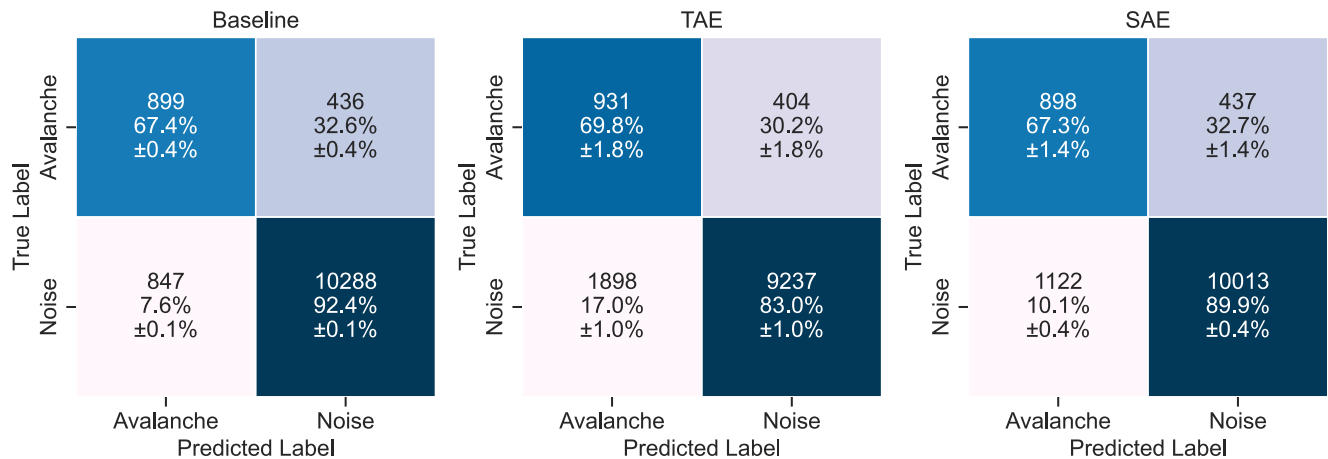


Figure 8. Confusion matrices of the binary classification results for the three feature sets on the held-out test fold data, including all five sensors. The rows indicate the true (expert) labels, while the columns provide the predicted labels of the random forest classifiers. The colours code the percentage numbers values.

Table 1. Classification metrics on the (unseen) test fold data comprising 1335 avalanche and 11135 noise samples for the three feature sets. Due to the strong class imbalance, the weighted averages of the metrics are not shown.

Model	Class	Precision	Recall	F1 Support-
Baseline	Avalanche	0.51 0.52 ± 0.00	0.67 ± 0.00	0.58 1335 ± 0.00
	Noise	0.96 ± 0.00	0.92 ± 0.00	0.94 11135 ± 0.00
	Macro Avg	0.74 ± 0.00	0.80 ± 0.00	0.76 12470 ± 0.00
	Accuracy			0.90 ± 0.00
TAE	Avalanche	0.33 ± 0.01	0.71 0.70 ± 0.02	0.45 1335 ± 0.01
	Noise	0.96 ± 0.00	0.83 ± 0.01	0.89 11135 ± 0.01
	Macro Avg	0.64 ± 0.01	0.77 ± 0.01	0.67 12470 ± 0.01
	Accuracy			0.81 0.82 ± 0.01
SAE	Avalanche	0.45 0.44 ± 0.01	0.70 0.67 ± 0.01	0.54 1335 ± 0.01
	Noise	0.96 ± 0.00	0.90 ± 0.00	0.93 11135 ± 0.00
	Macro Avg	0.70 ± 0.00	0.80 0.79 ± 0.01	0.74 124700.73 ± 0.00
	Accuracy			0.87 ± 0.00

Latent space visualization of the most important features according to the impurity-based feature importance of random forest models for the seismic attributes (left), the temporal autoencoder features (middle) and the spectral autoencoder features (right). In parenthesis, the impurity-based importance of each feature is shown.

5.2 ~~Array-based~~ Sensor array-based predictions

485 In addition to the predictions on the individual 10 s windows, we aggregated the ~~window~~ single-sensor predictions over the ~~5-five~~ sensors in the seismic array by averaging the ~~per-sensor~~ single-sensor output probabilities, resulting in improved model performance (Fig. 9). The macro-average ~~f1-score increased by 2.6% (seismic attributes), 4.5% f1-scores increased by 2.6% (baseline), 4.5% (TAE) and 5.4%–5.5% (SAE).~~ After ensembling, the seismic attribute This improvement particularly originated from lower false positive rates, while the rate of missed avalanche windows remained at about 30% in all models.

490 After aggregation, the baseline and the SAE feature classification yielded similar performance in the classification metrics (see Table 2). ~~Despite this improvement, the~~ The TAE feature classification, however, still showed approximately double the number of false alarms, i.e. ~~323 (14.7%)~~ 308 (14.0% ± 0.8%), compared to the other models. ~~The despite this improvement.~~ The sensor array-based aggregation further enabled us to investigate how predictions evolve over an entire seismic signal ~~evolve across the array~~ (Fig. 10). For the avalanche shown in Fig. 1 and ~~2~~ Fig. 2 (left), the models ~~are comparably unsure were~~ uncertain in the starting phase, ~~i.e. when it emerges from background noise~~ when the avalanche amplitudes slowly emerged from the background noise signal. However, as the signal ~~becomes~~ became more energetic, the avalanche probability ~~increases~~ increased for all models. Overall, this post-processing strategy reduced the number of false alarms and slightly improved the avalanche recall.

495

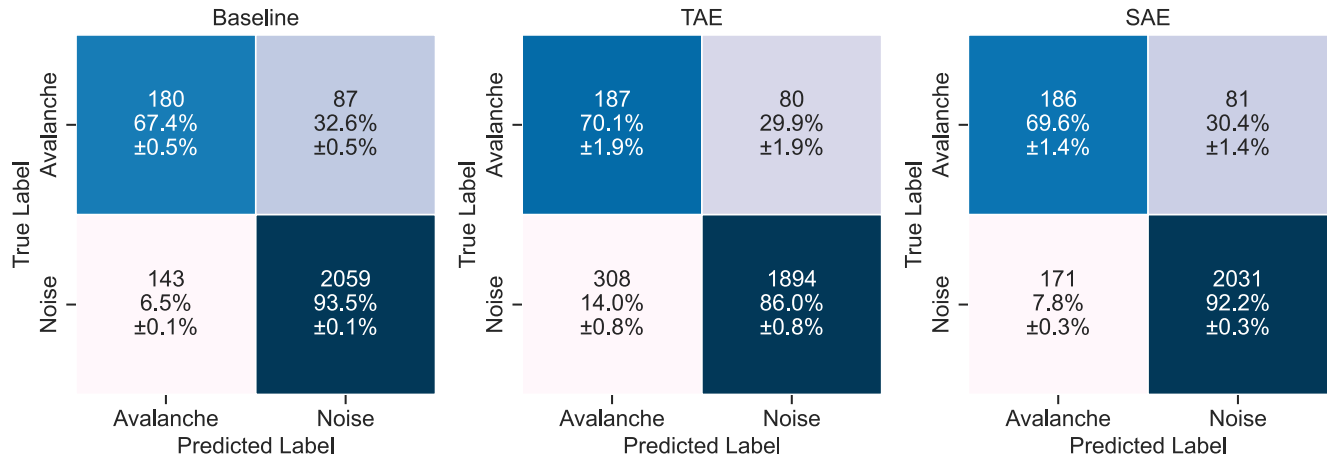


Figure 9. Results on the held-out test ~~set-fold data~~ after applying a probabilistic aggregation of the ~~single-sensor~~ 10 s predictions over the ~~5-five~~ sensors of the ~~sensor~~ array. The rows indicate the true (expert) labels, while the columns provide the predicted labels of the random forest classifiers. The colours code the percentage ~~numbers~~ values.

Table 2. Classification metrics on the (unseen) test fold data set comprising 267 avalanche and 2202 noise samples after probabilistic aggregation over the 5-five sensors. Due to the strong class imbalance and bias towards the noise class, the weighted averages of the metrics are not shown.

Model	Class	Precision	Recall	F1 Support-
Baseline	Avalanche	0.56 ± 0.01	0.68 0.67 ± 0.00	0.61 267 ± 0.00
	Noise	0.96 ± 0.00	0.93 ± 0.00	0.95 2202 ± 0.00
	Macro Avg	0.76 ± 0.00	0.81 0.80 ± 0.00	0.78 2469 ± 0.00
	Accuracy			0.91 ± 0.00
TAE	Avalanche	0.37 0.38 ± 0.01	0.71 ± 0.02	0.49 267 ± 0.01
	Noise	0.96 ± 0.00	0.85 0.86 ± 0.01	0.90 2202 0.91 ± 0.00
	Macro Avg	0.67 ± 0.01	0.78 ± 0.01	0.70 2469 ± 0.01
	Accuracy			0.84 ± 0.01
SAE	Avalanche	0.53 0.52 ± 0.01	0.71 0.70 ± 0.01	0.60 267 ± 0.01
	Noise	0.96 ± 0.00	0.92 ± 0.00	0.94 2202 ± 0.00
	Macro Avg	0.75 0.74 ± 0.01	0.82 0.81 ± 0.01	0.77 2469 ± 0.01
	Accuracy			0.90 ± 0.00

5.3 Event-based predictions

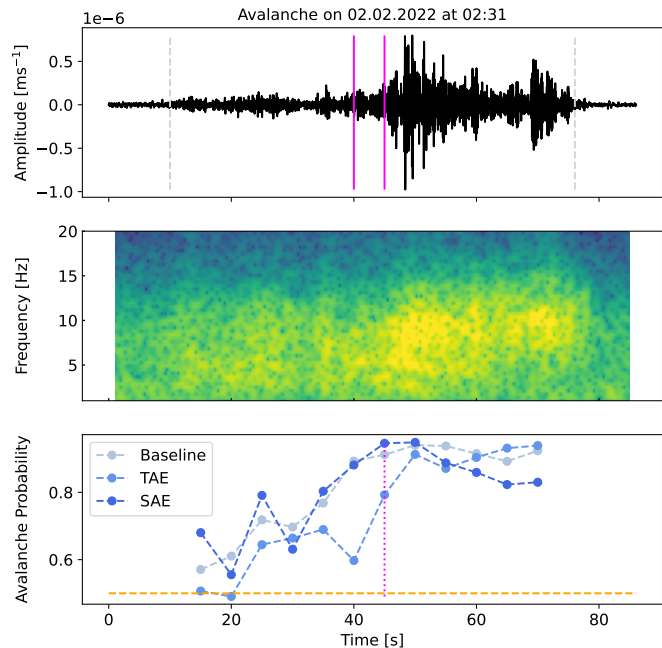


Figure 10. Waveform and spectrogram generated by the avalanche in Fig. 1 and the array-based output probabilities for each model over the entire avalanche signal (bottom). The signals have been filtered from 1 to 10 Hz corresponding to the input frequency band of the models. In pink, the same 10 s seismic window as in Fig. 2 (left) and Fig. 4 is shown and the according probabilities are highlighted (lower plot). The probabilities are computed as the average of the single-sensor probabilities predicted every 5 seconds (10 s windows with 50% of overlap). The manually defined event onset and end are highlighted in dashed grey lines (upper plot), and the classification threshold 0.5 is in orange (lower plot).

500 Besides the single-sensor

5.3 Event-based predictions

Besides the single-sensor and array-based predictions (Sect. 5.1 and 5.2), we investigated the predictions on the event-level an event basis to close the gap to avalanche activity assessment and provide a broader outlook. This for, we aggregated the array-level predictions in Fig. 9 over the entire duration of an event. We applied the rule that if at least two consecutive windows (or 15For this, we assigned an event to the avalanche class if two consecutive 10 s of an event) were positively predicted, the entire event was positive, i.e. an avalanche. This threshold of two windows was not optimized. However, considering that the shortest avalanche in the dataset is 13 s, this boundary was feasiblewindows (50% overlap) of the sensor array-based predictions were detected as avalanche signals. This post-processing led to the results in Appendix ??.

505 Figure E2 shows a significant increase in avalanche recall with values of 81.8% (seismic attributes), 87.9% Figure E2 and Table E6 in the

510 Appendix E2. Although the overall performance of the three models decreased by about 5% (see Table E6), the true positive rates (avalanche recall) increased significantly to 81.4% ($\pm 1.1\%$) (baseline), 84.8% ($\pm 2.6\%$) (TAE) and ~~5.4%~~ 89.3% ($\pm 4.3\%$) (SAE). Nevertheless, the overall performance of the three models decreases by about 5% (see Table E6)Hence, by applying this step, the spectral autoencoder could successfully detect 89.3% ($\pm 4.3\%$) of all avalanches in the test fold.

515 ~~Example of the seismic signal generated by an avalanche (up) and the mean output probabilities for each developed model over the entire avalanche signal (down). The probability is computed as the average of the individual probabilities predicted by each sensor every 5 seconds (10 s windows with 50% of overlap). The manual cuts are highlighted in dashed grey lines (upper plot), and the classification threshold 0.5 is in orange (lower plot).~~

6 Discussion

So far, we compared the performance of ~~a human-engineered~~ the baseline, an expert-engineered seismic attribute classification ~~approach,~~ and the autoencoder feature ~~classification results~~ classifications based on a dataset containing 10 s seismic signals ~~on a single sensor level and multiple sensor level (aggregation). With the latter in a single-sensor, sensor array-based and event-based setting. In the single-sensor setting, the models missed approximately 30% of all avalanche windows and produced false alerts at rates between 7.6% ($\pm 0.1\%$) and 17.0% ($\pm 1.0\%$). With the sensor array-based aggregation, we observed a significant reduction in false alarms and a slight improvement in recall for the avalanche class. Furthermore~~ avalanche recall. In

525 the event-based setting, we compromised an improvement in avalanche recall with an increase in false alarms. Moreover, we noticed that the automatically learned features, ~~and~~ specifically the ones from the spectral autoencoder, performed ~~better than the seismic attributes comparably to the baseline.~~ Hence, the results showed that spectral input information seemed favourable. In the following, we contextualise the results by investigating the detection errors and their possible origins. Therefore, we ~~summarize~~ summarise the model development (Sect. 6.1) and ~~dived into~~ focus on the false predictions of the models to find

530 potential limitations ~~and reasons~~ (Sect. 6.2 and 6.3). Finally, we ~~compared the~~ argue about the applicability of these models (Sect. 6.4) and ~~compare the~~ results to previous ~~works~~ work (Sect. 6.5).

6.1 Model performance and limitations

~~Machine-learning models are strongly influenced by the~~ The quality and size of the dataset strongly influence deep learning models. The relatively small size constrained us to design autoencoder architectures with ~~rather few trainable weights~~ few

535 trainable parameters. In addition, we used each sensor independently to compensate for dataset size, as each sensor can be considered ~~as~~ a different view of the ~~events~~ same event. However, this came at the cost of introducing correlation among dataset samples as the sensors were installed nearby (Fig. 1) and thus recorded very similar signals, yet not necessarily adding much new and enriching information to the dataset. Given that the dataset will increase in the ~~next years~~ upcoming winters, we will consider incorporating the ~~5~~ five sensors as distinct channels in a convolutional and/or recurrent model in future studies. With

540 this, the sensor array-based aggregation and fusion would be implicitly implemented into the model.

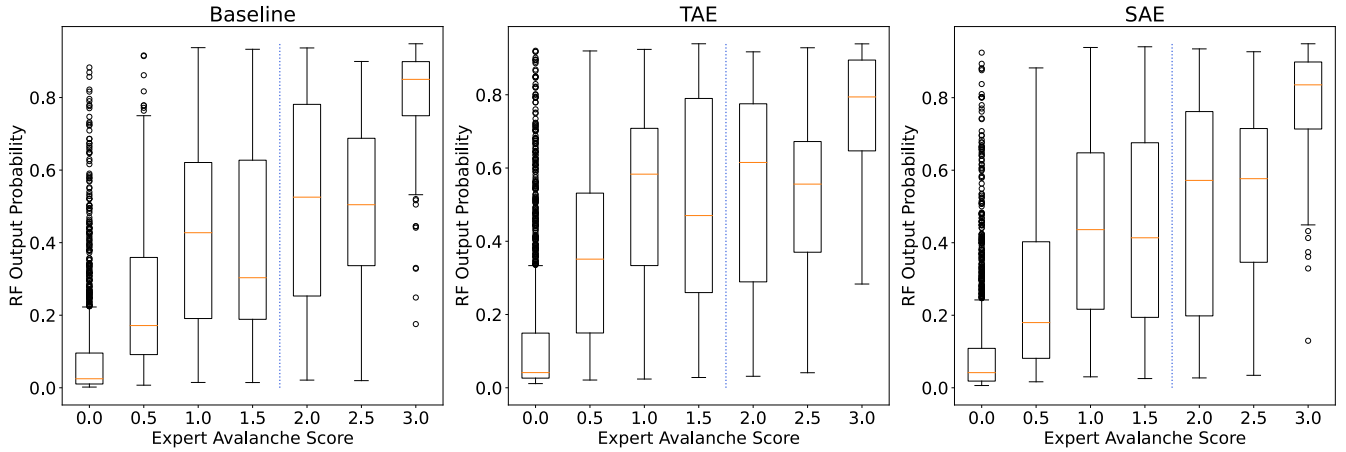


Figure 11. ~~Array-based~~ Sensor array-based output probabilities of the random forest models for their respective input features ~~with~~ plotted ~~against~~ expert avalanche scores. The blue dashed line indicates the threshold applied to the expert scores to assign avalanche class labels.

Another aspect to ~~bear in mind was the input normalization.~~ Normalizing ~~consider~~ was our approach to normalise each 10 s seismic window independently. Normalising input data has proven crucial when training neural networks (Sola and Sevilla, 1997). The temporal autoencoder, in particular, therefore ~~loses~~ lost information on absolute and relative amplitudes. Yet, both autoencoders could still capture signal characteristics and remarkably ~~show~~ showed similar patterns when looking at continuous predictions ~~and comparing with the baseline~~ (see Fig. 10). Alternatively, a ~~normalization~~ normalisation over the entire signal before ~~windowing~~ applying the windowing algorithm could be envisioned to preserve information on relative amplitudes. However, this ~~is not~~ normalisation is not applicable during an online inference, as it would require looking ahead at the amplitudes of the incoming waveforms. Therefore, it is ~~not~~ practical for (near) real-time signal ~~processing-classification.~~ Alternatively, normalising by a characteristic value of the training dataset is unfavourable considering the heterogeneity of the data and a future implementation at another study site with potentially completely different characteristics. Also, note that normalising by class characteristics of the training data would violate the unsupervised learning regime.

~~Further, the dataset drove the decision to separate the~~ Further, the separation of the feature extraction and classification ~~.The process~~ was driven by the dataset at hand and the success of representation learning in various applications (Bengio et al., 2013; Långkvist et al., 2014). Considering the data, the unsupervised feature extraction ~~is not constrained to a labelled dataset~~ was not constrained by class labels (only the model selection and ~~hyperparameter tuning~~ are hyper-parameter tuning of the classifiers were), an advantage when dealing with non-ground-truth labels (two-thirds of the avalanches were ~~not verified~~ neither verified by the radar nor the cameras). The ~~performance of the classifier is then decoupled from the feature extraction.~~ This applied expert labelling to the non-verified events was subject to an unknown degree of subjectivity and belief. We found the average agreement rate of the avalanche expert probabilities to be 58%, meaning two experts agreed on 58% of the avalanches. In addition, having decided upon a hard threshold to convert expert scores to class labels further blurred the boundaries between the avalanche and noise class, potentially including minor avalanches in the noise class (false

negatives). Apart from the event label uncertainty, we considered the subjectivity of manually defining event onset and end and the uncertainty of adopting the event labels to the 10 s snippets after applying the windowing algorithm. Due to the attenuation of avalanche signals with the distance to the sensors and the low initial energy of avalanches, some 10 s windows containing primarily background noise within an avalanche event were inevitably mislabelled (false positives). This particularly applies to a signal's starting and ending sections (see the upper plot in Fig. 10).

In summary, all of the above led to the conclusion to explicitly separate the feature extraction from the classification and implement an unsupervised learning approach, which is more robust to uncertainty and noise in the labels and could leverage more unlabelled data. In contrast, a fully supervised neural network might suffer from the relatively low number of labels and bias, tending to overfit these expert labels rather than learn avalanche characteristic patterns in seismic signals. Moreover, the developed autoencoder approaches offered better comparability with the baseline model, i.e. feature engineering.

This separation then allowed us to analyze a lower-dimensional embedding of the dataset by inspecting the feature space distributions (Fig. 7). Here As labels for earthquakes were available, we visualised the earthquake class separately, as them separately. Moreover, earthquake and avalanche signals can be similar in the time domain (Heck et al., 2018b), which we, thus, thus we wanted to investigate them in the feature domain. We also had labels for earthquakes simplifying the visualization. In an early stage, we trained models with three classes (earthquake separately), without seeing an increase in overall model performance. Moreover, note that training a model to also classify earthquakes was out of scope as these can be detected with other methods. Overall, the three event types, i.e. avalanches, earthquakes and rest, varied in the encoding locations, yet also showed considerable overlap. Interestingly though, the avalanche and earthquake signals were well separated (blue and orange in Fig. 7). The rest (grey) resembled a connecting cloud between avalanche and earthquake signals. The reason for this might be two-fold; first, the heterogeneity of these noise events by potentially comprising minor avalanches and low magnitude earthquakes (false negatives), and second, the strong attenuation in some sections of avalanche signals resulting in low amplitude avalanche windows. The heterogeneity within the noise class originated from including former noise class heterogeneity originated from comprising different sources in comparable amplitude ranges, e.g., earthquakes, aeroplanes or strong wind. However, the different types of seismic sources of comparable amplitude range these various sources are definitive to be expected and need to be considered in a real-time detection system.

Finally, the applied expert labelling was subject to an unknown degree of subjectivity and belief for the non-verified events. In addition, having decided upon a hard threshold to convert expert scores to class labels further blurred the boundaries between the avalanche and noise class, i.e. the noise class might include minor avalanches (false negatives). We, therefore, investigated the relationship between the random forest's output probabilities and Despite actually having earthquake labels, we opted for a binary classification. In an early stage, we trained models with three classes (earthquake separately), without seeing an increase in overall model performance. This came as no surprise when looking at the clear separation of the expert scores of potential avalanche signals (Fig. 11). Also, we found the average expert agreement rate on the avalanche samples to be 58%, i.e. on average, two experts agree on 58% of the avalanche signals. earthquake from the avalanche samples in latent space. Moreover, training a model to also classify earthquakes was out of scope as these can be detected with other methods. Thus, we did not consider earthquakes a separate class in the classification. However, considering the avalanche class, investigations could also

be conducted by differentiating between type and size in future implementations. Since the primary goal of this study was to develop and compare models to detect avalanches regardless of their type or size, we trained the models considering all the recorded avalanches. Therefore, we ensured that various avalanche types were included in the train and test set by separating them based on appropriate dates (Sect. 3.3). According to radar and image data, most avalanches detected at our study site ranged between sizes 2 and 3, based on the European avalanche size classification (EAWS, 2021). Given that seismic patterns of avalanches are influenced by the avalanche type (Pérez-Guillén et al., 2016), an alternative approach could be to develop two independent models to detect dry-snow and wet-snow avalanches separately. However, the current dataset was too small to further categorise the avalanche events by size and type, and accurate ground-truth data was often also missing. Instead, we focused on the given and analysed the misclassification of the current models.

Finally, to obtain an intuition and analyse how the supervised random forest classifiers related to the expert scores, we plotted the expert scores of potential avalanche signals against the model's output probabilities (Fig. 11). Overall, the output probabilities of the random forest models positively increased with the expert scores. As expected, we also noted the highest uncertainty at the selected threshold (dotted blue line in Fig. 11). When comparing the feature sets, the classification with the seismic attributes yielded clearer baseline features yielded more apparent steps over expert scores and more distinctive probabilities for the highest and lowest expert scores. A measure to mitigate having to deal with such noisy labels in future works might be to solely include verified avalanches solely and discard the non-verified ones for training the autoencoders. Another noticeable observation, which bridges to the upcoming Sect. 6.2 and 6.3, was the number of outliers for the expert scores of 0.5 (false positives) and 3.0 (false negatives), most prominently in the seismic attributes classification models. However, the unsupervised autoencoders are entirely independent of any labels or class information. Thus, by considering only verified avalanches, we would not reduce class ambiguity from the autoencoder's perspective, but the dataset size and with it, valuable information might be lost.

6.2 Missed avalanche windows

Two types of errors are inherent in a binary classification problem, namely As avalanches were this work's main objective, we first analysed the missed avalanche windows, i.e. the false negatives (FNs) and false positives (FPs), which are the focus of this and the following Sect. 6.3 respectively.

Looking again at Fig. 11, we accredited the outliers relatively high number of outliers (FNs) in the expert score of 3.0, i.e. FNs3, i.e. verified avalanches, to the nature of avalanche-mass movement signals. Concretely, avalanche signals slowly emerge from the background noise due to source-receiver distance and the low generation of energy in the initial and very end stages of avalanche motion, resulting in the typical spindle-shape signal with a relatively low signal-to-noise ratio at the beginning and end of the signal (Suriñach et al., 2001; van Herwijnen and Schweizer, 2011; Pérez-Guillén et al., 2016). We suspect that the models had difficulties correctly classifying these parts of an avalanche signal, producing FN predictions. Further, the manual cutting definition of event onset and end was rather generous in including the entire avalanche signal with parts characterised by very low amplitudes. The selection of the initial and end of the signals was subjective, and we cannot exclude that and potentially also some background noise was included. For instance, Fig. 12 a) shows a comparison of the time

series of sensor array-based ~~averaged~~-predictions for each model with the misclassified onset of an avalanche event in the left plot, while in Fig. 12 b) the right, the end portion was characterised by a very low signal-to-noise ratio and hence misclassified. In Fig. 12 a(left), the first few time windows from 10 s to approx. 35 s are arguably rather ~~noisy~~noisy, as suggested by the model probabilities. Tough as the signal strength increases, model probabilities also increase. Concretely, if we considered the first five predictions or time windows ~~as noise~~, this sample accounts for 5 (non) FNs in the results in Fig. 9 and ~~approximately~~ 25 (5 sensors * 5 windows) in Fig. 8 per model. The sensor array-based prediction aggregation did not reduce these missed ‘avalanche’ windows (Fig. 9) since all the sensors predicted low probabilities of being an avalanche. Thus, we were left with approximately ~~one-third of 30%~~ FNs in all three models. ~~In a potential early-warning operation, an effective model should be able to detect all signal parts generated by avalanches, particularly the onset, to identify the avalanche movement in its early stages and trigger a corresponding alarm. Thus, as the models tend to miss the start of an avalanche, the current classifiers might not be suited for avalanche warning. In addition, when trying to assess the overall avalanche activity, missed avalanches are not favourable. Installing an additional sensor near the release area and avalanche path could address this issue. However, considering the characteristics of our test site (Fig. 1), where avalanches can flow over multiple paths, a single sensor will not be enough for the detection of all the avalanches.~~

~~For a general outlook, we further post-processed the array-based predictions (Fig. 9) to formulate event-based predictions. We considered an entire signal an avalanche if at least two consecutive windows (i.e. 15 s that is approximately the minimum duration of an avalanche signal) were positively predicted. In theory, this should eliminate the FNs in the tails of the actual signal and provide us with event-based detectors. For instance, in Fig. 12, we then would detect avalanches with this post-processing. Indeed, in Fig. E2, we observe a drastic reduction in missed avalanches for the three models, which achieved a high avalanche recall of 0.82 (seismic attributes), 0.88 (TAE) and 0.91% (SAE).~~

~~In closing, we reduced the missed avalanches by applying the presented post-processing steps. Furthermore, we observed that the models struggle to detect the starting and ending of an event (Fig. 12). We argued that this behaviour is reasonable and in part desirable as these parts of an event often resemble background noise. However, in most cases, the entire (unique) event is detected (Fig. E2). Thus, the models could, in turn, be considered to annotate large datasets, which in turn can be used to detect fine precursor signals.~~

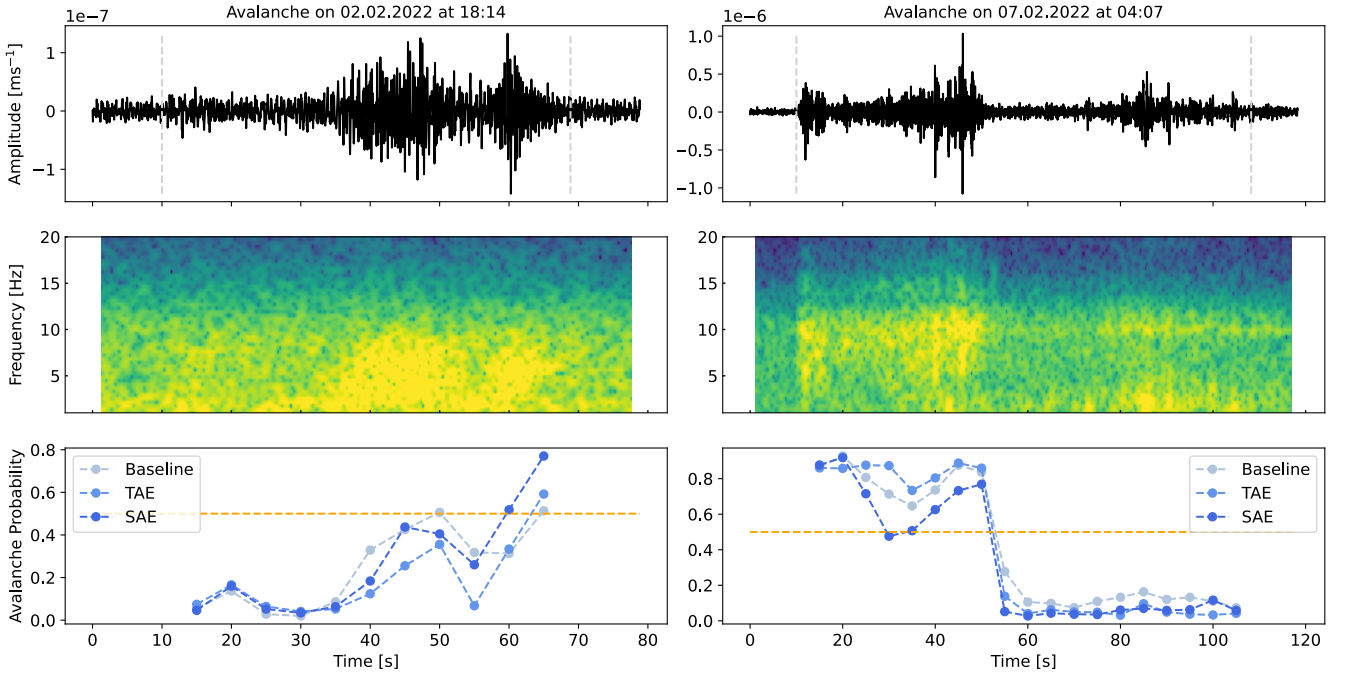


Figure 12. Signals-Waveform and spectrogram generated by avalanches triggered on 2 February 2022 at 18:14 (top-left) and 7 February 2022 at 04:07 (top-right) and-. The signals have been filtered from 1 to 10 Hz corresponding to the input frequency band of the models. At the bottom, a comparison of the sensor array-based averaged probabilities by-of each model over the entire length of the avalanche signals (bottom) signal is shown. The dashed-vertical-lines manually defined event onset and end are highlighted in dashed grey indicate-lines (upper plot), and the manual-cuts classification threshold 0.5 is in orange (lower plot).

6.3 False alarms

The second type of error, i.e. false positives (FPs) or false avalanche-alarms, showed greater variation in numbers across the three models. With 7.8% the seismic attributes produced the smallest portion 7.6% ($\pm 0.1\%$) (Fig. 8), the baseline produced the least amount of false positives. Predicting with the TAE features resulted in roughly three-times-twice as many false positives, with the SAE feature prediction in between. However, we observed a more-significant improvement in these errors when aggregating over the sensor array (Fig. 9). This suggested that the 5-recordings-of-a-specific-event, particularly noise events, can-show-strong-five recordings of some noise events showed substantial variations across the sensor array, which we filtered by this averaging. As the noise class is extremely-dominant-highly dominant (11135 windows) and, for instance, 10% FPs result in approximately 1000 FP samples (compared to 1335 avalanche samples), the avalanche precision of all three models is relatively low with 0.51 (Seismic-Attributes), 0.33-0.52 (± 0.00) (baseline), 0.33 (± 0.01) (TAE) and 0.45-0.44 (± 0.01) (SAE)

We-therefore-analyzed (Table. 1). We therefore analysed the origins of FPs to find potential tendencies or failure cases (Fig. 13). Most FPs, i.e. 76% (seismic-attributes), 65%-77% (baseline), 66% (TAE) and 71%-72% (SAE), were generated by

windows either carrying a non-zero avalanche score or belonging to an earthquake. Interestingly, the highest portion of false positives ~~falls-fell~~ to windows with an avalanche score of 0.5, i.e. 'one' expert ~~thinks-thought~~ it might be an avalanche. This ~~might-could~~ indicate that minor-size avalanches, or larger avalanches that flowed at the detection limits of the system, ~~are-not well-recognized-were not well recognised~~ by the experts yet by the models. Considering the earthquakes, the test fold ~~comprises comprised~~ a total of 3880 earthquake windows, of which only ~~135-132~~ (Seismic), ~~200-214~~ (TAE) and ~~158-146~~ (SAE) ~~are-were~~ misclassified as avalanches, i.e. ~~3.5%, 5.2%, 4.1%, 3.4%, 5.5% and 3.8%~~. ~~This underscored the earlier observation of good separation between avalanches and earthquakes in the latent spaces~~. The remaining approx. 30% FPs in all models originated from unknown sources.

~~Overall~~First, our results thus showed that using an array of sensors helped to reduce the number of false avalanche detections by averaging the ~~predictions-of-the-sensors~~single-sensor predictions. This can be viewed as model ensembling and is generally known to improve results (Mohammed and Kora, 2023). Second, including ~~features-from-the-frequency-domain~~frequency domain features tended to show fewer FPs. Third, an interesting and positive finding was that the models rarely confused earthquakes for avalanches (on average ~~4.3%-4.2%~~ of all earthquake windows). ~~Finally~~Moreover, the models ~~generate-generated~~ false alerts to a similar extent to previous studies in avalanche detection (~~e.g. Bessason et al., 2007; Rubin et al., 2012; Hammer et al., 2017; Thus, they might~~ (Bessason et al., 2007; Rubin et al., 2012; Hammer et al., 2017; Heck et al., 2018a). In pursuit of reducing the number of false alerts, one might consider including other types of recordings, e.g. infrasound data (Mayer et al., 2020). ~~In addition, considering longer seismic windows in future implementations might help reduce the number of false alerts. However, this would require more avalanche data to start with and to train models.~~

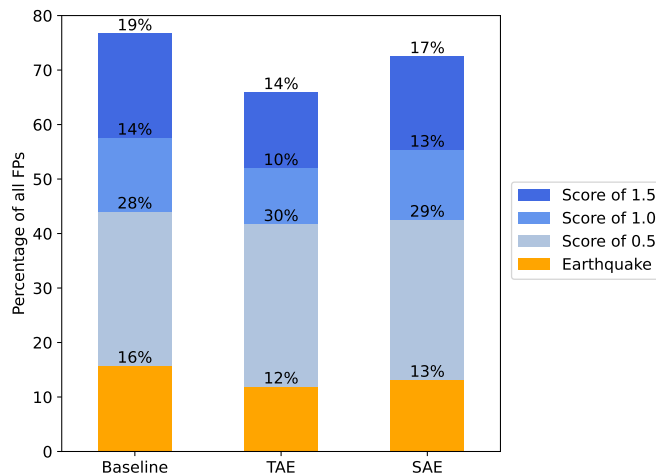


Figure 13. Analysis of origins for false positives as a percentage of the total amount of false positives per model.

6.4 Applicability to early warning and monitoring systems

In a potential early-warning operation, a practical model must detect all key parts of the signal, particularly the onset, to identify avalanche movement in its early stages and trigger an appropriate alert. The current classifiers, which often failed to capture these avalanche onsets, may not yet be suited for an suitable for this purpose. To improve early-warning application. However, the models, future studies should focus on examining avalanche onsets in more detail and developing specialised models that target these specific signal windows. For avalanche activity monitoring, false negatives at the start or end of each event are not very problematic. As long as the most energetic part of the signal is well detected, the overall avalanche activity can still be accurately recorded. However, when assessing overall avalanche activity, missed detections can be problematic. Therefore, we further post-processed the sensor array-based predictions (Fig. 9) to formulate event-based predictions (Sect. 5.3) and give a broader outlook. In theory, this should eliminate the FNs in the tails of the actual signal and provide us with event-based detectors. For instance, in Fig. 12, the models then would detect avalanches with this post-processing. And indeed, in Fig. E2, we observed a drastic reduction in missed avalanches for the three models, which achieved a high true positive rate of 81.4% ($\pm 1.1\%$) (baseline), 84.8% ($\pm 2.6\%$) (TAE) and 89.3% ($\pm 4.3\%$) (SAE).

In conclusion, we observed that the models struggled to detect the starting and ending of an event (Fig. 12). We argued that this behaviour was reasonable and, in part, desirable as these parts of an event often resemble background noise. However, in most cases, the entire (unique) event was detected (Fig. E2). Thus, the models could be implemented in an avalanche activity assessment process or to label-unverified-events-annotate large datasets in the future by being aware of the limitations and their limitations and the fact that they tend to produce too many avalanche detections. In pursuit of reducing the number of false alerts, one might consider including other types of recordings, e.g. infrasound data (Mayer et al., 2020). Also, implementing specialised-Another compelling prerequisite for avalanche activity monitoring in future studies is the transferability to other study sites. We would expect variations in the detection performance to arise from different configurations in the study site setup, sensor location and configuration, and the characteristics of the terrain and the avalanches. Therefore, also implementing specialised data augmentation techniques to increase the variety and number of the avalanche recordings, e.g. seismic data augmentation techniques (Zhu et al., 2020) or generative models (Wang et al., 2021), might help to make the classifiers more robust to changing environments and setups.

~~Analysis of origins for false positives as a percentage of the total amount of false positives per model.~~

6.5 Comparison to previous studies

To conclude, we put our results in a broader context by comparing them with previous studies. Provost et al. (2017) used a random forest model based on the 71 engineered seismic attributes to classify landslides. They reported stunning true positive rates of 94%, 93% and 94% for the rockfall, quake and earthquake class and a true negative rate of 92% for the noise class. The setting, however, is difficult to compare, as they-Therefore, we adopted their feature extraction approach as our baseline model, though our dataset differed significantly. They used non-windowed signals from an evenly distributed dataset comprising 418 rockfalls, 239 quakes, 407 earthquakes, and 395 noise events. Also, these event types typically generate signals with a higher signal-to-noise ratio than avalanches. Moreover, they included polarity and network attributes in the features, which for the classification turned out to be most important. Nevertheless-However, with 92% true negativesnegative rate, their model

is comparably prone to producing ~~false alerts~~ FPs (false alerts) as the models in this study ~~are. Also, for were. For~~ avalanche detection, several studies ~~also~~ presented the approach of ~~engineering features~~ feature engineering and subsequent classification (e.g. Bessason et al., 2007; Rubin et al., 2012; Hammer et al., 2017; Heck et al., 2018a) ~~(Bessason et al., 2007; Rubin et al., 2012; Hamme~~

725 . Rubin et al. (2012) used 10 engineered features in the frequency domain and tested 12 classification models, of which the decision stump classifier showed the highest overall accuracy of ~~93%~~ 0.93. However, the model showed a poor precision of ~~13.2%, hence, 0.13,~~ producing many more false alerts ~~. In contrast to our approach, they only considered avalanches verified on-camera images or manually picked events compared to our classifiers.~~ Heck et al. (2018a) used the same avalanche catalogue of 283 avalanches, of which 25 were confirmed and the rest were labelled by three experts. They implemented engineered tem-

730 poral and spectral features and used an HMM as a classifier. Similar to most previous studies, they also noted high values of FPs. Moreover, they observed improvements when aggregating ~~single sensor to~~ single sensor to sensor array-based predictions as we did in this study. In conclusion, based on the results of this and previous studies, we expect that an avalanche predictor based on solely seismic data will always produce false alarms, as it remains a difficult task to identify low-energy avalanche signals. Therefore, installing a secondary seismic detection system ~~in the proximity of the~~ near the avalanche path would be

735 advantageous in mitigating false alarms. ~~However, given the terrain characteristics at our study site (Fig. 1), where avalanches can occur along multiple paths, a single additional detection system may not be sufficient to detect all events.~~ Alternatively, integrating a complementary detection system ~~, such as like~~ an infrasound system ~~, could also could~~ be beneficial but less cost-effective.

~~In summary, the classification results met the performance of previous studies on avalanche detection. However, the core contribution of this study is two alternatives to extract features from seismic signals. We showed that the proposed encoder features are applicable for avalanche detection and compare well to engineered features. In particular, the learned feature extraction does not depend on prior expertise or knowledge and thus can be adapted easily to new settings, e.g. changing environments, without having to set some parametrisations of expert features. Moreover, with growing dataset size or larger datasets, it can improve over time. Finally, a future interesting comparison would be to evaluate the models on how they generalize to other test sites and settings.~~

740

745

7 Conclusions

We proposed two ~~unsupervised seismic feature extraction methods based on deep learning algorithms and a standard seismic attributes set~~ autoencoder-based feature extractors and retrieved a set of standard engineered seismic attributes (Provost et al., 2017) to train three random forest classifiers for avalanche detection. ~~The dataset was compiled~~ We compiled and annotated a dataset

750 from seismic avalanche data recorded during two winter seasons in Davos, Switzerland. While in earlier studies, seismic data classification mostly followed the approach of ~~extracting engineering~~ well-defined signal attributes to train classifiers, the proposed ~~deep learning models bridge~~ autoencoder models bridged the gap to a purely learned (automatic) pipeline.

Overall, the classifiers achieved macro-average f1-scores ranging from ~~0.70 to 0.78~~ 0.70 (± 0.01) to 0.78 (± 0.00) with avalanche recall values ranging from ~~0.68 to 0.71. Our results clearly show~~ 0.67 (± 0.00) to 0.71 (± 0.02). Moreover, the

755 ~~results clearly suggested~~ that including features from the frequency domain improves model performance. ~~As the~~ ~~Further, as~~
~~we observed that the models often misclassified the~~ onset and end of avalanche signals ~~were often misclassified as noise, due~~
~~to low signal-to-noise ratios, but not the most energetic signal parts,~~ we proposed a ~~simple~~ ~~straightforward~~ post-processing
~~step to reduce the missed avalanches by.~~ ~~By~~ imposing that at least two consecutive prediction windows, i.e. 15 s, ~~are positive~~
~~must be positive for an entire event to be positive, we drastically reduced the missed avalanches (false negatives).~~ This criterion
760 significantly ~~improves~~ ~~improved~~ the avalanche recall, ranging from ~~0.82 to 0.91~~ ~~0.81 (± 0.01) to 0.89 (± 0.04).~~ Lastly, contrary
to previous expectations, earthquakes ~~are~~ ~~were~~ rarely mistaken for avalanches at our study site.

Revisiting ~~our primary goal of comparing human-engineered with automatic feature extraction, there is no denying that the~~
~~standard seismic attributes classification is a robust approach. These predefined attributes~~ ~~the primary objective of advancing~~
~~and automating avalanche detection through seismic monitoring systems, we believe that both the baseline implementation~~
765 ~~and the novel autoencoder-based approaches for avalanche data analysis bear strong potential for future implementations. We~~
~~demonstrated that autoencoders can learn characteristic avalanche features from merely 84 seismic avalanche signals and are~~
~~performing equally on an avalanche detection task as expert-engineered features, which have been studied and applied for a~~
~~decade and optimized and tuned throughout over a decade, optimised and fine-tuned through~~ various studies. ~~The unsupervised~~
~~representation learning, in contrast, is a completely new approach to seismic avalanche data analysis. We have shown that it~~
770 ~~bears potential for future implementations and applications. Compared to engineered features, the learned features require no~~
~~prior expertise and, therefore, can easily be adapted to changing environments without having to set some parametrisations~~
~~of expert features. Also, they can improve with growing dataset size in future~~ ~~Therefore, we argue that as seismic datasets~~
~~grow, i.e. with more (diverse) avalanche signals available for learning, unsupervised representation learning methods could~~
~~potentially surpass the conventional feature engineering approach in the future. In conclusion, the proposed methods represent~~
775 ~~a step towards enhancing the throughput of avalanche detection systems and the automatic and continuous documentation of~~
~~events. Acquiring avalanche detections from such systems across different locations spanning wider areas has the potential to~~
~~improve and validate avalanche warning services. This, however, necessitates future work on investigating the scalability and~~
~~transferability of such methods to new environments.~~

Code and data availability. The code to reproduce the results and test the models is available on Zenodo (DOI: 10.5281/zenodo.15001358).
780 It is predominately written in Python using the PyTorch library (Paszke et al., 2019) for the autoencoder design, the random forest implemen-
tation of the Scikit-learn library (Pedregosa et al., 2011), the Pandas library (Wes McKinney, 2010) for handling the data and more standard
Python libraries such as NumPy (Harris et al., 2020) and SciPy (Virtanen et al., 2020). Additionally, the event catalogue with the raw seismic
waveforms is found on Zenodo (DOI: 10.5281/zenodo.14892926).

Appendix A: Dataset

785 ~~Table A1 depicts the date ranges in each fold and the respective number of events. We used folds 1, 2 and 3 for the cross-validation, i.e. the model development, and the test fold (number 4) to obtain the final results on unseen data. In general, we picked the folds consecutive in time, with a minor exception in the test fold, where we moved the 2nd of February from fold 3 to the test fold. This balanced the number of events in the folds more evenly.~~

Table A1. Detailed view on the applied splits of the dataset. For each fold, the table shows the number of respective events. The folds were picked consecutive in time, with a minor exception in the test fold, which included the 2nd of February from fold 3. This balanced the number of events in the folds more evenly.

Fold	Date	Avalanches	Earthquakes	Noise
1	13.01.2021 - 28.01.2021	17	39	196
2	29.01.2021 - 24.05.2021	16	39	100
3	10.01.2022 - 04.02.2022 (excl. 02.02.2022)	18	39	138
4	06.02.2022 - 17.05.2022 (incl. 02.02.2022)	33	66	211

Appendix B: Seismic attributes

790 The implemented engineered feature extraction ~~follows~~ followed the work of Provost et al. (2017) and Turner et al. (2021). In
contrast ~~to these, by defining our frequency band to~~, by using bandpass-filtered signals (1-10 Hz), we modified the attributes
correspondingly. Also, we discarded network ~~or~~ and polarity-related attributes as we developed ~~individual models per sensor,~~
~~and most of our sensors only contained one vertical component~~ models for a single-sensor setting, and our study site only
used one-component sensors. In summary, we extracted 22 waveform attributes (Table B1), 17 spectral (Table B2) and 18
795 spectrogram attributes (Table B3).

Table B1. Waveform attributes extracted from the 10 s seismic signals.

Number	Description
1 – 2	Ratio of the mean and median over the maximum of the normalised envelop signal
3	Ratio between ascending and descending time
4	Kurtosis of the raw signal
5	Kurtosis of the envelope
6	Skewness of the raw signal
7	Skewness of the envelope
8	Number of peaks in the autocorrelation function
9	Energy in the first third part of the autocorrelation function
10	Energy in the remaining part of the autocorrelation function
11	Ratio of 10 and 9
12 – 16	Energy of the signal filtered in [1, 3], [3, 6], [5, 7], [6, 9] and [8, 10] Hz
17 – 21	Kurtosis of the signal in [1, 3], [3, 6], [5, 7], [6, 9] and [8, 10] Hz
22	RMS between the decreasing part of the signal and $I(t) = Y_{max} - \frac{Y_{max}}{t_f - t_{max}}t$

Table B2. Spectral attributes extracted from the 10 s seismic signals. ~~The Nyquist frequency (NyF) is 100 Hz, i.e. half of the sampling rate.~~

Number	Description
23 – 24	Mean and Max of the FFT
25	Frequency at the maximum
26 – 27	Central frequency of the 1st quartile and 2nd quartile
28 – 29	Median and Variance of the normalized <u>normalised</u> FFT
30	Number of peaks
31	Number of peaks in the autocorrelation function
32	Mean value for the peaks
33–36 <u>33–37</u>	Energy in [1, 3], [3, 6], [5, 7], [6, 9] and [8, 10] Hz
37 <u>38</u>	Spectral centroid
38 <u>39</u>	Gyration radius
39 <u>40</u>	Spectral centroid width

Table B3. Spectrogram attributes extracted from the 10 s seismic signals.

40 <u>Number</u>	<u>Description</u>
41	Kurtosis of the maximum of all fast Fourier transforms (FFTs) over time
42	Kurtosis of the maximum of all FFTs as a function of time
43	Mean ratio between the maximum and the mean of all FFTs
44 — 46 <u>44</u>	Mean ratio between the maximum and the median of all FFTs
47 <u>45</u> — <u>47</u>	Ratio between 44 and 45 Number of peaks in the curve showing the temporal evolution of the FFTs maximum (45), mean (46) and median (47)
48	Ratio between 44 <u>45</u> and 46
49	<u>Ratio between 46 and 47</u>
50	Number of peaks in the curve of the temporal evolution of the FFTs central frequency
51	Number of peaks in the curve of the temporal evolution of the FFTs maximum frequency
<u>52</u>	Ratio between 50 and 51
52 53	Mean distance between the curves of the temporal evolution of the FFTs maximum frequency and mean frequency
54	Mean distance between the curves of the temporal evolution of the FFTs maximum frequency and median frequency
55	Mean distance between the 1st quartile and the median of all FFTs as a function of time
56	Mean distance between the 3rd quartile and the median of all FFTs as a function of time
57	Number of gaps in the signal Mean distance between the 3rd quartile and the 1st quartile of all FFTs as a function of time

Appendix C: Metrics

Besides the classifiers, we also evaluated the unsupervised clustering of the autoencoders in the latent space. Therefore, we used the classification and clustering metrics defined here. We used the reconstruction, classification and clustering metrics defined here to evaluate the autoencoders and the classifiers.

800 C1 Reconstruction metrics

Since autoencoders aim at reconstructing a given input signal y , they are trained using a reconstruction loss. In this study, we implemented the mean squared error loss (MSE), which is defined for a batch of size B as follows.

$$\text{MSE}(y, \hat{y}) = \frac{1}{B} \sum_{i=0}^{B-1} (y_i - \hat{y}_i)^2 \quad (\text{C1})$$

$\hat{y}$ is the autoencoder's predicted output, i.e., the reconstruction.

805 C2 Classification metrics

Various metrics exist to evaluate binary classification problems and are all. All are tailored to specific objectives. For instance, the precision is chosen when false alerts, i.e. false positives, are critical, the recall is sensitive to missed events, i.e. false negatives, and the f1-score combines both to form the harmonic mean of both as follows:

$$F1 = 2 * \frac{\text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \quad (\text{C2})$$

810 The macro average summarizes-summarises the per-class results within a single value. This value is an unweighted mean over the given classes and ensures that the values are not biased towards the most frequent class, i.e. noise majority class.

$$\text{Macro} - F1 = \frac{1}{K} * \sum_{k=0}^K F1_k, \text{ where } K = 2 \quad (\text{C3})$$

C3 Clustering metrics

A natural metric choice when evaluating different autoencoders is a autoencoders is the reconstruction loss, e.g. the mean squared error on which, on which we trained the autoencoders in this work were trained. In pursuit of good autoencoder features for later classification, however, we aimed to optimize-optimise the latent space representation. Since a good reconstruction does not necessarily imply a sufficient separation in latent space, we explored clustering metrics to compare the latent space distribution of different models with the given (expert) labels. We, therefore, implemented the silhouette score (Rousseeuw, 1987) and the Calinski-Harabasz index (Caliński and Harabasz, 1974). These scores are usually used to evaluate clustering algorithms that predict classes, e.g. k-means. The silhouette score computes the mean intra-cluster and inter-cluster distances per sample. For instance, given a sample, it calculates the distance to the cluster it is part of (a) and the distance to the nearest

cluster it is not part of (b) and forms the sample score:

$$S_i = \frac{b - a}{\max(a, b)} \quad (\text{C4})$$

825 After taking the mean over all samples, the silhouette score ranges from -1 (worst) to 1 (best). The Calinski–Harabasz index, or variance ratio criterion, on the other hand, is the ratio of between- and within-cluster dispersion. The between-cluster dispersion is defined as the weighted sum of squared Euclidean distances of the cluster centroids and the overall centroid (higher ~~-,better~~), and the ~~better~~). The within-cluster dispersion is given as the sum of the squared Euclidean distance of the samples and their respective cluster centre (lower better). Thus, a good clustering algorithm is supposed to yield a high Calinski–Harabasz score.

Appendix D: ~~Weighted-random-sampler~~Random forest optimisation

830 ~~Training a deep learning model on a dataset characterised by a severe class imbalance can bias the model predictions towards focusing solely on the most frequent class. The model can thus achieve high accuracy by accurately predicting this class. Therefore, it can fail to predict events in the minority class, which in our study is the most interesting one, i.e., avalanches. To mitigate this problem, we applied a weighted bootstrapping technique during the training of the autoencoders, a so-called weighted random sampler, as implemented in PyTorch (Paszke et al., 2019). Therefore, we assign the following weights to~~
835 ~~each sample of the avalanche (w_{av}) or noise class (w_{no}).~~

$$w_{av} = \frac{N_{no}}{N_{av}} \frac{P_{av}}{1 - P_{av}}; \quad w_{no} = 1$$

~~P_{av} is the user-defined portion of expected avalanches within each batch. Internally, these weights are rescaled and interpreted as probabilities.~~

Appendix E: ~~Random forest optimization~~

840 ~~The random forest models and their optimizations were implemented using the scikit-learn library (Pedregosa et al., 2011). Table D1 presents the three selected random forest models that were optimized on the same hyper-parameters grid and ranked based on the avalanche class f1-score.~~

Table D1. Selected ~~Random Forest Models~~random forest models

Parameter	<u>Baseline</u>	TAE	SAE
Number of Estimators	512	512	512
Maximum Depth	8	8	8
Maximum Number of Features	log2	sqrt	sqrt
Maximum Number of Samples	0.1	0.2	0.2
Class Weight	Balanced		
Criterion	Gini		
Bootstrap	True		

Appendix E: Autoencoder ~~optimization~~optimisation

Table E1. Selected ~~Autoencoders~~autoencoders

Parameter	<u>TAE</u>	<u>SAE</u>
Number of Weights	514'337	81'330
Feature Dimension	32	16
Hidden Dimension	[200, 20, 2]	[139, 78, 16]
Filters	[32, 64, 128]	-
Number of Layers	3	3
Kernel Size	20	-
Stride	10	-
Expected Avalanche Portion in Batch	0.6	0.5
Learning Rate	$1e^{-4}$	$1e^{-4}$
Batch Size	128	128

To select the autoencoder hyper-parameters, we opted ~~to first optimize~~ first to optimise model intrinsic parameters, e.g., such
845 as hidden dimensions or the number of layers, instead of training strategy parameters. This separation reduced the computation time.

The temporal autoencoder architecture ~~optimization~~ optimisation proved to be more sensitive and critical. First, we ~~optimized~~ optimised the kernel size, stride, number of filters, feature dimension and activation function. We observed that the kernel size and stride combinations of (20, 10) and (8, 4) showed the best clustering metrics. Moreover, concerning the non-linear activa-
850 tion, the leaky ReLU outperformed the Tanh function in most tests. Since the overall performance was not ~~entirely~~-satisfying, we tested the weighted random sampler (Sect. ~~??~~ 4.2.1 with 50% expected avalanches in each batch. This addition to the training strategy showed a considerable improvement for most models with kernel size 20 and stride 10. Although using a kernel size of 8 and stride of 4 tended to show better clustering metrics, the reconstruction of the signals was comparably poor. Based on these observations, we implemented a kernel size of 20 and stride of 10. Also, we found the feature dimension 32 better
855 suited than 64 or 16. Lastly, we selected ~~the number of filters as~~ 32, 64, and 128 ~~within the encoder~~ filters within each encoder layer. See Table E2 for a summary of the best 10 models of this process and Table E1 for the selected autoencoders. Having defined the intrinsic parameters, we tested different training strategies. In particular, we ~~optimized~~ optimised the learning rate, the batch size and the expected portion of avalanches ~~in a~~ per batch. This test led to values of $1e^{-4}$, 128 and 0.6 for the temporal autoencoder (Table E3). Finally, we found that augmenting the data by randomly shifting input samples by 0 to 1 s to the left
860 or right ~~helps~~ improved robustness.

Table E2. ~~The Table summarizes~~ Summary of the TAE hyper-parameter ~~optimization~~optimisation. ~~It shows only~~ Only the models for which all three metrics are ranked in the top ~~20. 20 are shown.~~ The best metrics ~~are highlighted in bold,~~ and the selected model ~~architecture is~~ are ~~highlighted in orange~~bold.

Weights	Filters in first Layer	Feature Dimension	Kernel Size	Stride	Expected Avalanche Portion	Augmentation	Silhouette Score	Calinski–Harabasz Index	MSE
109865	8	64	8	4	default	False	0.191	849.959	0.078
109865	8	64	8	4	0.5	False	0.024	357.494	0.073
109865	8	64	8	4	0.5	True	0.018	345.684	0.076
156945	16	32	20	10	0.5	False	0.033	374.174	0.06
156945	16	32	20	10	0.5	True	0.011	567.276	0.055
514337	32	32	20	10	default	True	-0.072	368.876	0.054
514337	32	32	20	10	0.5	False	0.061	333.174	0.061
514337 <u>514337</u>	32 <u>32</u>	32 <u>32</u>	20 <u>20</u>	10 <u>10</u>	0.5 <u>0.5</u>	True <u>True</u>	0.041	613.917	0.054
625185	32	64	20	10	0.5	False	-0.095	292.78	0.063
625185	32	64	20	10	0.5	True	-0.105	307.477	0.064

~~While optimizing~~

Table E3. Summary of the TAE learning rate and batch size optimisation. The best metrics and the selected model are highlighted in bold.

<u>batch</u>	<u>lr</u>	Silhouette Score	Calinski–Harabasz Index	<u>MSE</u>
<u>16</u>	<u>1e-05</u>	<u>-0.093</u>	<u>259.029</u>	<u>0.057</u>
<u>32</u>	<u>1e-05</u>	<u>-0.123</u>	<u>191.291</u>	<u>0.058</u>
<u>16</u>	<u>0.0001</u>	<u>0.019</u>	<u>435.901</u>	<u>0.053</u>
<u>32</u>	<u>0.0001</u>	<u>-0.006</u>	<u>460.183</u>	<u>0.055</u>
<u>64</u>	<u>0.0001</u>	<u>0.013</u>	<u>525.536</u>	<u>0.054</u>
<u>128</u>	<u>0.0001</u>	<u>0.051</u>	<u>696.984</u>	<u>0.054</u>
<u>16</u>	<u>0.001</u>	<u>0.039</u>	<u>352.668</u>	<u>0.051</u>
<u>32</u>	<u>0.001</u>	<u>0.011</u>	<u>373.105</u>	<u>0.053</u>
<u>64</u>	<u>0.001</u>	<u>0.034</u>	<u>381.183</u>	<u>0.052</u>
<u>128</u>	<u>0.001</u>	<u>0.007</u>	<u>347.923</u>	<u>0.052</u>

While optimising the spectral autoencoder, we found faster convergence. We started by testing combinations of the number of layers with hidden dimensions, feature dimensions and activation functions. ~~The Table E4 shows the~~ results for the best ~~8 models are shown in Table E4~~ eight models. We foremost noted that 16 features were optimal for this task. Moreover, we observed that the Tanh activation function was favourable in comparable architectures. Finally, we selected the model highlighted in ~~orange bold~~ since it showed a good compromise between the number of weights ~~of in~~ the network and performance. Following the same training strategy as for the temporal autoencoder, we ~~optimized~~ optimised the learning rate, the batch size and the expected portion of avalanches ~~in a per~~ batch. In contrast to the temporal autoencoder, we used an expected portion of 0.5 avalanches within a batch, a learning rate of $1e^{-4}$ and a batch size of 128 (Table E5).

Table E4. ~~The Table summarizes~~ Summary of the SAE hyper-parameter ~~optimization~~optimisation. ~~It shows only~~ Only the models for which all three metrics are ranked in the top ~~10~~. 10 are shown. A “default” hidden dimension ~~of 0.0~~ indicates that the dimensions in the layers of the encoder linearly decrease from the input dimension (200) to the feature dimension. The best clustering metrics ~~are highlighted in bold,~~ and the selected model ~~architecture is~~ are highlighted in ~~orange~~bold.

Weights	Layers	Feature Dimension	Activation Function	Hidden Dimensions	Silhouette Score	Calinski–Harabasz Index	MSE
47552	2	16	Tanh	0.0 <u>default</u>	0.227	1205.952	0.014
47552	2	16	leaky ReLU	0.0 <u>default</u>	0.218	1088.234	0.012
70880	2	64	Tanh	0.0 <u>default</u>	0.198	999.475	0.014
81330 <u>81330</u>	3 <u>3</u>	16 <u>16</u>	Tanh <u>Tanh</u>	0.0 <u>default</u>	0.224	1237.579	0.013
81330	3	16	leaky ReLU	0.0 <u>default</u>	0.217	1015.357	0.012
112432	4	16	Tanh	0.0 <u>default</u>	0.238	1111.027	0.013
112432	4	16	leaky ReLU	0.0 <u>default</u>	0.223	1013.013	0.012
146120	5	16	leaky ReLU	0.0 <u>default</u>	0.223	968.953	0.012

Table E5. Summary of the SAE learning rate and batch size optimisation. Only the top ten models are shown. The best clustering metrics and the selected model are highlighted in bold.

batch	lr	Silhouette Score	Calinski–Harabasz Index	MSE
16	1e-05	0.216	1295.275	0.015
32	1e-05	0.225	1337.226	0.015
128	1e-05	0.219	1339.248	0.015
16	0.0001	0.25	1062.001	0.009
32	0.0001	0.24	1131.993	0.009
64	0.0001	0.241	1283.843	0.013
128	0.0001	0.245	1391.865	0.014
16	0.001	0.268	872.865	0.009
32	0.001	0.272	831.938	0.009
64	0.001	0.261	852.354	0.009

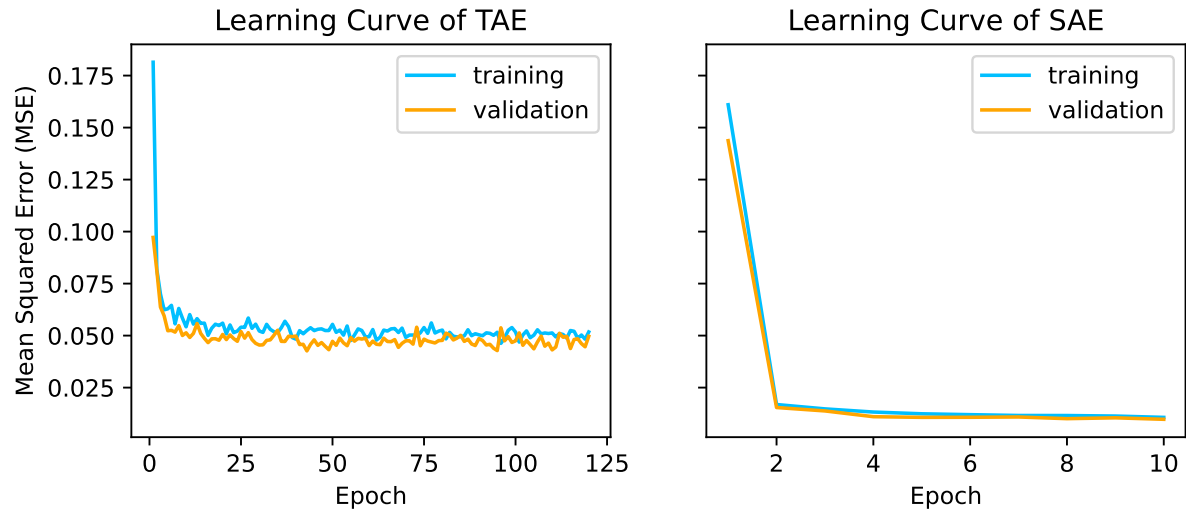


Figure E1. Learning curves of the TAE (left) and SAE (right). The blue line shows the mean squared error (MSE) loss on the training set, while the orange line shows the loss progression on the held-out test set (Fold 4 in Fig. 3).

E2 Event-based prediction results

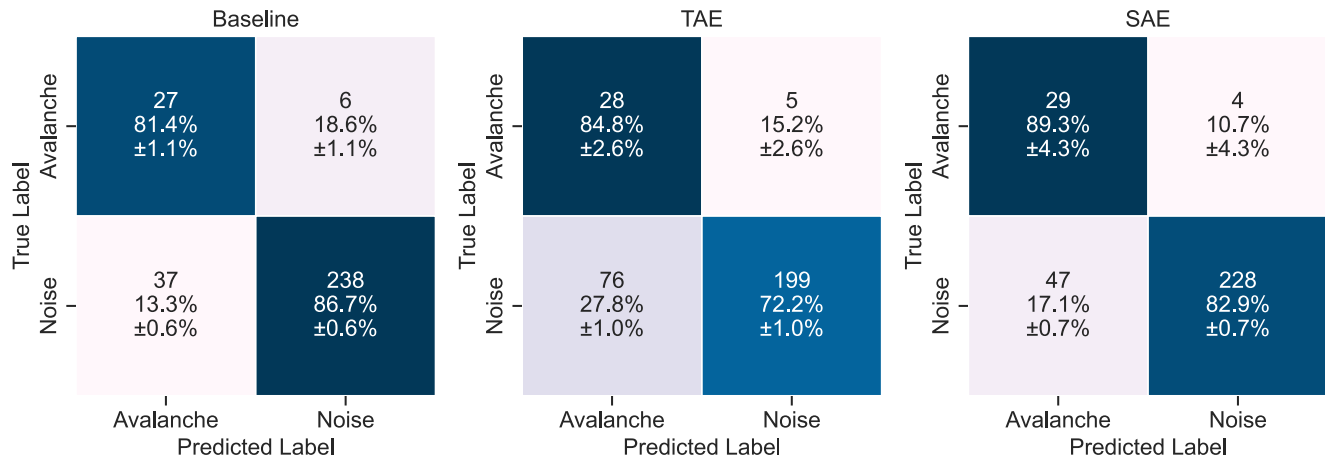


Figure E2. Confusion matrices of the results for the three feature sets aggregated on an event basis level. The rows indicate the true (expert) labels, while the columns provide the predicted labels of the random forest classifiers. The colours code the percentage numbers.

Table E6. Classification metrics on the (unseen) test fold data ~~set~~ comprising 33 avalanche and 275 noise samples after the aggregation over entire events of the ~~sensor~~ array-based predictions. Due to the strong class imbalance and bias towards the noise class, the weighted averages of the metrics are not shown.

Model	Class	Precision	Recall	F1 Support-
Baseline	Avalanche	0.42 ± 0.01	0.82 0.81 ± 0.01	0.55 33 0.56 ± 0.01
	Noise	0.98 0.97 ± 0.00	0.86 0.87 ± 0.01	0.92 275 ± 0.00
	Macro Avg	0.70 ± 0.01	0.84 ± 0.01	0.73 308 0.74 ± 0.01
	Accuracy			0.86 ± 0.01
TAE	Avalanche	0.27 ± 0.01	0.88 0.85 ± 0.03	0.41 33 ± 0.01
	Noise	0.98 ± 0.00	0.72 ± 0.01	0.83 275 ± 0.01
	Macro Avg	0.63 ± 0.01	0.8 0.79 ± 0.02	0.62 308 ± 0.01
	Accuracy			0.73 0.74 ± 0.01
SAE	Avalanche	0.41 0.39 ± 0.01	0.91 0.89 ± 0.04	0.56 33 0.54 ± 0.02
	Noise	0.99 0.98 ± 0.01	0.84 0.83 ± 0.01	0.91 275 0.90 ± 0.01
	Macro Avg	0.7 0.68 ± 0.01	0.87 0.86 ± 0.02	0.73 308 0.72 ± 0.01
	Accuracy			0.85 0.84 ± 0.01

Author contributions. AS: concept and design of the study, data collection and curation, model development, computational framework, analysis, writing, CP: concept and design of the study, data collection and curation, model development, computational framework, analysis, writing, reviewing, MV: concept and design of the study, model development, analysis, reviewing, CS: data collection and curation, computational framework, reviewing, AH: concept and design of the study, data collection and curation, analysis, reviewing

Competing interests. The authors declare that they have no conflict of interest.

Acknowledgements. This study was supported by a grant from the Innosuisse - Swiss Innovation Agency (37619.1 IP-ENG). We thank Prof. Fernando Perez-Cruz for the helpful discussions and numerous colleagues from SLF for help with fieldwork and maintaining the instrumentation. We thank Geoprevent, and in particular Lino Schmid and Johannes Gassner, for sharing the radar data with us and helping with the interpretation.

References

- EMSC-CSEM, <https://www.emsc-csem.org/#2>, accessed: May 2023, 2023.
- Swiss Seismological Service (SED), <http://www.seismo.ethz.ch/de/home/>, accessed: May 2023, 2023.
- Barandas, M., Folgado, D., Fernandes, L., Santos, S., Abreu, M., Bota, P., Liu, H., Schultz, T., and Gamboa, H.: TSFEL: Time Series Feature
885 Extraction Library, *SoftwareX*, 11, 100 456, <https://doi.org/10.1016/j.softx.2020.100456>, 2020.
- Bengio, Y., Courville, A., and Vincent, P.: Representation Learning: A Review and New Perspectives, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 35, 1798–1828, <https://doi.org/10.1109/TPAMI.2013.50>, 2013.
- Bessason, B., Eiríksson, G., Thórarinnsson, Ó., Thórarinnsson, A., and Einarsson, S.: Automatic detection of avalanches and debris flows by seismic methods, *J. Glaciol.*, 53, 461–472, <https://doi.org/https://doi.org/10.3189/002214307783258468>, 2007.
- 890 Biescas, B., Dufour, F., Furdada, G., Khazaradze, G., and Suriñach, E.: Frequency content evolution of snow avalanche seismic signals, *Surv. Geophys.*, 24, 447–464, <https://doi.org/https://doi.org/10.1023/B:GEOP.00000006076.38174.31>, 2003.
- Breiman, L.: Random Forests, <https://doi.org/https://doi.org/10.1023/A:1010933404324>, 2001.
- Breiman, L.: Classification and regression trees, Routledge, <https://doi.org/https://doi.org/10.1201/9781315139470>, 2017.
- Bründl, M., Etter, H.-J., Steiniger, M., Klingler, C., Rhyner, J., and Ammann, W. J.: IFKIS-a basis for managing avalanche risk in settlements
895 and on roads in Switzerland, *Natural Hazards and Earth System Sciences*, 4, 257–262, <https://doi.org/https://doi.org/10.5194/nhess-4-257-2004>, 2004.
- Bühler, Y., Bebi, P., Christen, M., Margreth, S., Stoffel, L., Stoffel, A., Marty, C., Schmucki, G., Caviezel, A., Kühne, R., et al.: Automated avalanche hazard indication mapping on a statewide scale, *Natural Hazards and Earth System Sciences*, 22, 1825–1843, <https://doi.org/10.5194/nhess-22-1825-2022>, 2022.
- 900 Caliński, T. and Harabasz, J.: A dendrite method for cluster analysis, *Communications in Statistics*, 3, 1–27, <https://doi.org/10.1080/03610927408827101>, 1974.
- Chmiel, M., Walter, F., Wenner, M., Zhang, Z., McArdell, B. W., and Hibert, C.: Machine Learning Improves Debris Flow Warning, *Geophysical Research Letters*, 48, <https://doi.org/10.1029/2020GL090874>, 2021.
- Clinton, J., Cauzzi, C., Fäh, D., Michel, C., Zweifel, P., Olivieri, M., Cua, G., Haslinger, F., and Giardini, D.: The Current State of Strong
905 Motion Monitoring in Switzerland, pp. 219–233, Springer Netherlands, https://doi.org/10.1007/978-94-007-0152-6_15, 2011.
- Dammeier, F., Moore, J. R., Hammer, C., Haslinger, F., and Loew, S.: Automatic detection of alpine rockslides in continuous seismic data using hidden Markov models, *Journal of Geophysical Research: Earth Surface*, 121, 351–371, <https://doi.org/10.1002/2015JF003647>, 2016.
- EAWS: European Avalanche Size Scale, <https://www.avalanches.org/standards/avalanche-size/>, [Online; last access 3-September-2024],
910 2021.
- Gu, S., Kelly, B., and Xiu, D.: Autoencoder asset pricing models, *Journal of Econometrics*, 222, 429–450, <https://doi.org/10.1016/j.jeconom.2020.07.009>, 2021.
- Hammer, C., Ohrnberger, M., and Fäh, D.: Classifying seismic waveforms from scratch: a case study in the alpine environment, *Geophysical Journal International*, 192, 425–439, <https://doi.org/10.1093/gji/ggs036>, 2013.
- 915 Hammer, C., Fäh, D., and Ohrnberger, M.: Automatic detection of wet-snow avalanche seismic signals, *Natural Hazards*, 86, 601–618, <https://doi.org/10.1007/s11069-016-2707-0>, 2017.

- Harris, C. R., Millman, K. J., van der Walt, S. J., Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., van Kerkwijk, M. H., Brett, M., Haldane, A., del Río, J. F., Wiebe, M., Peterson, P., Gérard-Marchant, P., Sheppard, K., Reddy, T., Weckesser, W., Abbasi, H., Gohlke, C., and Oliphant, T. E.: Array programming with NumPy, *Nature*, 585, 357–362, <https://doi.org/10.1038/s41586-020-2649-2>, 2020.
- 920 Heck, M., Hammer, C., Herwijnen, A. V., Schweizer, J., and Fäh, D.: Automatic detection of snow avalanches in continuous seismic data using hidden Markov models, *Natural Hazards and Earth System Sciences*, 18, 383–396, <https://doi.org/10.5194/nhess-18-383-2018>, 2018a.
- Heck, M., Hobiger, M., van Herwijnen, A., Schweizer, J., and Fäh, D.: Localization of seismic events produced by avalanches using multiple signal classification, *Geophysical Journal International*, 216, 201–217, <https://doi.org/10.1093/gji/ggy394>, 2018b.
- 925 Heck, M., van Herwijnen, A., Hammer, C., Hobiger, M., Schweizer, J., and Fäh, D.: Automatic detection of avalanches using combining array classification and localization, *Earth Surface Dynamics*, 7, 491–503, <https://doi.org/10.5194/esurf-7-491-2019>, 2019.
- Hendrick, M., Techel, F., Volpi, M., Olevski, T., Pérez-Guillén, C., van Herwijnen, A., and Schweizer, J.: Automated prediction of wet-snow avalanche activity in the Swiss Alps, *Journal of Glaciology*, pp. 1–14, <https://doi.org/10.1017/jog.2023.24>, 2023.
- 930 Hibert, C., Mangeney, A., Grandjean, G., Baillard, C., Rivet, D., Shapiro, N. M., Satriano, C., Maggi, A., Boissier, P., Ferrazzini, V., et al.: Automated identification, location, and volume estimation of rockfalls at Piton de la Fournaise volcano, *Journal of Geophysical Research: Earth Surface*, 119, 1082–1105, <https://doi.org/10.1002/2013JF002970>, 2014.
- Hinton, G. E. and Salakhutdinov, R. R.: Reducing the Dimensionality of Data with Neural Networks, *Science*, 313, 504–507, <https://doi.org/10.1126/science.1127647>, 2006.
- 935 Hochreiter, S. and Schmidhuber, J.: Long Short-Term Memory, *Neural Comput.*, 9, 1735–1780, <https://doi.org/10.1162/neco.1997.9.8.1735>, 1997.
- Ioffe, S. and Szegedy, C.: Batch Normalization: Accelerating Deep Network Training by Reducing Internal Covariate Shift, *CoRR*, abs/1502.03167, <https://doi.org/https://doi.org/10.48550/arXiv.1502.03167>, 2015.
- Ismail Fawaz, H., Forestier, G., Weber, J., Idoumghar, L., and Muller, P.-A.: Deep learning for time series classification: a review, *Data Mining and Knowledge Discovery*, 33, 917–963, <https://doi.org/10.1007/s10618-019-00619-1>, 2019.
- 940 Kingma, D. P. and Ba, J.: Adam: A Method for Stochastic Optimization, <https://doi.org/https://doi.org/10.48550/arXiv.1412.6980>, 2014.
- Kiranyaz, S., Avci, O., Abdeljaber, O., Ince, T., Gabbouj, M., and Inman, D. J.: 1D convolutional neural networks and applications: A survey, *Mechanical Systems and Signal Processing*, 151, 107 398, <https://doi.org/https://doi.org/10.1016/j.ymssp.2020.107398>, 2021.
- Kong, Q., Chiang, A., Aguiar, A. C., Fernández-Godino, M. G., Myers, S. C., and Lucas, D. D.: Deep convolutional au-
toencoders as generic feature extractors in seismological applications, *Artificial Intelligence in Geosciences*, 2, 96–106, <https://doi.org/https://doi.org/10.1016/j.aiig.2021.12.002>, 2021.
- 945 Lacroix, P., Grasso, J. R., Roulle, J., Giraud, G., Goetz, D., Morin, S., and Helmstetter, A.: Monitoring of snow avalanches using a seismic array: Location, speed estimation, and relationships to meteorological variables, *J. Geophys. Res. Earth Surface*, 117, 1–15, <https://doi.org/10.1029/2011JF002106>, 2012.
- 950 Leprettre, B., Navarre, J.-P., Taillefer, A., Danielou, Y., organisms Panel, J. T. M., and Touvier, F.: Reliable Estimation of Avalanche Activity Using Seismic Methods, <https://api.semanticscholar.org/CorpusID:54986472>, 1996.
- Li, Z., Meier, M. A., Hauksson, E., Zhan, Z., and Andrews, J.: Machine Learning Seismic Wave Discrimination: Application to Earthquake Early Warning, *Geophysical Research Letters*, 45, 4773–4779, <https://doi.org/10.1029/2018GL077870>, 2018.

- Lima, F. T. and Souza, V. M.: A Large Comparison of Normalization Methods on Time Series, *Big Data Research*, 34, 100407, <https://doi.org/https://doi.org/10.1016/j.bdr.2023.100407>, 2023.
- Lin, G. W., Hung, C., Chien, Y. F. C., Chu, C. R., Liu, C. H., Chang, C. H., and Chen, H.: Towards automatic landslide-quake identification using a random forest classifier, *Applied Sciences (Switzerland)*, 10, <https://doi.org/10.3390/app10113670>, 2020.
- Långkvist, M., Karlsson, L., and Loutfi, A.: A review of unsupervised feature learning and deep learning for time-series modeling, *Pattern Recognition Letters*, 42, 11–24, <https://doi.org/https://doi.org/10.1016/j.patrec.2014.01.008>, 2014.
- Marchetti, E., Ripepe, M., Ulivieri, G., and Kogelnig, A.: Infrasound array criteria for automatic detection and front velocity estimation of snow avalanches: towards a real-time early-warning system, *Natural Hazards and Earth System Sciences*, 15, 2545–2555, <https://doi.org/10.5194/nhess-15-2545-2015>, 2015.
- Mayer, S., van Herwijnen, A., Ulivieri, G., and Schweizer, J.: Evaluating the performance of an operational infrasound avalanche detection system at three locations in the Swiss Alps during two winter seasons, *Cold regions science and technology*, 173, 102962, <https://doi.org/https://doi.org/10.1016/j.coldregions.2019.102962>, 2020.
- Mayer, S., Techel, F., Schweizer, J., and van Herwijnen, A.: Prediction of natural dry-snow avalanche activity using physics-based snowpack simulations, *Natural hazards and earth system sciences*, 23, 3445–3465, <https://doi.org/10.5194/egusphere-2023-646>, 2023.
- McClung, D. and Schaerer, P. A.: *The avalanche handbook*, The Mountaineers Books, 2006.
- Meier, L., Jacquemart, M., Blattmann, B., and Arnold, B.: Real-time avalanche detection with long-range, wide-angle radars for road safety in Zermatt, Switzerland, in: *Proceedings of the International Snow Science Workshop*, Breckenridge, CO, pp. 304–308, <https://api.semanticscholar.org/CorpusID:59408658>, 2016.
- Mohammed, A. and Kora, R.: A comprehensive review on ensemble deep learning: Opportunities and challenges, *Journal of King Saud University - Computer and Information Sciences*, 35, 757–774, <https://doi.org/https://doi.org/10.1016/j.jksuci.2023.01.014>, 2023.
- Mousavi, S. M. and Beroza, G. C.: Deep-learning seismology, *Science*, 377, eabm4470, <https://doi.org/10.1126/science.abm4470>, 2022.
- Mousavi, S. M., Zhu, W., Ellsworth, W., and Beroza, G.: Unsupervised Clustering of Seismic Signals Using Deep Convolutional Autoencoders, *IEEE Geoscience and Remote Sensing Letters*, 16, 1693–1697, <https://doi.org/10.1109/LGRS.2019.2909218>, 2019.
- Paszke, A., Gross, S., Massa, F., Lerer, A., Bradbury, J., Chanan, G., Killeen, T., Lin, Z., Gimelshein, N., Antiga, L., Desmaison, A., Köpf, A., Yang, E., DeVito, Z., Raison, M., Tejani, A., Chilamkurthy, S., Steiner, B., Fang, L., Bai, J., and Chintala, S.: PyTorch: An Imperative Style, High-Performance Deep Learning Library, <https://doi.org/https://doi.org/10.48550/arXiv.1912.01703>, 2019.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., and Duchesnay, E.: Scikit-learn: Machine Learning in Python, *Journal of Machine Learning Research*, 12, 2825–2830, <https://doi.org/https://doi.org/10.48550/arXiv.1201.0490>, 2011.
- Pérez-Guillén, C., Sovilla, B., Suriñach, E., Tapia, M., and Köhler, A.: Deducing avalanche size and flow regimes from seismic measurements, *Cold Regions Science and Technology*, 121, 25–41, <https://doi.org/https://doi.org/10.1016/j.coldregions.2015.10.004>, 2016.
- Pérez-Guillén, C., Tsunematsu, K., Nishimura, K., and Issler, D.: Seismic location and tracking of snow avalanches and slush flows on Mt. Fuji, Japan, *Earth Surface Dynamics*, 7, 989–1007, <https://doi.org/10.5194/esurf-7-989-2019>, 2019.
- Provost, F., Hibert, C., and Malet, J. P.: Automatic classification of endogenous landslide seismicity using the Random Forest supervised classifier, *Geophysical Research Letters*, 44, 113–120, <https://doi.org/10.1002/2016GL070709>, 2017.
- Rakthanmanon, T., Campana, B., Mueen, A., Batista, G., Westover, B., Zhu, Q., Zakaria, J., and Keogh, E.: Searching and mining trillions of time series subsequences under dynamic time warping, in: *Proceedings of the 18th ACM SIGKDD International Conference*

- on Knowledge Discovery and Data Mining, KDD '12, p. 262–270, Association for Computing Machinery, New York, NY, USA, <https://doi.org/10.1145/2339530.2339576>, 2012.
- Rousseeuw, P. J.: Silhouettes: A graphical aid to the interpretation and validation of cluster analysis, *Journal of Computational and Applied Mathematics*, 20, 53–65, [https://doi.org/https://doi.org/10.1016/0377-0427\(87\)90125-7](https://doi.org/https://doi.org/10.1016/0377-0427(87)90125-7), 1987.
- 995 Rubin, M. J., Camp, T., Herwijnen, A. V., and Schweizer, J.: Automatically detecting avalanche events in passive seismic data, vol. 1, pp. 13–20, <https://doi.org/10.1109/ICMLA.2012.12>, 2012.
- Rumelhart, D. E., Hinton, G. E., and Williams, R. J.: Learning internal representations by error propagation, p. 318–362, MIT Press, Cambridge, MA, USA, 1986.
- Schimmel, A., Hübl, J., Koschuch, R., and Reiweger, I.: Automatic detection of avalanches: evaluation of three different approaches, *Natural Hazards*, 87, <https://doi.org/10.1007/s11069-017-2754-1>, 2017.
- 1000 Schweizer, J., Mitterer, C., Techel, F., Stoffel, A., and Reuter, B.: On the relation between avalanche occurrence and avalanche danger level, *The Cryosphere*, 14, 737–750, <https://doi.org/10.5194/tc-14-737-2020>, 2020.
- Seydoux, L., Balestrieri, R., Poli, P., Hoop, M. d., Campillo, M., and Baraniuk, R.: Clustering earthquake signals and background noises in continuous seismic data with unsupervised deep learning, *Nature Communications*, 11, <https://doi.org/10.1038/s41467-020-17841-x>, 2020.
- 1005 Sielenou, P. D., Viallon-Galinier, L., Hagenmuller, P., Naveau, P., Morin, S., Dumont, M., Verfaillie, D., and Eckert, N.: Combining random forests and class-balancing to discriminate between three classes of avalanche activity in the French Alps, *Cold Regions Science and Technology*, 187, 103 276, <https://doi.org/10.1016/j.coldregions.2021.103276>, 2021.
- Sola, J. and Sevilla, J.: Importance of input data normalization for the application of neural networks to complex industrial problems, *IEEE Transactions on Nuclear Science*, 44, 1464–1468, <https://doi.org/10.1109/23.589532>, 1997.
- 1010 Suriñach, E., Furdada, G., Sabot, F., Biescas, B., and Vilaplana, J.: On the characterization of seismic signals generated by snow avalanches for monitoring purposes, *Ann. Glaciol.*, 32, 268–274, <https://doi.org/10.3189/172756401781819634>, 2001.
- Suriñach, E., Vilajosana, I., Khazaradze, G., Biescas, B., Furdada, G., and Vilaplana, J.: Seismic detection and characterization of landslides and other mass movements, *Nat. Hazards Earth Syst. Sci.*, 5, 791–798, <https://doi.org/10.5194/nhess-5-791-2005>, 2005.
- 1015 Techel, F., Jarry, F., Kronthaler, G., Mitterer, S., Nairz, P., Pavšek, M., Valt, M., and Darms, G.: Avalanche fatalities in the European Alps: long-term trends and statistics, *Geographica Helvetica*, 71, 147–159, <https://doi.org/10.5194/gh-71-147-2016>, 2016.
- Turner, R. J., Latto, R. B., and Reading, A. M.: An ObsPy Library for Event Detection and Seismic Attribute Calculation: Preparing Waveforms for Automated Analysis, *Journal of Open Research Software*, <https://doi.org/10.5334/jors.365>, 2021.
- van Herwijnen, A. and Schweizer, J.: Monitoring avalanche activity using a seismic sensor, *Cold Reg. Sci. Tech.*, 69, 165–176, <https://doi.org/10.1016/j.coldregions.2011.06.008>, 2011.
- 1020 van Herwijnen, A., Heck, M., and Schweizer, J.: Forecasting snow avalanches using avalanche activity data obtained through seismic monitoring, *Cold Regions Science and Technology*, 132, 68–80, <https://doi.org/https://doi.org/10.1016/j.coldregions.2016.09.014>, 2016.
- van Herwijnen, A., Heck, M., Richter, B., Sovilla, B., and Techel, F.: When do avalanches release: investigating time scales in avalanche formation, in: *International snow science workshop proceedings 2018, ISSW, Innsbruck, Austria*, <https://www.dora.lib4ri.ch/wsl/islandora/object/wsl:18935>, 2018.
- 1025 Vilajosana, I., Khazaradze, G., Suriñach, E., Lied, E., and Kristensen, K.: Snow avalanche speed determination using seismic methods, *Cold Reg. Sci. Tech.*, 49, 2–10, <https://doi.org/10.1016/j.coldregions.2006.09.007>, 2007.

- Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., Carey, C. J., Polat, İ., Feng, Y., Moore, E. W., VanderPlas, J., Laxalde, D., Perktold, J., Cimrman, R., Henriksen, I., Quintero, E. A., Harris, C. R., Archibald, A. M., Ribeiro, A. H., Pedregosa, F., van Mulbregt, P., and SciPy 1.0 Contributors: SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python, *Nature Methods*, 17, 261–272, <https://doi.org/10.1038/s41592-019-0686-2>, 2020.
- 1030 Wang, T., Trugman, D., and Lin, Y.: SeismoGen: Seismic Waveform Synthesis Using GAN With Application to Seismic Data Augmentation, *Journal of Geophysical Research: Solid Earth*, 126, e2020JB020077, <https://doi.org/https://doi.org/10.1029/2020JB020077>, e2020JB020077 2020JB020077, 2021.
- 1035 Wenner, M., Hibert, C., Herwijnen, A. V., Meier, L., and Walter, F.: Near-real-time automated classification of seismic signals of slope failures with continuous random forests, *Natural Hazards and Earth System Sciences*, 21, 339–361, <https://doi.org/10.5194/nhess-21-339-2021>, 2021.
- Wes McKinney: Data Structures for Statistical Computing in Python, in: *Proceedings of the 9th Python in Science Conference*, edited by Stéfan van der Walt and Jarrod Millman, pp. 56 – 61, <https://doi.org/10.25080/Majora-92bf1922-00a>, 2010.
- 1040 Xu, B., Wang, N., Chen, T., and Li, M.: Empirical Evaluation of Rectified Activations in Convolutional Network, <https://doi.org/10.48550/arXiv.1505.00853>, 2015.
- Xugang, L., Yu, T., Shigeki, M., and Chiori, H.: Speech Enhancement Based on Deep Denoising Autoencoder, <https://doi.org/https://doi.org/10.48550/arXiv.2001.01538>, 2013.
- 1045 Zhu, W., Mousavi, S. M., and Beroza, G. C.: Chapter Four - Seismic signal augmentation to improve generalization of deep neural networks, in: *Machine Learning in Geosciences*, edited by Moseley, B. and Krischer, L., vol. 61 of *Advances in Geophysics*, pp. 151–177, Elsevier, <https://doi.org/https://doi.org/10.1016/bs.agph.2020.07.003>, 2020.