

Towards robust fracture mapping: benchmarking automatic fracture mapping in 2D outcrop imagery

Ayoub Fatihi¹, Jefter Caldeira¹, Tom Beucler^{2,3}, Samuel T. Thiele⁴, and Anindita Samsu¹

¹Institute of Earth Sciences, University of Lausanne, 1015 Lausanne, Switzerland

²Institute of Earth Surface Dynamics, University of Lausanne, 1015 Lausanne, Switzerland

³Expertise Center for Climate Extremes, University of Lausanne, 1015 Lausanne, Switzerland

⁴Helmholtz Institute Freiberg, Helmholtz-Zentrum Dresden-Rossendorf, Chemnitz Str. 40, 09599 Freiberg, Germany

Correspondence: Ayoub Fatihi (ayoub.fatihi@unil.ch)

Abstract. ~~Extracting consistent and accurate~~ Analysis of fracture geometries, orientation, distribution, and connectivity is commonly conducted to characterise the mechanical and hydraulic properties of fractured rock mass and to interpret their deformation history. These studies increasingly leverage high-resolution drone imagery (e.g., orthomosaics or orthophotographs). However, consistently and accurately extracting fracture traces from ~~large volumes of high-resolution imagery~~ these large datasets remains a persistent challenge ~~in structural analysis. We~~. In this contribution, we present a harmonised benchmarking dataset, FraXet, for pixel-wise fracture segmentation in ~~combined~~ high-resolution RGB ~~orthophotos~~ orthophotographs and digital elevation models (DEMs) (~~ground sampling distance ranging from approximately 0.5 mm to 32 mm~~). FraXet curates images from three publicly available datasets, totalling ~~8953~~ 8,953 256×256 RGB+DEM patches spanning diverse lithologies and imaging conditions. ~~We use this dataset~~ (~~ground sampling distance, illumination, etc.~~) to systematically assess ~~traditional~~ the effectiveness of conventional image-processing ~~filters~~ approaches for fracture extraction (Canny, Sobel, Gabor, Sato, and phase congruency) and two deep-learning (DL) models ~~(U-Net and SegFormer, for per-pixel fracture detection. Quantitative comparison)~~. Quantitative comparisons using image-quality (e.g., MSE, PSNR), segmentation (e.g., Precision, Recall, F1, IoU) ~~and proposed similarity FraeSim metrics suggest~~, and new task-specific error metrics show that the deep models substantially outperform classical filters ($F1 \approx 0.3$ -0.5 vs ≤ 0.29) ~~, giving and produce~~ smoother, more continuous fracture traces ~~with reduced noise~~. Training on the combined dataset (M_all) improves cross-site generalisation ~~relative compared~~ to models trained on ~~the~~ individual sub-datasets. ~~Challenges remain in handling annotation misalignments, illumination artifacts, and thin traces. More importantly, probability used in this study. Probability~~ maps derived from the DL approaches enable confidence-based triage and visualisation of model uncertainty. This work ~~thus~~ establishes a unified benchmark, curated dataset, and reproducible baseline ~~to support further development of robust automated tools for fracture detection~~ for developing robust automated fracture-detection tools.

1 Introduction

Fractures, formed through brittle deformation when stress exceeds rock strength, are important structures that influence both rock stability and fluid flow (Twiss and Moores, 2006). They can reduce cohesion, posing risks in seismically active areas and engineered settings (Cappa et al., 2018). They can also enhance permeability—especially in low-porosity rocks like limestone—by creating pathways for fluid movement (Aydin, 2000). Fractures are therefore key in exploring for and extracting hydrocarbons and geothermal energy, as well as assessing sites for nuclear waste storage.

Researchers often use outcrop analogues to better understand subsurface fracture geometries (Smeraglia et al., 2021). Mapping natural fractures in outcrops is fundamental to studies of brittle tectonics, assessments of rock stability, and predictions of subsurface fluid flow pathways for geo-energy applications (Aydin, 2000; Berkowitz, 2002; Smeraglia et al., 2021). Recent advances in remote sensing and the uptake of uncrewed aerial vehicle (UAV) photogrammetry by the structural geology community have transformed how geological fractures in outcrops are documented. Drone-based imaging now allows the creation of fracture data that are collected (Bemis et al., 2014). UAV photogrammetry enables the generation of high-resolution, geo-referenced orthophotos—orthophotographs—that capture rock surfaces in remarkable detail. These digital data enable precise mapping, measurement, and analysis of structural features like orientation and spacing, complementing traditional, including outcrops that are difficult or unsafe to reach (Villarreal et al., 2022). The resulting orthophotographs enable precise tracing of thousands of fractures on a single outcrop, which can then be analysed for orientation, length, distribution, and connectivity, complementing direct field observations and providing access to outcrops that are difficult or unsafe to reach. However, while data acquisition measurements (Palamakumbura et al., 2020).

A fracture trace is the linear to curvilinear intersection of a fracture with an exposed rock surface, commonly mapped as a piecewise-linear polyline (Potts, 2022; Bonnet et al., 2001; Sanderson and Nixon, 2015). In RGB orthophotographs it appears as a dark, high-contrast linear feature produced by differential weathering and illumination (Vasuki et al., 2014; Thiele et al., 2017b; Ren et al., 2017), whereas in the DEM it shows as a subtle linear relief or step (Koike et al., 1995; Raghavan et al., 1993). Its apparent geometry therefore depends on the projection of the discontinuity: surface intersection onto the orthorectification plane (Potts, 2022; Bemis et al., 2014).

While the acquisition of high-resolution orthophotographs has become faster and easier, the interpretation of manual and semi-automated interpretation of fractures from these images remains time-consuming and subjective. The visibility of fractures depends on lighting, surface weathering, vegetation cover, and image resolution, and the process of manual or semi-automated mapping is often influenced by interpreter bias (Bond et al., 2007; Scheiber et al., 2015; Peacock et al., 2019; Andrews et al., 2019). Furthermore, mapping fails to fully leverage the available data (Vasuki et al., 2014). For example, mapping fractures within a 10 × m by 10 m area with using an orthophotograph at 1 cm resolution can still take over a pixel resolution can take more than half an hour, even with semi-automated tools (Thiele et al., 2017b). These challenges highlight the growing need for faster, more objective, and more reproducible fracture mapping methods. Extrapolating from this, manually mapping an entire 200 m by 50 m outcrop requires roughly 55 hours of dedicated interpreter time; a constraint that becomes still more limiting for regional-scale studies involving multiple outcrops. Even approaches described as automatic often still require substantial

55 user intervention for parameter tuning, quality control, and post-processing, resulting in processing times of several hours per outcrop (Weismüller et al., 2020).

~~With the rapid progress of computer vision (CV)~~ Manual and semi-automated fracture tracing are also subject to various biases related to image quality (e.g., lighting, surface weathering, vegetation cover, and image resolution) and to the experience and preferences of the interpreter (Bond et al., 2007; Scheiber et al., 2015; Peacock et al., 2019; Andrews et al., 2019). As a
60 result, fracture maps produced by different interpreters, or even by the same interpreter at different times, may vary in fracture identification, segmentation, and connectivity (Bond et al., 2007; Scheiber et al., 2015). These inconsistencies can propagate into subsequent quantitative analyses, affecting the interpretation of fracture network properties and reducing the reproducibility of geological studies (Prabhakaran et al., 2019).

These challenges motivate faster, more reproducible fracture-tracing methods. Rapid advances in computer vision and ma-
65 chine learning (ML) ~~have made~~ automated fracture detection ~~has become an increasingly appealing alternative an appealing~~ alternative to manual and semi-automated methods (Thiele et al., 2017b; Mattéo et al., 2021; Chudasama et al., 2024). Various techniques have been developed ~~, ranging for~~ fracture detection from orthophotographs (including satellite imagery), digital elevation models (DEMs), and digital terrain models (DTMs). These techniques range from classical image processing meth-
ods—including, including colorimetry-based segmentation, edge detection, phase symmetry and phase congruency, and Hough
70 transforms, ~~and color-based segmentation~~—to more advanced deep learning (DL) approaches (Table 1). Each method ~~offers different benefits depending~~ has benefits and limitations that depend on data type and ~~imaging conditions. Among these, deep learning has emerged as particularly promising, because it can automatically learn spatial features~~ image quality.

Among the classical approaches, colorimetry-based segmentation exploits the contrast between fractures and host rock but is highly sensitive to lighting and shadowing (Ren and Malik, 2003; Vasuki et al., 2017). DEM and DTM-based feature extraction
75 methods, such as segment tracing and directional detection algorithms (Koike et al., 1995; Raghavan et al., 1993, 1995), can reveal terrain-related structures but depend heavily on the resolution and quality of the underlying elevation data and are computationally demanding. Edge-detection filters (e.g., Canny, Sobel, Laplacian of Gaussian) are fast and well-established but are sensitive to noise and provide no contextual information about what they detect (Masoud and Koike, 2011; Soto-Pinto et al., 2013; Adiri
, Phase symmetry and phase congruency methods improve robustness to variable illumination (Kovesi, 1999, 2000; Vasuki et al., 2014)
80 , though at greater computational cost, while the Hough transform is effective for identifying straight linear features but is intrinsically limited to linear geometries and prone to false positives (Duda and Hart, 1972). Wavelet and multi-scale transforms (Mallat and Hwang, 1992; Candès and Guo, 2002; Candès and Donoho, 2005; Do and Vetterli, 2005; Prabhakaran et al., 2019) and dedicated line-segment detection and tracking algorithms (Rahnama and Gloaguen, 2014; Masoud and Koike, 2017; Saint Jean Patrick
improve the handling of curvilinear and multi-scale features, but classical wavelets lack directionality. Their more advanced
85 variants are complex to implement, and line-tracking approaches remain sensitive to parameter tuning and prone to fragmenting continuous lineaments. A common shortcoming is reliance on hand-crafted rules and fixed-scale filters, which limits robustness to variable image quality (lighting, weathering, vegetation) and resolution typical of natural outcrop imagery, and constrains generalisation across datasets (Aghaee et al., 2021).

Deep learning and machine learning approaches form a distinct, rapidly growing category. These include convolutional
90 neural network architectures such as U-Net for pixel-wise fracture segmentation (Chudasama et al., 2024), incrementally
trained networks designed to adapt to new geological settings such as the Geological Adaptive Incremental Network (Zhang et al., 2024)
, hybrid approaches that combine DL-based feature extraction with classical line detection (Oliveira et al., 2019), multi-feature
DL integration strategies that combine several input modalities (Zhang et al., 2024), and combinations of graph attention
networks with fast line detection algorithms. DL methods have also been applied directly to 3D data, for example by coupling
95 photogrammetric reconstruction with ML-based fracture extraction (Pola et al., 2024).

The main drawbacks of DL and ML approaches are reliance on large labelled training sets, their tendency to produce false
positives in the presence of vegetation, shadows, and other artefacts, and the computational expense of training (An et al., 2023; Yaqoob et al., 2023).
Despite these disadvantages, DL and ML approaches offer clear advantages over classical methods: they are more robust
to noise, can capture complex non-linear spatial patterns inherent to fracture networks, and once trained are commonly
100 transferable across similar datasets (Mattéo et al., 2021; Chudasama et al., 2024; LeCun et al., 2015). The key advantage of
deep learning over classical feature extraction (Table 1) is learning spatial features directly from data at multiple scales
(LeCun et al., 2015), allowing models to distinguish complex but distinctive simultaneously, rather than relying on hand-crafted
rules and fixed-scale filters (LeCun et al., 2015). This is especially valuable for fracture mapping because fractures are inherently
multi-scale, ranging from microfractures that are only visible in thin section to fault systems spanning tens, hundreds, or
105 even thousands of meters in length. Furthermore, fractures normally present as sets or networks rather than isolated features.
Learning various representations of fracture networks across scales allows a model to combine fine-scale edge detail with
broader-scale network context, helping it distinguish fracture geometry from noise and other “edges” commonly found in
drone imagery” edges” common in orthophotographs, such as vegetation boundaries, shadows, and weathering features.

Table 1. Summary of methods and their characteristics for fracture mapping

Method	Algorithms / Key studies	Data types	Description	Advantages	Limitations	Automation
Colorimetry-Based Segmentation	Thresholding approaches (Ren and Malik, 2003; Vasuki et al., 2017)	Orthophotos orthophotographs	Segments image features based on pixel intensity. Fractures appear darker due to illumination differences, while the host rock appears lighter.	Simple and intuitive; effective in high-contrast conditions.	Strongly affected by lighting and shadows; not reliable in heterogeneous or low-contrast scenes.	Manual or semi-automatic
	DEM/DTM-Based Feature Extraction	DEMs, DTMs, satellite imagery	Uses terrain derivatives (curvature, slope, relief) to reveal lineaments. Segment tracing improves feature continuity.	Reveals terrain-related or hidden subsurface structures.	Dependent on resolution and quality of DEMs; computationally demanding.	Semi-automatic (ML used in some)
Edge Detection (traditional filters)*	Canny Edge Detection (Masoud and Koike, 2011; Soto-Pinto et al., 2013; Adiri et al., 2017), Sobel, Laplacian of Gaussian; combinations such as Canny + Hough Transform (Han et al., 2018)	Orthophotos satellite imagery, DEMs	Gradient filters highlight intensity changes; often used as preprocessing before other algorithms.	Fast, well established, interpretable.	Sensitive to noise and illumination; lacks context.	Semi-automatic
	Phase Symmetry and Congruency (Kovesi, 1999, 2000; Vasuki et al., 2014)	Orthophotos orthophotographs	Uses local phase information to detect edges invariant to brightness or contrast.	Robust under varying illumination; noise-tolerant.	Computationally heavy; more complex to implement.	Semi-automatic
Hough Transform	Classical Hough Transform (Duda and Hart, 1972); combinations such as Canny + Hough Transform (Soto-Pinto et al., 2013; Han et al., 2018)	Binary edge maps (from other detectors)	Converts edge pixels into parameter space and accumulates votes to identify linear structures.	Good for linear fractures; interpretable.	Limited to straight lines; prone to false positives.	Semi-automatic

* evaluated in this study
Table continued on next page

Table 2. Summary of methods and their characteristics for fracture mapping

Method	Algorithms / Key studies	Data types	Description	Advantages	Limitations	Automation
Wavelet and Multi-Scale Transforms	Wavelet Transform (Mallat and Hwang, 1992), Ridgelets and Curvelets (Candès and Guo, 2002; Candès and Donoho, 2005; Do and Vetterli, 2005), Complex Shearlet Transform (Prabhakaran et al., 2019)	Orthophotos satellite imagery, DEMs	Multi-scale decomposition; orthophotos wavelets capture curvilinear and branching structures.	Multi-scale, effective for curved features.	Classical wavelets lack directionality; advanced transforms are complex and computationally intensive.	Semi-automatic
Line Segment Detection / Tracking	Line Segment Detection (Rahnama and Gloaguen, 2014; Masoud and Koike, 2017; Saint Jean Patrick Coulibaly et al., 2021), Line Segment Tracking (Fan and Ni, 2023; Gaikwad et al., 2023)	Satellite imagery, DEMs	Detects line segments directly; tracking improves continuity across scales.	Captures both short and long features; efficient.	Sensitive to parameter tuning; may fragment lineaments.	Automatic (ML used in some)
Deep Learning and Machine Learning Approaches*	CNN U-Net (Chudasama et al., 2024), Geological Adaptive Incremental Network (Zhang et al., 2024), DL + Line Detection (Oliveira et al., 2019), Multi-feature DL integration (Zhang et al., 2024), Graph Attention Network + Fast Line Detection, Photogrammetry + ML (Pola et al., 2024)	Orthophotos DEMs, satellite imagery, 3D point clouds	Learns hierarchical spatial features for segmentation and fracture extraction.	Robust to noise; captures complex nonlinear spatial patterns; transferable across similar datasets.	Requires large labelled data; prone to false positives (e.g., vegetation, shadows); can be expensive to train.	Fully automatic (DL/ML-based)

* evaluated in this study

However, a persisting issue is that ~~Several issues still need to be addressed as DL-based~~ automated fracture detection ~~still~~ ~~struggles~~ ~~continues to develop~~. First, these methods still struggle with false positives and negatives, particularly under natural and uncontrolled imaging conditions ~~-(e.g., white balance, illumination patterns, resolution, etc.)~~ (Mattéo et al., 2021; Yaqoob et al., 2024; ~~, e.g., topographic shadows mimicking fracture traces, vegetation creating false linear features, or weathering textures producing edges indistinguishable from fractures.~~ Natural outcrops contain shadows, vegetation, uneven lighting, and ~~erosion~~ ~~erosional features~~, all of which can confuse detection algorithms. ~~Moreover~~ ~~Secondly~~, fractures are an unusual target for semantic segmentation, as they are better represented as linear segments with arbitrary ~~width~~ ~~widths~~ (Fig. 1a) rather than as continuous areas. ~~Most fracture analyses also require instance-level outputs—such as fracture length, orientation, spacing, and connectivity—which depend directly on the correct topology of each trace. As a result, even minor misclassification can drastically alter fracture connectivity and the derived measurements. Furthermore, the~~ (Fig. 1b). ~~Third~~, ground-truth labels used for training are often drawn at ~~coarser scales than pixel-level precision, leading a coarser scale than the maximum image resolution allows: a time-saving compromise that leads to~~ misalignment between the labelled ~~and actual fracture edges~~ ~~fracture and the pixels that represent the fracture in the orthophotograph~~ (Fig. 1). ~~These inconsistencies affect both model learning and evaluation accuracy.~~

Example of annotation misalignment. (a) Outcrop orthophoto (Nordbäck and Ovaskainen, 2025) overlaid with fracture traces in white from the ground-truth labels (Ovaskainen and Nordbäck, 2022). (b) Zoomed-in view showing how manually drawn fracture lines deviate from the actual visible fracture edges.

For fracture mapping and similar tasks, two main computer vision approaches are commonly used: semantic segmentation and instance segmentation (Sharma et al., 2022). Semantic segmentation labels each pixel as a fracture or not, producing a binary mask without separating individual fractures. Instance segmentation, on the other hand, identifies and labels each distinct fracture, allowing direct measurement of geometric attributes. This study focuses on semantic segmentation because it is simpler, more robust with current data, and does not require instance-level labels. Instance segmentation remains the ultimate goal for full fracture analysis but is highly challenging in this context and beyond the scope of this work.

~~Algorithm performance also often drops when~~ ~~c,d~~). While these inconsistencies may influence analyses of fracture lengths, orientations, and network topology, they have an even greater impact on model training and evaluation accuracy. This is important because annotation scale and interpretation can significantly affect the derived properties of fracture networks (Peacock and Sanderson, 2026). Finally, algorithm performance commonly drops when a DL-based model is applied to new datasets with different ~~lithologies~~ ~~fracture patterns, lithologies, topographical complexity, topographies,~~ or imaging conditions, limiting ~~generalizability~~. This underscores the ~~generalisability~~ (Mattéo et al., 2021).

As automated fracture detection advances, there is an urgent need for standardised benchmarking frameworks and shared datasets that ~~allow~~ ~~enable~~ consistent and fair comparison of methods (An et al., 2023). While initiatives like GeoCrack (Yaqoob et al., 2024), a publicly available benchmark dataset for automated geological fracture detection in RGB images of rock outcrops have begun to address this gap, current resources remain limited to RGB imagery and predominantly vertical outcrops and ~~prone to incomplete annotations~~ ~~contain incomplete annotations in some image patches where only a subset of visible fractures are labelled.~~

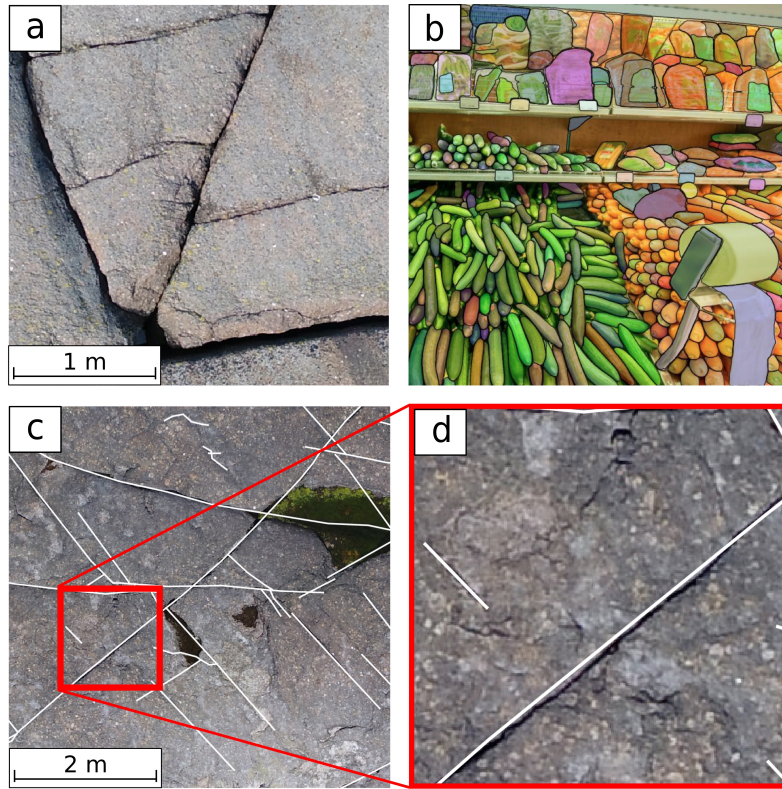


Figure 1. Example of annotation misalignment. (a) Outcrop orthophotograph (Nordbäck and Ovaskainen, 2025) overlaid with fracture traces in white from the ground-truth labels (Ovaskainen and Nordbäck, 2022). (b) Zoomed-in view showing how manually drawn fracture lines deviate from the actual visible fracture edges. (c) Example of fractures of different widths. (d) Example of a segmentation task represented as a continuous area from Segment Anything paper (Kirillov et al., 2023).

Our approach addresses this limitation by curating three The primary goal of this study is to establish a standardised evaluation framework for pixel-wise fracture segmentation from 2D outcrop imagery, using both traditional computer vision and deep learning methods. We present FraXet, comprising three curated, heterogeneous benchmark datasets and applying clear and consistent preprocessing, hyperparameter optimisation, and evaluation procedures. Performance is assessed using both on which a suite of traditional image-processing filters (Canny, Sobel, Gabor, Sato, and phase congruency) and deep learning models (U-Net, SegFormer) were applied to generate per-pixel fracture probability maps. The performance of the different methods was assessed using image-quality metrics (e.g., MSE, PSNR) and segmentation metrics (e.g., precision, F1-score, IoU), as well as a novel geological and a novel fracture-trace similarity metric. The primary goal of this study is to establish a standardised evaluation framework for pixel-wise fracture segmentation from 2D outcrop imagery, incorporating both traditional computer vision and deep learning methods. This By applying consistent preprocessing, hyperparameter optimisation, and evaluation metrics, our framework enables systematic comparison of fracture detection performance across

155 diverse datasets, geological settings, and imaging conditions. ~~By harmonising data processing, parameter tuning, and evaluation metrics, it promotes~~ FraXet is intended as a living benchmark, to be expanded with additional datasets representing different geological settings, lithologies, and fracture network patterns as more annotated public datasets become available. Our aim is to promote transparency, reproducibility, and comparability in automated fracture mapping research, while also providing a useful test dataset and benchmark for future developments.

160 2 ~~Materials and Methods~~Methodology

~~FraXet (Fatihi et al., 2025a) integrates three-~~

~~We designed a benchmarking workflow (Fig. 3) for three publicly available,~~ annotated outcrop datasets ~~—(Ovaskainen22~~ (Nordbäck and Ovaskainen, 2025; Ovaskainen and Nordbäck, 2022), **Matteo21** (Mattéo et al., 2020), and **Samsu19** (Samsu et al., 2019)~~—selected for their combination of-)~~ that make up the first version of **FraXet** (Fatihi et al., 2025a). FraXet is a
165 ~~curated benchmark dataset for training and evaluating automatic fracture-trace extraction models, comprising~~ high-resolution ~~orthomosaic and digital elevation models (DEMs), orthophotographs and DEMs across~~ diverse lithologies and ~~varied~~ outcrop geometries. ~~From these sources, we compile-~~

~~From the original orthophotographs and DEMs, we compiled~~ 8,953 co-registered 256 pixel × 256 ~~patches~~ pixel patches (see Fig. 2), each consisting of an RGB orthomosaic tile, a DEM tile, and a corresponding binary ~~1-pixel-wide~~ 1-pixel-wide fracture
170 label. We ~~standardise and pre-process all~~ ~~standardised and pre-processed all the~~ patches, then ~~apply~~ applied a suite of traditional image-processing filters (Canny, Sobel, Gabor, Sato, phase congruency) and deep learning models (U-Net, SegFormer) to generate per-pixel fracture probability maps. All methods ~~are~~ were evaluated using a set of ~~image-quality, segmentation~~ image quality, segmentation, and proposed similarity metrics on held-out test splits, with deep models tuned on validation subsets before final testing.

175 2.1 Data Compilation

2.1.1 Data description

Ovaskainen22 captures fracture networks in the Mesoproterozoic Wiborg Rapakivi Granite Batholith of southeastern Finland, mostly isotropic coarse-grained ~~wiborgite facies~~ ~~wiborgite facies~~ granite with K-feldspar megacrystals up to 5–10 cm (Härmä, 2020). Matteo21 (Mattéo et al., 2021) presents data from the Granite Dells, Arizona, an anorogenic granite of similar age
180 (~1.40 Ga) but with medium-grained, ~~and~~ generally equigranular textures showing weak porphyritic tendencies (Krieger, 1965). Samsu19 (Samsu et al., 2019) ~~map~~ maps fractures in a very different geological setting: a fluvial–lacustrine syn-rift sediment succession in the Lower Cretaceous Strzelecki Group (~~Southeastern~~ ~~southeastern~~ Australia), comprising mud- and sand-dominated siliciclastic strata with conglomeratic or organic-rich interbeds (Constantine, 2001).

Together, these three datasets cover varied geological contexts (~~from~~ isotropic crystalline to anisotropic sedimentary litholo-
185 gies) with fractures mapped at different scales, providing a diverse testbed for evaluating model generalisation. An overview

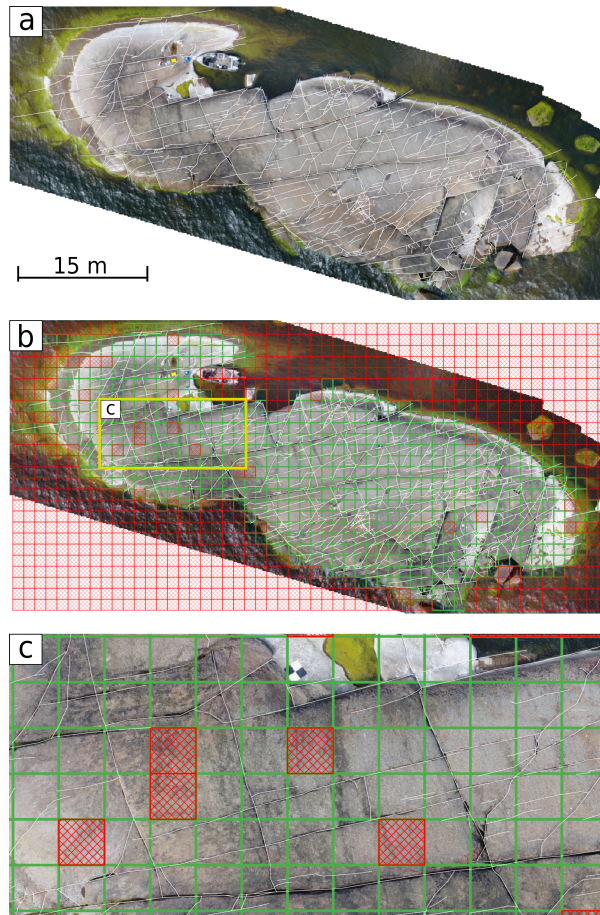


Figure 2. Overview of the benchmarking workflow. The three datasets (Matteo21, Samsu19, Ovaskainen22) are processed into the [Example RGB-DEM-label patches](#) from [FraXetv0.1](#) database, used to train classical filters and deep learning models, the results of which are evaluated on the test set through qualitative visualisation and quantitative metrics and proposed similarity metric.

of the datasets, their mapping scales, original study purposes, their resolutions, and split statistics is provided in Table 3. For completeness, overview maps of the sites used in this study are provided in the Appendix (Fig. A1, Fig. A2, Fig. A3).

We acknowledge that three datasets covering two granite types and one clastic sedimentary setting, while providing meaningful lithological contrast for a first benchmark, do not represent the full diversity of geological settings encountered in practice; notably absent are carbonate, metamorphic, and volcanic lithologies. FraXet is intended as a living benchmark to be expanded as further annotated public datasets become available; including these other lithological settings is a priority for future work.

In addition, a single site from the Lapiés di Bou karst surface was included to enable qualitative visual comparison across methods. This locality lies within the Helvetic domain of the Swiss Western Alps, specifically within the Wildhorn Nappe complex (Steck et al., 2001; swisstopo, 2024), where fine limestones to marls, locally oolitic, of the Aptian–Barremian Schrat-
tenkalk Formation crop out (Badoux et al., 1959). Two patches from the Bingie Bingie area were also used for the timing

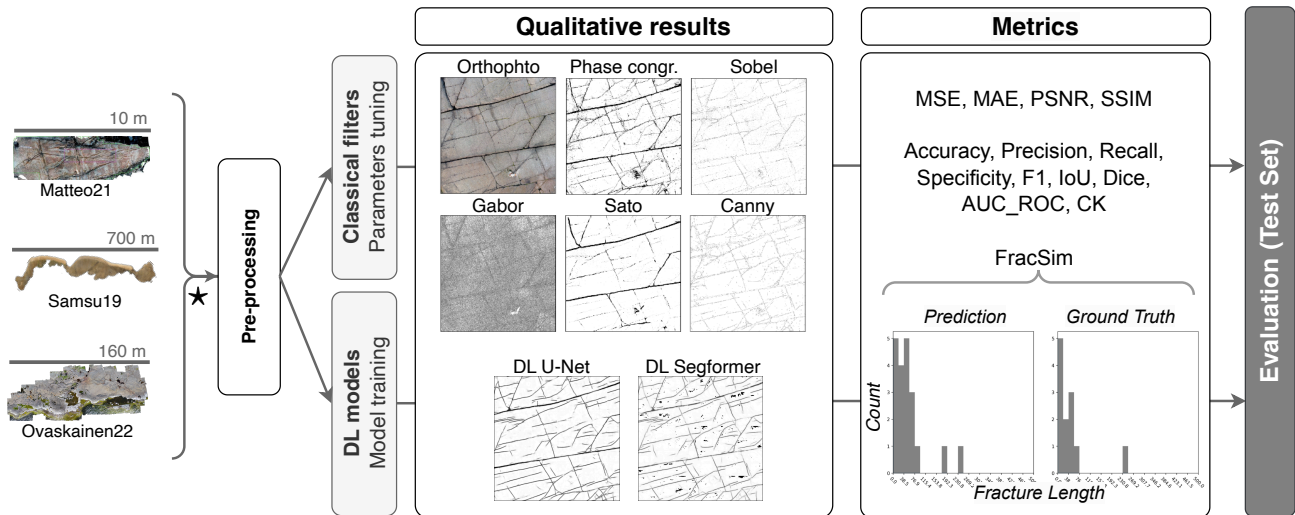


Figure 3. Overview of the benchmarking workflow. The three datasets (Matteo21, Samsu19, Ovaskainen22) are processed into the FraXet v0.1 database, used to train classical filters and deep learning models, the results of which are evaluated on the test set through qualitative visualisation and quantitative metrics and proposed similarity metric.

★: not all outcrops used shown here.

experiment, allowing direct comparison with the manual and semi-automatic mapping workflow of Thiele et al. (2017a). Neither the Lapiés di Bou nor the Bingie Bingie data were included in the training, validation, or test splits; they were used exclusively for qualitative visual comparison and runtime evaluation, respectively.

2.1.2 Test, train and validation splits

To ensure reliable model assessment and minimise spatial autocorrelation—a known issue in geospatial machine learning where spatial overlap inflates accuracy metrics by reducing the statistical independence of training and testing data (Wang et al., 2023)—we have defined spatially disjoint data splits by dividing each of the three datasets into training, validation, and test regions (with no spatial overlap). Specifically, here the Ovaskainen22 dataset consists of Orrengrund (training), Kasaberget (validation), and Kampuslandet (testing) islands off the coast of the Loviisa region; the Samsu19 dataset comprises Eagles Nest (training) and Harmers Haven north (split between validation and testing); and the Matteo21 dataset is split into sites A and B (training), held-out regions of A and B (validation), and site C (testing). Only tiles containing at least one labelled fracture pixel were retained, to reduce challenges with class imbalance and to focus learning on relevant features.

The ~~orthophotos~~ orthophotographs and DEMs were resampled to have matching spatial resolution, normalised, and tiled into non-overlapping 256×256 pixel patches, each with four channels (RGB+DEM). This patch size ~~was chosen as a~~ compromise between ~~balances~~ field of view, feature scale, and computational efficiency—: it is large enough to preserve contextual information while remaining compatible with typical convolutional neural network (CNN) input constraints.

Table 3. Overview of datasets and their metadata [and split statistics](#)

Dataset Resolution (m) Train-patches Validation-patches Test-patches Total-patches Total-Area-of-used-patches (m^2)
Ovaskainen22 0.005–0.006 2808 966 671 4445 7220
Matteo21 0.0005–0.0013 2174 323 912 3409 142
Samsu19 0.029–0.032 642 228 229 1099 68271
All –62.82% 16.94% 20.24% 8953 (100%) 75633

Dataset	Study purpose	Mapping scale	Resolution (m)	Patches				Total Area (m^2)
				Train	Validation	Test	Total	
Ovaskainen22	Fracture-network characterisation	1:10*	0.005 - 0.006	2808	966	671	4445	7220
Matteo21	Automatic fault/fracture mapping (tectonic)	-	0.0005 - 0.0013	2174	323	912	3409	142
Samsu19	Fracture patterns & structural inheritance	1:250	0.029 - 0.032	642	228	229	1099	68271
All	-	-	-	62.82%	16.94%	20.24%	8953 (100%)	75633

*As shared by the authors, no fixed mapping scale was used for fracture interpretation. Instead, fractures were digitized at the full image resolution (approximately 0.0055 m pixel size for data acquired from a 20 m drone flight altitude), allowing the interpreter to zoom freely as needed. Based on the image resolution, the effective fracture extraction scale is approximately 1:10 as in Ovaskainen et al. (2023).

Ground truth annotations for Ovaskainen22 and Samsu19 were provided as vector shapefiles and were subsequently rasterised to the corresponding image resolution, producing binary masks with 1-pixel-wide white fracture lines on a black background. These binary images match the raster-formatted annotations in Matteo21 to ensure consistent label representation.

215 [Given the spatial resolutions of the datasets, a 256x256 pixel patch represents a square region with side lengths ranging from approximately 0.13-0.33 m \(Matteo21\), 1.28-1.54 m \(Ovaskainen22\), and 7.4-8.2 m \(Samsu19\).](#)

Probability Map Representation. Because our goal is to generate per-pixel probability maps rather than hard binary labels, we designed all preprocessing steps with this output in mind. Probability maps provide a continuous estimate (~~0-1~~[0-1](#)) of the likelihood that each pixel corresponds to a fracture, capturing confidence and uncertainty rather than forcing discrete
220 predictions. This representation is well suited to fracture mapping, where annotations are often noisy or slightly misaligned, and where soft boundaries reflect the inherent ambiguity of thin linear features.

It also enables flexible post-processing: thresholds can be adjusted to balance precision and recall, high-confidence regions can be skeletonised to extract fracture traces, and outputs can be integrated into human-in-the-loop workflows or combined with traditional filters. Moreover, probability maps support richer evaluation metrics (e.g., ROC analysis), and improve robustness
225 when using ensembles or multi-scale fusion. For all these reasons, probability maps serve as the most informative and practical output of the methods.

2.2 Pre-processing

Several preprocessing and augmentation steps were applied prior to model training and evaluation, to standardise inputs, refine ground-truth annotations, and improve model generalisation. All preprocessing scripts and procedures are publicly released as
230 the FraXtex2D ~~github repository~~ ([gitlab repository](#) (<https://gitlab.com/ayoubft/fractex2D.pt>) to ensure reproducibility. These procedures are summarised below.

Depth. For all deep learning experiments, we used the full RGB imagery together with the corresponding DEM channel, which was normalised at the patch level using min–max normalisation. This scaling ensures that elevation values within each

patch fall between 0 and 1, reducing the influence of absolute elevation differences across sites and improving numerical
 235 stability during training.

Channel selection. Most traditional edge-detection filters operate on a single image band. Therefore, each band was first z-standardised (zero mean, unit variance) on the patch-level to reduce sensitivity to illumination differences and overall brightness. PCA (principal component analysis) was then applied to the normalised four-band data to obtain a single-band representation containing a maximal amount of variance.

240 **Label refinement.** We implemented two complementary label-processing techniques to correct inconsistencies in the original fracture annotations and enhance their spatial accuracy: wide-fracture expansion and multi-scale label smoothing.

Wide-fracture expansion. Preliminary experiments revealed that the models underperformed on wide ~~and~~ visually prominent fractures. Many such fractures were annotated as 1-pixel-wide lines, underrepresenting their true width. To address this, we developed a region-growing algorithm that widens ~~the~~ single-pixel annotations to fill thick fracture zones. This algorithm
 245 (Fig. 4c) fills dark linear regions ~~(in the green channel)~~; identified by thresholding at 30 (on a 0-255 scale); by applying a ~~maximum filter~~ 2-pixel maximum filter, followed by morphological dilation ~~and~~, then merging the resulting ~~(dark and connected)~~ dark, connected regions with the original binary mask. Only expanded areas connected to existing labelled pixels are retained to prevent false positives. This operation improved annotation fidelity for wide fractures.

Multi-scale label smoothing. Manual fracture tracing also often ~~leads to~~ introduces small misalignments between annotations
 250 and ~~the~~ actual fracture pixels, especially in high-resolution orthophotos. ~~We applied a multi-scale label smoothing procedure to mitigate this issue, using successive dilations with decreasing weights to produce a graded boundary around each fracture orthophotographs.~~ First, labels are expanded with a distance of 2 pixels to fill small gaps and buffer the reference traces. This is followed by three successive morphological dilations applied to the expanded mask using disk-shaped structuring elements with radii of 2, 5, and 7 pixels. These bands are then combined into a graded representation using decreasing weights of $\frac{1}{3}$, $\frac{1}{5}$, and $\frac{1}{9}$ respectively. This produces a smooth boundary around fractures (Fig. 4d). This approach ~~smooths the input binary classification labels, accounts for positional uncertainty, and helps stabilise the model's learning process~~ reduces sensitivity to annotation noise and improves training stability by explicitly modelling spatial uncertainty.

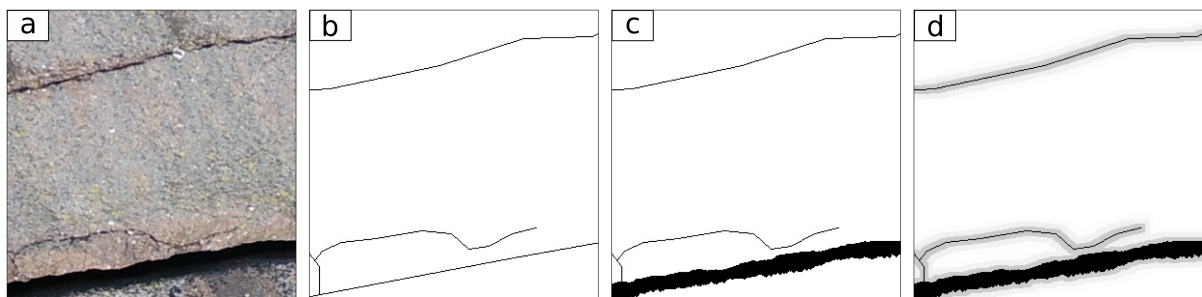


Figure 4. Label refinement steps. (a) Original RGB image; (b) manually traced ground truth with 1-pixel-wide fractures; (c) widened annotations after region-growing; (d) smoothed probabilistic labels produced by multi-scale dilation.

Together, these two steps improved correspondence between fracture labels and actual image structures, increasing the effective proportion of positive (fracture) pixels and slightly reducing class imbalance (Table B1 in the Appendix).

260 **2.3 Data augmentation**

To further enhance model robustness and generalisation, we applied the following data transformations randomly to the input patches (Fig. 5) during each training epoch:

- (1) Flipping horizontally and vertically. These transformations are applied to both the RGB+D images and the ground truth labels to encourage geometric invariance, helping the model detect fractures regardless of their orientation.
- 265 (2) Gaussian blurring, brightness, contrast, and saturation adjustment. These are applied only to the RGB channels to promote photometric invariance, improving robustness to changes in lighting and appearance.
- Table C1 in the Appendix summarises the applied augmentations and their parameters.

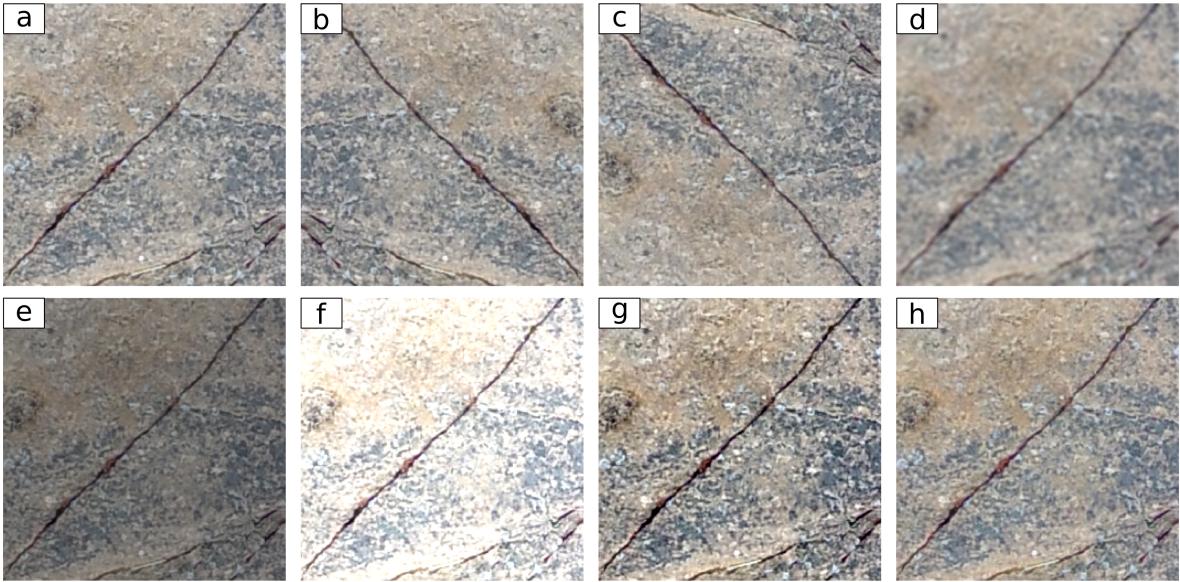


Figure 5. Data augmentations applied during training: (a) original, (b) horizontal flip, (c) vertical flip, (d) gaussian blur, (e) brightness decrease, (f) brightness increase, (g) contrast increase, (h) saturation increase.

2.4 Image filter-based approaches

~~The following~~ This section outlines our implementation of several established ~~image processing filters~~, image-processing filters as a baseline ~~to which we can compare the~~ for comparing deep learning results. These methods do not require training data and operate directly on the image, offering fast, interpretable, and reproducible outputs. While not specifically designed for fracture

270

detection, they are widely used in geoscientific and remote sensing applications to extract features with similar morphology. All filters were applied to the ~~single channel~~first principal component (channel) resulting from the PCA reduction.

For the classical filters, which do not produce probabilistic outputs, we applied the same label-dilation step (Step 2 in preprocessing; §2.3subsection 2.3) to their binary masks. This ensures that all methods are evaluated against labels that better reflect the actual fracture width and account for the misalignment between annotations and true pixel-level fracture geometry observed earlier.

~~The filters are grouped~~We grouped the filters into three main categories, also see Table 1:

- Edge detection (Sobel and Canny): Computes spatial intensity gradients to highlight abrupt changes. These filters are simple and efficient but sensitive to noise and lighting, and some require thresholding to generate binary edges.
- Ridge detection (Gabor and Sato): Identifies elongated, linear structures by analyzing second-order derivatives (curvature). These filters can capture fracture-like ridges at tuned scales but may also respond to non-fracture textures.
- Phase-based filters (Congruency): Use Fourier phase information to detect edges. These methods handle varying illumination more robustly, but are computationally intensive and involve more tunable parameters.

Each of these methods relies on user-specified parameters (Table 4; §2.4.1subsubsection 2.4.1) to suppress background clutter and isolate relevant target features (fractures in our case).

Table 4. Summary of parameters adjusted for each algorithm and their descriptions

Algorithm	Parameter	Parameter’s description
Edge detectors	Sobel	-
	Canny	sigma
		low_threshold
		high_threshold
Ridge detectors	Gabor	frequency
	Sato	sigmas
Phase Congruency		nscale
		norient
		minWaveLength
		mult
		sigmaOnf
		k
		cutOff
		g
	noiseMethod	-1=median, -2=mode, >=0=fixed threshold

2.4.1 Parameter Selection

To explore the behavior of each filter across different datasets, we first conducted a manual visual tuning phase. This provided insight into which parameter settings produced plausible results and helped define sensible parameter ranges. We then applied a data-driven parameter search to select the optimal settings for each filter. Specifically, we performed a grid search with cross-validation, which is justified here due to the low dimensionality of the parameter space and the relatively small number of candidate values per method. For each configuration within the predefined parameter ranges, the filter response was dilated (Step 2 in preprocessing), thresholded, and evaluated against the refined ground truth using the F1 score (definition defined in Table 5). The parameter set yielding the highest score was selected as optimal. This grid search standardises filter hyperparameters across datasets and reduces subjectivity in parameter selection.

2.5 Deep Learning-Based Models

Two deep learning architectures are evaluated in this work: a convolutional U-Net (Ronneberger et al., 2015) and a transformer-based SegFormer (Xie et al., 2021). the latter initialised with pretrained ResNet34 weights as ~~the~~ its backbone. U-Net is widely used for semantic segmentation due to its ~~encoder-decoder~~ encoder-decoder architecture and skip connections, while SegFormer leverages attention mechanisms combined with the ResNet34 backbone for long-range context modelling and robustness to geometric variability.

Both models were trained with architecture-specific hyperparameters selected by cross-validation and sensitivity tests. For the U-Net, we used the Adam optimiser with an initial learning rate of 0.05, while the SegFormer employed RMSProp with an initial learning rate of 0.01. The input to each model consisted of 256×256 px patches with four channels (three RGB bands and one DEM band). We used Huber (smooth L1) loss for per-pixel probability targets ~~because~~ as it proved robust to label noise, spatial misalignment, and class imbalance compared ~~with~~ to binary cross-entropy or Dice loss (both popular for segmentation tasks). Early stopping based on validation loss was used in both cases to prevent overfitting.

The U-Net and SegFormer architectures are depicted in Fig. 6 and Fig. 7, respectively.

Both models produce per-pixel probability maps used for visual comparison and were thresholded to generate binary segmentation masks, which were then compared to the ground truth using the metrics described below.

2.6 Benchmark metrics

To evaluate segmentation performance, we used three complementary groups of metrics:

1. image-quality metrics that quantify how closely the predicted probability maps match the annotated targets,
2. pixel-wise classification and segmentation metrics that measure detection performance and spatial overlap, and
3. a proposed fracture-level similarity metric, FracSim, designed to compare the geometry of predicted fracture traces with those in the ground truth.

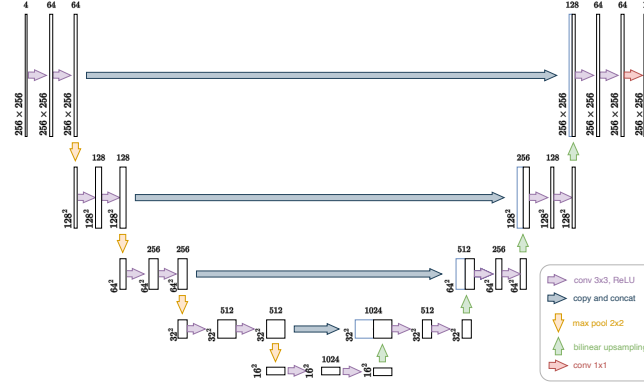


Figure 6. Overview of the U-Net encoder-decoder architecture with skip connections (Ronneberger et al., 2015). The encoder (left) progressively downsamples the 256x256x4 input through convolutional blocks (Conv → BatchNorm → ReLU) and max-pooling, extracting features at multiple scales. The decoder (right) upsamples these features via transposed convolutions and concatenates them with the corresponding encoder features via skip connections (grey arrows), preserving spatial detail. The final 1x1 convolution produces a per-pixel fracture probability map.

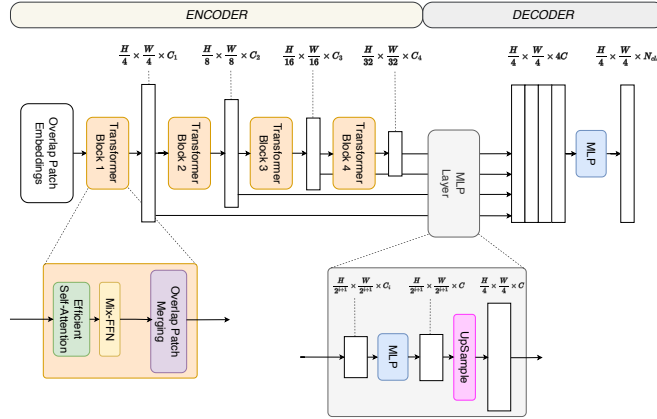


Figure 7. Overview of the SegFormer architecture combining a transformer encoder with a lightweight decoder (Xie et al., 2021). The encoder uses a hierarchical transformer backbone (ResNet34) with multi-head self-attention to capture long-range dependencies. The decoder aggregates multi-level features via a simple MLP.
Terms: Self-attention: mechanism allowing each pixel to attend to all others; MLP: multi-layer perceptron; Feature map: spatial representation at each encoder stage.

Together, these metrics (Table 5) capture prediction quality at the pixel, mask, and structural levels. Higher values generally indicate better performance, except for error metrics (MSE, AE), where lower values are preferable.

We include the background class in our evaluation to capture each model’s full performance across the entire image. Because fractures represent only a very small fraction of pixels, excluding the background can artificially inflate metrics such as precision and recall. It also tends to make poorly calibrated models appear better, as ignoring the dominant class often results in models overpredicting fractures. Including the background therefore provides a more realistic assessment of false positives, calibration, and overall segmentation integrity. Notably, many previous studies do not explicitly report whether the background class is included in the computation of evaluation metrics.

Among the ~~various~~ metrics computed, we ~~suggest that~~ consider the Dice coefficient (equivalent to the F1 score), recall, specificity, and intersection over union (IoU) ~~are as~~ are the most relevant for ~~the fracture segmentation task. In contrast, accuracy~~ fracture segmentation. Accuracy, in contrast, is the least informative metric here, ~~as~~ as: a model that predicts only background can achieve deceptively high scores due to class imbalance. Dice and IoU measure spatial overlap, which is critical for evaluating thin, linear features like fractures. Dice balances false positives and false negatives, while IoU penalises both over- and under-segmentation, making it a stricter metric. Recall ensures that fractures are not missed, while specificity quantifies how well the model avoids false positives in the dominant background class. Given the extreme class imbalance—~~where~~ background pixels can account for over 99% of the image—reporting recall alone ~~may can~~ may be misleading. Specificity completes the picture by measuring the number of false detections in non-fracture regions.

We also include ROC-AUC, which evaluates the model’s ability to distinguish between fracture and background pixels across thresholds. As a threshold-independent metric, ROC-AUC is particularly useful for probabilistic outputs. Similarly, Cohen’s Kappa measures agreement between prediction and ground truth while accounting for chance, offering a more meaningful alternative to raw accuracy in imbalanced settings.

In addition to segmentation metrics, we report image-quality metrics—Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Absolute Error (AE)—to assess how well the predicted probability maps match the annotations before thresholding. These metrics capture prediction fidelity in both intensity and structure. MSE and AE quantify raw pixel-wise error (lower is better), while PSNR measures signal degradation in a logarithmic scale (higher is better). SSIM accounts for human visual perception by evaluating structural and contrast similarity, which is especially valuable when preserving subtle linear patterns like fractures.

The different scenarios in Fig. 8 highlight how each metric responds to specific segmentation behaviors. Predicting only background (no segmentation) yields high accuracy and specificity but zero recall, precision, and overlap-based scores, illustrating how class imbalance can inflate accuracy despite complete failure to detect fractures. Conversely, full segmentation maximises recall while collapsing specificity and precision, resulting in low Dice and Intersection over Union values. Random segmentation produces near-chance values across most metrics, with Dice, Intersection over Union, Cohen’s kappa, and receiver operating characteristic scores reflecting the lack of spatial agreement. The Gabor filter segmentation shows intermediate performance, improving overlap, precision, and specificity by capturing some fracture structure, but still suffering from fragmentation and false positives. The U-Net prediction achieves the most balanced and consistently high scores across all metrics, with strong overlap, agreement, and classification performance, closely approaching the ground truth.

Table 5. Overview of metrics for evaluating image quality and segmentation

Metric	Formula	Definition / Use
MSE (Mean Squared Error)	$\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$	Average squared pixel error; lower is better.
PSNR (Peak Signal-to-Noise Ratio)	$10 \log_{10} \left(\frac{L^2}{\text{MSE}} \right)$	Log ratio of max intensity L to error; higher is better.
SSIM (Structural Similarity Index)	$\frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$	Perceptual similarity using luminance, contrast, and structure.
AE (Absolute Error)	$\frac{1}{N} \sum_{i=1}^N y_i - \hat{y}_i $	Absolute pixel-wise error; lower is better.
Accuracy (Acc)	$\frac{TP + TN}{TP + TN + FP + FN}$	Correctly classified proportion; sensitive to imbalance.
Precision (Prec)	$\frac{TP}{TP + FP}$	Correctness of predicted positives.
Recall / Sensitivity (Rec)	$\frac{TP}{TP + FN}$	Fraction of true positives detected.
Specificity (Spec)	$\frac{TN}{TN + FP}$	Fraction of negatives correctly identified.
F1 Score	$\frac{2 \text{Prec} \cdot \text{Rec}}{\text{Prec} + \text{Rec}}$	Harmonic mean of precision and recall.
Dice Coefficient	$\frac{2 A \cap B }{ A + B }$	Spatial overlap measure; equivalent to F1 in binary segmentation.
IoU (Intersection over Union)	$\frac{ A \cap B }{ A \cup B }$	Mask overlap ratio.
AUC_ROC	—	Area under ROC curve; reflects the probability that a model assigns a higher score to a positive instance than to a negative instance.
Average Precision (AP)	$\int_0^1 \text{Prec}(r) dr$	Area under precision–recall curve.
Cohen’s Kappa (CK)	$\kappa = \frac{p_o - p_e}{1 - p_e}$	Agreement corrected for chance.

Symbols: N = number of pixels; y_i = reference pixel value; $\hat{y}_i$ = predicted pixel value; L = maximum possible pixel intensity; μ_x, μ_y = means of image patches x and y ; σ_x^2, σ_y^2 = variances; σ_{xy} = covariance; C_1, C_2 = SSIM stability constants; TP, TN, FP, FN = true/false positives/negatives; A, B = predicted and reference binary masks; r = recall; p_o = observed agreement; p_e = expected chance agreement; ROC: receiver operating characteristic, is a graphical plot which illustrates the performance of a binary classifier system as its discrimination threshold is varied.

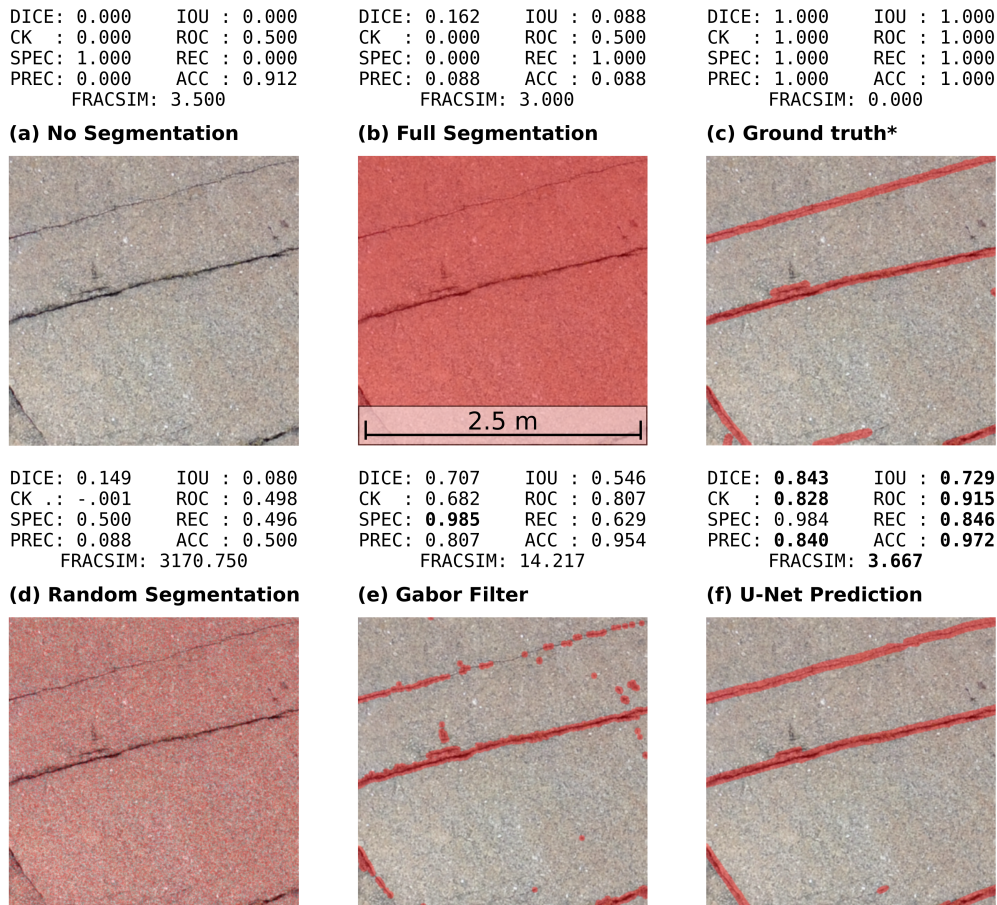


Figure 8. Illustration of metric behavior under different segmentation scenarios: (a) No segmentation (predicts all background), (b) Full segmentation (predicts all fracture), (c) Ground truth, (d) Random segmentation, (e) Gabor filter segmentation, (f) U-Net segmentation. Values in bold ~~showing highest values discarding~~ show the first row best scores, excluding scenarios a, b and c. Image from the Ovaskainen22, KL5 dataset. Abbreviations are defined in Table 5.

2.7 *FracSim*: a fracture-level similarity metric

~~Because one of the key characteristics relevant to fracture mapping is fracture length, we developed Pixel-wise metrics are~~
 355 widely used for segmentation evaluation but have limitations when applied to thin, linear features such as fracture traces. Small differences in line thickness or slight spatial offsets can disproportionately affect precision, recall, and F1-score. For example, a correctly detected fracture predicted slightly thinner than the annotation will incur false negatives along its edges, substantially reducing recall despite successful detection.

To address these limitations, we developed *FracSim*, a domain-specific similarity metric ~~-, termed FracSim, which that~~
 360 compares the distribution of extracted fracture segment lengths between a the predicted mask and the ground truth.

For each prediction and label, we:

- (1) convert the probability map to a binary mask (user threshold, default: 0.1);
- (2) skeletonise the binary masks to a one-pixel wide trace;
- (3) remove short noisy junctions using a small neighborhood filter (to avoid counting cross-overs and thick junction blobs as
365 segments);
- (4) label connected skeletal segments and compute their pixel lengths;
- (5) construct comparable histograms of segment lengths (same bin edges for prediction and ground truth); and
- (6) compute a symmetric chi-square distance between the two histograms (Equation 1).

$$d_{\chi^2}(h, g) = \frac{1}{2} \sum_{i=1}^N \frac{(h_i - g_i)^2}{h_i + g_i} \quad (1)$$

370 where

- $d_{\chi^2}(h, g)$ is the symmetric chi-square distance between the two histograms,
- h and g are the two histograms being compared,
- h_i and g_i denote the values of the i -th bin of histograms h and g , respectively,
- N is the total number of bins.

375 Lower χ^2 indicates closer agreement in the fracture length distribution. We compute *FracSim* only on patches that contain a high fracture-pixel count in the ground truth; empty or nearly empty patches are excluded because they lack a meaningful fracture-length distribution to compare, and even small prediction artifacts in these patches can otherwise produce misleading metric values.

Together, these metrics (§2.6 and §2.7 subsection 2.6 and subsection 2.7) provide a balanced framework for evaluating both
380 hard segmentation performance and the quality of soft probabilistic outputs.

2.8 Generalisation experiments

To evaluate the generalisation capability of a single model trained across diverse geological settings, we compared a multi-site model (trained on all datasets combined, M_all) against individual models trained separately on each dataset (M_ovas, M_sams, and M_matt). All models employed an identical architecture and training configuration, with no dataset-specific
385 hyperparameter tuning conducted. Each dataset-specific model was evaluated only on its corresponding test set, while M_all was tested independently on each dataset. This experiment aims to assess whether a generalist model can match or exceed the performance of models trained under dataset-specific conditions, offering insights into the feasibility of cross-domain fracture segmentation.

2.9 Deployment

390 As a first step toward practical deployment, we developed a lightweight web-based prototype that enables users to upload paired RGB images and DEMs and obtain deep-learning-based fracture predictions via the hassle-free Gradio interface (Abid et al., 2019). The tool, hosted on Hugging Face Spaces, illustrates how the trained model can be made accessible beyond a purely research-oriented setting. While still preliminary, this prototype highlights the potential of interactive platforms to broaden the adoption of automated fracture detection within the geoscience community and offers a concrete example of
395 integrating deep-learning outputs into field and laboratory workflows. The interface additionally allows users to explore a range of computer vision filters and metrics calculation.

3 Results

To assess ~~model~~ performance, we evaluated ~~both traditional computer vision~~ traditional computer vision filters and deep learning (DL) models on the ~~test dataset, using the image quality, segmentation~~ held-out test set using the image quality, segmentation, and similarity metrics described earlier. The following sections present ~~these results, qualitatively and quantitatively~~ qualitative and quantitative results.
400

3.1 Traditional Computer Vision-Based Algorithms

The optimal hyperparameters and thresholds that produced the best results, identified through grid search and manual visual inspection, are listed in Table D1.

405 3.1.1 Quantitative Results

For completeness, the full numerical results from both the grid-searched settings are provided in Table E1. The radar chart in Fig. 9 summarises how the traditional filters perform across image quality, segmentation, and similarity metrics. Overall, the filters cluster near the ~~center~~ centre of the plot, indicating ~~uniformly~~ limited fracture-detection ~~ability~~ capability across metrics. Canny, Sobel, Sato, and Phase Congruency exhibit similar profiles, with modest accuracy, precision, F1, and IoU, and
410 only small variations in recall, specificity, and ROC. For the structural similarity metric, they achieve an SSIM value of zero, indicating no structural similarity. In contrast, the error-based measures (MSE, AE, and loss) remain low, which is favorable. Gabor is the only method that diverges sharply from this pattern: it attains perfect recall but extremely low precision, yielding a highly unbalanced shape on the radar plot. Because it labels nearly all pixels as background class, the remaining metrics collapse to very low values.

415 3.1.2 Qualitative Results

Using grid-searched parameters across all test sites, the classical filters produced ~~somewhat~~ partially useful but generally sparse outputs (Fig. 10). ~~Phase Congruency and~~ For example, in the Ovaskainen22 test patch (Fig. 10a–f), Phase Congruency (panel

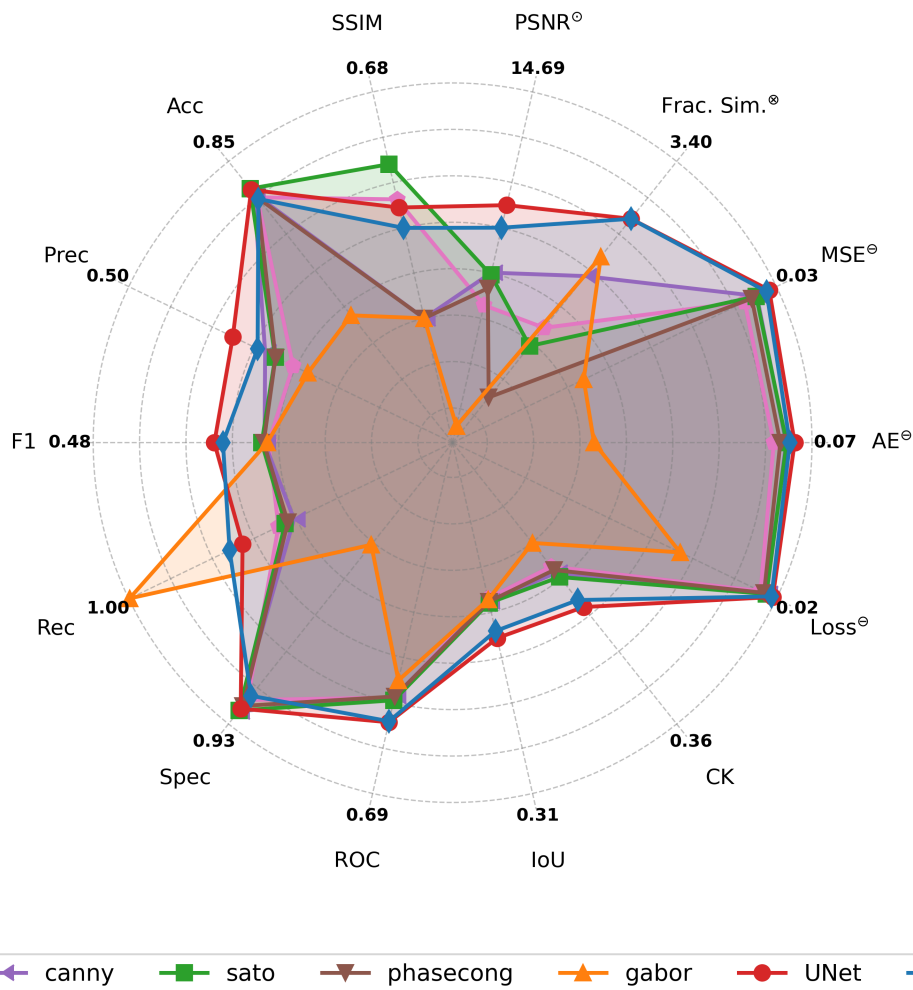


Figure 9. Radar chart summarizing the performance of the classical filters across all evaluation metrics. All metrics originally lie between 0 and 1, except $PSNR^{\ominus}$ and $FracSim^{\otimes}$. And metrics where lower values indicate better performance ($AE^{\ominus}$, $MSE^{\ominus}$, $Loss^{\ominus}$ and $FracSim^{\otimes}$) were flipped by computing $(1 - \text{value})$ so that the chart consistently displays better performance toward the outer radius. $FracSim^{\otimes}$ was calculated on the modified test set. Abbreviations are defined in Table 5.

b) detected several fracture segments but introduced substantial noise, while Sato (panel e) captured only the most prominent ridges. In the Samsu19 patch (Fig. 10m–x), all filters struggled with the coarser resolution and sedimentary texture. Phase Congruency and Canny often highlighted many true fracture segments, but their responses included substantial noise and many thin lines. Sobel and Sato tended to be very sparse, picking up only the strongest edges or ridge cores, while Gabor largely failed to isolate fractures and instead responded to texture, producing noisy, non-fracture patterns. In short, the grid search

showed that some filters can detect fracture signals, but ~~the~~ universal parameter sets are not optimal for every site and yield noisy or incomplete maps.

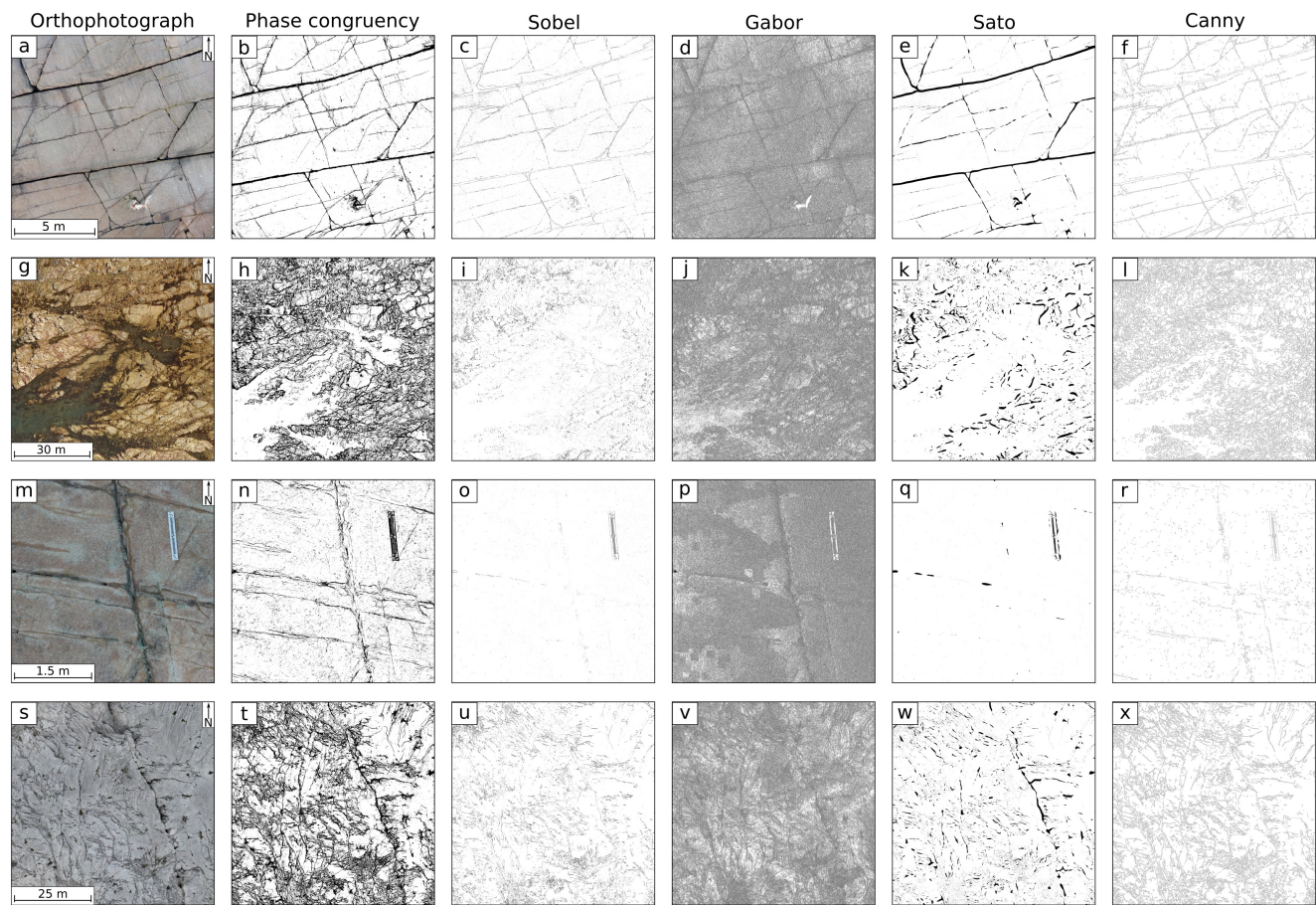


Figure 10. Comparison of traditional filters applied to four representative orthophotographs, using parameters selected by grid search. Each row shows an original orthophotograph (a, g, m, s) alongside results from Phase Congruency (b, h, n, t), Sobel (c, i, o, u), Gabor (d, j, p, v), Sato (e, k, q, w), and Canny (f, l, r, x) filters.

425 Using manually tuned parameters on each test site separately, some filters were able to highlight fracture segments more clearly (Fig. 11). Sobel and Canny captured more pronounced edges along major traces, while Sato produced thicker and more continuous lines. However, the outputs also included numerous spurious detections of non-fracture features.

While manually tuned parameters can produce visually plausible outputs on individual test sites, this performance does not generalise well ~~across other locations—or even across~~ to other locations, or even to different regions within the same
430 image. Traditional filters are sensitive to local contrast, scale, and texture, requiring site-specific adjustments to capture relevant features. These tuned parameters, although effective in isolated cases, often fail ~~when applied to~~ on heterogeneous datasets.

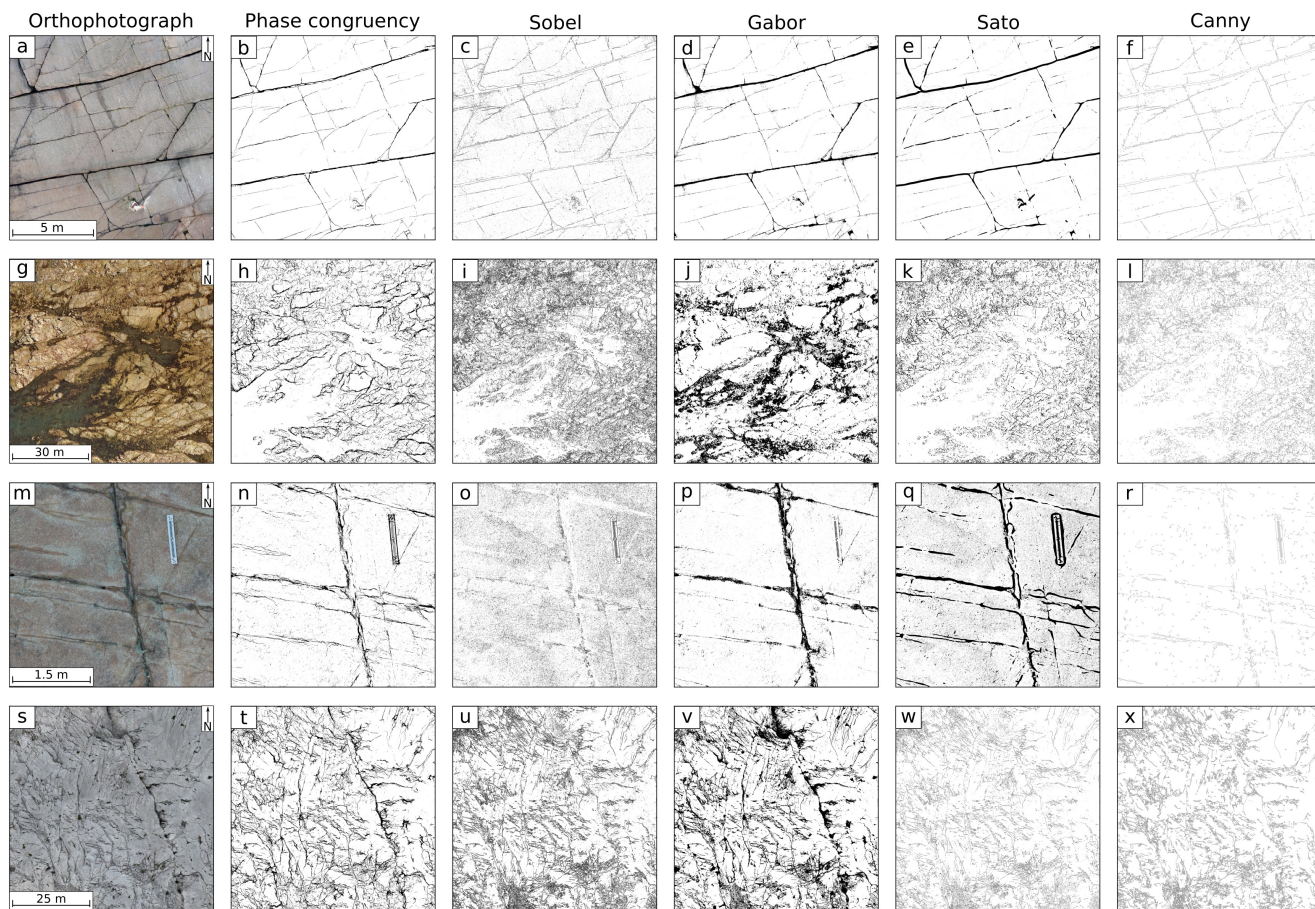


Figure 11. Comparison of traditional filters applied to four representative orthophotographs, using parameters selected manually for each site. Each row shows an original orthophotograph (a, g, m, s) alongside results from Phase Congruency (b, h, n, t), Sobel (c, i, o, u), Gabor (d, j, p, v), Sato (e, k, q, w), and Canny (f, l, r, x) filters.

~~The limitations described above~~ These limitations expose a core issue: ~~both~~ fixed-rule and parameter-tuned ~~methods on~~ traditional filters lack the flexibility to handle ~~the variability of~~ complex, real-world ~~geology~~. ~~Thus, they motivate the adoption of geological variability~~. They motivate deep learning approaches, ~~which that~~ do not rely on hand-crafted features or globally
435 fixed parameters. Instead, they learn hierarchical representations directly from the data, enabling better adaptation to diverse fracture patterns and geological contexts. Deep networks can, in principle, generalise beyond specific sites by capturing shared structures across datasets.

3.2 Deep Learning Models

3.2.1 Training Dynamics

440 For model Model and hyperparameter selection, ~~cross-validation was performed~~ was performed via cross-validation using the training and validation subsets. Fig. 12 shows a representative training run for both architectures using the fixed hyperparameters ~~mentioned~~ described in the Methods section and a single random seed (42), ~~which ensures that weight initialization and any ensuring that weight initialisation and~~ other stochastic processes are reproducible ~~and consistent~~ across runs. The training curves illustrate the model learning process on the fracture datasets, showing how the segmentation error changes as the models
 445 learn to identify fracture patterns from the annotated RGB+DEM patches over successive epochs. The U-Net exhibits a smooth decrease in training loss and a validation curve that stabilises around epoch 43. The gap between the two curves remains small, with only mild overfitting toward the end of training. The checkpoint with the lowest validation loss was used for evaluation. SegFormer follows a similar downward trend but with higher loss values and more fluctuation, particularly during the first half of training. Its slower convergence suggests that the model adapts less effectively to this dataset than the U-Net, or alternatively,
 450 that it requires additional training data and longer training to achieve a comparable fit.

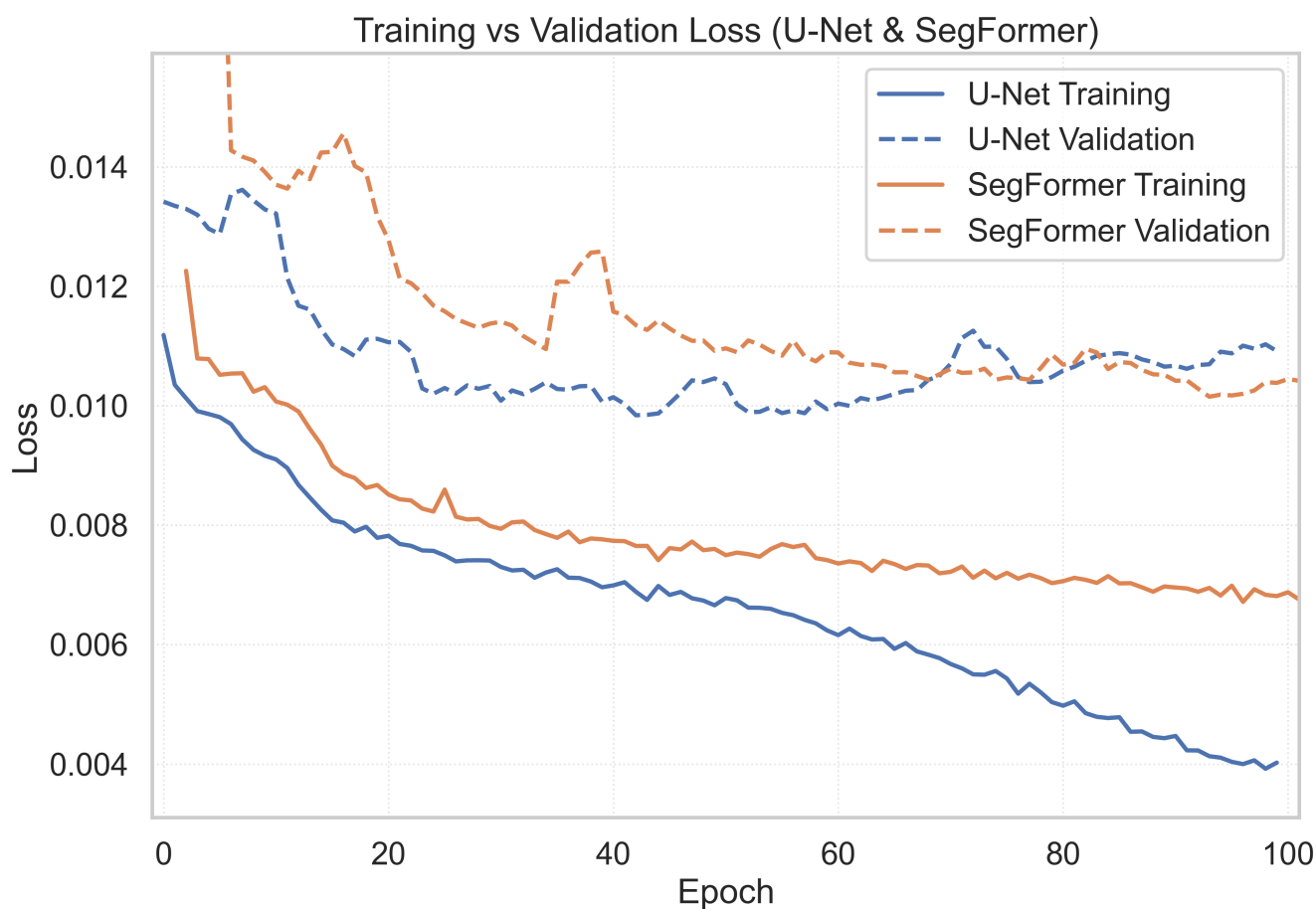


Figure 12. Training and validation loss curves for U-Net and SegFormer (range: [0, 1])

3.2.2 Quantitative Results

As shown in the spider diagram (Fig. 9) and ~~in~~ Table E1, the U-Net model achieved a mean ~~F1-score~~ F1 score of 0.48 and IoU of 0.31, substantially higher than any traditional baseline ($F1 < 0.29$, $IoU < 0.17$). Precision reached 0.50 ~~, indicating that~~ (half of the predicted pixels presenting fractures corresponded to true positives pixels predicted as fractures were true positives), while recall remained moderate (0.45), ~~showing that some pixels of the fractures were missed~~ indicating missed fracture pixels. SSIM (0.49) and PSNR (14.7 dB) confirm that the reconstructed fracture masks deviate notably from the ground truth in terms of image similarity, ~~but yet~~ the segmentation metrics demonstrate reliable decent detection of fracture structures.

The SegFormer model was trained using the same data splits and evaluation protocol as the U-Net. While SegFormer produced competitive results, its F1 (0.44) and IoU (0.28) were consistently lower than those of the U-Net. Standard deviations across runs were similarly low, indicating stable but suboptimal convergence. Although the U-Net and SegFormer models clearly outperform filter-based methods, their absolute performance remains well below standard deep learning studies ($F1 > 0.8$, $IoU > 0.6$) (Guo, 2023; Kuş and Aydin, 2024; Sumi et al., 2024), ~~emphasising~~ . This emphasises the challenging nature of ~~this task and relatively limited available training data~~ fracture segmentation as a task and the relatively limited training data currently available.

Notably, ~~our experiments show that the DL~~ the DL models (U-Net and SegFormer) ~~models~~ achieve substantially lower FracSim (better agreement of length distributions) than classical filters. ~~This demonstrates that~~ Thus DL predictions not only overlap ground truth spatially (IoU, F1) but also better reproduce ~~fracture segment~~ fracture segment length statistics.

3.2.3 Qualitative Results

Example outputs are shown in Fig. 13. Across the different datasets, the U-Net CNN consistently produced fracture maps that were smoother, more continuous, and closer to the ground-truth annotations than those ~~of~~ from traditional filters. The model often reconnected segments that filters left broken, yielding fracture networks that were both cleaner and more interpretable. These improvements were observed even under varying lithologies and illumination conditions, ~~confirming~~ consistent with the CNN's ability to generalise across a wide range of datasets. Remaining errors included omission of faint fractures and occasional short false positives in textured or shadowed areas. These qualitative results reinforce the quantitative findings: deep learning methods ~~provide~~ produce more reliable fracture maps than traditional filters, with notable improvements in continuity and interpretability across diverse geological settings.

~~When comparing~~ Comparing the two deep learning models, ~~the SegFormer model~~ SegFormer generated continuous predictions (Fig. 13) ~~, in some cases capturing and sometimes captured~~ long-range structures more effectively than ~~the CNN~~ U-Net. However, it introduced more false positives in complex textures, occasionally produced random hot spots, and overall ~~its outputs were yielded~~ less confident and less precise ~~compared to the outputs than~~ U-Net ~~model~~ across the test sites.

3.2.4 General vs. Dataset-Specific Models

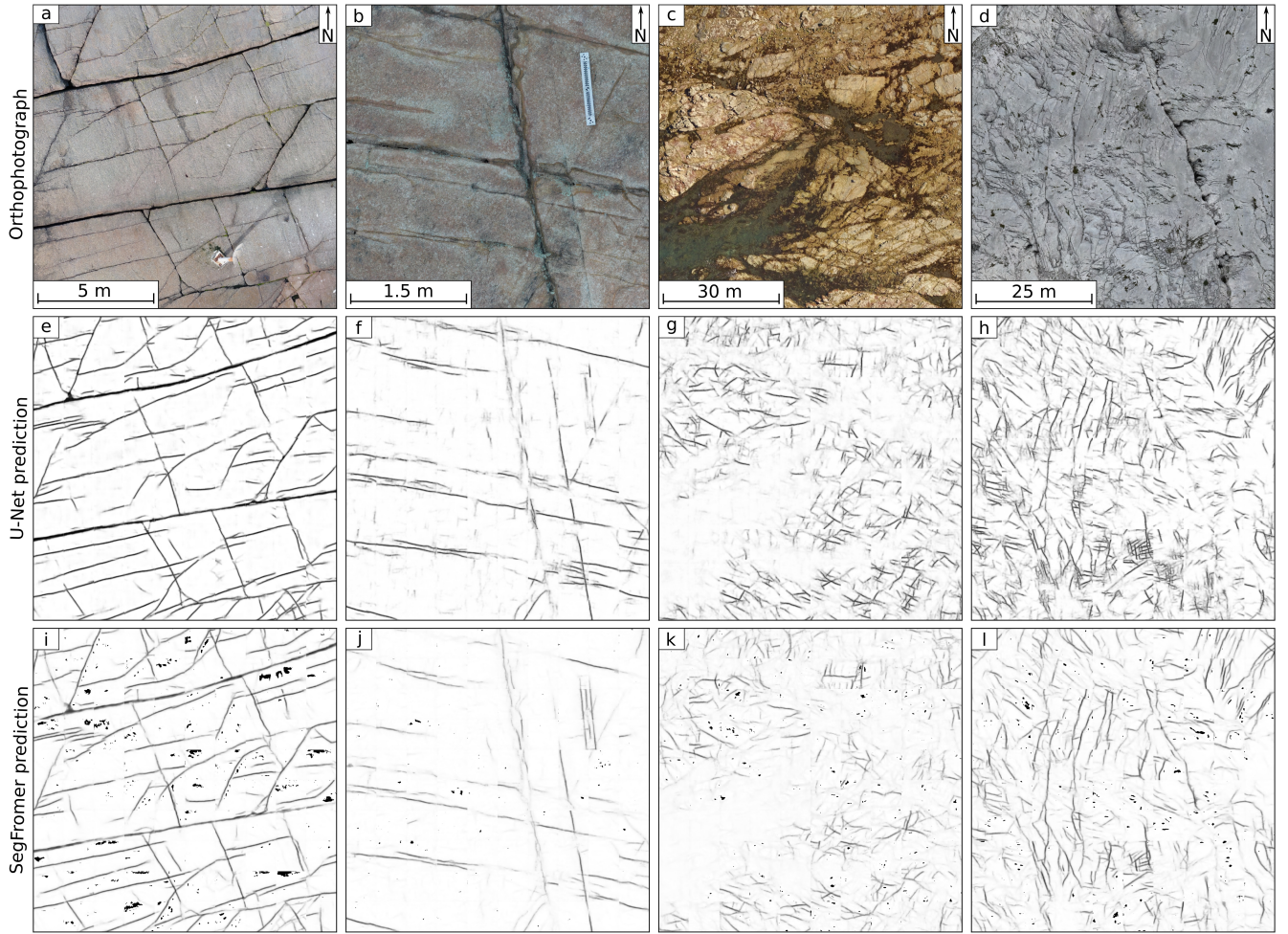


Figure 13. Deep-learning fracture-trace predictions for four representative orthophotographs. Panels (a–d) show the original orthophotographs. Panels (e–h) present corresponding U-Net predictions, and panels (i–l) show SegFormer predictions.

The comparison of models within each site (Table 6) shows that the combined model (M_all) provides clear advantages over outperforms dataset-specific models, particularly in terms of F1 and IoU.

For the SegFormer architecture on the On the D_ovas dataset, M_all and M_ovas exhibit comparable performance with the SegFormer architecture. M_all achieves an F1-score of 0.70 and an IoU of 0.54, closely matching M_ovas (F1 = 0.67, IoU = 0.51). This indicates that training on multiple datasets does not degrade performance on the Ovaskainen dataset Ovaskainen22, where fractures are relatively clear and annotations are well defined.

The advantages of M_all become more pronounced on the more challenging sites. On D_sams, the site-specific model (M_sams) performs poorly, achieving very low scores (F1 = 0.11, IoU = 0.06 for U-Net, and zero for SegFormer), despite high specificity, indicating weak fracture identification relative to the ground truth. In contrast, M_all substantially improves

Table 6. Comparison between multi-site model (M_all) and dataset-specific models (M_ovas, M_sams, M_matt)

Arch	Sub-dataset	Model	AE↓	MSE↓	SSIM↑	PSNR↑	Acc↑	Prec↑	F1↑	Rec↑	Spec↑	ROC↑	IoU↑	CK↑	FracSim*↓	Loss↓
U-Net	D_ovas	M_all	0.05	0.02	0.64	16.51	0.93	0.77	0.73	0.68	0.97	0.83	0.57	0.69	2.99	0.01
		M_ovas	0.06	0.02	0.60	16.03	0.91	0.63	0.67	0.72	0.93	0.83	0.51	0.62	3.04	0.01
	D_sams	M_all	0.06	0.03	0.58	15.48	0.86	0.32	0.34	0.38	0.92	0.65	0.21	0.27	7.54	0.01
		M_sams	0.05	0.03	0.57	15.99	0.91	0.58	0.11	0.06	1.00	0.53	0.06	0.09	3.26	0.01
	D_matt	M_all	0.08	0.04	0.57	14.27	0.80	0.45	0.39	0.34	0.90	0.62	0.24	0.27	4.01	0.02
		M_matt	0.06	0.02	0.61	16.53	0.81	0.47	0.24	0.17	0.96	0.56	0.14	0.16	4.78	0.01
	D_ovas	M_all	0.06	0.02	0.53	16.34	0.93	0.77	0.70	0.64	0.97	0.80	0.54	0.66	2.94	0.01
		M_ovas	0.05	0.02	0.58	16.12	0.93	0.81	0.70	0.61	0.98	0.79	0.54	0.66	3.16	0.01
SegFormer	D_sams	M_all	0.06	0.03	0.39	15.96	0.85	0.29	0.33	0.39	0.90	0.65	0.20	0.25	7.85	0.01
		M_sams	0.05	0.03	0.35	15.83	0.91	0.00	0.00	0.00	1.00	0.50	0.00	-0.00	1.65	0.01
	D_matt	M_all	0.08	0.03	0.38	15.37	0.81	0.48	0.41	0.35	0.91	0.63	0.25	0.29	4.47	0.01
		M_matt	0.06	0.03	0.67	16.01	0.81	0.51	0.06	0.03	0.99	0.51	0.03	0.04	5.55	0.01

* run only on modified test set

performance, reaching F1-scores of 0.34/0.33 and IoU values of 0.21/0.20. This represents more than a twofold increase in overlap metrics, suggesting that the ~~increased~~ greater variability in the combined training set enables better ~~generalization~~ generalisation to the more complex fracture patterns ~~present~~ in the Samsu19 dataset.

A similar trend is observed for D_matt. ~~The site-specific model,~~ where M_matt attains only F1 = 0.24 and IoU = 0.14 with U-Net, ~~and~~ (F1 = 0.06 ~~and~~, IoU = 0.03 with SegFormer. ~~In contrast,~~). M_all improves performance to F1 = 0.39/0.41 and IoU = 0.24/0.25. This ~~near-doubling~~ near-doubling of overlap metrics demonstrates that M_all is considerably better suited to handling the lithological and textural variability of the Matteo21 dataset.

Overall, these results indicate that while dataset-specific models can capture local patterns, they are constrained by limited training data and ~~are~~ prone to overfitting, resulting in reduced robustness.

3.2.5 Error Case Analysis

~~We note that despite~~ Despite its stronger overall performance, the U-Net still produced errors (Fig. 14). These fall into two categories: (1) cases where the model was highly confident yet disagreed with the annotations, and (2) cases where the model was uncertain, assigning low probabilities and yielding fragmented or unstable predictions under challenging visual conditions.

High-confidence errors. In several cases, the CNN produced confident predictions that did not match the annotations. A common source was annotation misalignment, where fractures in the ground truth were traced coarsely or offset from the true pixel locations, e.g., the over-simplified traces and omissions visible in panels (h) and (i) of Fig. 14. In these cases, the CNN model is arguably more accurate than the ground truth. This misalignment was particularly evident in the Samsu19 dataset, where manual traces did not precisely follow pixel-level fracture geometry.

Another high-confidence error type was input data artifacts, especially in Matteo21, where corrupted pixel values (NaNs, which PyTorch converts to 0, rendering them black in RGB) in the RGB channels led to localised false positives or spurious losses unrelated to actual geological structures, as illustrated by the missing pixel data in panel (e) and the resulting spurious responses in the corresponding probability map.

Low-confidence errors. Other errors occurred when the model was less certain and produced scattered or incomplete predictions. Confounding visual features such as vegetation, weathering textures, or shadows were occasionally misclassified as fractures, but with lower confidence values in the probability maps—as seen in the water- and shadow-affected orthophotographs in panels (a–c). Additionally, dataset outliers and preprocessing failures (e.g., unusual lithologies, lighting conditions, ~~or mislabelled patches~~ mislabelled patches, or the black-and-white scale panel in (d)) caused the model to generate unstable or inconsistent outputs, while panel (f), which contains no visible fractures, illustrates how the absence of true structure was nonetheless handled by the model. These low-confidence cases reflected the difficulty of ~~generalizing~~ generalising across heterogeneous field conditions not fully represented in the training data.

Taken together, this analysis suggests that many errors stemmed not from the CNN architecture itself but from ~~limitations in the data~~ data limitations: annotation quality, ~~artifacts in inputs~~ input artifacts, and domain heterogeneity. Probability maps proved useful here, ~~as~~ they allowed us to distinguish between errors where the model was confident but the labels were unreliable, and those where the model itself was uncertain—as summarised across the panels of Fig. 14, including the varying fracture thickness, orientation, and illumination shown in panels (g–i).

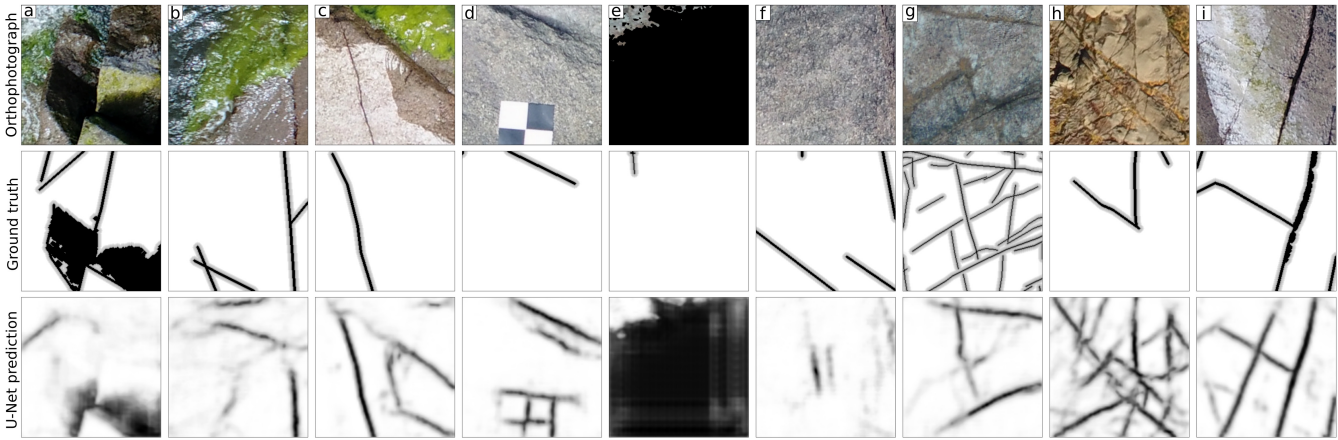


Figure 14. Error case analysis of U-Net predictions

Top row: Orthophotographs (a–c) with water and large shadows, (d) with a black-and-white scale panel, (e) containing missing pixel data, (f) showing no visible fractures, and (g–i) displaying fractures of varying thickness, orientation, and illumination

Middle row: Ground-truth annotations. Some overrepresent shadows due to preprocessing (a), contain labelling errors (c), have over-simplified traces (h), or show omissions (i)

Bottom row: U-Net probability maps. Faux responses appear in (a–e) due to input artifacts or preprocessing issues, while the model captures more realistic fracture geometry than the annotations in (f–i)

3.2.6 Time Required

We compared the time required for fracture mapping across manual, assisted, and automatic approaches (Fig. 15). Timing data for manual and assisted interpretation are taken from Thiele et al. (2017b), where mapping fractures in a 10 × 10 m area at 1 cm/pixel resolution took 54–57 minutes manually and 35–37 minutes using semi-automatic tools. In contrast, our automatic deep learning approach generated probability maps in 6 seconds (on [free-tier-huggingface-space \(2vCPU and 16GB RAM\)](#))
530 [Hugging Face Spaces free-tier instance with 2 vCPUs and 16 GB RAM](#)). While post-processing is still required to derive a fracture map (instance segmentation and vectorisation), this speed-up could ~~enable a substantial reduction in~~ [substantially reduce the](#) effort and time ~~during-needed for~~ large-scale fracture interpretation.

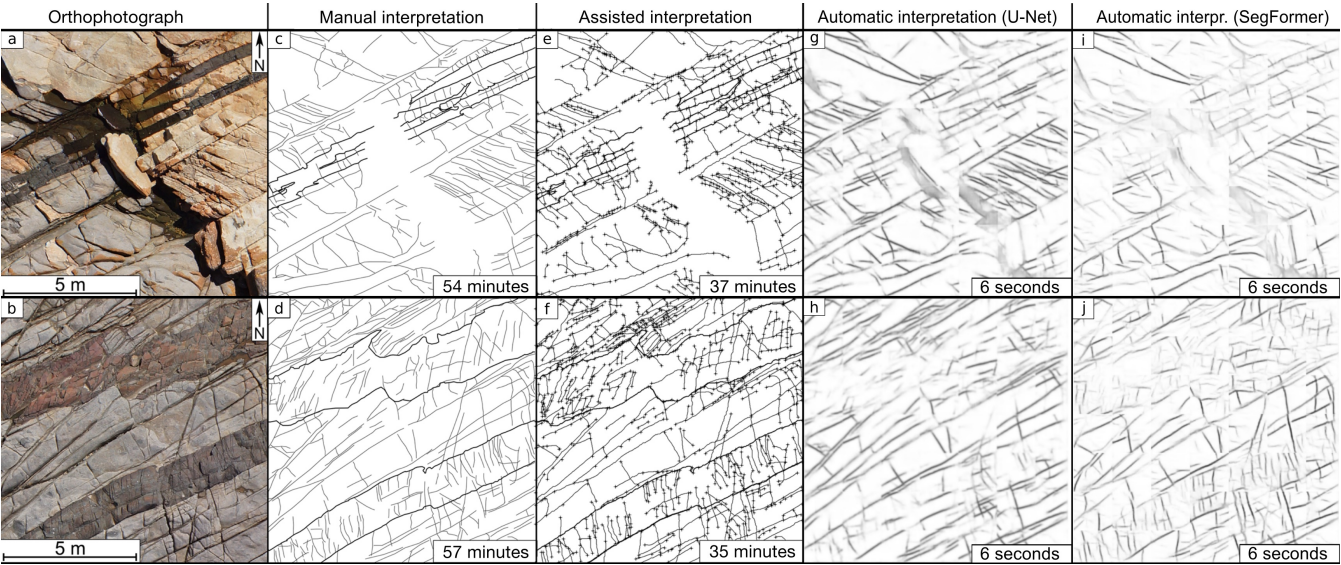


Figure 15. Two 10 × 10 m orthophotographs (Thiele et al., 2017b) (a, b) with corresponding fracture traces digitised manually (Thiele et al., 2017b) (c, d), semi-automatically using the assisted method of (Thiele et al., 2017b) (e, f), automatically with the U-Net model (g, h) and with SegFormer model (i, j)

4 Discussion

535 ~~We now~~ [Here we](#) discuss key observations from the benchmarking experiments and their implications for automated fracture mapping.

4.1 Model Performance

~~Unsurprisingly, traditional~~ [Traditional](#) edge and ridge filters proved inadequate for robust fracture mapping across heterogeneous datasets ~~. Their outputs~~ (Fig. 10, Fig. 11, Table E1). [Outputs](#) were highly sensitive to parameter choices, and ~~hyperparameter~~

540 ~~selections-hyperparameters optimal at one site~~ often failed to generalise ~~well~~-across combined sites. In practice, ~~these~~-traditional methods remain useful for rapid visualisation~~or~~, exploratory work, or ~~tailored-application-to-relatively-small-datasets~~. ~~However, small, tailored datasets, but~~ they are ill-suited for mapping ~~of~~-complex fracture systems ~~,which-is-required-for-needed~~ ~~for quantitative~~ fracture and structural analyses.

Our results are consistent with previous U-Net fracture-detection studies. Chudasama et al. (2024) reported F1 scores of
545 0.78–0.926 on granite outcrops in Finland using U-Net, though their evaluation did not include the background class, which inflates metrics relative to our methodology. Mattéo et al. (2021) achieved a Tversky Index (similar to IoU) of 0.35–0.68 using a similar architecture but on a single lithology. Our M_all model achieves F1 = 0.48 and IoU = 0.31 across heterogeneous datasets with the background class included, suggesting that cross-site generalisation incurs a performance cost that should decrease as more training data become available.

550 The tested deep learning models ~~were-shown-to-significantly-outperform-outperformed~~ the traditional filters, producing smoother and more continuous traces ~~and-with~~ substantially better overlap with annotated fractures. Nevertheless, absolute performance remained modest compared with segmentation benchmarks in other domains. This ~~is-likely-due-to-the-highly~~ ~~likely reflects the~~ unusual nature of ~~this-semantic-segmentation-task—the-selection-of-the-task—selecting~~ thin (high-aspect-ratio) pixel groupings (~~edges~~) ~~in-a-highly-in-a-strongly~~ class-imbalanced dataset ~~—and-the-variety-of—~~and geological and
555 environmental factors that ~~change-alter~~ fracture appearance or introduce ~~obfuscating-confounding~~ features. Label noise and misalignment are also likely contributors, although practical ~~limitations-around-limits-on~~ data collection and manual labelling make ~~it-challenging-to-acquire~~-better training data ~~hard to acquire~~.

Interestingly, the ~~The~~ transformer-based ~~models-model~~ (SegFormer) behaved ~~quite~~-differently from the CNNs in our experiments (see subsection 3.2 ~~,Their-and~~ Fig. 13). ~~SegFormer’s~~ results were less robust, ~~producing-with~~ spurious detections that
560 we attribute to ~~the-tendency-of~~-global-attention mechanisms ~~to-over-interpret-over-interpreting~~ background structure when the training signal is weak. This is consistent with known properties of transformers: they can excel when supplied with large, diverse, and clean datasets, but are more data-hungry than convolutional architectures.

~~Thus, while transformers-Transformers~~ showed some promise, ~~their-advantages-are-likely-to-but~~ their advantages likely emerge only with ~~substantial-improvements-in-dataset-size-and-annotation-quality~~~~substantially larger and cleaner datasets—although~~
565 ~~practical-limitations-around-data-collection-and-manual-labelling-make-acquiring-such-high-quality-training-data-particularly~~ ~~challenging-in-the-context-of-geological-fractures~~. In the meantime, the tested CNN ~~(difficult given practical limits on collecting and labelling geological fracture data~~. For current data scales, U-Net ~~)-architecture-appears-most-promising~~ ~~remains the recommended architecture~~.

Our cross-dataset experiments show that diverse training data improves ~~model~~-performance. A general model trained on all
570 sites consistently outperformed models trained on individual datasets, especially on overlap- and detection-sensitive metrics ~~like~~ (F1 score and IoU). This suggests that ~~exposure~~, IoU). ~~Exposure~~ to varied lithologies, lighting, and fracture patterns ~~helps~~ ~~the-model-learn-appears-to-yield~~ more transferable features and ~~reduces-reduce~~ overfitting to site-specific conditions. These results ~~highlight-the-importance-underscore-the-value~~ of multi-site datasets for robust fracture segmentation.

4.2 The Need for Post-processing

575 A critical bottleneck in automated fracture mapping is post-processing, ~~which is needed to convert~~ converting model outputs to polylines or ~~some other vectorised representation of fracture instances that are better suited~~ other vectorised fracture instances suitable for topological analyses (e.g., ~~for~~ assessing fracture connectivity). Pixel-wise probability maps are valuable, but ~~they are only the only a~~ first step toward usable fracture traces. Converting semantic masks into instance-level polylines for length, orientation, and spacing measurements requires robust, standardised post-processing pipelines (skeletonisation, connected-component analysis, cleaning, linking, and polyline extraction). Semantic segmentation models do not explicitly preserve fracture connectivity, so intersections and network topology are often poorly reconstructed even when the main fracture geometries are correctly detected. Without these steps, downstream fracture statistics remain noisy and ~~difficult~~ hard to interpret.

Post-processing ~~can and~~ should also incorporate domain knowledge (for example, weak orientation priors) to reduce spurious short segments and improve the geological plausibility of extracted traces. Furthermore, ~~we suggest that it might be possible to develop~~ post-processing algorithms ~~that can could~~ leverage the rich information in probabilistic model outputs and local knowledge ~~on~~ (e.g., likely fracture orientations) to (1) identify and remove false-positive fracture detections, and (2) extrapolate detected fractures across small gaps ~~(based on their orientation)~~, as is commonly done by human interpreters.

4.3 ~~Future Work Together, our~~ Deployment

590 As a first step toward practical deployment, we developed lightweight interfaces so users can apply the trained models without machine-learning expertise. A web-based application, built with Gradio (Abid et al., 2019) and hosted on Hugging Face Spaces (<https://ayoubft-fractex2d-tuto.hf.space>), enables users to upload paired RGB images and DEMs to obtain deep-learning-based fracture predictions. The interface also provides access to other computer-vision filters and evaluation metrics.

To facilitate integration into existing geological workflows, we additionally developed a simple QGIS plugin (<https://plugins.qgis.org/plugins/fraXtex/>) that enables inference directly within QGIS. Together, these tools show how the proposed workflow can be adopted in geoscience workflows.

4.4 Future Work

Our results highlight several concrete next steps ~~that could enable automated and toward automated, more~~ objective fracture mapping: improving annotation precision (multi-scale labels, consensus labelling) in training data, expanding dataset diversity by including more sites ~~(as more public data becomes available)~~ as additional public data become available, and adopting architectures and loss functions tailored to the unusual ~~(thin -)~~ thin geometry of fractures. Complementary strategies such as ensembling, transfer learning, and self-supervised pretraining offer promising avenues to improve performance and robustness. Ensembling multiple models can reduce variance and improve prediction stability, particularly for thin and discontinuous fracture traces. Transfer learning from larger geospatial or remote sensing datasets can provide stronger low-level feature representations, enabling better ~~generalization when labeled~~ generalisation when labelled fracture data are limited. Self-supervised

605

pretraining on ~~unlabeled data~~ unlabelled imagery can further leverage abundant data to learn domain-specific texture and structure features, improving downstream segmentation accuracy while reducing dependence on extensive manual annotations.

5 Conclusions

We present a harmonised benchmarking framework for fracture mapping in high-resolution outcrop imagery and use it to
610 compare traditional image filters ~~to with~~ deep learning methods, including a U-Net convolutional network and a ~~transformer~~
~~based~~ transformer-based model (SegFormer). Our experiments show that ~~the~~ deep learning models consistently outperform
traditional edge and ridge filters ~~by producing~~ yielding smoother, more continuous, and qualitatively ~~reasonable results~~ more
plausible traces. This gap ~~highlights~~ shows that algorithmic improvements alone are insufficient: ~~limited~~ incomplete post-
processing ~~techniques~~, variable label quality, dataset heterogeneity, and the complex information (e.g., ~~topological understanding~~ topology)
615 needed to ~~accurately identify high-aspect-ratio and~~ identify high-aspect-ratio, typically continuous fractures are the primary
barriers to reliable, fully automated fracture extraction. Beyond these empirical results, the principal ~~contribution of this work~~
contributions are the resources we release: the curated datasets, evaluation protocol, and open-source code. We hope ~~that~~ these
resources will ~~foster further developments to address~~ support further work on the challenges outlined above.

Code and data availability. The FraXet dataset, including all RGB tiles, DEMs, masks, and metadata, is archived and publicly accessible on
620 Zenodo at <https://doi.org/10.5281/zenodo.17069947> (Fatihi et al., 2025a).

The full source code used in this study is openly available at <https://gitlab.com/ayoubft/fractex2D.pt> (Last access: July 31, 2026) and the
version associated with this publication is archived at <https://doi.org/10.5281/zenodo.17953223> (Fatihi and Thiele, 2025).

All trained models associated with this work are available on both Hugging Face and Zenodo. The model weights can be accessed on
Hugging Face at <https://huggingface.co/ayoubft/fraXteX> (Last access: July 31, 2026) and are archived on Zenodo at [https://doi.org/10.5281/](https://doi.org/10.5281/zenodo.17866853)
625 [zenodo.17866853](https://doi.org/10.5281/zenodo.17866853) (Fatihi et al., 2025b).

A live deployment of the model is hosted on Hugging Face at https://huggingface.co/spaces/ayoubft/fractex2D_tuto, providing an inter-
active interface for running inference of the trained deep learning models and also try the computer vision filters.

Appendix A: Dataset overviews

Overview maps and example tiles for each of the three datasets are provided in Fig. A1, Fig. A2, and Fig. A3, complementing the metadata in Table 3.

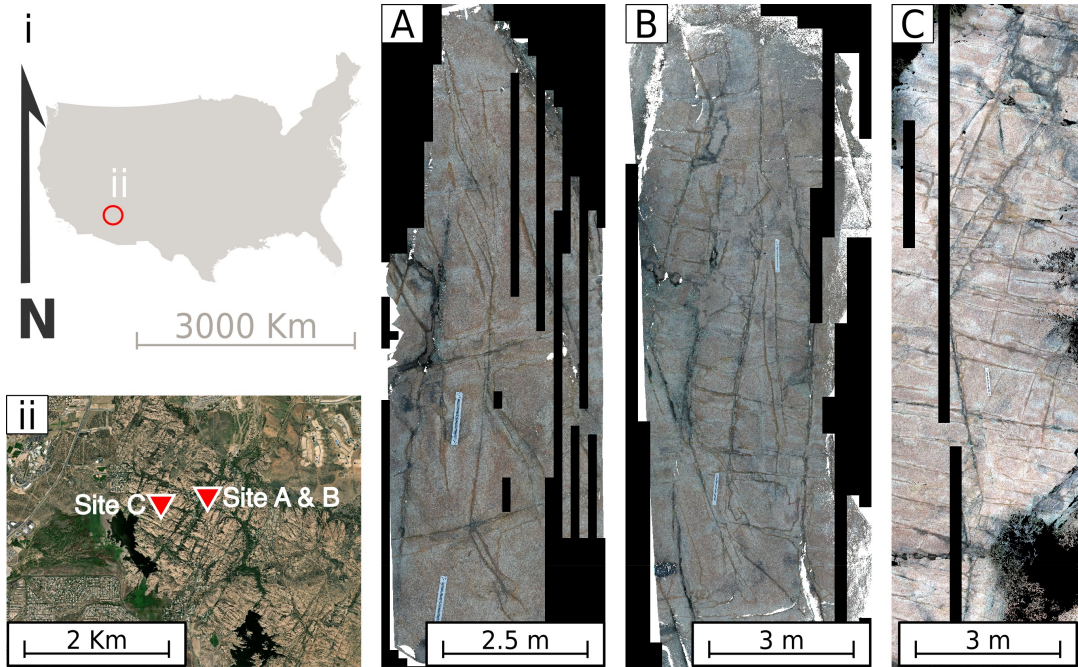


Figure A1. Overview of the Matteo21 dataset. (i) Location map of the Granite Dells, Arizona, USA. (ii) Zoom in to sites A, B and C. (A) Site A (training + validation site). (B) Site B (training + validation site). (C) Site C (test site).

Appendix B: Pre-processing effect

Table B1. Effect of preprocessing on fracture-class pixel proportions across datasets

Dataset	Before pre-processing			After preprocessing		
	train	valid	test	train	valid	test
Ovaskainen22	0.45	0.57	0.68	3.08	3.32	4.14
Matteo21	0.29	0.58	0.55	0.39	0.60	1.51
Samsu19	0.43	0.35	0.49	2.17	1.73	2.41

Table C1. Data augmentation techniques and corresponding probabilities and parameter ranges

Augmentation Technique	Probability	Parameter Range
Horizontal Flip	0.5	-
Vertical Flip	0.5	-
Gaussian Blur	0.05	Sigma $\in$ [0.1, 2.0]
Brightness Decrease	0.05	Factor $\in$ [0.7, 0.9]
Brightness Increase	0.15	Factor $\in$ [1.1, 1.7]
Contrast Adjustment	0.05	Factor $\in$ [0.7, 1.5]
Saturation Adjustment	0.05	Factor $\in$ [0.7, 1.5]

Appendix C: Data Augmentation Setup

Appendix D: Optimal Filters’ Parameters

Table D1. Optimal filters’ parameters using the grid search and visually (Ovaskainen22/Matteo21/Samsu19/LapiesdiBou)

Algorithm	Parameter	Opt. Value (grid)	Threshold (grid)	Opt. Value (visual)	Threshold (visual)
Edge detectors	Sobel	-	0.8	-	0.19/0.1/0.11/0.11
	sigma	1.9		1.5/0./0.53/1.	
	Canny	low_threshold	-	0.3/0.65/0.66/0.1	-
		high_threshold		0.5/1./1./1.	
Ridge detector	Gabor	frequency	0.0	0.7/1./1./1.	0.12/0.35/0.26/0.5
	Sato	sigmas	range(2, 8, 2)	range(1, 20, 4)/idem /range(1,4)/(1,)	0.6/.04/0.07/0.6
		nscale	5	6/5/6/6	
		noorient	5	6/5/6/6	
Phase Congruency		minWaveLength	3	5/3/5/5	
		mult	2	2.3/2/2.3/2.3	
		sigmaOnf	0.5	0.6/0.5/0.6/0.6	0.002/0.0011/0.15
		k	2	3.6/3/3.6/3.6	
		cutOff	0.3	0.36/0.3/0.36/0.36	
		g	10	41.6 /10/41.6/41.6	
	noiseMethod	-1		-1	

Appendix E: Quantitative Results

Table E1. Quantitative results: evaluation metrics on the test set

	AE↓	MSE↓	SSIM↑	PSNR↑	Acc↑	Prec↑	F1↑	Rec↑	Spec↑	ROC↑	IoU↑	CK↑	FracSim*↓	Loss↓
phasecong	0.15	0.14	0.0	8.68	0.79	0.28	0.27	0.27	0.88	0.58	0.16	0.15	214.53	<u>0.07</u>
sobel	0.46	0.44	0.0	3.59	0.55	0.18	0.28	<u>0.57</u>	0.55	0.56	0.16	0.06	132.27	0.22
gabor	0.94	0.92	0.0	0.35	0.15	0.14	0.25	1.00	0.01	0.50	0.14	0.00	48.12	0.46
sato	0.11	0.10	0.0	10.2	0.85	0.30	0.27	0.25	0.93	0.59	0.16	0.19	153.76	0.05
canny	0.28	0.27	0.0	5.76	0.69	0.22	0.29	0.42	0.74	0.58	0.17	0.12	71.10	0.13
U-Net	<u>0.07</u>	0.03	<u>0.49</u>	14.7	<u>0.84</u>	0.50	0.48	0.45	<u>0.92</u>	0.69	0.31	0.39	3.40	0.02
SegFormer	0.10	<u>0.05</u>	0.40	13.2	0.79	<u>0.38</u>	<u>0.44</u>	0.52	0.84	<u>0.68</u>	<u>0.28</u>	<u>0.32</u>	<u>3.43</u>	0.02
All 1	0.95	0.93	0.01	0.33	0.16	0.16	0.27	1.00	0.00	0.50	0.16	0.00	Undef	0.47
All 0	0.05	0.03	0.82	<u>14.69</u>	0.84	0.00	0.00	0.00	0.00	0.50	0.00	0.00	Undef	0.02

* was calculated on the modified test set

635 *Author contributions.* AF: Conceptualisation, Formal analysis, Data curation, Code development, Investigation, Methodology, Visualisation, Writing – original draft; JC: Writing - review & editing; TB: Methodology, Writing - review & editing; STT: Conceptualisation, Code development, Methodology, Writing - review & editing; AS: Conceptualisation, Methodology, Writing - review & editing;

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

Acknowledgements. This study was supported by the University of Lausanne (Université de Lausanne).

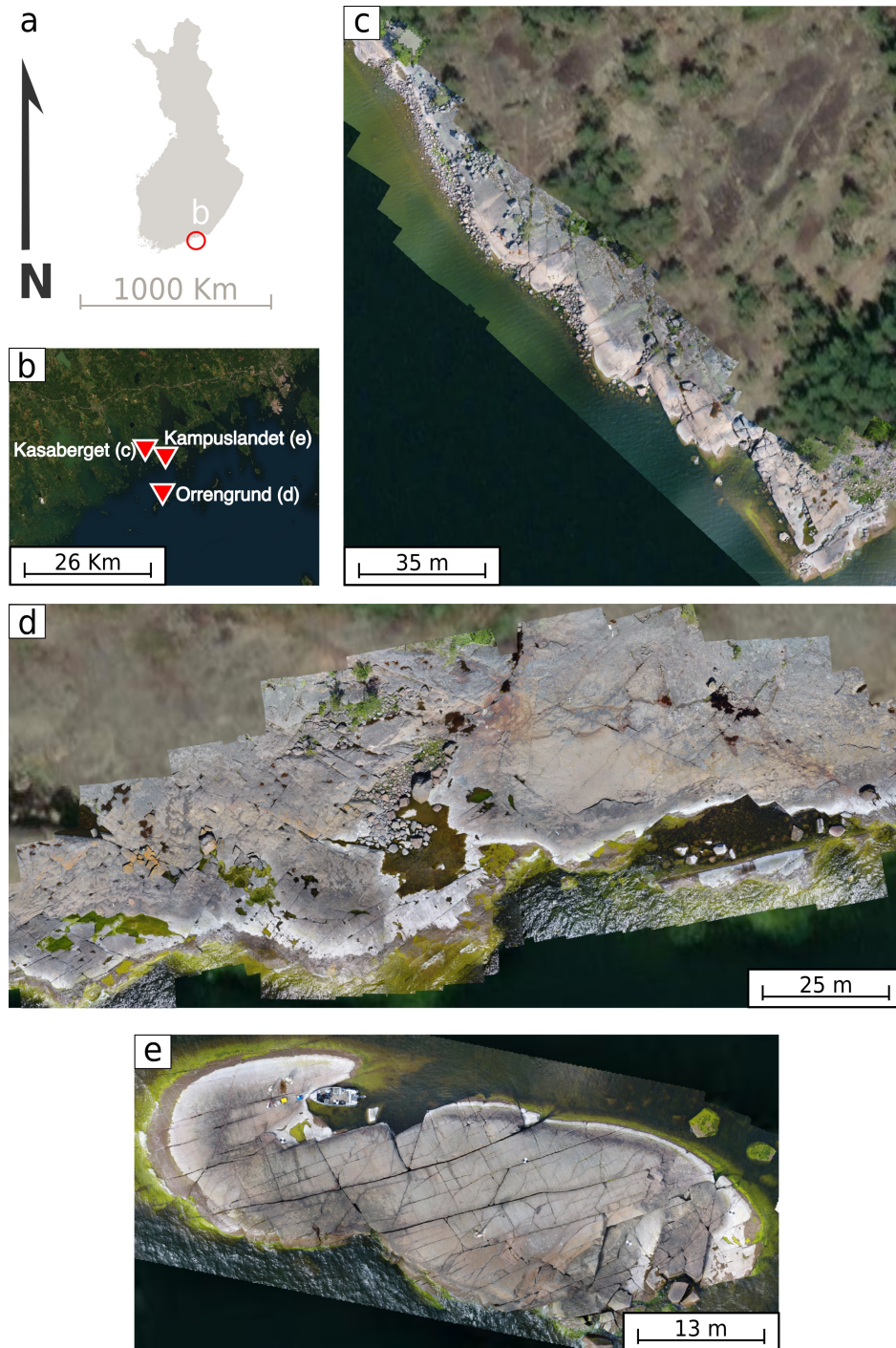


Figure A2. Overview of the Ovaskainen22 dataset. (a) Location map of the Wiborg Rapakivi Granite Batholith, southeastern Finland. (b) Zoom in to the Loviisa region showing the islands of Orrengrund, Kasaberget, and Kampuslandet. (c) Orrengrund (training site) orthophotograph. (d) Kasaberget (validation site) orthophotograph. (e) Kampuslandet (test site) orthophotograph.

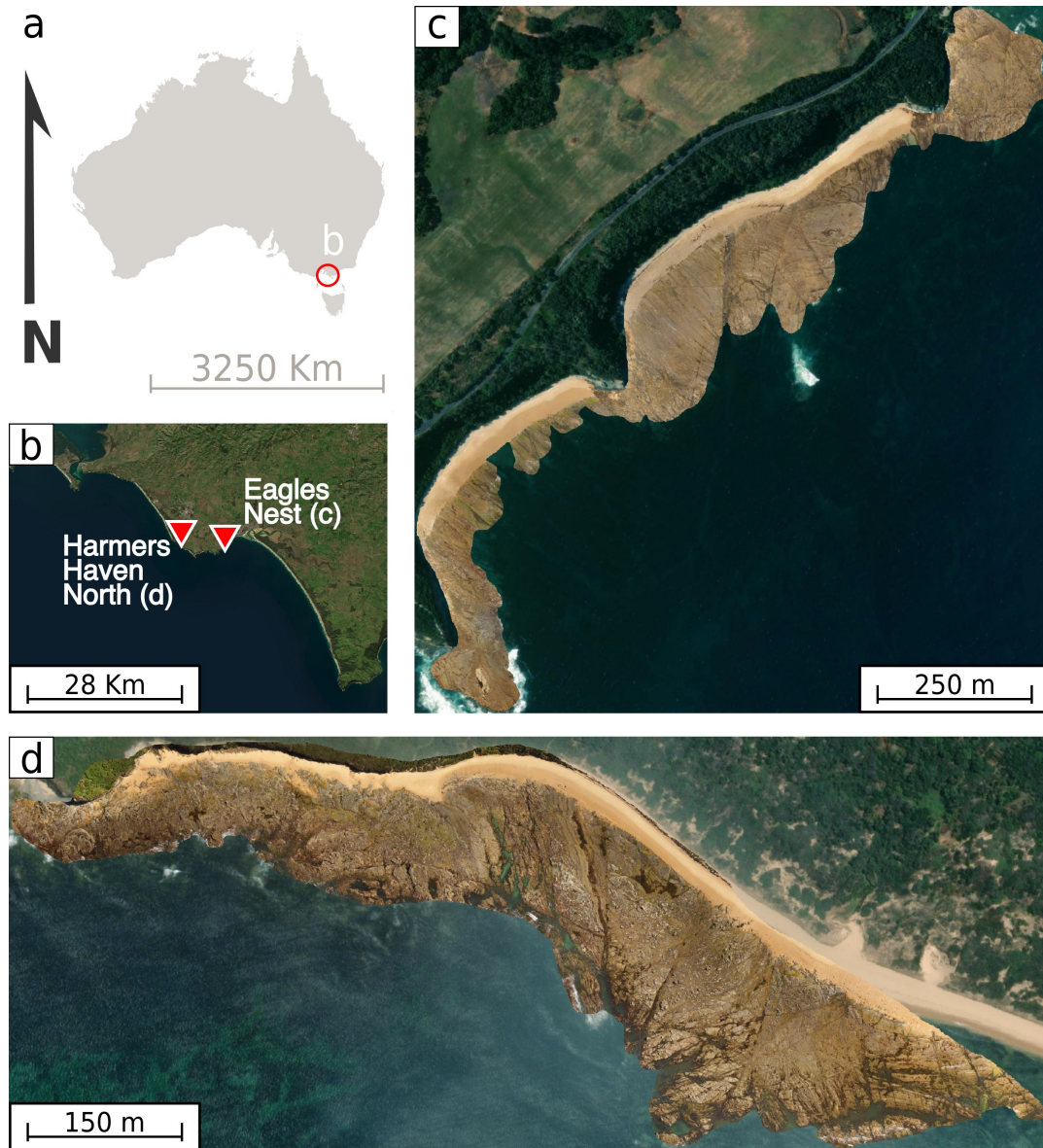


Figure A3. Overview of the Samsu19 dataset. (a) Location map of the Strzelecki Group, southeastern Australia. (b) Zoom in to the Harpers Haven area showing Eagles Nest and Harpers Haven north. (c) Eagles Nest (training site) orthophotograph. (d) Harpers Haven north (validation/test site) orthophotograph.

640 References

- Abid, A., Abdalla, A., Abid, A., Khan, D., Alfozan, A., and Zou, J.: Gradio: Hassle-Free Sharing and Testing of ML Models in the Wild, <https://doi.org/10.48550/arXiv.1906.02569>, 2019.
- Adiri, Z., El Harti, A., Jellouli, A., Lhissou, R., Maacha, L., Azmi, M., Zouhair, M., and Bachaoui, E. M.: Comparison of Landsat-8, ASTER and Sentinel 1 Satellite Remote Sensing Data in Automatic Lineaments Extraction: A Case Study of Sidi Flah-Bouskour Inlier, Moroccan
645 Anti Atlas, *Advances in Space Research*, 60, 2355–2367, <https://doi.org/10.1016/j.asr.2017.09.006>, 2017.
- Aghaee, A., Shamsipour, P., Hood, S., and Haugaard, R.: A Convolutional Neural Network for Semi-Automated Lineament Detection and Vectorisation of Remote Sensing Data Using Probabilistic Clustering: A Method and a Challenge, *Computers & Geosciences*, 151, 104 724, <https://doi.org/10.1016/j.cageo.2021.104724>, 2021.
- An, Y., Du, H., Ma, S., Niu, Y., Liu, D., Wang, J., Du, Y., Childs, C., Walsh, J., and Dong, R.: Current State and Future Direc-
650 tions for Deep Learning Based Automatic Seismic Fault Interpretation: A Systematic Review, *Earth-Science Reviews*, 243, 104 509, <https://doi.org/10.1016/j.earscirev.2023.104509>, 2023.
- Andrews, B. J., Roberts, J. J., Shipton, Z. K., Bigi, S., Tartarello, M. C., and Johnson, G.: How Do We See Fractures? Quantifying Subjective Bias in Fracture Data Collection, *Solid Earth*, 10, 487–516, <https://doi.org/10.5194/se-10-487-2019>, 2019.
- Aydin, A.: Fractures, Faults, and Hydrocarbon Entrapment, Migration and Flow, *Marine and Petroleum Geology*, 17, 797–814,
655 [https://doi.org/10.1016/S0264-8172\(00\)00020-9](https://doi.org/10.1016/S0264-8172(00)00020-9), 2000.
- Badoux, H., Bonnard, E. G., and Burri, M.: *Geologischer Atlas der Schweiz. 35 = Bl. 546: St.-Léonard: avec annexe de la feuille Sion / levé géologique par: H. Badoux, E. G. Bonnard, M. Burri*, 1959.
- Bemis, S. P., Micklethwaite, S., Turner, D., James, M. R., Akciz, S., Thiele, S. T., and Bangash, H. A.: Ground-Based and UAV-Based Pho-
togrammetry: A Multi-Scale, High-Resolution Mapping Tool for Structural Geology and Paleoseismology, *Journal of Structural Geology*,
660 69, 163–178, <https://doi.org/10.1016/j.jsg.2014.10.007>, 2014.
- Berkowitz, B.: Characterizing Flow and Transport in Fractured Geological Media: A Review, *Advances in Water Resources*, 25, 861–884, [https://doi.org/10.1016/S0309-1708\(02\)00042-8](https://doi.org/10.1016/S0309-1708(02)00042-8), 2002.
- Bond, C., Gibbs, A., Shipton, Z., and Jones, S.: What Do You Think This Is? “Conceptual Uncertainty” in Geoscience Interpretation, *GSA Today*, 17, 4, <https://doi.org/10.1130/GSAT01711A.1>, 2007.
- Bonnet, E., Bour, O., Odling, N. E., Davy, P., Main, I., Cowie, P., and Berkowitz, B.: Scaling of Fracture Systems in Geological Media,
665 *Reviews of Geophysics*, 39, 347–383, <https://doi.org/10.1029/1999RG000074>, 2001.
- Candès, E. J. and Donoho, D. L.: Continuous Curvelet Transform: I. Resolution of the Wavefront Set, *Applied and Computational Harmonic Analysis*, 19, 162–197, <https://doi.org/10.1016/j.acha.2005.02.003>, 2005.
- Candès, E. J. and Guo, F.: New Multiscale Transforms, Minimum Total Variation Synthesis: Applications to Edge-Preserving Image Recon-
670 struction, *Signal Processing*, 82, 1519–1543, [https://doi.org/10.1016/S0165-1684\(02\)00300-6](https://doi.org/10.1016/S0165-1684(02)00300-6), 2002.
- Cappa, F., Guglielmi, Y., Nussbaum, C., and Birkholzer, J.: On the Relationship Between Fault Permeability Increases, Induced Stress Perturbation, and the Growth of Aseismic Slip During Fluid Injection, <https://doi.org/10.1029/2018GL080233>, 2018.
- Chudasama, B., Ovaskainen, N., Tamminen, J., Nordbäck, N., Engström, J., and Aaltonen, I.: Automated Mapping of Bedrock-Fracture Traces from UAV-acquired Images Using U-Net Convolutional Neural Networks, *Computers & Geosciences*, 182, 105 463,
675 <https://doi.org/10.1016/j.cageo.2023.105463>, 2024.

- Constantine, A.: Sedimentology, Stratigraphy and Palaeoenvironment of the Upper Jurassic-Lower Cretaceous Non-Marine Strzelecki Group, Gippsland Basin, Southeastern Australia, Ph.D. thesis, Monash University, 2001.
- Do, M. and Vetterli, M.: The Contourlet Transform: An Efficient Directional Multiresolution Image Representation, *IEEE Transactions on Image Processing*, 14, 2091–2106, <https://doi.org/10.1109/TIP.2005.859376>, 2005.
- 680 Duda, R. O. and Hart, P. E.: Use of the Hough Transformation to Detect Lines and Curves in Pictures, *Communications of the ACM*, 15, 11–15, <https://doi.org/10.1145/361237.361242>, 1972.
- Fan, J. and Ni, C.: Comparative Studies on the Extraction of Lineaments and Its Variability Based on an Improved Line Segment Tracking Method—Taking the Gaosong Ore Field in the Gejiu Gejiu Tin Ore Deposit as an Example, *Applied Sciences*, 13, 1314, <https://doi.org/10.3390/app13031314>, 2023.
- 685 Fatihi, A. and Thiele, S.: Ayoubft/fractex2D.Pt, Zenodo, <https://doi.org/10.5281/zenodo.17953223>, 2025.
- Fatihi, A., Caldeira, J., Beucler, T., Thiele, S., and Samsu, A.: FraXet, <https://doi.org/10.5281/zenodo.17069947>, 2025a.
- Fatihi, A., Caldeira, J., Beucler, T., Thiele, S., and Samsu, A.: Fracture Mapping Models Trained on FraXet, <https://doi.org/10.5281/zenodo.17866853>, 2025b.
- Gaikwad, V., Singh, K., Salunke, V., and Kudnar, N.: GIS-based Comparative Analysis of Lineament Extraction by Using Different Azimuth
- 690 Angles: A Case Study of Mula River Basin, Maharashtra, India, *Arabian Journal of Geosciences*, 16, 538, <https://doi.org/10.1007/s12517-023-11636-2>, 2023.
- Guo, Y.: Augmentation Is AUtO-Net: Augmentation-Driven Contrastive Multiview Learning for Medical Image Segmentation, <https://doi.org/10.48550/arXiv.2311.01023>, 2023.
- Han, L., Liu, Z., Ning, Y., and Zhao, Z.: Extraction and Analysis of Geological Lineaments Combining a DEM and Remote Sensing Images
- 695 from the Northern Baoji Loess Area, *Advances in Space Research*, 62, 2480–2493, <https://doi.org/10.1016/j.asr.2018.07.030>, 2018.
- Härmä, P.: Natural Stone Exploration in the Classic Wiborg Rapakivi Granite Batholith of Southeastern Finland – New Insights from Integration of Lithological, Geophysical and Structural Data, Ph.D. thesis, Department of Geosciences and Geography, University of Helsinki, 2020.
- Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A. C., Lo, W.-Y., Dollár, P., and
- 700 Girshick, R.: Segment Anything, <https://doi.org/10.48550/arXiv.2304.02643>, 2023.
- Koike, K., Nagano, S., and Ohmi, M.: Lineament Analysis of Satellite Images Using a Segment Tracing Algorithm (STA), *Computers & Geosciences*, 21, 1091–1104, [https://doi.org/10.1016/0098-3004\(95\)00042-7](https://doi.org/10.1016/0098-3004(95)00042-7), 1995.
- Kovesi, P.: Image Features from Phase Congruency, *Videre: Journal of Computer Vision Research*, 1999.
- Kovesi, P.: Phase Congruency: A Low-Level Image Invariant, *Psychological Research*, 64, 136–148, <https://doi.org/10.1007/s004260000024>,
- 705 2000.
- Krieger, M. L. H.: Geology of the Prescott and Paulden Quadrangles, Arizona, Tech. Rep. 467, U. S. Govt. Print. Off., ISSN 2330-7102, <https://doi.org/10.3133/pp467>, 1965.
- Kuş, Z. and Aydin, M.: MedSegBench: A Comprehensive Benchmark for Medical Image Segmentation in Diverse Data Modalities, *Scientific Data*, 11, 1283, <https://doi.org/10.1038/s41597-024-04159-2>, 2024.
- 710 LeCun, Y., Bengio, Y., and Hinton, G.: Deep Learning, *Nature*, 521, 436–444, <https://doi.org/10.1038/nature14539>, 2015.
- Mallat, S. and Hwang, W.: Singularity Detection and Processing with Wavelets, *IEEE Transactions on Information Theory*, 38, 617–643, <https://doi.org/10.1109/18.119727>, 1992.

- Masoud, A. and Koike, K.: Applicability of Computer-Aided Comprehensive Tool (LINDA: LINEament Detection and Analysis) and Shaded Digital Elevation Model for Characterizing and Interpreting Morphotectonic Features from Lineaments, *Computers & Geosciences*, 106, 89–100, <https://doi.org/10.1016/j.cageo.2017.06.006>, 2017.
- Masoud, A. A. and Koike, K.: Auto-Detection and Integration of Tectonically Significant Lineaments from SRTM DEM and Remotely-Sensed Geophysical Data, *ISPRS Journal of Photogrammetry and Remote Sensing*, 66, 818–832, <https://doi.org/10.1016/j.isprsjprs.2011.08.003>, 2011.
- Mattéo, L., Manighetti, I., Tarabalka, Y., Gaucel, J.-M., Van Den Ende, M., Mercier, A., Tasar, O., Girard, N., Leclerc, F., Giampetro, T., Dominguez, S., and Malavieille, J.: Dataset of Manuscript "Automatic Fault Mapping in Remote Optical Images and Topographic Data with Deep Learning", *Journal of Geophysical Research - Solid Earth*, 2021, 2020.
- Mattéo, L., Manighetti, I., Tarabalka, Y., Gaucel, J.-M., van den Ende, M., Mercier, A., Tasar, O., Girard, N., Leclerc, F., Giampetro, T., Dominguez, S., and Malavieille, J.: Automatic Fault Mapping in Remote Optical Images and Topographic Data With Deep Learning, *Journal of Geophysical Research: Solid Earth*, 126, e2020JB021 269, <https://doi.org/10.1029/2020JB021269>, 2021.
- Nordbäck, N. and Ovaskainen, N.: UAV-acquired Orthomosaics of Loviisa Shoreline Outcrops, <https://doi.org/10.5281/zenodo.17878870>, 2025.
- Oliveira, M. J., Savastano, V., Matos, G., Schmitt, R., Valente, V., Araujo, M., and Inocencio, L.: The Use of Drones and Deep Learning to Identify Igneous Rocks and Fractures, in: *Offshore Technology Conference Brasil*, <https://doi.org/10.4043/29829-MS>, 2019.
- Ovaskainen, N. and Nordbäck, N.: Manually Mapped Traces from UAV-acquired Images of Loviisa Shoreline Outcrops, <https://doi.org/10.5281/zenodo.7077846>, 2022.
- Ovaskainen, N., Skyttä, P., Nordbäck, N., and Engström, J.: Detailed Investigation of Multi-Scale Fracture Networks in Glacially Abraded Crystalline Bedrock at Åland Islands, Finland, *Solid Earth*, 14, 603–624, <https://doi.org/10.5194/se-14-603-2023>, 2023.
- Palamakumbura, R., Krabbendam, M., Whitbread, K., and Arnhardt, C.: Data Acquisition by Digitizing 2-D Fracture Networks and Topographic Lineaments in Geographic Information Systems: Further Development and Applications, *Solid Earth*, 11, 1731–1746, <https://doi.org/10.5194/se-11-1731-2020>, 2020.
- Peacock, D. C. P. and Sanderson, D. J.: Influences of Map Resolution, Quality and Interpretation on Fault Network Topology, *Earth-Science Reviews*, 277, 105 461, <https://doi.org/10.1016/j.earscirev.2026.105461>, 2026.
- Peacock, D. C. P., Sanderson, D. J., Bastesen, E., Rotevatn, A., and Storstein, T. H.: Causes of Bias and Uncertainty in Fracture Network Analysis, *NORWEGIAN JOURNAL OF GEOLOGY*, 2019.
- Pola, A., Herrera-Díaz, A., Tinoco-Martínez, S. R., Macias, J. L., Soto-Rodríguez, A. N., Soto-Herrera, A. M., Sereno, H., and Ramón Avelán, D.: Rock Characterization, UAV Photogrammetry and Use of Algorithms of Machine Learning as Tools in Mapping Discontinuities and Characterizing Rock Masses in Acoculco Caldera Complex, *Bulletin of Engineering Geology and the Environment*, 83, 260, <https://doi.org/10.1007/s10064-024-03743-5>, 2024.
- Potts, G. J.: Simple Rule to Assist in the Construction of the Outcrop Trace of an Inclined Surface, *Journal of Structural Geology*, 165, 104 749, <https://doi.org/10.1016/j.jsg.2022.104749>, 2022.
- Prabhakaran, R., Bruna, P.-O., Bertotti, G., and Smeulders, D.: An Automated Fracture Trace Detection Technique Using the Complex Shearlet Transform, *Solid Earth*, 10, 2137–2166, <https://doi.org/10.5194/se-10-2137-2019>, 2019.
- Raghavan, V., Wadatsumi, K., and Masumoto, S.: Automatic Extraction of Lineament Information from Satellite Images Using Digital Elevation Data, *Nonrenewable Resources*, 2, 148–155, <https://doi.org/10.1007/BF02272811>, 1993.

- 750 Raghavan, V., Masumoto, S., Koike, K., and Nagano, S.: Automatic Lineament Extraction from Digital Images Using a Segment Tracing and Rotation Transformation Approach, *Computers & Geosciences*, 21, 555–591, [https://doi.org/10.1016/0098-3004\(94\)00097-E](https://doi.org/10.1016/0098-3004(94)00097-E), 1995.
- Rahnama, M. and Gloaguen, R.: TecLines: A MATLAB-Based Toolbox for Tectonic Lineament Analysis from Satellite Images and DEMs, Part 1: Line Segment Detection and Extraction, *Remote Sensing*, 6, 5938–5958, <https://doi.org/10.3390/rs6075938>, 2014.
- Ren and Malik: Learning a Classification Model for Segmentation, in: *Proceedings Ninth IEEE International Conference on Computer Vision*, pp. 10–17 vol.1, IEEE, Nice, France, ISBN 978-0-7695-1950-0, <https://doi.org/10.1109/ICCV.2003.1238308>, 2003.
- 755 Ronneberger, O., Fischer, P., and Brox, T.: U-Net: Convolutional Networks for Biomedical Image Segmentation, in: *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, edited by Navab, N., Hornegger, J., Wells, W. M., and Frangi, A. F., *Lecture Notes in Computer Science*, pp. 234–241, Springer International Publishing, Cham, ISBN 978-3-319-24574-4, https://doi.org/10.1007/978-3-319-24574-4_28, 2015.
- 760 Saint Jean Patrick Coulibaly, H., Talnan Jean Honoré, C., Naga, C., Claude Alain Kouadio, K., Régis Mailly DIDI, S., Diedhiou, A., and Savane, I.: Groundwater Exploration Using Extraction of Lineaments from SRTM DEM and Water Flows in Béré Region, *The Egyptian Journal of Remote Sensing and Space Science*, 24, 391–400, <https://doi.org/10.1016/j.ejrs.2020.07.003>, 2021.
- Samsu, A., Cruden, A., and Vollgger, S.: Scale Matters: The Influence of Structural Inheritance on Fracture Patterns - Supplementary Material, <https://doi.org/10.26180/5CDCAD0A73FE0>, 2019.
- 765 Sanderson, D. J. and Nixon, C. W.: The Use of Topology in Fracture Network Characterization, *Journal of Structural Geology*, 72, 55–66, <https://doi.org/10.1016/j.jsg.2015.01.005>, 2015.
- Scheiber, T., Fredin, O., Viola, G., Jarna, A., Gasser, D., and Łapińska-Viola, R.: Manual Extraction of Bedrock Lineaments from High-Resolution LiDAR Data: Methodological Bias and Human Perception, *GFF*, 137, 362–372, <https://doi.org/10.1080/11035897.2015.1085434>, 2015.
- 770 Sharma, R., Saqib, M., Lin, C. T., and Blumenstein, M.: A Survey on Object Instance Segmentation, *SN Computer Science*, 3, 499, <https://doi.org/10.1007/s42979-022-01407-3>, 2022.
- Smeraglia, L., Mercuri, M., Tavani, S., Pignalosa, A., Kettermann, M., Billi, A., and Carminati, E.: 3D Discrete Fracture Network (DFN) Models of Damage Zone Fluid Corridors within a Reservoir-Scale Normal Fault in Carbonates: Multiscale Approach Using Field Data and UAV Imagery, *Marine and Petroleum Geology*, 126, 104902, <https://doi.org/10.1016/j.marpetgeo.2021.104902>, 2021.
- 775 Soto-Pinto, C., Arellano-Baeza, A., and Sánchez, G.: A New Code for Automatic Detection and Analysis of the Lineament Patterns for Geophysical and Geological Purposes (ADALGEO), *Computers & Geosciences*, 57, 93–103, <https://doi.org/10.1016/j.cageo.2013.03.019>, 2013.
- Steck, A., Epard, J.-L., Escher, A., Gouffon, Y., and Masson, H.: *Carte tectonique des Alpes de Suisse occidentale 1:100 000*, Office féd. Eaux Géologie (Berne), ISBN 978-3-906723-44-0, 2001.
- 780 Sumi, M. R., Das, P., Hossain, A., Dey, S., and Schuckers, S.: A Comprehensive Evaluation of Iris Segmentation on Benchmarking Datasets, *Sensors*, 24, 7079, <https://doi.org/10.3390/s24217079>, 2024.
- swisstopo: *Tectonic Map of Switzerland 1: 500 000*, Federal Office of Topography Swisstopo, Wabern, 2024.
- Thiele, S., Vollgger, S., and Anindita Samsu: *GeoTrace and Compass Rapid Trace-Mapping (Example Data)*, <https://doi.org/10.4225/03/5981B31091AF9>, 2017a.
- 785 Thiele, S. T., Grose, L., Samsu, A., Micklethwaite, S., Vollgger, S. A., and Cruden, A. R.: Rapid, Semi-Automatic Fracture and Contact Mapping for Point Clouds, Images and Geophysical Data, *Solid Earth*, 8, 1241–1253, <https://doi.org/10.5194/se-8-1241-2017>, 2017b.
- Twiss, R. J. and Moores, E. M.: *Structural Geology*, W. H. Freeman, New York, NY, second edition edn., ISBN 978-0-7167-4951-6, 2006.

- Vasuki, Y., Holden, E.-J., Kovesi, P., and Micklethwaite, S.: Semi-Automatic Mapping of Geological Structures Using UAV-based Photogrammetric Data: An Image Analysis Approach, *Computers & Geosciences*, 69, 22–32, <https://doi.org/10.1016/j.cageo.2014.04.012>, 2014.
- Vasuki, Y., Holden, E.-J., Kovesi, P., and Micklethwaite, S.: An Interactive Image Segmentation Method for Lithological Boundary Detection: A Rapid Mapping Tool for Geologists, *Computers & Geosciences*, 100, 27–40, <https://doi.org/10.1016/j.cageo.2016.12.001>, 2017.
- Villarreal, C. A., Garzón, C. G., Mora, J. P., Rojas, J. D., and Ríos, C. A.: Workflow for Capturing Information and Characterizing Difficult-to-Access Geological Outcrops Using Unmanned Aerial Vehicle-Based Digital Photogrammetric Data, *Journal of Industrial Information Integration*, 26, 100 292, <https://doi.org/10.1016/j.jii.2021.100292>, 2022.
- Wang, Y., Khodadadzadeh, M., and Zurita-Milla, R.: Spatial+: A New Cross-Validation Method to Evaluate Geospatial Machine Learning Models, *International Journal of Applied Earth Observation and Geoinformation*, 121, 103 364, <https://doi.org/10.1016/j.jag.2023.103364>, 2023.
- Weismüller, C., Prabhakaran, R., Passchier, M., Urai, J. L., Bertotti, G., and Reicherter, K.: Mapping the Fracture Network in the Lillstock Pavement, Bristol Channel, UK: Manual versus Automatic, *Solid Earth*, 11, 1773–1802, <https://doi.org/10.5194/se-11-1773-2020>, 2020.
- Xie, E., Wang, W., Yu, Z., Anandkumar, A., Alvarez, J. M., and Luo, P.: SegFormer: Simple and Efficient Design for Semantic Segmentation with Transformers, <https://doi.org/10.48550/arXiv.2105.15203>, 2021.
- Yaqoob, M., Ishaq, M., Ansari, M. Y., Konagandla, V. R. S., Tamimi, T. A., Tavani, S., Corradetti, A., and Seers, T. D.: GeoCrack: A High-Resolution Dataset For Segmentation of Fracture Edges in Geological Outcrops, *Scientific Data*, 11, 1318, <https://doi.org/10.1038/s41597-024-04107-0>, 2024.
- Zhang, R., Yi, X., Li, H., and Lu, G.: Automatic Extraction of Geological Discontinuities of a Tunnel Surface by Integrating Multiple Features, *Tunnelling and Underground Space Technology*, 154, 106 072, <https://doi.org/10.1016/j.tust.2024.106072>, 2024.

Towards robust fracture mapping: benchmarking automatic fracture mapping in 2D outcrop imagery

Ayoub Fatihi¹, Jeter Caldeira¹, Tom Beucler^{2,3}, Samuel T. Thiele⁴, and Anindita Samsu¹

¹Institute of Earth Sciences, University of Lausanne, 1015 Lausanne, Switzerland

²Institute of Earth Surface Dynamics, University of Lausanne, 1015 Lausanne, Switzerland

³Expertise Center for Climate Extremes, University of Lausanne, 1015 Lausanne, Switzerland

⁴Helmholtz Institute Freiberg, Helmholtz-Zentrum Dresden-Rossendorf, Chemnitz Str. 40, 09599 Freiberg, Germany

Correspondence: Ayoub Fatihi (ayoub.fatihi@unil.ch)

Abstract. ~~Extracting consistent and accurate~~ Analysis of fracture geometries, orientation, distribution, and connectivity is commonly conducted to characterise the mechanical and hydraulic properties of fractured rock mass and to interpret their deformation history. These studies increasingly leverage high-resolution drone imagery (e.g., orthomosaics or orthophotographs). However, consistently and accurately extracting fracture traces from ~~large volumes of high-resolution imagery~~ these large datasets remains a persistent challenge ~~in structural analysis. We~~. In this contribution, we present a harmonised benchmarking dataset, FraXet, for pixel-wise fracture segmentation in ~~combined~~ high-resolution RGB orthophotographs and digital elevation models (DEMs) (~~ground sampling distance ranging from approximately 0.5 mm to 32 mm~~). FraXet curates images from three publicly available datasets, totalling ~~8953~~ 8,953 256×256 RGB+DEM patches spanning diverse lithologies and imaging conditions. ~~We use this dataset~~ (~~ground sampling distance, illumination, etc.~~) to systematically assess ~~traditional~~ the effectiveness of conventional image-processing ~~filters~~ approaches for fracture extraction (Canny, Sobel, Gabor, Sato, ~~and~~ phase congruency) and two deep-learning (DL) models ~~(U-Net and SegFormer, for per-pixel fracture detection. Quantitative comparison)~~. Quantitative comparisons using image-quality (e.g., MSE, PSNR), segmentation (e.g., Precision, Recall, F1, IoU) ~~and proposed similarity FraeSim metrics suggest~~, and new task-specific error metrics show that the deep models substantially outperform classical filters ($F1 \approx \text{03-0.3-0.5}$ vs ≤ 0.29) ~~, giving and produce~~ smoother, more continuous fracture traces ~~with reduced noise~~. Training on the combined dataset (M_all) improves cross-site generalisation ~~relative compared~~ to models trained on the individual sub-datasets. ~~Challenges remain in handling annotation misalignments, illumination artifacts, and thin traces. More importantly, probability used in this study. Probability~~ maps derived from the DL approaches enable confidence-based triage and visualisation of model uncertainty. This work ~~thus~~ establishes a unified benchmark, curated dataset, and reproducible baseline ~~to support further development of robust automated tools for fracture detection~~ for developing robust automated fracture-detection tools.

1 Introduction

Fractures, formed through brittle deformation when stress exceeds rock strength, are important structures that influence both rock stability and fluid flow (?). They can reduce cohesion, posing risks in seismically active areas and engineered settings (?). They can also enhance permeability—especially in low-porosity rocks like limestone—by creating pathways for fluid movement (?). Fractures are therefore key in exploring for and extracting hydrocarbons and geothermal energy, as well as assessing sites for nuclear waste storage.

Researchers often use outcrop analogues to better understand subsurface fracture geometries (?). Mapping natural fractures in outcrops is fundamental to studies of brittle tectonics, assessments of rock stability, and predictions of subsurface fluid flow pathways for geo-energy applications (???). Recent advances in remote sensing and the uptake of uncrewed aerial vehicle (UAV) photogrammetry by the structural geology community have transformed how geological fractures in outcrops are documented. Drone-based imaging now allows the creation of fracture data that are collected (?). UAV photogrammetry enables the generation of high-resolution, georeferenced orthophotographs that capture rock surfaces in remarkable detail. These digital data enable precise mapping, measurement, and analysis of structural features like orientation and spacing, complementing traditional, including outcrops that are difficult or unsafe to reach (?). The resulting orthophotographs enable precise tracing of thousands of fractures on a single outcrop, which can then be analysed for orientation, length, distribution, and connectivity, complementing direct field observations and providing access to outcrops that are difficult or unsafe to reach. However, while data acquisition measurements (?).

A fracture trace is the linear to curvilinear intersection of a fracture with an exposed rock surface, commonly mapped as a piecewise-linear polyline (???). In RGB orthophotographs it appears as a dark, high-contrast linear feature produced by differential weathering and illumination (???), whereas in the DEM it shows as a subtle linear relief or step (?). Its apparent geometry therefore depends on the projection of the discontinuity: surface intersection onto the orthorectification plane (?).

While the acquisition of high-resolution orthophotographs has become faster and easier, the interpretation of manual and semi-automated interpretation of fractures from these images remains time-consuming and subjective. The visibility of fractures depends on lighting, surface weathering, vegetation cover, and image resolution, and the process of manual or semi-automated mapping is often influenced by interpreter bias (????). Furthermore, mapping fails to fully leverage the available data (?). For example, mapping fractures within a 10 × m by 10 m area with using an orthophotograph at 1 cm resolution can still take over /pixel resolution can take more than half an hour, even with semi-automated tools (?). These challenges highlight the growing need for faster, more objective, and more reproducible fracture mapping methods. Extrapolating from this, manually mapping an entire 200 m by 50 m outcrop requires roughly 55 hours of dedicated interpreter time; a constraint that becomes still more limiting for regional-scale studies involving multiple outcrops. Even approaches described as automatic often still require substantial user intervention for parameter tuning, quality control, and post-processing, resulting in processing times of several hours per outcrop (?).

With the rapid progress of computer vision (CV) Manual and semi-automated fracture tracing are also subject to various biases related to image quality (e.g., lighting, surface weathering, vegetation cover, and image resolution) and to the experience

55 and preferences of the interpreter (???). As a result, fracture maps produced by different interpreters, or even by the same
interpreter at different times, may vary in fracture identification, segmentation, and connectivity (?). These inconsistencies
can propagate into subsequent quantitative analyses, affecting the interpretation of fracture network properties and reducing
the reproducibility of geological studies (?).

These challenges motivate faster, more reproducible fracture-tracing methods. Rapid advances in computer vision and ma-
60 chine learning (ML) ,have made automated fracture detection ~~has become an increasingly appealing alternative an appealing~~
~~alternative to manual and semi-automated methods (??).~~ Various techniques have been developed ~~,ranging for fracture~~
detection from orthophotographs (including satellite imagery), digital elevation models (DEMs), and digital terrain models
(DTMs). These techniques range from classical image processing methods—including, including colorimetry-based segmentation,
edge detection, phase symmetry and phase congruency, and Hough transforms, and color-based segmentation—to more ad-
65 vanced deep learning (DL) approaches (?). Each method ~~offers different benefits depending~~ has benefits and limitations that
depend on data type and imaging conditions. Among these, deep learning has emerged as particularly promising, because it
~~can automatically learn spatial features~~ image quality.

Among the classical approaches, colorimetry-based segmentation exploits the contrast between fractures and host rock but
is highly sensitive to lighting and shadowing (?). DEM and DTM-based feature extraction methods, such as segment tracing
70 and directional detection algorithms (??), can reveal terrain-related structures but depend heavily on the resolution and quality
of the underlying elevation data and are computationally demanding. Edge-detection filters (e.g., Canny, Sobel, Laplacian of
Gaussian) are fast and well-established but are sensitive to noise and provide no contextual information about what they detect
(??). Phase symmetry and phase congruency methods improve robustness to variable illumination (??), though at greater
computational cost, while the Hough transform is effective for identifying straight linear features but is intrinsically limited
75 to linear geometries and prone to false positives (?). Wavelet and multi-scale transforms (????) and dedicated line-segment
detection and tracking algorithms (????) improve the handling of curvilinear and multi-scale features, but classical wavelets
lack directionality. Their more advanced variants are complex to implement, and line-tracking approaches remain sensitive
to parameter tuning and prone to fragmenting continuous lineaments. A common shortcoming is reliance on hand-crafted
rules and fixed-scale filters, which limits robustness to variable image quality (lighting, weathering, vegetation) and resolution
80 typical of natural outcrop imagery, and constrains generalisation across datasets (?).

Deep learning and machine learning approaches form a distinct, rapidly growing category. These include convolutional
neural network architectures such as U-Net for pixel-wise fracture segmentation (?), incrementally trained networks designed
to adapt to new geological settings such as the Geological Adaptive Incremental Network (?), hybrid approaches that combine
DL-based feature extraction with classical line detection (?), multi-feature DL integration strategies that combine several input
85 modalities (?), and combinations of graph attention networks with fast line detection algorithms. DL methods have also been
applied directly to 3D data, for example by coupling photogrammetric reconstruction with ML-based fracture extraction (?).

The main drawbacks of DL and ML approaches are reliance on large labelled training sets, their tendency to produce false
positives in the presence of vegetation, shadows, and other artefacts, and the computational expense of training (???). Despite
these disadvantages, DL and ML approaches offer clear advantages over classical methods: they are more robust to noise, can

90 capture complex non-linear spatial patterns inherent to fracture networks, and once trained are commonly transferable across similar datasets (???). The key advantage of deep learning over classical feature extraction (??) is learning spatial features directly from data at multiple scales (?), ~~allowing models to distinguish complex but distinctive~~ simultaneously, rather than relying on hand-crafted rules and fixed-scale filters (?). This is especially valuable for fracture mapping because fractures are inherently multi-scale, ranging from microfractures that are only visible in thin section to fault systems spanning tens, hundreds, 95 or even thousands of meters in length. Furthermore, fractures normally present as sets or networks rather than isolated features. Learning various representations of fracture networks across scales allows a model to combine fine-scale edge detail with broader-scale network context, helping it distinguish fracture geometry from noise and other ~~“edges” commonly found in drone imagery~~ "edges" common in orthophotographs, such as vegetation boundaries, shadows, and weathering features.

Table 1. Summary of methods and their characteristics for fracture mapping

Method	Algorithms / Key studies	Data types	Description	Advantages	Limitations	Automation
Colorimetry-Based Segmentation	Thresholding approaches (??)	Orthophotos	Segments image features based on pixel intensity.	Simple and intuitive;	Strongly affected by lighting and shadows;	Manual
		orthophotographs	Fractures appear darker due to illumination differences, while the host rock appears lighter.	effective in high-contrast conditions.	not reliable in heterogeneous or low-contrast scenes.	or automatic
DEM/DTM-Based Feature Extraction	Segment Tracing Algorithm (?),	DEMs,	Uses terrain derivatives (curvature, slope, relief) to reveal lineaments. Segment tracing improves feature continuity.	Reveals terrain-related or hidden subsurface structures.	Dependent on resolution and quality of DEMs; computationally demanding.	Semi-automatic (ML used in some)
	Segment Tracing and Rotation Transformation (?), Directional Detection (?), Line Segment Tracking (??)	DTMs, satellite imagery				automatic or automatic
Edge Detection (traditional filters)*	Canny Edge Detection (???), Sobel, Laplacian of Gaussian; combinations such as Canny + Hough Transform (?)	Orthophotos	Gradient filters highlight intensity changes; often used as preprocessing before other algorithms.	Fast, well established, interpretable.	Sensitive to noise and illumination; lacks context.	Semi-automatic
		satellite imagery, DEMs				
Phase Symmetry / Phase Congruency*	Phase Symmetry and Congruency (???)	Orthophotos	Uses local phase information to detect edges invariant to brightness or contrast.	Robust under varying illumination; noise-tolerant.	Computationally heavy; more complex to implement.	Semi-automatic
		orthophotographs				
Hough Transform	Classical Hough Transform (?); combinations such as Canny + Hough Transform (??)	Binary edge maps (from other detectors)	Converts edge pixels into parameter space and accumulates votes to identify linear structures.	Good for linear fractures; interpretable.	Limited to straight lines; prone to false positives.	Semi-automatic

* evaluated in this study
Table continued on next page

Table 2. Summary of methods and their characteristics for fracture mapping

Method	Algorithms / Key studies	Data types	Description	Advantages	Limitations	Automation
Wavelet and Multi-Scale Transforms	Wavelet Transform (?), Ridgelets	Orthophotos, satellite imagery, DEMs	Multi-scale decomposition; directional wavelets capture curvilinear and branching structures.	Multi-scale, effective for curved fractures.	Classical wavelets lack directionality; advanced transforms are complex and computationally intensive.	Semi-automatic
	and Curvelets (??), Complex Shearlet Transform (?)					
Line Segment Detection / Tracking	Line Segment Detection (??), Line Segment Tracking (??)	Satellite imagery, DEMs	Detects line segments directly; tracking improves continuity across scales.	Captures both short and long features; efficient.	Sensitive to parameter tuning; may fragment lineaments.	Automatic (ML used in some)
Deep Learning and Machine Learning Approaches*	CNN U-Net (?), Geological Adaptive Incremental Network (?), DL + Line Detection (?), Multi-feature DL integration (?), Graph Attention Network + Fast Line Detection, Photogrammetry + ML (?)	Orthophotos, DEMs, satellite imagery, 3D point clouds	Learns hierarchical spatial features for segmentation and fracture extraction.	Robust to noise; captures complex nonlinear spatial patterns; transferable across similar datasets.	Requires large labelled data; prone to false positives (e.g., vegetation, shadows); can be expensive to train.	Fully automatic (DL/ML-based)

* evaluated in this study

However, ~~a persisting issue is that~~ Several issues still need to be addressed as DL-based automated fracture detection ~~still struggles~~ continues to develop. First, these methods still struggle with false positives and negatives, particularly under natural and uncontrolled imaging conditions ~~-(e.g., white balance, illumination patterns, resolution, etc.) (???)~~, e.g., topographic shadows mimicking fracture traces, vegetation creating false linear features, or weathering textures producing edges indistinguishable from fractures. Natural outcrops contain shadows, vegetation, uneven lighting, and ~~erosion~~ erosional features, all of which can confuse detection algorithms. ~~Moreover~~ Secondly, fractures are an unusual target for semantic segmentation, as they are better represented as linear segments with arbitrary ~~width~~ widths (??a) rather than as continuous areas. ~~Most fracture analyses also require instance-level outputs—such as fracture length, orientation, spacing, and connectivity—which depend directly on the correct topology of each trace. As a result, even minor misclassification can drastically alter fracture connectivity and the derived measurements. Furthermore, the (??b).~~ Third, ground-truth labels used for training are often drawn at ~~coarser scales than pixel-level precision, leading a coarser scale than the maximum image resolution allows: a time-saving compromise that leads~~ to misalignment between the labelled ~~and actual fracture edges~~ fracture and the pixels that represent the fracture in the orthophotograph (??). ~~These inconsistencies affect both model learning and evaluation accuracy.~~

~~Example of annotation misalignment. (a) Outcrop orthophoto (?) overlaid with fracture traces in white from the ground-truth labels (?). (b) Zoomed-in view showing how manually drawn fracture lines deviate from the actual visible fracture edges.~~

For fracture mapping and similar tasks, two main computer vision approaches are commonly used: semantic segmentation and instance segmentation (?). Semantic segmentation labels each pixel as a fracture or not, producing a binary mask without separating individual fractures. Instance segmentation, on the other hand, identifies and labels each distinct fracture, allowing direct measurement of geometric attributes. This study focuses on semantic segmentation because it is simpler, more robust with current data, and does not require instance-level labels. Instance segmentation remains the ultimate goal for full fracture analysis but is highly challenging in this context and beyond the scope of this work.

~~Algorithm performance also often drops when c,d).~~ While these inconsistencies may influence analyses of fracture lengths, orientations, and network topology, they have an even greater impact on model training and evaluation accuracy. This is important because annotation scale and interpretation can significantly affect the derived properties of fracture networks (?). Finally, algorithm performance commonly drops when a DL-based model is applied to new datasets with different lithologies ~~fracture patterns, lithologies, topographical complexity, topographies, or imaging conditions, limiting generalizability. This underscores the generalisability (?).~~

As automated fracture detection advances, there is an urgent need for standardised benchmarking frameworks and shared datasets that allow enable consistent and fair comparison of methods (?). While initiatives like GeoCrack (?), a publicly available benchmark dataset for automated geological fracture detection in RGB images of rock outcrops have begun to address this gap, current resources remain limited to RGB imagery and predominantly vertical outcrops and ~~prone to incomplete annotations~~ contain incomplete annotations in some image patches where only a subset of visible fractures are labelled.

~~Our approach addresses this limitation by curating three~~ The primary goal of this study is to establish a standardised evaluation framework for pixel-wise fracture segmentation from 2D outcrop imagery, using both traditional computer vision

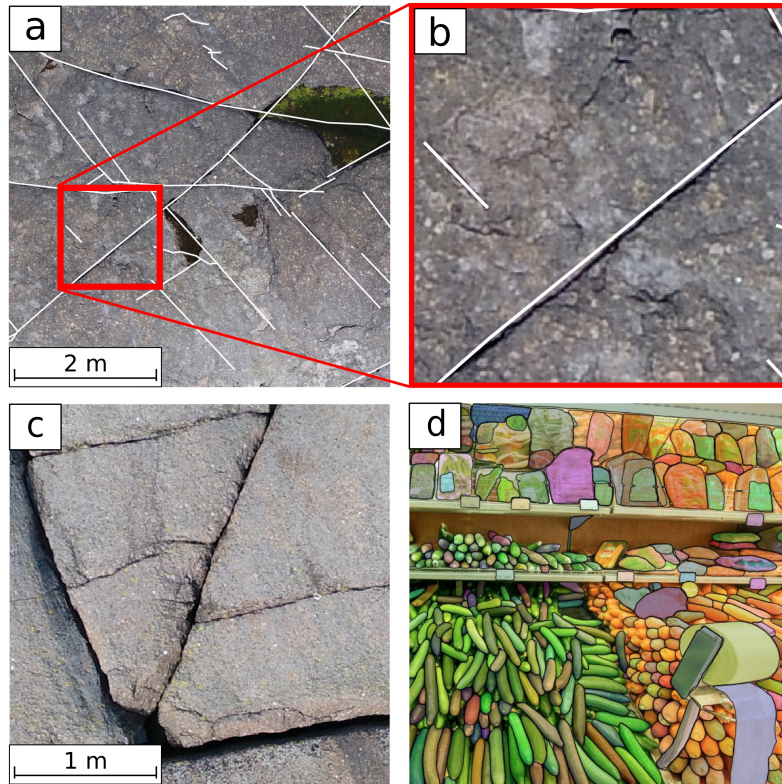


Figure 1. Example of annotation misalignment. (a) Outcrop orthophotograph (?) overlaid with fracture traces in white from the ground-truth labels (?). (b) Zoomed-in view showing how manually drawn fracture lines deviate from the actual visible fracture edges. (c) Example of fractures of different widths. (d) Example of a segmentation task represented as a continuous area from Segment Anything paper (?).

and deep learning methods. We present FraXet, comprising three curated, heterogeneous benchmark datasets and applying clear and consistent preprocessing, hyperparameter optimisation, and evaluation procedures. Performance is assessed using both on which a suite of traditional image-processing filters (Canny, Sobel, Gabor, Sato, and phase congruency) and deep learning models (U-Net, SegFormer) were applied to generate per-pixel fracture probability maps. The performance of the different methods was assessed using image-quality metrics (e.g., MSE, PSNR) and, segmentation metrics (e.g., precision, F1-score, IoU), as well as a novel geological and a novel fracture-trace similarity metric. The primary goal of this study is to establish a standardised evaluation framework for pixel-wise fracture segmentation from 2D outcrop imagery, incorporating both traditional computer vision and deep learning methods. This By applying consistent preprocessing, hyperparameter optimisation, and evaluation metrics, our framework enables systematic comparison of fracture detection performance across diverse datasets, geological settings, and imaging conditions. By harmonising data processing, parameter tuning, and evaluation metrics, it promotes FraXet is intended as a living benchmark, to be expanded with additional datasets representing different geological settings, lithologies, and fracture network patterns as more annotated public datasets become available. Our aim is

to promote transparency, reproducibility, and comparability in automated fracture mapping research, while ~~also~~ providing a useful test dataset and benchmark for future developments.

2 ~~Materials and Methods~~Methodology

~~FraXet (?) integrates three-~~

150 We designed a benchmarking workflow (??) for three publicly available, annotated outcrop datasets ~~—(Ovaskainen22 (??), Matteo21 (?), and Samsu19 (?)—selected for their combination of)~~ that make up the first version of FraXet (?). FraXet is a
curated benchmark dataset for training and evaluating automatic fracture-trace extraction models, comprising high-resolution
~~orthomosaic and digital elevation models (DEMs), orthophotographs and DEMs across~~ diverse lithologies and ~~varied~~ outcrop
geometries. ~~From these sources, we compile-~~

155 From the original orthophotographs and DEMs, we compiled 8,953 co-registered 256 pixel × 256 ~~patches~~ pixel patches (see
??), each consisting of an RGB orthomosaic tile, a DEM tile, and a corresponding binary ~~1-pixel-wide 1-pixel-wide~~ fracture
label. We ~~standardise and pre-process all~~ standardised and pre-processed all the patches, then ~~apply~~ applied a suite of traditional
image-processing filters (Canny, Sobel, Gabor, Sato, phase congruency) and deep learning models (U-Net, SegFormer) to
generate per-pixel fracture probability maps. All methods ~~are~~ were evaluated using a set of ~~image-quality, segmentation~~ image
160 quality, segmentation, and proposed similarity metrics on held-out test splits, with deep models tuned on validation subsets
before final testing.

2.1 Data Compilation

2.1.1 Data description

Ovaskainen22 captures fracture networks in the Mesoproterozoic Wiborg Rapakivi Granite Batholith of southeastern Fin-
165 land, mostly isotropic coarse-grained ~~wiborgite facies~~ wiborgite facies granite with K-feldspar megacrystals up to 5–10 cm
(?). Matteo21 (?) presents data from the Granite Dells, Arizona, an anorogenic granite of similar age (~1.40 Ga) but with
medium-grained, ~~and~~ generally equigranular textures showing weak porphyritic tendencies (?). Samsu19 (?) maps fractures
in a very different geological setting: a fluvial–lacustrine syn-rift sediment succession in the Lower Cretaceous Strzelecki
Group (~~Southeastern~~ southeastern Australia), comprising mud- and sand-dominated siliciclastic strata with conglomeratic or
170 organic-rich interbeds (?).

Together, these three datasets cover varied geological contexts (from isotropic crystalline to anisotropic sedimentary litholo-
gies) with fractures mapped at different scales, providing a diverse testbed for evaluating model generalisation. An overview
of the datasets, their mapping scales, original study purposes, their resolutions, and split statistics is provided in ??. For
completeness, overview maps of the sites used in this study are provided in the Appendix (??, ??, ??).

175 We acknowledge that three datasets covering two granite types and one clastic sedimentary setting, while providing meaningful
lithological contrast for a first benchmark, do not represent the full diversity of geological settings encountered in practice;

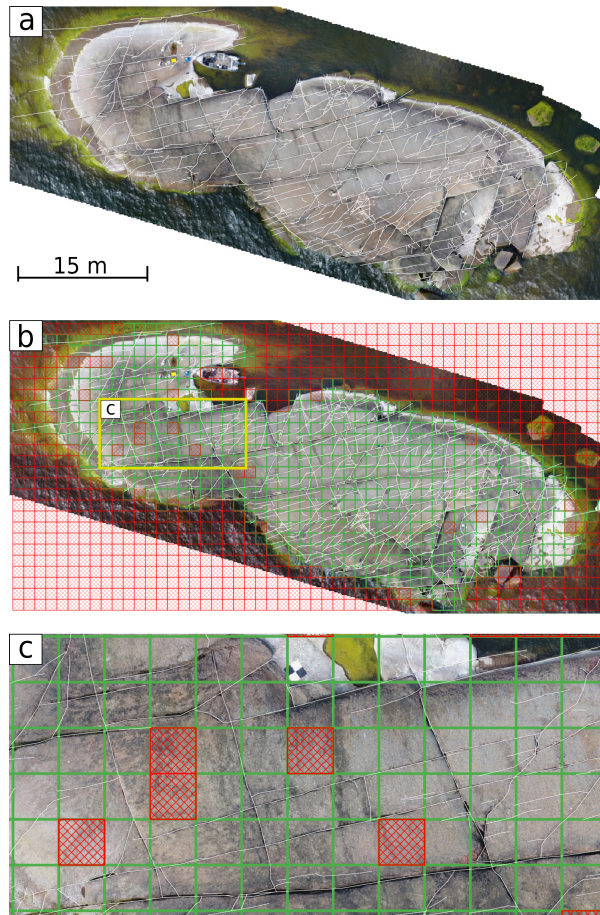


Figure 2. Overview of the benchmarking workflow. The three datasets (Matteo21, Samsu19, Ovaskainen22) are processed into the [Example RGB-DEM-label patches from FraXetv0.1 database](#), used to train classical filters and deep learning models, the results of which are evaluated on the test set through qualitative visualisation and quantitative metrics and proposed similarity metric.

[notably absent are carbonate, metamorphic, and volcanic lithologies. FraXet is intended as a living benchmark to be expanded as further annotated public datasets become available; including these other lithological settings is a priority for future work.](#)

In addition, a single site from the Lapiés di Bou karst surface was included to enable qualitative visual comparison across
 180 methods. This locality lies within the Helvetic domain of the Swiss Western Alps, specifically within the Wildhorn Nappe complex (??), where fine limestones to marls, locally oolitic, of the Aptian–Barremian Schrattenkalk Formation crop out (?). Two patches from the Bingie Bingie area were also used for the timing experiment, allowing direct comparison with the manual and semi-automatic mapping workflow of ?. [Neither the Lapiés di Bou nor the Bingie Bingie data were included in the training, validation, or test splits; they were used exclusively for qualitative visual comparison and runtime evaluation, respectively.](#)

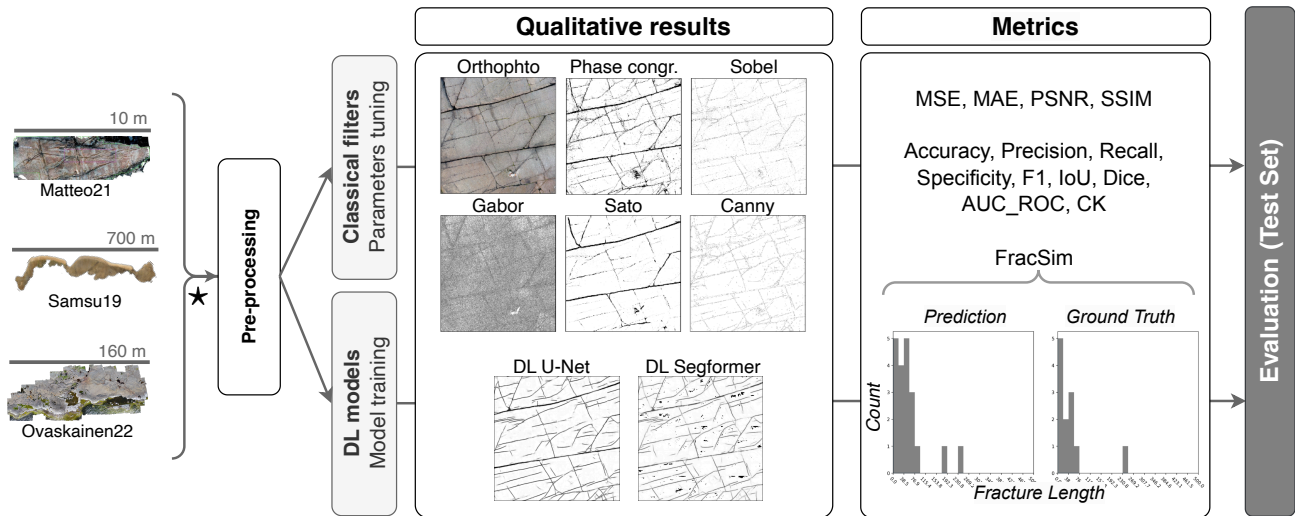


Figure 3. Overview of the benchmarking workflow. The three datasets (Matteo21, Samsu19, Ovaskainen22) are processed into the FraXet v0.1 database, used to train classical filters and deep learning models, the results of which are evaluated on the test set through qualitative visualisation and quantitative metrics and proposed similarity metric.
 *: not all outcrops used shown here.

2.1.2 Test, train and validation splits

To ensure reliable model assessment and minimise spatial autocorrelation—a known issue in geospatial machine learning where spatial overlap inflates accuracy metrics by reducing the statistical independence of training and testing data (?)—we have defined spatially disjoint data splits by dividing each of the three datasets into training, validation, and test regions (with no spatial overlap). Specifically, here the Ovaskainen22 dataset consists of Orrengrund (training), Kasaberget (validation), and Kampuslandet (testing) islands off the coast of the Loviisa region; the Samsu19 dataset comprises Eagles Nest (training) and Harmers Haven north (split between validation and testing); and the Matteo21 dataset is split into sites A and B (training), held-out regions of A and B (validation), and site C (testing). Only tiles containing at least one labelled fracture pixel were retained, to reduce challenges with class imbalance and to focus learning on relevant features.

The orthophotographs and DEMs were resampled to have matching spatial resolution, normalised, and tiled into non-overlapping 256 × 256 pixel patches, each with four channels (RGB+DEM). This patch size was chosen as a compromise between balances field of view, feature scale, and computational efficiency—it is large enough to preserve contextual information while remaining compatible with typical convolutional neural network (CNN) input constraints.

Ground truth annotations for Ovaskainen22 and Samsu19 were provided as vector shapefiles and were subsequently rasterised to the corresponding image resolution, producing binary masks with 1-pixel-wide white fracture lines on a black background. These binary images match the raster-formatted annotations in Matteo21 to ensure consistent label representation.

Table 3. Overview of datasets and their metadata [and split statistics](#)

Dataset Resolution (m) Train-patches Validation-patches Test-patches Total-patches Total-Area-of-used-patches (m^2)
Ovaskainen22 0.005 - 0.006 2808 966 671 4445 7220
Matteo21 0.0005 - 0.0013 2174 323 912 3409 142
Samsu19 0.029 - 0.032 642 228 229 1099 68271
All -62.82% 16.94% 20.24% 8953 (100%) 75633

Dataset	Study purpose	Mapping scale	Resolution (m)	Patches				Total Area (m^2)
				Train	Validation	Test	Total	
Ovaskainen22	Fracture-network characterisation	1:10*	0.005 - 0.006	2808	966	671	4445	7220
Matteo21	Automatic fault/fracture mapping (tectonic)	-	0.0005 - 0.0013	2174	323	912	3409	142
Samsu19	Fracture patterns & structural inheritance	1:250	0.029 - 0.032	642	228	229	1099	68271
All	-	-	-	62.82%	16.94%	20.24%	8953 (100%)	75633

*As shared by the authors, no fixed mapping scale was used for fracture interpretation. Instead, fractures were digitized at the full image resolution (approximately 0.0055 m pixel size for data acquired from a 20 m drone flight altitude), allowing the interpreter to zoom freely as needed. Based on the image resolution, the effective fracture extraction scale is approximately 1:10 as in ?.

[Given the spatial resolutions of the datasets, a 256x256 pixel patch represents a square region with side lengths ranging from approximately 0.13-0.33 m \(Matteo21\), 1.28-1.54 m \(Ovaskainen22\), and 7.4-8.2 m \(Samsu19\).](#)

Probability Map Representation. Because our goal is to generate per-pixel probability maps rather than hard binary labels, we designed all preprocessing steps with this output in mind. Probability maps provide a continuous estimate (~~0-1~~⁰⁻¹⁰⁻¹) of the likelihood that each pixel corresponds to a fracture, capturing confidence and uncertainty rather than forcing discrete predictions. This representation is well suited to fracture mapping, where annotations are often noisy or slightly misaligned, and where soft boundaries reflect the inherent ambiguity of thin linear features.

It also enables flexible post-processing: thresholds can be adjusted to balance precision and recall, high-confidence regions can be skeletonised to extract fracture traces, and outputs can be integrated into human-in-the-loop workflows or combined with traditional filters. Moreover, probability maps support richer evaluation metrics (e.g., ROC analysis), and improve robustness when using ensembles or multi-scale fusion. For all these reasons, probability maps serve as the most informative and practical output of the methods.

2.2 Pre-processing

Several preprocessing and augmentation steps were applied prior to model training and evaluation, to standardise inputs, refine ground-truth annotations, and improve model generalisation. All preprocessing scripts and procedures are publicly released as the FraXtex2D ~~github repository~~ ([gitlab repository](#) (<https://gitlab.com/ayoubft/fractex2D.pt>) to ensure reproducibility. These procedures are summarised below.

Depth. For all deep learning experiments, we used the full RGB imagery together with the corresponding DEM channel, which was normalised at the patch level using min-max normalisation. This scaling ensures that elevation values within each patch fall between 0 and 1, reducing the influence of absolute elevation differences across sites and improving numerical stability during training.

Channel selection. Most traditional edge-detection filters operate on a single image band. Therefore, each band was first z-standardised (zero mean, unit variance) on the patch-level to reduce sensitivity to illumination differences and overall brightness. PCA (principal component analysis) was then applied to the normalised four-band data to obtain a single-band representation containing a maximal amount of variance.

Label refinement. We implemented two complementary label-processing techniques to correct inconsistencies in the original fracture annotations and enhance their spatial accuracy: wide-fracture expansion and multi-scale label smoothing.

Wide-fracture expansion. Preliminary experiments revealed that the models underperformed on wide and visually prominent fractures. Many such fractures were annotated as 1-pixel-wide lines, underrepresenting their true width. To address this, we developed a region-growing algorithm that widens the single-pixel annotations to fill thick fracture zones. This algorithm fills dark linear regions (in the green channel); identified by thresholding at 30 (on a 0-255 scale); by applying a maximum filter-2-pixel maximum filter, followed by morphological dilation and then merging the resulting (dark and connected) dark, connected regions with the original binary mask. Only expanded areas connected to existing labelled pixels are retained to prevent false positives. This operation improved annotation fidelity for wide fractures.

Multi-scale label smoothing. Manual fracture tracing also often leads to introduces small misalignments between annotations and the actual fracture pixels, especially in high-resolution orthophotos. We applied a multi-scale label smoothing procedure to mitigate this issue, using successive dilations with decreasing weights to produce a graded boundary around each fracture orthophotographs. First, labels are expanded with a distance of 2 pixels to fill small gaps and buffer the reference traces. This is followed by three successive morphological dilations applied to the expanded mask using disk-shaped structuring elements with radii of 2, 5, and 7 pixels. These bands are then combined into a graded representation using decreasing weights of $\frac{1}{3}$, $\frac{1}{5}$, and $\frac{1}{9}$ respectively. This produces a smooth boundary around fractures. This approach smooths the input binary classification labels, accounts for positional uncertainty, and helps stabilise the model's learning process reduces sensitivity to annotation noise and improves training stability by explicitly modelling spatial uncertainty.

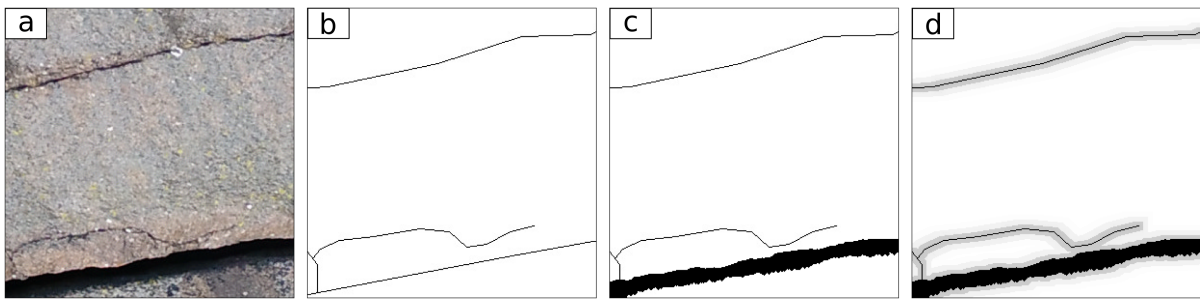


Figure 4. Label refinement steps. (a) Original RGB image; (b) manually traced ground truth with 1-pixel-wide fractures; (c) widened annotations after region-growing; (d) smoothed probabilistic labels produced by multi-scale dilation.

Together, these two steps improved correspondence between fracture labels and actual image structures, increasing the effective proportion of positive (fracture) pixels and slightly reducing class imbalance (in the Appendix).

2.3 Data augmentation

To further enhance model robustness and generalisation, we applied the following data transformations randomly to the input patches (??) during each training epoch:

- 250
- (1) Flipping horizontally and vertically. These transformations are applied to both the RGB+D images and the ground truth labels to encourage geometric invariance, helping the model detect fractures regardless of their orientation.
- (2) Gaussian blurring, brightness, contrast, and saturation adjustment. These are applied only to the RGB channels to promote photometric invariance, improving robustness to changes in lighting and appearance.
- ?? in the Appendix summarises the applied augmentations and their parameters.

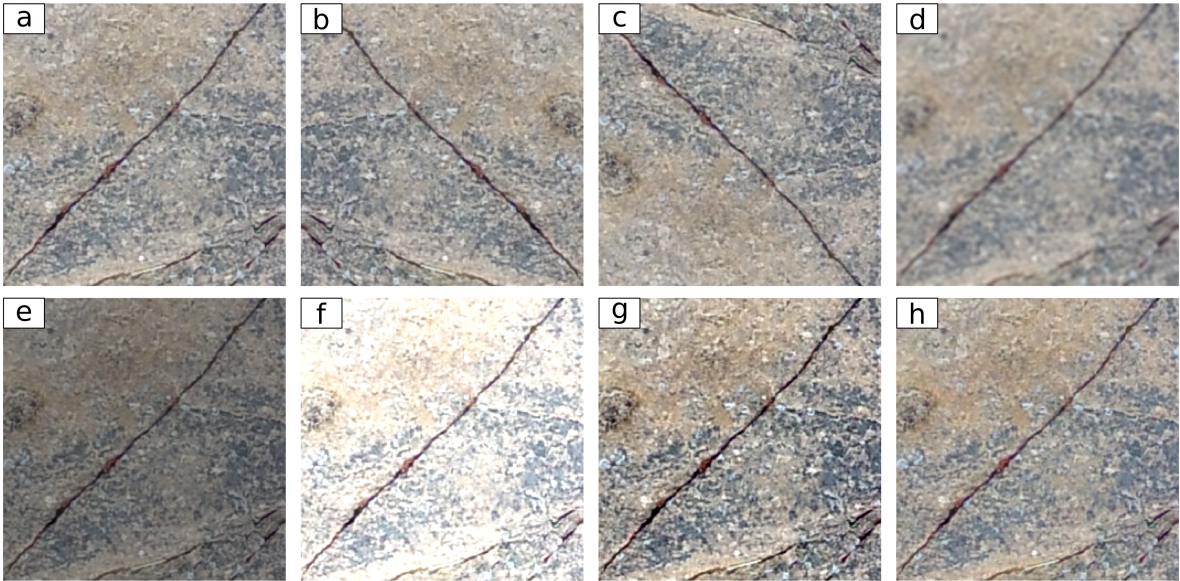


Figure 5. Data augmentations applied during training: (a) original, (b) horizontal flip, (c) vertical flip, (d) gaussian blur, (e) brightness decrease, (f) brightness increase, (g) contrast increase, (h) saturation increase.

2.4 Image filter-based approaches

255

~~The following~~This section outlines our implementation of several established ~~image-processing filters~~,image-processing filters as a baseline ~~to which we can compare the~~for comparing deep learning results. These methods do not require training data and operate directly on the image, offering fast, interpretable, and reproducible outputs. While not specifically designed for fracture detection, they are widely used in geoscientific and remote sensing applications to extract features with similar morphology. All filters were applied to the ~~single-channel~~first principal component (channel) resulting from the PCA reduction.

260 For the classical filters, which do not produce probabilistic outputs, we applied the same label-dilation step (Step 2 in preprocessing; §???) to their binary masks. This ensures that all methods are evaluated against labels that better reflect the actual fracture width and account for the misalignment between annotations and true pixel-level fracture geometry observed earlier.

~~The filters are grouped~~ We grouped the filters into three main categories, also see ??:

- 265
- Edge detection (Sobel and Canny): Computes spatial intensity gradients to highlight abrupt changes. These filters are simple and efficient but sensitive to noise and lighting, and some require thresholding to generate binary edges.
 - Ridge detection (Gabor and Sato): Identifies elongated, linear structures by analyzing second-order derivatives (curvature). These filters can capture fracture-like ridges at tuned scales but may also respond to non-fracture textures.
 - Phase-based filters (Congruency): Use Fourier phase information to detect edges. These methods handle varying illumination more robustly, but are computationally intensive and involve more tunable parameters.
- 270

Each of these methods relies on user-specified parameters (??; §???) to suppress background clutter and isolate relevant target features (fractures in our case).

Table 4. Summary of parameters adjusted for each algorithm and their descriptions

Algorithm	Parameter	Parameter’s description
Edge detectors	Sobel	-
	Canny	sigma
		low_threshold
		high_threshold
Ridge detectors	Gabor	frequency
	Sato	sigmas
Phase Congruency	nscale	Number of wavelet scales
	norient	Number of orientations used
	minWaveLength	Wavelength of the smallest filter
	mult	Factor to scale filter size across scales
	sigmaOnf	Bandwidth of the log-Gabor filter
	k	Multiplier for noise threshold
	cutOff	Frequency spread threshold
	g	Controls sharpness of sigmoid weighting
	noiseMethod	-1=median, -2=mode, >=0=fixed threshold

2.4.1 Parameter Selection

To explore the behavior of each filter across different datasets, we first conducted a manual visual tuning phase. This provided insight into which parameter settings produced plausible results and helped define sensible parameter ranges. We then applied a data-driven parameter search to select the optimal settings for each filter. Specifically, we performed a grid search with cross-validation, which is justified here due to the low dimensionality of the parameter space and the relatively small number of candidate values per method. For each configuration within the predefined parameter ranges, the filter response was dilated (Step 2 in preprocessing), thresholded, and evaluated against the refined ground truth using the F1 score (definition defined in ??). The parameter set yielding the highest score was selected as optimal. This grid search standardises filter hyperparameters across datasets and reduces subjectivity in parameter selection.

2.5 Deep Learning-Based Models

Two deep learning architectures are evaluated in this work: a convolutional U-Net (?) and a transformer-based SegFormer (?), the latter initialised with pretrained ResNet34 weights as the-its backbone. U-Net is widely used for semantic segmentation due to its ~~eneoder-deeoder~~ encoder-decoder architecture and skip connections, while SegFormer leverages attention mechanisms combined with the ResNet34 backbone for long-range context modelling and robustness to geometric variability.

Both models were trained with architecture-specific hyperparameters selected by cross-validation and sensitivity tests. For the U-Net, we used the Adam optimiser with an initial learning rate of 0.05, while the SegFormer employed RMSProp with an initial learning rate of 0.01. The input to each model consisted of 256×256 px patches with four channels (three RGB bands and one DEM band). We used Huber (smooth L1) loss for per-pixel probability targets ~~because~~ as it proved robust to label noise, spatial misalignment, and class imbalance compared ~~with~~ to binary cross-entropy or Dice loss (both popular for segmentation tasks). Early stopping based on validation loss was used in both cases to prevent overfitting.

The U-Net and SegFormer architectures are depicted in ?? and ??, respectively.

Both models produce per-pixel probability maps used for visual comparison and were thresholded to generate binary segmentation masks, which were then compared to the ground truth using the metrics described below.

2.6 Benchmark metrics

To evaluate segmentation performance, we used three complementary groups of metrics:

1. image-quality metrics that quantify how closely the predicted probability maps match the annotated targets,
2. pixel-wise classification and segmentation metrics that measure detection performance and spatial overlap, and
- 300 3. a proposed fracture-level similarity metric, FracSim, designed to compare the geometry of predicted fracture traces with those in the ground truth.

Together, these metrics (??) capture prediction quality at the pixel, mask, and structural levels. Higher values generally indicate better performance, except for error metrics (MSE, AE), where lower values are preferable.

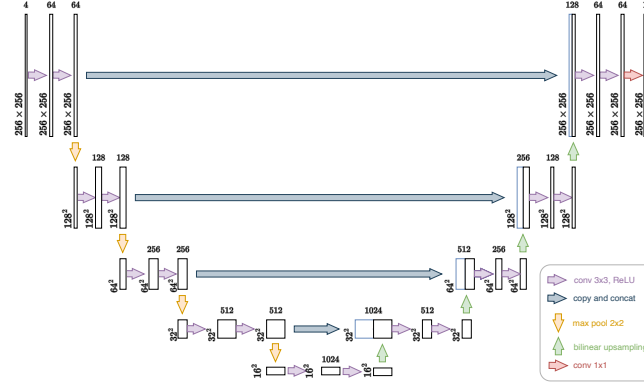


Figure 6. Overview of the U-Net encoder-decoder architecture with skip connections (?). The encoder (left) progressively downsamples the 256x256x4 input through convolutional blocks (Conv → BatchNorm → ReLU) and max-pooling, extracting features at multiple scales. The decoder (right) upsamples these features via transposed convolutions and concatenates them with the corresponding encoder features via skip connections (grey arrows), preserving spatial detail. The final 1x1 convolution produces a per-pixel fracture probability map.

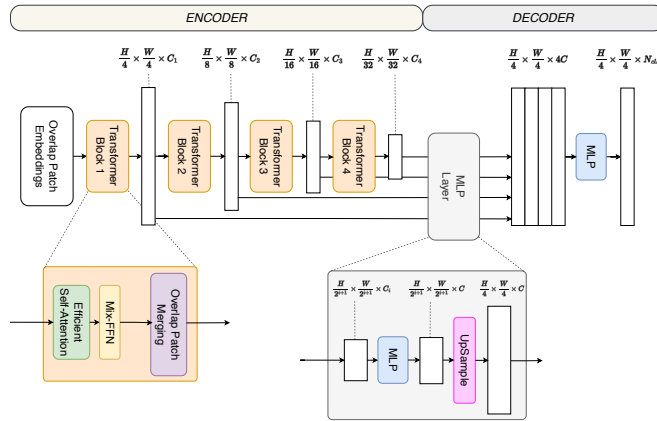


Figure 7. Overview of the SegFormer architecture combining a transformer encoder with a lightweight decoder (?). The encoder uses a hierarchical transformer backbone (ResNet34) with multi-head self-attention to capture long-range dependencies. The decoder aggregates multi-level features via a simple MLP.

Terms: Self-attention: mechanism allowing each pixel to attend to all others; MLP: multi-layer perceptron; Feature map: spatial representation at each encoder stage.

We include the background class in our evaluation to capture each model’s full performance across the entire image. Because fractures represent only a very small fraction of pixels, excluding the background can artificially inflate metrics such as precision and recall. It also tends to make poorly calibrated models appear better, as ignoring the dominant class often results in models overpredicting fractures. Including the background therefore provides a more realistic assessment of false positives,

calibration, and overall segmentation integrity. Notably, many previous studies do not explicitly report whether the background class is included in the computation of evaluation metrics.

310 Among the ~~various~~ metrics computed, we ~~suggest that~~ consider the Dice coefficient (equivalent to the F1 score), recall, specificity, and intersection over union (IoU) ~~are as~~ the most relevant for ~~the fracture segmentation task. In contrast, accuracy~~ fracture segmentation. Accuracy, in contrast, is the least informative metric here, ~~as~~ a model that predicts only background can achieve deceptively high scores due to class imbalance. Dice and IoU measure spatial overlap, which is critical for evaluating thin, linear features like fractures. Dice balances false positives and false negatives, while IoU penalises both over- and under-
315 segmentation, making it a stricter metric. Recall ensures that fractures are not missed, while specificity quantifies how well the model avoids false positives in the dominant background class. Given the extreme class imbalance—~~where~~ background pixels can account for over 99% of the image—reporting recall alone ~~may can~~ be misleading. Specificity completes the picture by measuring the number of false detections in non-fracture regions.

We also include ROC-AUC, which evaluates the model’s ability to distinguish between fracture and background pixels across
320 thresholds. As a threshold-independent metric, ROC-AUC is particularly useful for probabilistic outputs. Similarly, Cohen’s Kappa measures agreement between prediction and ground truth while accounting for chance, offering a more meaningful alternative to raw accuracy in imbalanced settings.

In addition to segmentation metrics, we report image-quality metrics—Mean Squared Error (MSE), Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Absolute Error (AE)—to assess how well the predicted probability
325 maps match the annotations before thresholding. These metrics capture prediction fidelity in both intensity and structure. MSE and AE quantify raw pixel-wise error (lower is better), while PSNR measures signal degradation in a logarithmic scale (higher is better). SSIM accounts for human visual perception by evaluating structural and contrast similarity, which is especially valuable when preserving subtle linear patterns like fractures.

The different scenarios in ?? highlight how each metric responds to specific segmentation behaviors. Predicting only back-
330 ground (no segmentation) yields high accuracy and specificity but zero recall, precision, and overlap-based scores, illustrating how class imbalance can inflate accuracy despite complete failure to detect fractures. Conversely, full segmentation maximises recall while collapsing specificity and precision, resulting in low Dice and Intersection over Union values. Random segmentation produces near-chance values across most metrics, with Dice, Intersection over Union, Cohen’s kappa, and receiver operating characteristic scores reflecting the lack of spatial agreement. The Gabor filter segmentation shows intermediate
335 performance, improving overlap, precision, and specificity by capturing some fracture structure, but still suffering from fragmentation and false positives. The U-Net prediction achieves the most balanced and consistently high scores across all metrics, with strong overlap, agreement, and classification performance, closely approaching the ground truth.

2.7 *FracSim*: a fracture-level similarity metric

~~Because one of the key characteristics relevant to fracture mapping is fracture length, we developed~~ Pixel-wise metrics are
340 widely used for segmentation evaluation but have limitations when applied to thin, linear features such as fracture traces. Small differences in line thickness or slight spatial offsets can disproportionately affect precision, recall, and F1-score. For example, a

Table 5. Overview of metrics for evaluating image quality and segmentation

Metric	Formula	Definition / Use
MSE (Mean Squared Error)	$\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$	Average squared pixel error; lower is better.
PSNR (Peak Signal-to-Noise Ratio)	$10 \log_{10} \left(\frac{L^2}{\text{MSE}} \right)$	Log ratio of max intensity L to error; higher is better.
SSIM (Structural Similarity Index)	$\frac{(2\mu_x\mu_y + C_1)(2\sigma_{xy} + C_2)}{(\mu_x^2 + \mu_y^2 + C_1)(\sigma_x^2 + \sigma_y^2 + C_2)}$	Perceptual similarity using luminance, contrast, and structure.
AE (Absolute Error)	$\frac{1}{N} \sum_{i=1}^N y_i - \hat{y}_i $	Absolute pixel-wise error; lower is better.
Accuracy (Acc)	$\frac{TP + TN}{TP + TN + FP + FN}$	Correctly classified proportion; sensitive to imbalance.
Precision (Prec)	$\frac{TP}{TP + FP}$	Correctness of predicted positives.
Recall / Sensitivity (Rec)	$\frac{TP}{TP + FN}$	Fraction of true positives detected.
Specificity (Spec)	$\frac{TN}{TN + FP}$	Fraction of negatives correctly identified.
F1 Score	$\frac{2\text{Prec} \cdot \text{Rec}}{\text{Prec} + \text{Rec}}$	Harmonic mean of precision and recall.
Dice Coefficient	$\frac{2 A \cap B }{ A + B }$	Spatial overlap measure; equivalent to F1 in binary segmentation.
IoU (Intersection over Union)	$\frac{ A \cap B }{ A \cup B }$	Mask overlap ratio.
AUC_ROC	—	Area under ROC curve; reflects the probability that a model assigns a higher score to a positive instance than to a negative instance.
Average Precision (AP)	$\int_0^1 \text{Prec}(r) dr$	Area under precision–recall curve.
Cohen’s Kappa (CK)	$\kappa = \frac{p_o - p_e}{1 - p_e}$	Agreement corrected for chance.

Symbols: N = number of pixels; y_i = reference pixel value; $\hat{y}_i$ = predicted pixel value; L = maximum possible pixel intensity; μ_x, μ_y = means of image patches x and y ; σ_x^2, σ_y^2 = variances; σ_{xy} = covariance; C_1, C_2 = SSIM stability constants; TP, TN, FP, FN = true/false positives/negatives; A, B = predicted and reference binary masks; r = recall; p_o = observed agreement; p_e = expected chance agreement; ROC: receiver operating characteristic, is a graphical plot which illustrates the performance of a binary classifier system as its discrimination threshold is varied.

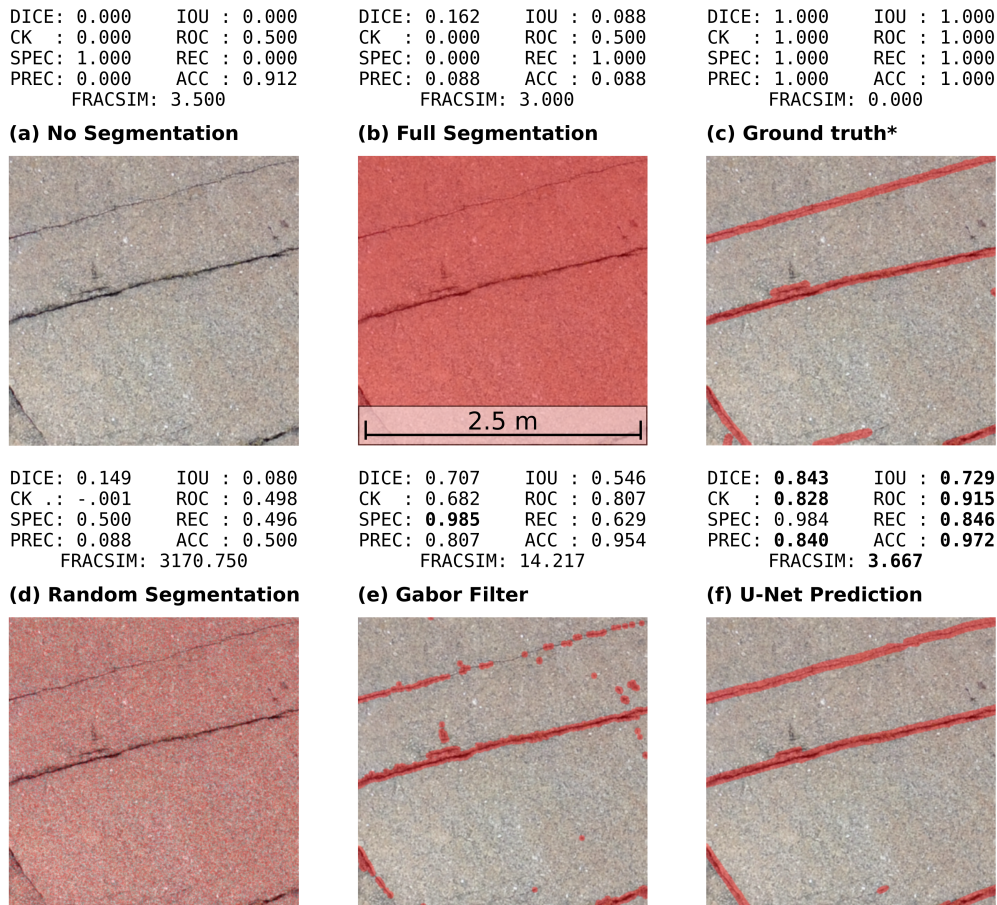


Figure 8. Illustration of metric behavior under different segmentation scenarios: (a) No segmentation (predicts all background), (b) Full segmentation (predicts all fracture), (c) Ground truth, (d) Random segmentation, (e) Gabor filter segmentation, (f) U-Net segmentation. Values in bold ~~showing highest values discarding~~ show the ~~first row~~ best scores, excluding scenarios a, b and c. Image from the Ovaskainen22, KL5 dataset. Abbreviations are defined in ??.

~~correctly detected fracture predicted slightly thinner than the annotation will incur false negatives along its edges, substantially reducing recall despite successful detection.~~

~~To address these limitations, we developed *FracSim*, a domain-specific similarity metric, termed *FracSim*, which that~~
345 compares the distribution of extracted fracture segment lengths between ~~a~~ the predicted mask and the ground truth.

For each prediction and label, we:

- (1) convert the probability map to a binary mask (user threshold, default: 0.1);
 - (2) skeletonise the binary masks to a one-pixel wide trace;
 - (3) remove short noisy junctions using a small neighborhood filter (to avoid counting cross-overs and thick junction blobs as
- 350 segments);

- (4) label connected skeletal segments and compute their pixel lengths;
- (5) construct comparable histograms of segment lengths (same bin edges for prediction and ground truth); and
- (6) compute a symmetric chi-square distance between the two histograms (??).

$$d_{\chi^2}(h, g) = \frac{1}{2} \sum_{i=1}^N \frac{(h_i - g_i)^2}{h_i + g_i} \quad (1)$$

355 where

- $d_{\chi^2}(h, g)$ is the symmetric chi-square distance between the two histograms,
- h and g are the two histograms being compared,
- h_i and g_i denote the values of the i -th bin of histograms h and g , respectively,
- N is the total number of bins.

360 Lower χ^2 indicates closer agreement in the fracture length distribution. We compute *FracSim* only on patches that contain a high fracture-pixel count in the ground truth; empty or nearly empty patches are excluded because they lack a meaningful fracture-length distribution to compare, and even small prediction artifacts in these patches can otherwise produce misleading metric values.

Together, these metrics (~~§?? and §???~~ and ??) provide a balanced framework for evaluating both hard segmentation per-
365 formance and the quality of soft probabilistic outputs.

2.8 Generalisation experiments

To evaluate the generalisation capability of a single model trained across diverse geological settings, we compared a multi-site model (trained on all datasets combined, M_all) against individual models trained separately on each dataset (M_ovas, M_sams, and M_matt). All models employed an identical architecture and training configuration, with no dataset-specific
370 hyperparameter tuning conducted. Each dataset-specific model was evaluated only on its corresponding test set, while M_all was tested independently on each dataset. This experiment aims to assess whether a generalist model can match or exceed the performance of models trained under dataset-specific conditions, offering insights into the feasibility of cross-domain fracture segmentation.

2.9 Deployment

375 ~~As a first step toward practical deployment, we developed a lightweight web-based prototype that enables users to upload paired RGB images and DEMs and obtain deep-learning-based fracture predictions via the hassle-free Gradio interface (?). The tool, hosted on Hugging Face Spaces, illustrates how the trained model can be made accessible beyond a purely research-oriented setting. While still preliminary, this prototype highlights the potential of interactive platforms to broaden the adoption of~~

automated fracture detection within the geoscience community and offers a concrete example of integrating deep-learning
380 outputs into field and laboratory workflows. The interface additionally allows users to explore a range of computer vision
filters and metrics calculation.

3 Results

To assess ~~model~~ performance, we evaluated ~~both traditional computer vision~~ traditional computer vision filters and deep
learning (DL) models on the ~~test dataset, using the image quality, segmentation~~ held-out test set using the image quality,
385 segmentation, and similarity metrics described earlier. The following sections present ~~these results, qualitatively and quantitatively~~ qualitatively
and quantitative results.

3.1 Traditional Computer Vision-Based Algorithms

The optimal hyperparameters and thresholds that produced the best results, identified through grid search and manual visual
inspection, are listed in ??.

390 3.1.1 Quantitative Results

For completeness, the full numerical results from both the grid-searched settings are provided in ??. The radar chart in ??
summarises how the traditional filters perform across image quality, segmentation, and similarity metrics. Overall, the filters
cluster near the ~~center~~ centre of the plot, indicating ~~uniformly~~ limited fracture-detection ~~ability~~ capability across metrics. Canny,
Sobel, Sato, and Phase Congruency exhibit similar profiles, with modest accuracy, precision, F1, and IoU, and only small
395 variations in recall, specificity, and ROC. For the structural similarity metric, they achieve an SSIM value of zero, indicating
no structural similarity. In contrast, the error-based measures (MSE, AE, and loss) remain low, which is favorable. Gabor is
the only method that diverges sharply from this pattern: it attains perfect recall but extremely low precision, yielding a highly
unbalanced shape on the radar plot. Because it labels nearly all pixels as background class, the remaining metrics collapse to
very low values.

400 3.1.2 Qualitative Results

Using grid-searched parameters across all test sites, the classical filters produced ~~somewhat~~ partially useful but generally sparse
outputs (?). ~~Phase Congruency and~~ For example, in the Ovaskainen22 test patch (??a–f), Phase Congruency (panel b) detected
several fracture segments but introduced substantial noise, while Sato (panel e) captured only the most prominent ridges. In
the Samsu19 patch (??m–x), all filters struggled with the coarser resolution and sedimentary texture. Phase Congruency and
405 Canny often highlighted many true fracture segments, but their responses included substantial noise and many thin lines. Sobel
and Sato tended to be very sparse, picking up only the strongest edges or ridge cores, while Gabor largely failed to isolate
fractures and instead responded to texture, producing noisy, non-fracture patterns. In short, the grid search showed that some

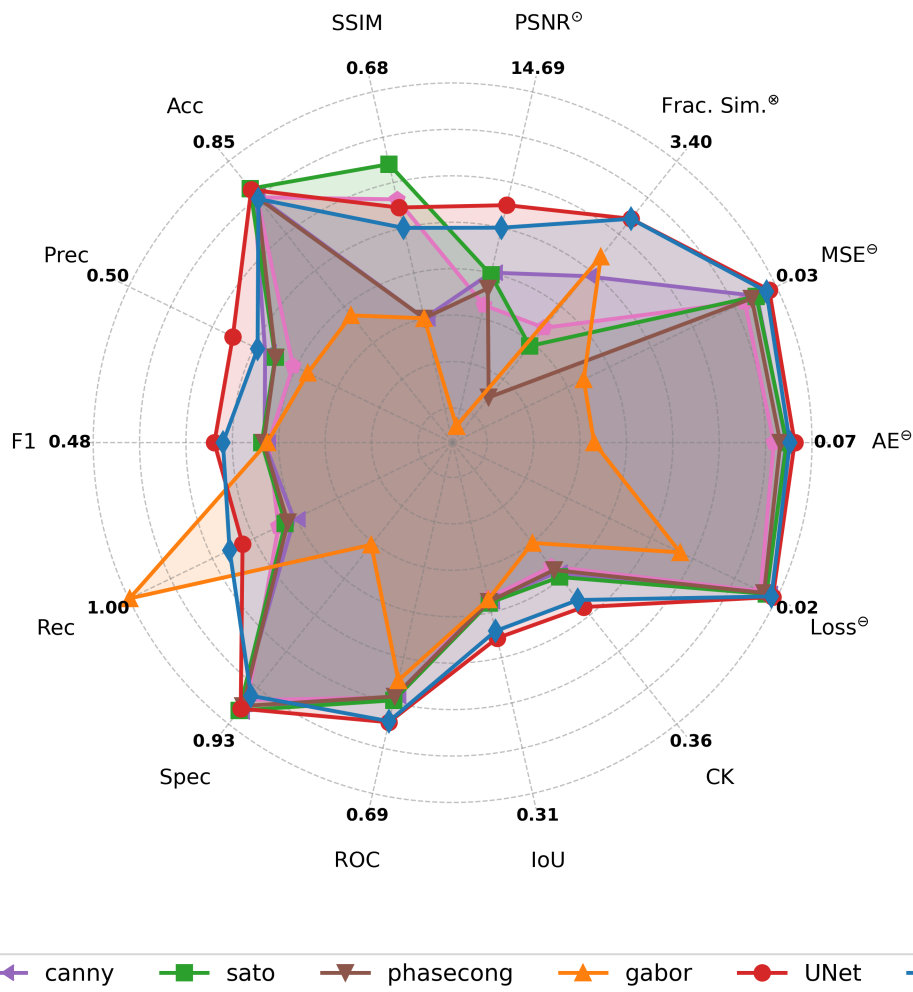


Figure 9. Radar chart summarizing the performance of the classical filters across all evaluation metrics. All metrics originally lie between 0 and 1, except $PSNR^{\odot}$ and $FracSim^{\otimes}$. And metrics where lower values indicate better performance ($AE^{\ominus}$, $MSE^{\ominus}$, $Loss^{\ominus}$ and $FracSim^{\otimes}$) were flipped by computing $(1 - value)$ so that the chart consistently displays better performance toward the outer radius. $FracSim^{\otimes}$ was calculated on the modified test set. Abbreviations are defined in ??.

filters can detect fracture signals, but ~~the~~ universal parameter sets are not optimal for every site and yield noisy or incomplete maps.

410 Using manually tuned parameters on each test site separately, some filters were able to highlight fracture segments more clearly (??). Sobel and Canny captured more pronounced edges along major traces, while Sato produced thicker and more continuous lines. However, the outputs also included numerous spurious detections of non-fracture features.

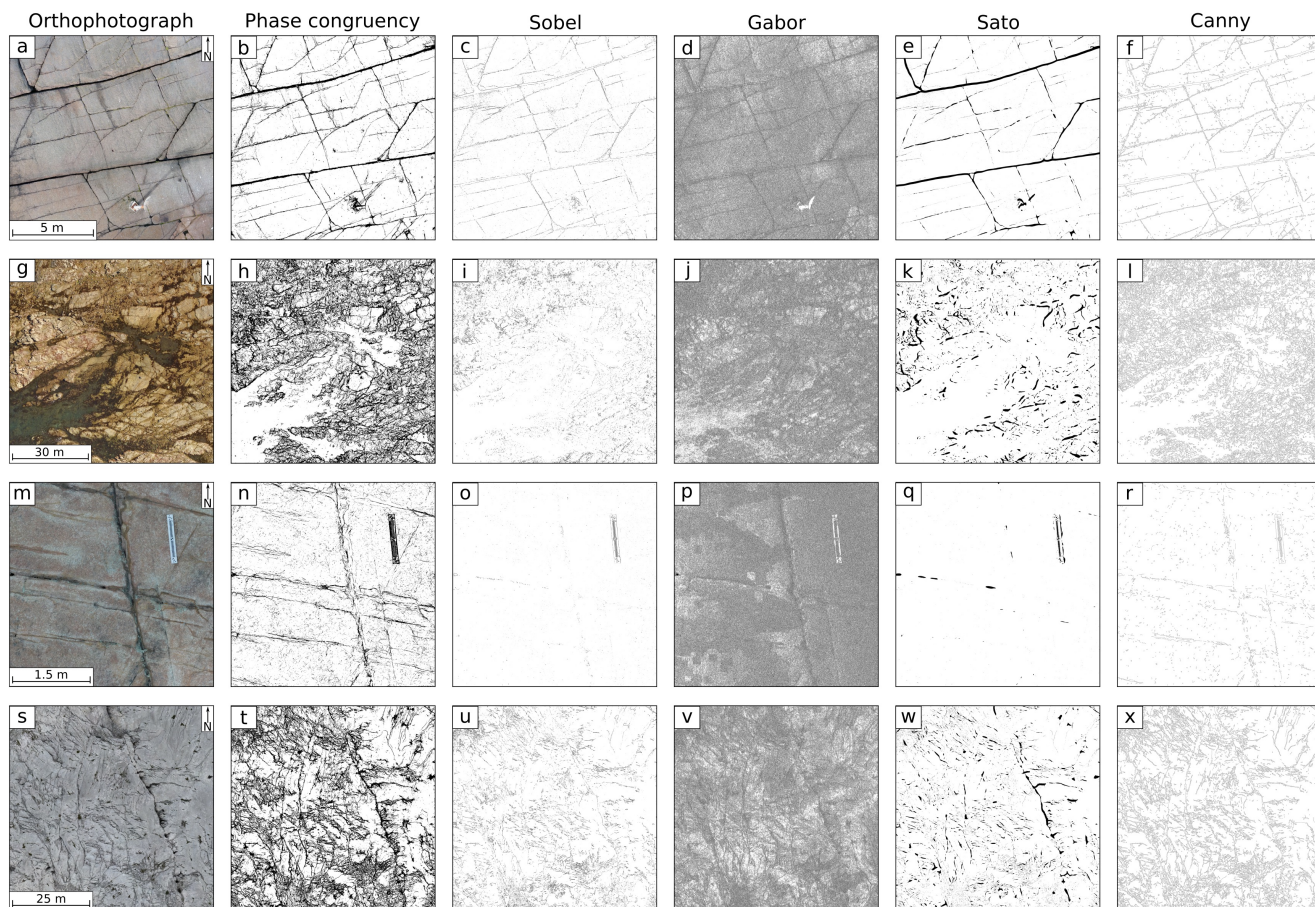


Figure 10. Comparison of traditional filters applied to four representative orthophotographs, using parameters selected by grid search. Each row shows an original orthophotograph (a, g, m, s) alongside results from Phase Congruency (b, h, n, t), Sobel (c, i, o, u), Gabor (d, j, p, v), Sato (e, k, q, w), and Canny (f, l, r, x) filters.

While manually tuned parameters can produce visually plausible outputs on individual test sites, this performance does not generalise well ~~across other locations—or even across~~ to other locations, or even to different regions within the same
415 image. Traditional filters are sensitive to local contrast, scale, and texture, requiring site-specific adjustments to capture relevant features. These tuned parameters, although effective in isolated cases, often fail ~~when applied to on~~ heterogeneous datasets.

~~The limitations described above~~ These limitations expose a core issue: ~~both~~ fixed-rule and parameter-tuned ~~methods on~~ traditional filters lack the flexibility to handle ~~the variability of~~ complex, real-world geology. ~~Thus, they motivate the adoption~~ of geological variability. They motivate deep learning approaches, ~~which that~~ do not rely on hand-crafted features or globally
420 fixed parameters. Instead, they learn hierarchical representations directly from the data, enabling better adaptation to diverse fracture patterns and geological contexts. Deep networks can, in principle, generalise beyond specific sites by capturing shared structures across datasets.

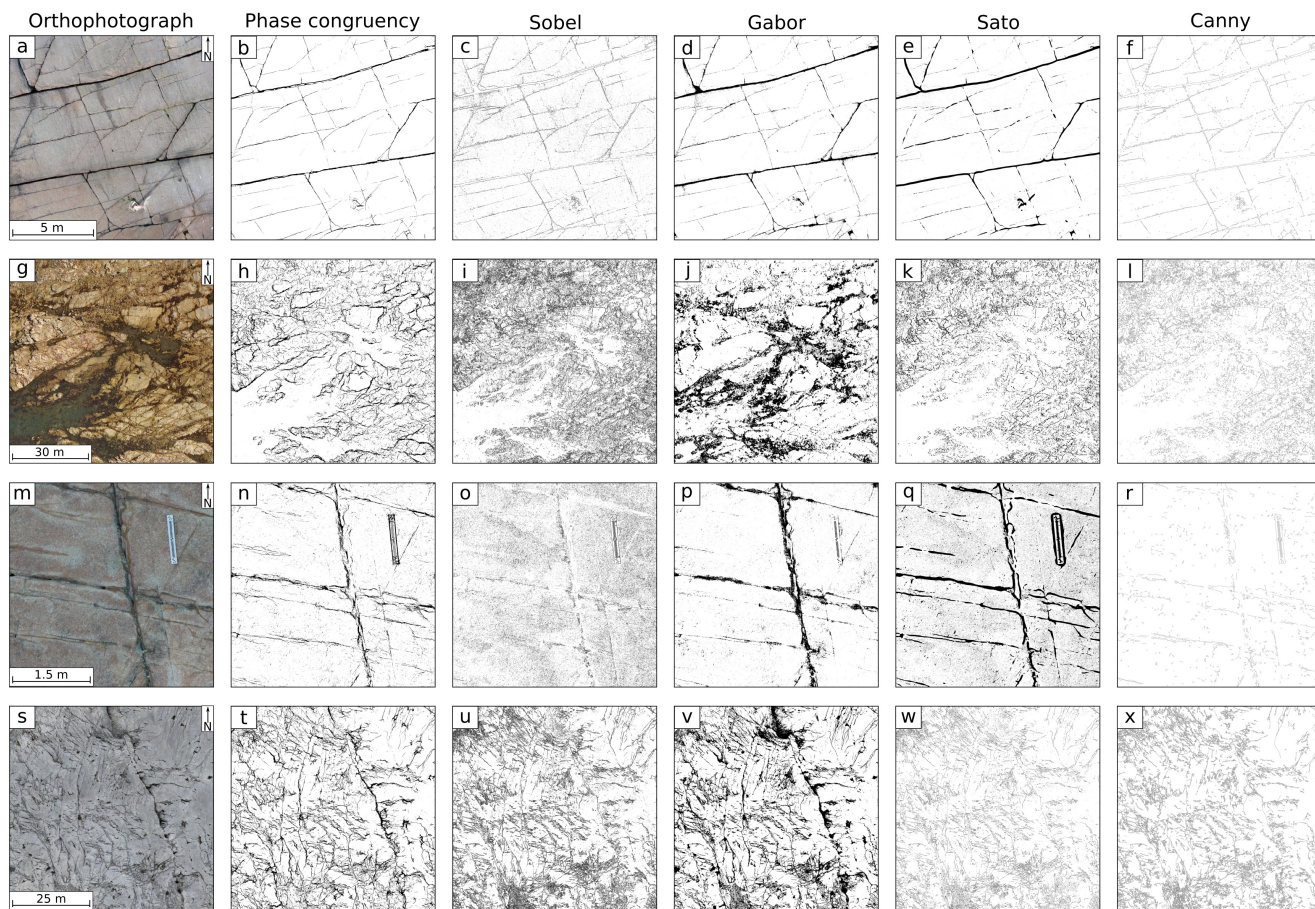


Figure 11. Comparison of traditional filters applied to four representative orthophotographs, using parameters selected manually for each site. Each row shows an original orthophotograph (a, g, m, s) alongside results from Phase Congruency (b, h, n, t), Sobel (c, i, o, u), Gabor (d, j, p, v), Sato (e, k, q, w), and Canny (f, l, r, x) filters.

3.2 Deep Learning Models

3.2.1 Training Dynamics

425 For model [Model](#) and hyperparameter selection, ~~cross-validation was performed~~ [was performed via cross-validation](#) using the training and validation subsets. ?? shows a representative training run for both architectures using the fixed hyperparameters ~~mentioned~~ [described](#) in the Methods section and a single random seed (42), ~~which ensures that weight initialization and~~ [any ensuring that weight initialisation and](#) other stochastic processes are reproducible ~~and consistent~~ across runs. The [training curves illustrate the model learning process on the fracture datasets, showing how the segmentation error changes as the models](#) learn to identify fracture patterns from the annotated RGB+DEM patches over successive epochs. The U-Net exhibits a smooth

430

decrease in training loss and a validation curve that stabilises around epoch 43. The gap between the two curves remains small, with only mild overfitting toward the end of training. The checkpoint with the lowest validation loss was used for evaluation. SegFormer follows a similar downward trend but with higher loss values and more fluctuation, particularly during the first half of training. Its slower convergence suggests that the model adapts less effectively to this dataset than the U-Net, or alternatively,

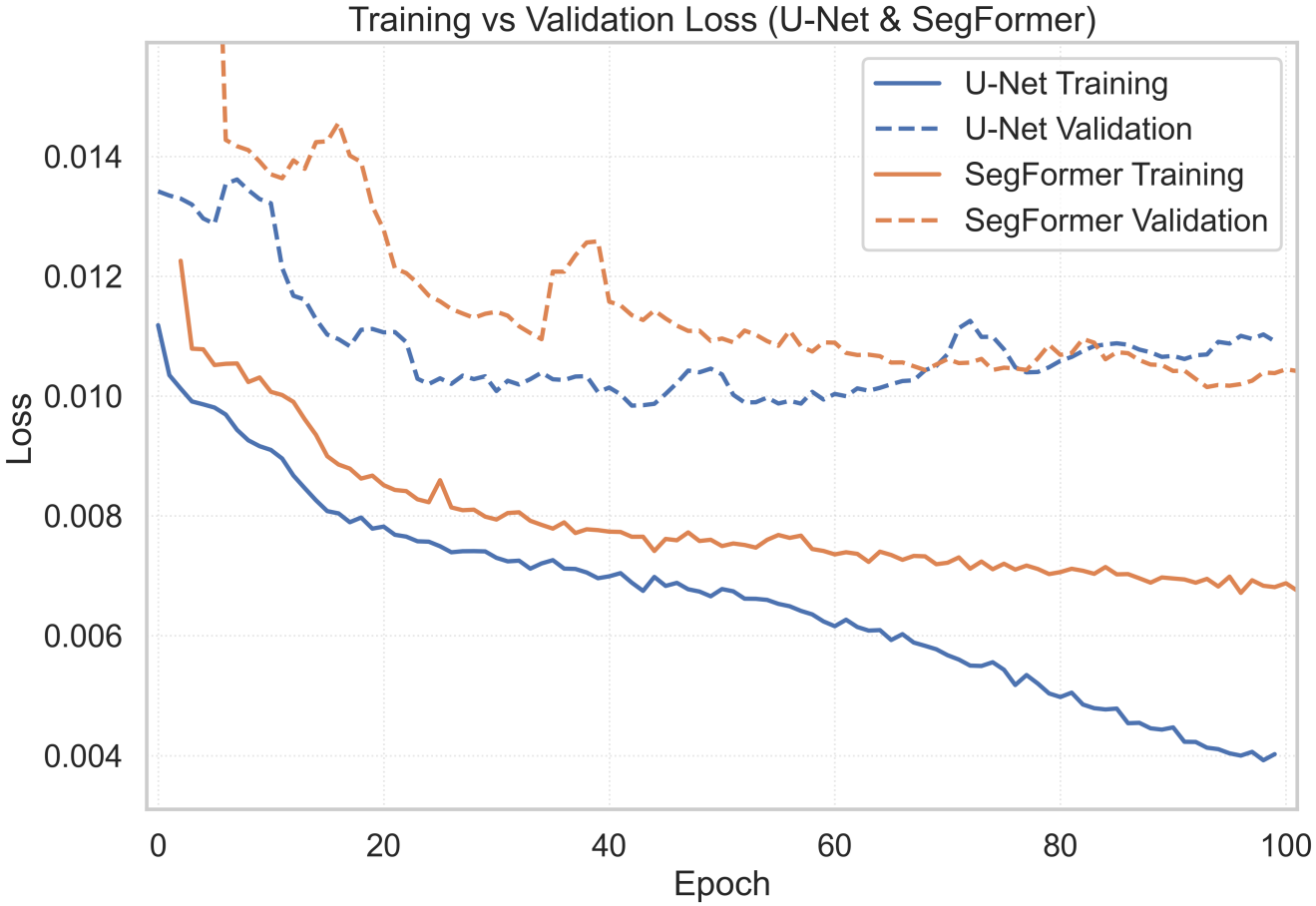


Figure 12. Training and validation loss curves for U-Net and SegFormer (range: [0, 1])

3.2.2 Quantitative Results

As shown in the spider diagram (??) and in??, the U-Net model achieved a mean ~~F1-score~~ F1 score of 0.48 and IoU of 0.31, substantially higher than any traditional baseline ($F1 < 0.29$, $IoU < 0.17$). Precision reached 0.50 ~~, indicating that~~ (half of the ~~predicted pixels presenting fractures corresponded to true positives~~ pixels predicted as fractures were true positives), while recall remained moderate (0.45), ~~showing that some pixels of the fractures were missed~~ indicating missed fracture pixels. SSIM

(0.49) and PSNR (14.7 dB) confirm that the reconstructed fracture masks deviate notably from the ground truth in terms of image similarity, ~~but yet~~ the segmentation metrics demonstrate ~~reliable~~ decent detection of fracture structures.

The SegFormer model was trained using the same data splits and evaluation protocol as the U-Net. While SegFormer produced competitive results, its F1 (0.44) and IoU (0.28) were consistently lower than those of the U-Net. Standard deviations
445 across runs were similarly low, indicating stable but suboptimal convergence. Although the U-Net and SegFormer models clearly outperform filter-based methods, their absolute performance remains well below standard deep learning studies ($F1 > 0.8$, $IoU > 0.6$) (???), ~~emphasising~~. This emphasises the challenging nature of ~~this task and relatively limited available training data~~ fracture segmentation as a task and the relatively limited training data currently available.

Notably, ~~our experiments show that the DL~~ the DL models (U-Net and SegFormer) ~~models~~ achieve substantially lower
450 FracSim (better agreement of length distributions) than classical filters. ~~This demonstrates that~~ Thus DL predictions not only overlap ground truth spatially (IoU, F1) but also better reproduce ~~fracture segment~~ fracture segment length statistics.

3.2.3 Qualitative Results

Example outputs are shown in ??. Across the different datasets, the U-Net CNN consistently produced fracture maps that were smoother, more continuous, and closer to the ground-truth annotations than those ~~of from~~ traditional filters. The model
455 often reconnected segments that filters left broken, yielding fracture networks that were both cleaner and more interpretable. These improvements were observed even under varying lithologies and illumination conditions, ~~confirming consistent with~~ the CNN's ability to generalise across a wide range of datasets. Remaining errors included omission of faint fractures and occasional short false positives in textured or shadowed areas. These qualitative results reinforce the quantitative findings: deep learning methods ~~provide~~ produce more reliable fracture maps than traditional filters, with notable improvements in
460 continuity and interpretability across diverse geological settings.

~~When comparing~~ Comparing the two deep learning models, ~~the SegFormer model~~ SegFormer generated continuous predictions (??) ~~, in some cases capturing and sometimes captured~~ long-range structures more effectively than ~~the CNN~~ U-Net. However, it introduced more false positives in complex textures, occasionally produced random hot spots, and overall ~~its outputs were~~ yielded less confident and less precise ~~compared to the outputs than~~ U-Net ~~model~~ across the test sites.

465 3.2.4 General vs. Dataset-Specific Models

~~The comparison of models within each site (??)~~ shows that the combined model (M_all) ~~provides clear advantages over~~ outperforms dataset-specific models, particularly in ~~terms of~~ F1 and IoU.

~~For the SegFormer architecture on the~~ On the D_ovas dataset, M_all and M_ovas exhibit comparable performance with the SegFormer architecture. M_all achieves an F1-score of 0.70 and an IoU of 0.54, closely matching M_ovas ($F1 = 0.67$, $IoU =$
470 0.51). This indicates that training on multiple datasets does not degrade performance on ~~the Ovaskainen dataset~~ Ovaskainen22, where fractures are relatively clear and annotations are well defined.

The advantages of M_all become more pronounced on the more challenging sites. On D_sams, the site-specific model (M_sams) performs poorly, achieving very low scores ($F1 = 0.11$, $IoU = 0.06$ for U-Net~~;~~ and zero for SegFormer) ~~;~~ despite

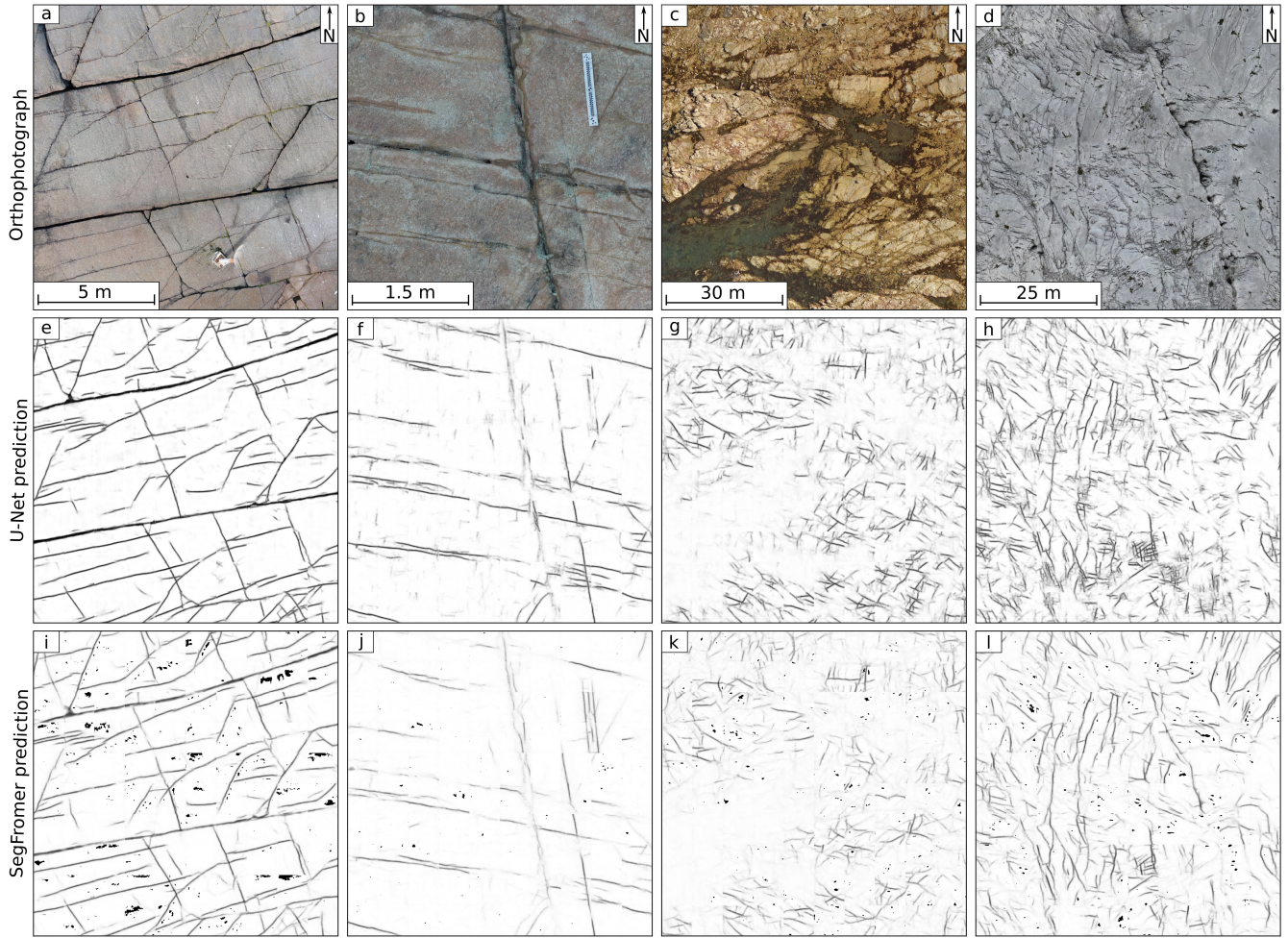


Figure 13. Deep-learning fracture-trace predictions for four representative orthophotographs. Panels (a–d) show the original orthophotographs. Panels (e–h) present corresponding U-Net predictions, and panels (i–l) show SegFormer predictions.

high specificity, indicating weak fracture identification relative to the ground truth. In contrast, M_{all} substantially improves performance, reaching F1-scores of 0.34/0.33 and IoU values of 0.21/0.20. This represents more than a twofold increase in overlap metrics, suggesting that the ~~increased-greater~~ variability in the combined training set enables better ~~generalization~~ generalisation to the more complex fracture patterns ~~present~~ in the Samsu19 dataset.

A similar trend is observed for D_{matt} . ~~The site-specific model, where~~ M_{matt} attains only $F1 = 0.24$ and $IoU = 0.14$ with U-Net, ~~and~~ ($F1 = 0.06$ ~~and~~, $IoU = 0.03$ with SegFormer. ~~In contrast,~~ M_{all} improves performance to $F1 = 0.39/0.41$ and $IoU = 0.24/0.25$. This ~~near-doubling near-doubling~~ of overlap metrics demonstrates that M_{all} is considerably better suited to handling the lithological and textural variability of the Matteo21 dataset.

Table 6. Comparison between multi-site model (M_all) and dataset-specific models (M_ovas, M_sams, M_matt)

Arch	Sub-dataset	Model	AE↓	MSE↓	SSIM↑	PSNR↑	Acc↑	Prec↑	F1↑	Rec↑	Spec↑	ROC↑	IoU↑	CK↑	FracSim*↓	Loss↓
U-Net	D_ovas	M_all	0.05	0.02	0.64	16.51	0.93	0.77	0.73	0.68	0.97	0.83	0.57	0.69	2.99	0.01
		M_ovas	0.06	0.02	0.60	16.03	0.91	0.63	0.67	0.72	0.93	0.83	0.51	0.62	3.04	0.01
	D_sams	M_all	0.06	0.03	0.58	15.48	0.86	0.32	0.34	0.38	0.92	0.65	0.21	0.27	7.54	0.01
		M_sams	0.05	0.03	0.57	15.99	0.91	0.58	0.11	0.06	1.00	0.53	0.06	0.09	3.26	0.01
	D_matt	M_all	0.08	0.04	0.57	14.27	0.80	0.45	0.39	0.34	0.90	0.62	0.24	0.27	4.01	0.02
		M_matt	0.06	0.02	0.61	16.53	0.81	0.47	0.24	0.17	0.96	0.56	0.14	0.16	4.78	0.01
	D_ovas	M_all	0.06	0.02	0.53	16.34	0.93	0.77	0.70	0.64	0.97	0.80	0.54	0.66	2.94	0.01
		M_ovas	0.05	0.02	0.58	16.12	0.93	0.81	0.70	0.61	0.98	0.79	0.54	0.66	3.16	0.01
	D_sams	M_all	0.06	0.03	0.39	15.96	0.85	0.29	0.33	0.39	0.90	0.65	0.20	0.25	7.85	0.01
		M_sams	0.05	0.03	0.35	15.83	0.91	0.00	0.00	0.00	1.00	0.50	0.00	-0.00	1.65	0.01
	D_matt	M_all	0.08	0.03	0.38	15.37	0.81	0.48	0.41	0.35	0.91	0.63	0.25	0.29	4.47	0.01
		M_matt	0.06	0.03	0.67	16.01	0.81	0.51	0.06	0.03	0.99	0.51	0.03	0.04	5.55	0.01

* run only on modified test set

Overall, these results indicate that while dataset-specific models can capture local patterns, they are constrained by limited training data and **are** prone to overfitting, resulting in reduced robustness.

3.2.5 Error Case Analysis

485 ~~We note that despite~~ Despite its stronger overall performance, the U-Net still produced errors (??). These fall into two categories: (1) cases where the model was highly confident yet disagreed with the annotations, and (2) cases where the model was uncertain, assigning low probabilities and yielding fragmented or unstable predictions under challenging visual conditions.

High-confidence errors. In several cases, the CNN produced confident predictions that did not match the annotations. A common source was annotation misalignment, where fractures in the ground truth were traced coarsely or offset from the true
490 pixel locations, e.g., the over-simplified traces and omissions visible in panels (h) and (i) of ??. In these cases, the CNN model is arguably more accurate than the ground truth. This misalignment was particularly evident in the Samsu19 dataset, where manual traces did not precisely follow pixel-level fracture geometry.

Another high-confidence error type was input data artifacts, especially in Matteo21, where corrupted pixel values (NaNs, which PyTorch converts to 0, rendering them black in RGB) in the RGB channels led to localised false positives or spurious
495 losses unrelated to actual geological structures, as illustrated by the missing pixel data in panel (e) and the resulting spurious responses in the corresponding probability map.

Low-confidence errors. Other errors occurred when the model was less certain and produced scattered or incomplete predictions. Confounding visual features such as vegetation, weathering textures, or shadows were occasionally misclassified as fractures, but with lower confidence values in the probability maps—as seen in the water- and shadow-affected

500 [orthophotographs in panels \(a–c\)](#). Additionally, dataset outliers and preprocessing failures (e.g., unusual lithologies, lighting conditions, ~~or mislabelled patches~~ [mislabelled patches](#), or [the black-and-white scale panel in \(d\)](#)) caused the model to generate unstable or inconsistent outputs, [while panel \(f\), which contains no visible fractures, illustrates how the absence of true structure was nonetheless handled by the model](#). These low-confidence cases reflected the difficulty of ~~generalizing~~ [generalising](#) across heterogeneous field conditions not fully represented in [the](#) training data.

505 Taken together, this analysis suggests that many errors stemmed not from the CNN architecture itself but from ~~limitations in the data~~ [data limitations](#): annotation quality, ~~artifacts in inputs~~ [input artifacts](#), and domain heterogeneity. Probability maps proved useful here, ~~as~~ they allowed us to distinguish between errors where the model was confident but the labels were unreliable, and those where the model itself was uncertain—[as summarised across the panels of ??, including the varying fracture thickness, orientation, and illumination shown in panels \(g–i\)](#).

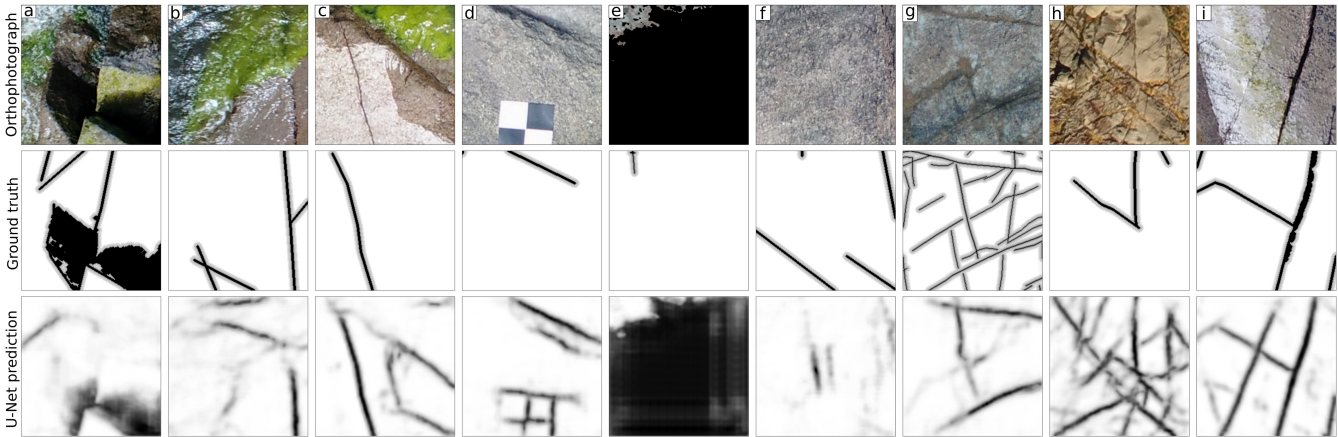


Figure 14. Error case analysis of U-Net predictions

Top row: Orthophotographs (a–c) with water and large shadows, (d) with a black-and-white scale panel, (e) containing missing pixel data, (f) showing no visible fractures, and (g–i) displaying fractures of varying thickness, orientation, and illumination

Middle row: Ground-truth annotations. Some overrepresent shadows due to preprocessing (a), contain labelling errors (c), have over-simplified traces (h), or show omissions (i)

Bottom row: U-Net probability maps. Faux responses appear in (a–e) due to input artifacts or preprocessing issues, while the model captures more realistic fracture geometry than the annotations in (f–i)

510 **3.2.6 Time Required**

We compared the time required for fracture mapping across manual, assisted, and automatic approaches (??). Timing data for manual and assisted interpretation are taken from ?, where mapping fractures in a 10 × 10 m area at 1 cm/pixel resolution took 54–57 minutes manually and 35–37 minutes using semi-automatic tools. In contrast, our automatic deep learning approach generated probability maps in 6 seconds (on ~~free-tier huggingface space (2vCPU and 16GB RAM)~~ [a Hugging Face Spaces](#)

515 free-tier instance with 2 vCPUs and 16 GB RAM). While post-processing is still required to derive a fracture map (instance segmentation and vectorisation), this speed-up could ~~enable a substantial reduction in~~ substantially reduce the effort and time ~~during-needed for~~ large-scale fracture interpretation.

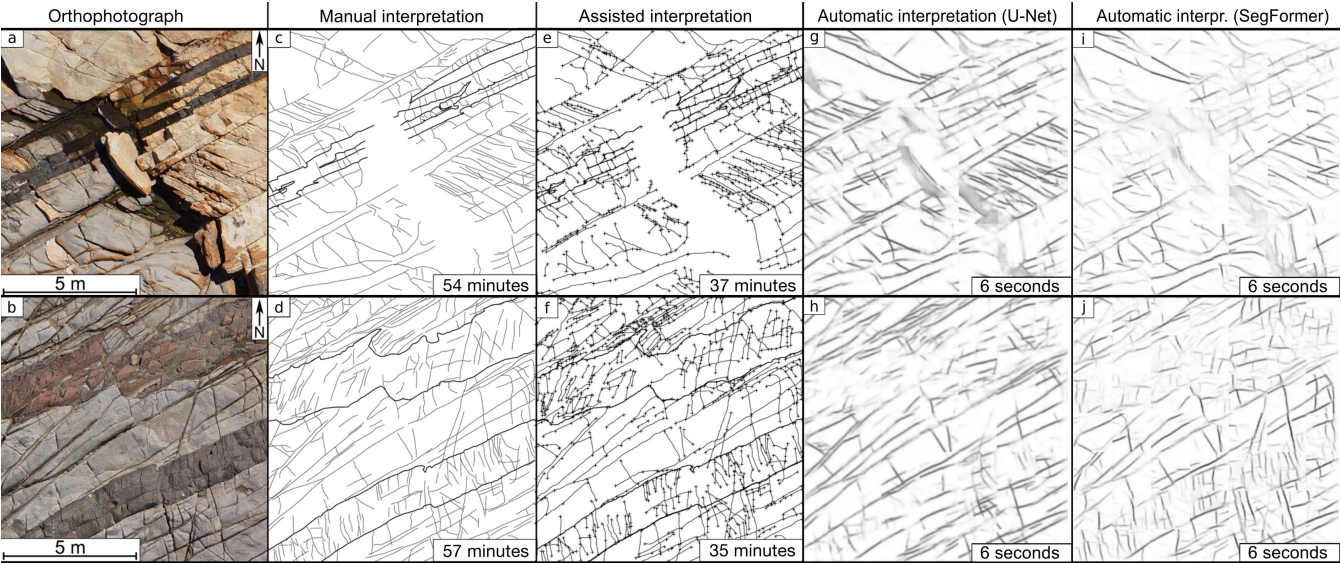


Figure 15. Two 10 × 10 m orthophotographs (?) (a, b) with corresponding fracture traces digitised manually (?) (c, d), semi-automatically using the assisted method of (?) (e, f), automatically with the U-Net model (g, h) and with SegFormer model (i, j)

4 Discussion

~~We now~~ Here we discuss key observations from the benchmarking experiments and their implications for automated fracture mapping.

4.1 Model Performance

~~Unsurprisingly, traditional~~ Traditional edge and ridge filters proved inadequate for robust fracture mapping across heterogeneous datasets ~~. Their outputs (??, ??, ??). Outputs~~ were highly sensitive to parameter choices, and ~~hyperparameter selections~~ hyperparameters optimal at one site often failed to generalise ~~well~~ across combined sites. In practice, ~~these~~ traditional methods remain useful for rapid visualisation ~~or~~ , exploratory work, or ~~tailored application to relatively small datasets. However, small, tailored datasets, but~~ they are ill-suited for mapping ~~of~~ complex fracture systems ~~, which is required for~~ needed for quantitative fracture and structural analyses.

Our results are consistent with previous U-Net fracture-detection studies. ? reported F1 scores of 0.78–0.926 on granite outcrops in Finland using U-Net, though their evaluation did not include the background class, which inflates metrics relative to our methodology. ? achieved a Tversky Index (similar to IoU) of 0.35–0.68 using a similar architecture but on a single

lithology. Our M_all model achieves $F1 = 0.48$ and $IoU = 0.31$ across heterogeneous datasets with the background class included, suggesting that cross-site generalisation incurs a performance cost that should decrease as more training data become available.

The tested deep learning models ~~were shown to significantly outperform~~ outperformed the traditional filters, producing smoother and more continuous traces ~~and with~~ substantially better overlap with annotated fractures. Nevertheless, absolute performance remained modest compared with segmentation benchmarks in other domains. This ~~is likely due to the highly likely reflects the~~ unusual nature of ~~this semantic segmentation task—the selection of the task—selecting~~ thin (high-aspect-ratio) pixel groupings ~~(edges) in a highly in a strongly~~ class-imbalanced dataset ~~—and the variety of—~~ and geological and environmental factors that ~~change alter~~ fracture appearance or introduce ~~obfuscating confounding~~ features. Label noise and misalignment are also likely contributors, although practical ~~limitations around limits on~~ data collection and manual labelling make ~~it challenging to acquire~~ better training data hard to acquire.

Interestingly, the ~~The~~ transformer-based models (SegFormer) behaved ~~quite~~ differently from the CNNs in our experiments (see ?? ~~—Their and ??~~). ~~SegFormer’s~~ results were less robust, ~~producing with~~ spurious detections that we attribute to ~~the tendency of~~ global-attention mechanisms ~~to over-interpret over-interpreting~~ background structure when the training signal is weak. This is consistent with known properties of transformers: they can excel when supplied with large, diverse, and clean datasets, but are more data-hungry than convolutional architectures.

~~Thus, while transformers~~ Transformers showed some promise, ~~their advantages are likely to but their advantages likely~~ emerge only with ~~substantial improvements in dataset size and annotation quality~~ substantially larger and cleaner datasets ~~—although practical limitations around data collection and manual labelling make acquiring such high-quality training data particularly~~ challenging in the context of geological fractures. In the meantime, the tested CNN (difficult given practical limits on collecting and labelling geological fracture data. For current data scales, U-Net) architecture appears most promising remains the recommended architecture.

Our cross-dataset experiments show that diverse training data improves ~~model~~ performance. A general model trained on all sites consistently outperformed models trained on individual datasets, especially on overlap- and detection-sensitive metrics ~~like (F1 score and IoU. This suggests that exposure, IoU). Exposure~~ to varied lithologies, lighting, and fracture patterns ~~helps the model learn appears to yield~~ more transferable features and reduces overfitting to site-specific conditions. These results ~~highlight the importance underscore the value~~ of multi-site datasets for robust fracture segmentation.

4.2 The Need for Post-processing

A critical bottleneck in automated fracture mapping is post-processing, ~~which is needed to convert~~ converting model outputs to polylines or ~~some other vectorised representation of fracture instances that are better suited other vectorised fracture instances suitable~~ for topological analyses (e.g., ~~for~~ assessing fracture connectivity). Pixel-wise probability maps are valuable, but ~~they are only the only a~~ first step toward usable fracture traces. Converting semantic masks into instance-level polylines for length, orientation, and spacing measurements requires robust, standardised post-processing pipelines (skeletonisation, connected-component analysis, cleaning, linking, and polyline extraction). Semantic segmentation models do not

565 explicitly preserve fracture connectivity, so intersections and network topology are often poorly reconstructed even when the
main fracture geometries are correctly detected. Without these steps, downstream fracture statistics remain noisy and ~~difficult~~
hard to interpret.

Post-processing ~~can and~~ should also incorporate domain knowledge (for example, weak orientation priors) to reduce spurious
short segments and improve the geological plausibility of extracted traces. Furthermore, ~~we suggest that it might be possible~~
570 ~~to develop~~ post-processing algorithms ~~that can~~ could leverage the rich information in probabilistic model outputs and local
knowledge ~~on~~ (e.g., likely fracture orientations) to (1) identify and remove false-positive fracture detections, and (2) extrapolate
detected fractures across small gaps ~~(based on their orientation)~~, as is commonly done by human interpreters.

4.3 ~~Future Work~~ Together, our Deployment

As a first step toward practical deployment, we developed lightweight interfaces so users can apply the trained models
575 without machine-learning expertise. A web-based application, built with Gradio (?) and hosted on Hugging Face Spaces
(<https://ayoubft-fractex2d-tuto.hf.space>), enables users to upload paired RGB images and DEMs to obtain deep-learning-based
fracture predictions. The interface also provides access to other computer-vision filters and evaluation metrics.

To facilitate integration into existing geological workflows, we additionally developed a simple QGIS plugin ([https://plugins.](https://plugins.qgis.org/plugins/fraXtex/)
qgis.org/plugins/fraXtex/) that enables inference directly within QGIS. Together, these tools show how the proposed workflow
580 can be adopted in geoscience workflows.

4.4 Future Work

Our results highlight several concrete next steps ~~that could enable automated and~~ toward automated, more objective fracture
mapping: improving annotation precision (multi-scale labels, consensus labelling) in training data, expanding dataset diver-
sity by including more sites ~~(as more public data becomes available)~~ as additional public data become available, and adopting
585 architectures and loss functions tailored to the unusual ~~(thin ->)~~ thin geometry of fractures. Complementary strategies such as
ensembling, transfer learning, and self-supervised pretraining offer promising avenues to improve performance and robust-
ness. Ensembling multiple models can reduce variance and improve prediction stability, particularly for thin and discontinuous
fracture traces. Transfer learning from larger geospatial or remote sensing datasets can provide stronger low-level feature repre-
sentations, enabling better ~~generalization when labeled~~ generalisation when labelled fracture data are limited. Self-supervised
590 pretraining on ~~unlabeled data~~ unlabelled imagery can further leverage abundant data to learn domain-specific texture and struc-
ture features, improving downstream segmentation accuracy while reducing dependence on extensive manual annotations.

5 Conclusions

We present a harmonised benchmarking framework for fracture mapping in high-resolution outcrop imagery and use it to
compare traditional image filters ~~to with~~ deep learning methods, including a U-Net convolutional network and a ~~transformer~~
595 ~~based~~ transformer-based model (SegFormer). Our experiments show that ~~the~~ deep learning models consistently outperform

traditional edge and ridge filters ~~by producing~~, yielding smoother, more continuous, and qualitatively ~~reasonable results~~ more plausible traces. This gap ~~highlights~~ shows that algorithmic improvements alone are insufficient: ~~limited~~ incomplete post-processing ~~techniques~~, variable label quality, dataset heterogeneity, and the complex information (e.g., ~~topological understanding~~ topology) needed to ~~accurately identify high-aspect-ratio and~~ identify high-aspect-ratio, typically continuous fractures are the primary
600 barriers to reliable, fully automated fracture extraction. Beyond these empirical results, the principal ~~contribution of this work~~ contributions are the resources we release: the curated datasets, evaluation protocol, and open-source code. We hope ~~that~~ these resources will ~~foster further developments to address~~ support further work on the challenges outlined above.

Code and data availability. The FraXet dataset, including all RGB tiles, DEMs, masks, and metadata, is archived and publicly accessible on Zenodo at <https://doi.org/10.5281/zenodo.17069947> (?).

605 The full source code used in this study is openly available at <https://gitlab.com/ayoubft/fractex2D.pt> (Last access: July 31, 2026) and the version associated with this publication is archived at <https://doi.org/10.5281/zenodo.17953223> (?).

All trained models associated with this work are available on both Hugging Face and Zenodo. The model weights can be accessed on Hugging Face at <https://huggingface.co/ayoubft/fraXteX> (Last access: July 31, 2026) and are archived on Zenodo at <https://doi.org/10.5281/zenodo.17866853> (?).

610 A live deployment of the model is hosted on Hugging Face at https://huggingface.co/spaces/ayoubft/fractex2D_tuto, providing an interactive interface for running inference of the trained deep learning models and also try the computer vision filters.

Appendix A: Dataset overviews

Overview maps and example tiles for each of the three datasets are provided in ??, ??, and ??, complementing the metadata in ??.

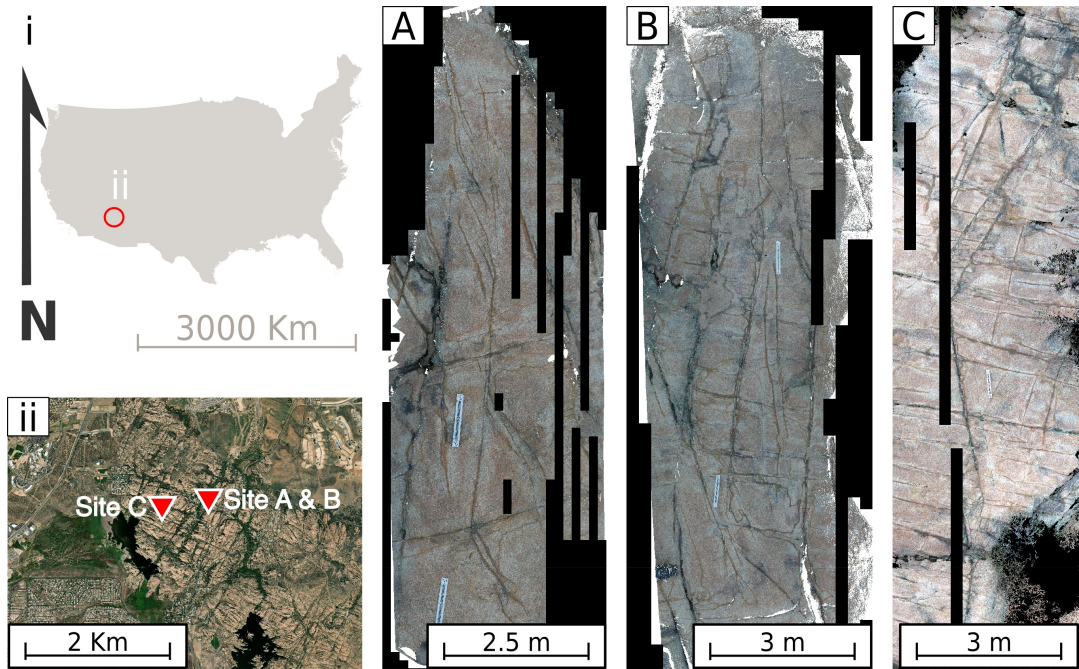


Figure A1. Overview of the Matteo21 dataset. (i) Location map of the Granite Dells, Arizona, USA. (ii) Zoom in to sites A, B and C. (A) Site A (training + validation site). (B) Site B (training + validation site). (C) Site C (test site).

615 Appendix B: Pre-processing effect

Table B1. Effect of preprocessing on fracture-class pixel proportions across datasets

Dataset	Before pre-processing			After preprocessing		
	train	valid	test	train	valid	test
Ovaskainen22	0.45	0.57	0.68	3.08	3.32	4.14
Matteo21	0.29	0.58	0.55	0.39	0.60	1.51
Samsu19	0.43	0.35	0.49	2.17	1.73	2.41

Table C1. Data augmentation techniques and corresponding probabilities and parameter ranges

Augmentation Technique	Probability	Parameter Range
Horizontal Flip	0.5	-
Vertical Flip	0.5	-
Gaussian Blur	0.05	Sigma ∈ [0.1, 2.0]
Brightness Decrease	0.05	Factor ∈ [0.7, 0.9]
Brightness Increase	0.15	Factor ∈ [1.1, 1.7]
Contrast Adjustment	0.05	Factor ∈ [0.7, 1.5]
Saturation Adjustment	0.05	Factor ∈ [0.7, 1.5]

Appendix C: Data Augmentation Setup

Appendix D: Optimal Filters’ Parameters

Table D1. Optimal filters’ parameters using the grid search and visually (Ovaskainen22/Matteo21/Samsu19/LapiesdiBou)

Algorithm	Parameter	Opt. Value (grid)	Threshold (grid)	Opt. Value (visual)	Threshold (visual)
Edge detectors	Sobel	-	0.8	-	0.19/0.1/0.11/0.11
	sigma	1.9		1.5/0./0.53/1.	
	Canny	low_threshold	-	0.3/0.65/0.66/0.1	-
		high_threshold		0.5/1./1./1.	
Ridge detector	Gabor	frequency	0.0	0.7/1./1./1.	0.12/0.35/0.26/0.5
	Sato	sigmas	range(2, 8, 2)	range(1, 20, 4)/idem /range(1,4)/(1,)	0.6/.04/0.07/0.6
		nscale	5	6/5/6/6	
		noorient	5	6/5/6/6	
Phase Congruency		minWaveLength	3	5/3/5/5	
		mult	2	2.3/2/2.3/2.3	
		sigmaOnf	0.5	0.6/0.5/0.6/0.6	0.002/0.0011/0.15
		k	2	3.6/3/3.6/3.6	
		cutOff	0.3	0.36/0.3/0.36/0.36	
		g	10	41.6 /10/41.6/41.6	
		noiseMethod	-1	-1	

Appendix E: Quantitative Results

Table E1. Quantitative results: evaluation metrics on the test set

	AE↓	MSE↓	SSIM↑	PSNR↑	Acc↑	Prec↑	F1↑	Rec↑	Spec↑	ROC↑	IoU↑	CK↑	FracSim*↓	Loss↓
phasecong	0.15	0.14	0.0	8.68	0.79	0.28	0.27	0.27	0.88	0.58	0.16	0.15	214.53	<u>0.07</u>
sobel	0.46	0.44	0.0	3.59	0.55	0.18	0.28	<u>0.57</u>	0.55	0.56	0.16	0.06	132.27	0.22
gabor	0.94	0.92	0.0	0.35	0.15	0.14	0.25	1.00	0.01	0.50	0.14	0.00	48.12	0.46
sato	0.11	0.10	0.0	10.2	0.85	0.30	0.27	0.25	0.93	0.59	0.16	0.19	153.76	0.05
canny	0.28	0.27	0.0	5.76	0.69	0.22	0.29	0.42	0.74	0.58	0.17	0.12	71.10	0.13
U-Net	<u>0.07</u>	0.03	<u>0.49</u>	14.7	<u>0.84</u>	0.50	0.48	0.45	<u>0.92</u>	0.69	0.31	0.39	3.40	0.02
SegFormer	0.10	<u>0.05</u>	0.40	13.2	0.79	<u>0.38</u>	<u>0.44</u>	0.52	0.84	<u>0.68</u>	<u>0.28</u>	<u>0.32</u>	<u>3.43</u>	0.02
All 1	0.95	0.93	0.01	0.33	0.16	0.16	0.27	1.00	0.00	0.50	0.16	0.00	Undef	0.47
All 0	0.05	0.03	0.82	<u>14.69</u>	0.84	0.00	0.00	0.00	0.00	0.50	0.00	0.00	Undef	0.02

* was calculated on the modified test set

Author contributions. AF: Conceptualisation, Formal analysis, Data curation, Code development, Investigation, Methodology, Visualisation, Writing – original draft; JC: Writing - review & editing; TB: Methodology, Writing - review & editing; STT: Conceptualisation, Code development, Methodology, Writing - review & editing; AS: Conceptualisation, Methodology, Writing - review & editing;

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

Acknowledgements. This study was supported by the University of Lausanne (Université de Lausanne).

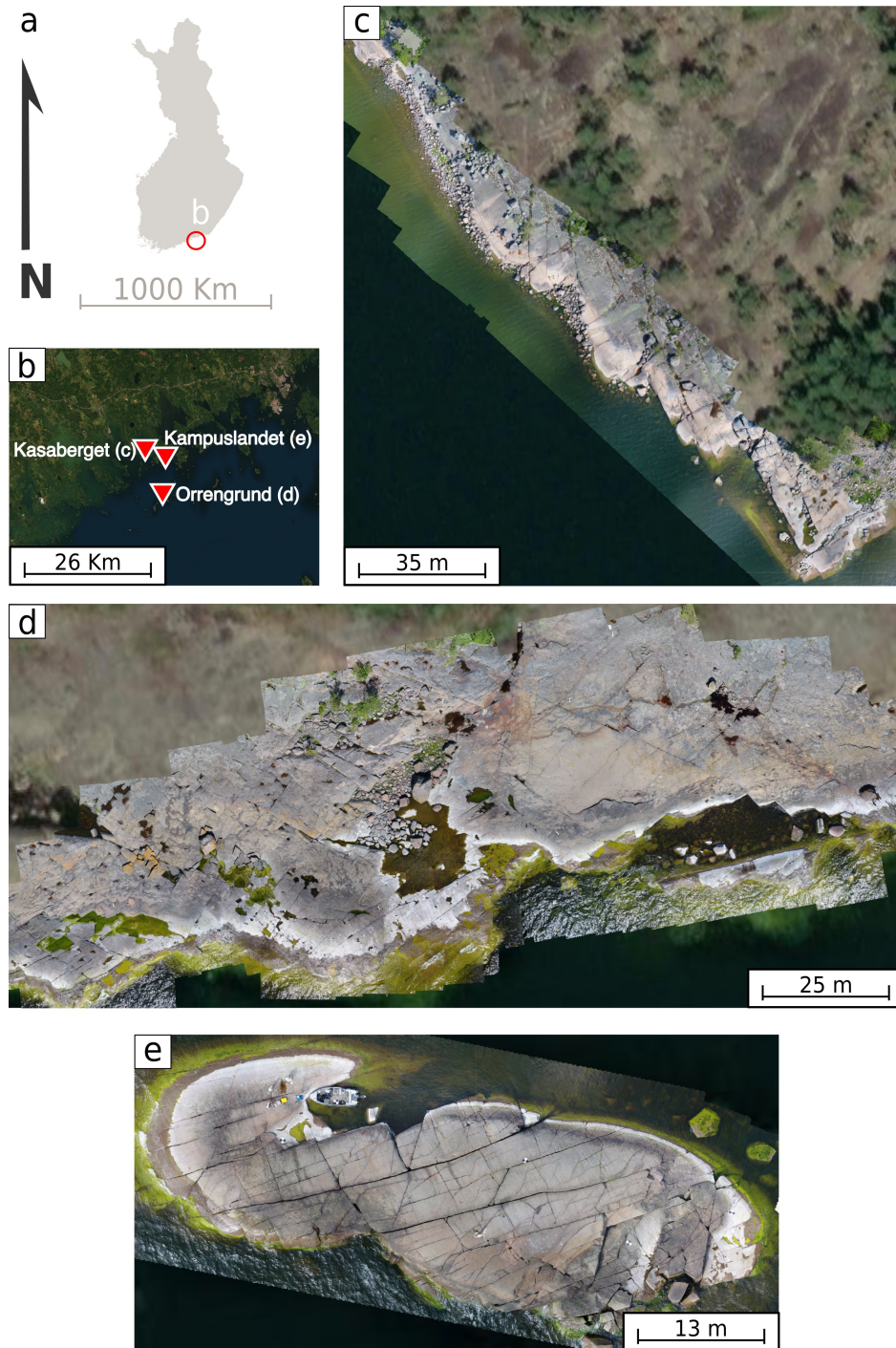


Figure A2. Overview of the Ovaskainen22 dataset. (a) Location map of the Wiborg Rapakivi Granite Batholith, southeastern Finland. (b) Zoom in to the Loviisa region showing the islands of Orregrund, Kasaberget, and Kampuslandet. (c) Orregrund (training site) orthophotograph. (d) Kasaberget (validation site) orthophotograph. (e) Kampuslandet (test site) orthophotograph.

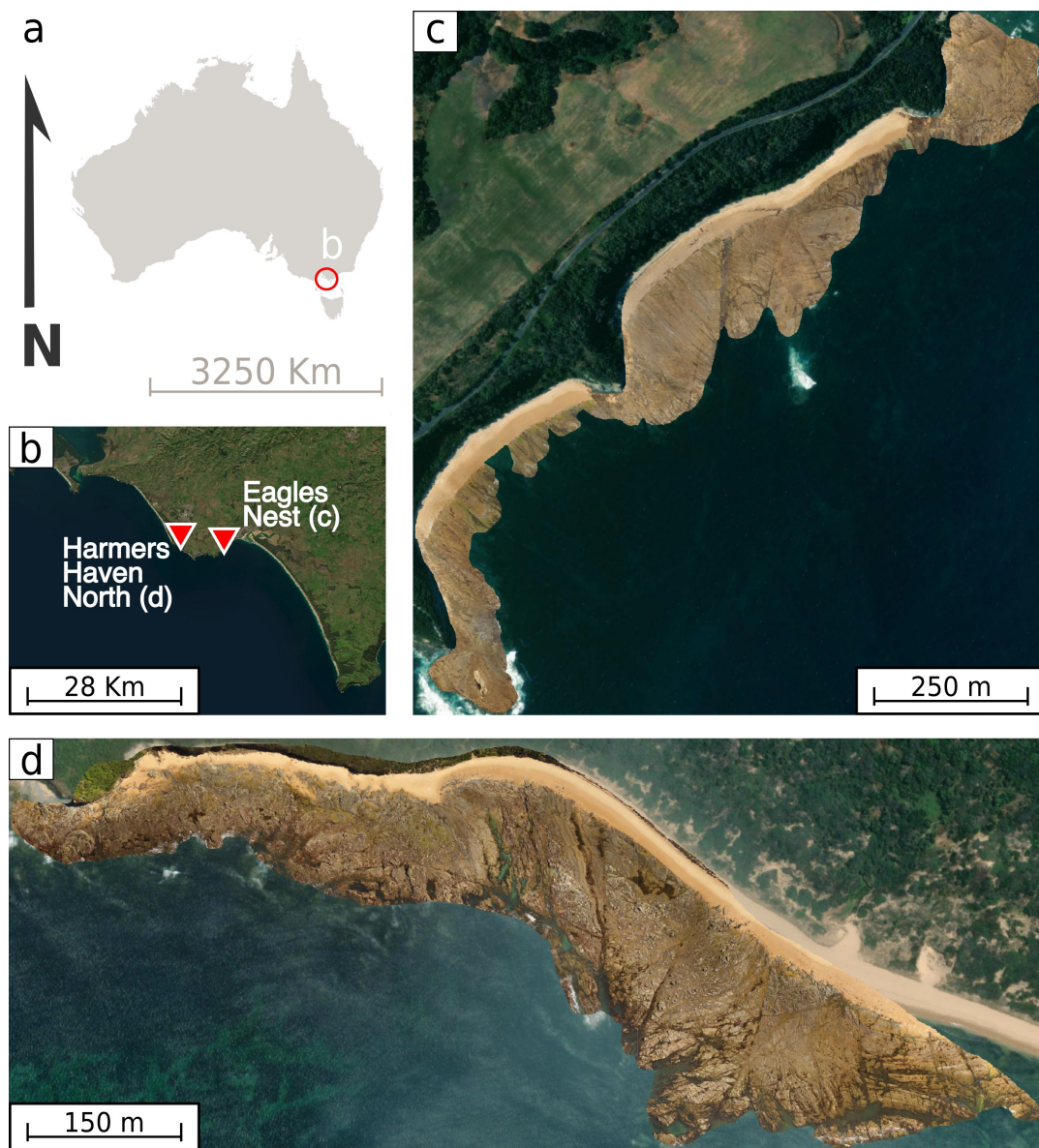


Figure A3. Overview of the Samsu19 dataset. (a) Location map of the Strzelecki Group, southeastern Australia. (b) Zoom in to the Harpers Haven area showing Eagles Nest and Harpers Haven north. (c) Eagles Nest (training site) orthophotograph. (d) Harpers Haven north (validation/test site) orthophotograph.

References

- 625 Abid, A., Abdalla, A., Abid, A., Khan, D., Alfozan, A., and Zou, J.: Gradio: Hassle-Free Sharing and Testing of ML Models in the Wild, <https://doi.org/10.48550/arXiv.1906.02569>, 2019.
- Adiri, Z., El Harti, A., Jellouli, A., Lhissou, R., Maacha, L., Azmi, M., Zouhair, M., and Bachaoui, E. M.: Comparison of Landsat-8, ASTER and Sentinel 1 Satellite Remote Sensing Data in Automatic Lineaments Extraction: A Case Study of Sidi Flah-Bouskour Inlier, Moroccan Anti Atlas, *Advances in Space Research*, 60, 2355–2367, <https://doi.org/10.1016/j.asr.2017.09.006>, 2017.
- 630 Aghaee, A., Shamsipour, P., Hood, S., and Haugaard, R.: A Convolutional Neural Network for Semi-Automated Lineament Detection and Vectorisation of Remote Sensing Data Using Probabilistic Clustering: A Method and a Challenge, *Computers & Geosciences*, 151, 104724, <https://doi.org/10.1016/j.cageo.2021.104724>, 2021.
- An, Y., Du, H., Ma, S., Niu, Y., Liu, D., Wang, J., Du, Y., Childs, C., Walsh, J., and Dong, R.: Current State and Future Directions for Deep Learning Based Automatic Seismic Fault Interpretation: A Systematic Review, *Earth-Science Reviews*, 243, 104509, <https://doi.org/10.1016/j.earscirev.2023.104509>, 2023.
- 635 Andrews, B. J., Roberts, J. J., Shipton, Z. K., Bigi, S., Tartarello, M. C., and Johnson, G.: How Do We See Fractures? Quantifying Subjective Bias in Fracture Data Collection, *Solid Earth*, 10, 487–516, <https://doi.org/10.5194/se-10-487-2019>, 2019.
- Aydin, A.: Fractures, Faults, and Hydrocarbon Entrapment, Migration and Flow, *Marine and Petroleum Geology*, 17, 797–814, [https://doi.org/10.1016/S0264-8172\(00\)00020-9](https://doi.org/10.1016/S0264-8172(00)00020-9), 2000.
- 640 Badoux, H., Bonnard, E. G., and Burri, M.: *Geologischer Atlas der Schweiz. 35 = Bl. 546: St.-Léonard: avec annexe de la feuille Sion / levé géologique par: H. Badoux, E. G. Bonnard, M. Burri*, 1959.
- Bemis, S. P., Micklethwaite, S., Turner, D., James, M. R., Akciz, S., Thiele, S. T., and Bangash, H. A.: Ground-Based and UAV-Based Photogrammetry: A Multi-Scale, High-Resolution Mapping Tool for Structural Geology and Paleoseismology, *Journal of Structural Geology*, 69, 163–178, <https://doi.org/10.1016/j.jsg.2014.10.007>, 2014.
- 645 Berkowitz, B.: Characterizing Flow and Transport in Fractured Geological Media: A Review, *Advances in Water Resources*, 25, 861–884, [https://doi.org/10.1016/S0309-1708\(02\)00042-8](https://doi.org/10.1016/S0309-1708(02)00042-8), 2002.
- Bond, C., Gibbs, A., Shipton, Z., and Jones, S.: What Do You Think This Is? “Conceptual Uncertainty” in Geoscience Interpretation, *GSA Today*, 17, 4, <https://doi.org/10.1130/GSAT01711A.1>, 2007.
- Bonnet, E., Bour, O., Odling, N. E., Davy, P., Main, I., Cowie, P., and Berkowitz, B.: Scaling of Fracture Systems in Geological Media, *Reviews of Geophysics*, 39, 347–383, <https://doi.org/10.1029/1999RG000074>, 2001.
- 650 Candès, E. J. and Donoho, D. L.: Continuous Curvelet Transform: I. Resolution of the Wavefront Set, *Applied and Computational Harmonic Analysis*, 19, 162–197, <https://doi.org/10.1016/j.acha.2005.02.003>, 2005.
- Candès, E. J. and Guo, F.: New Multiscale Transforms, Minimum Total Variation Synthesis: Applications to Edge-Preserving Image Reconstruction, *Signal Processing*, 82, 1519–1543, [https://doi.org/10.1016/S0165-1684\(02\)00300-6](https://doi.org/10.1016/S0165-1684(02)00300-6), 2002.
- 655 Cappa, F., Guglielmi, Y., Nussbaum, C., and Birkholzer, J.: On the Relationship Between Fault Permeability Increases, Induced Stress Perturbation, and the Growth of Aseismic Slip During Fluid Injection, <https://doi.org/10.1029/2018GL080233>, 2018.
- Chudasama, B., Ovaskainen, N., Tamminen, J., Nordbäck, N., Engström, J., and Aaltonen, I.: Automated Mapping of Bedrock-Fracture Traces from UAV-acquired Images Using U-Net Convolutional Neural Networks, *Computers & Geosciences*, 182, 105463, <https://doi.org/10.1016/j.cageo.2023.105463>, 2024.

- 660 Constantine, A.: Sedimentology, Stratigraphy and Palaeoenvironment of the Upper Jurassic-Lower Cretaceous Non-Marine Strzelecki Group, Gippsland Basin, Southeastern Australia, Ph.D. thesis, Monash University, 2001.
- Do, M. and Vetterli, M.: The Contourlet Transform: An Efficient Directional Multiresolution Image Representation, *IEEE Transactions on Image Processing*, 14, 2091–2106, <https://doi.org/10.1109/TIP.2005.859376>, 2005.
- Duda, R. O. and Hart, P. E.: Use of the Hough Transformation to Detect Lines and Curves in Pictures, *Communications of the ACM*, 15, 11–15, <https://doi.org/10.1145/361237.361242>, 1972.
- 665 Fan, J. and Ni, C.: Comparative Studies on the Extraction of Lineaments and Its Variability Based on an Improved Line Segment Tracking Method—Taking the Gaosong Ore Field in the Gejiu Gejiu Tin Ore Deposit as an Example, *Applied Sciences*, 13, 1314, <https://doi.org/10.3390/app13031314>, 2023.
- Fatihi, A. and Thiele, S.: Ayoubft/fractex2D.Pt, Zenodo, <https://doi.org/10.5281/zenodo.17953223>, 2025.
- 670 Fatihi, A., Caldeira, J., Beucler, T., Thiele, S., and Samsu, A.: FraXet, <https://doi.org/10.5281/zenodo.17069947>, 2025a.
- Fatihi, A., Caldeira, J., Beucler, T., Thiele, S., and Samsu, A.: Fracture Mapping Models Trained on FraXet, <https://doi.org/10.5281/zenodo.17866853>, 2025b.
- Gaikwad, V., Singh, K., Salunke, V., and Kudnar, N.: GIS-based Comparative Analysis of Lineament Extraction by Using Different Azimuth Angles: A Case Study of Mula River Basin, Maharashtra, India, *Arabian Journal of Geosciences*, 16, 538, <https://doi.org/10.1007/s12517-023-11636-2>, 2023.
- 675 Guo, Y.: Augmentation Is AUtO-Net: Augmentation-Driven Contrastive Multiview Learning for Medical Image Segmentation, <https://doi.org/10.48550/arXiv.2311.01023>, 2023.
- Han, L., Liu, Z., Ning, Y., and Zhao, Z.: Extraction and Analysis of Geological Lineaments Combining a DEM and Remote Sensing Images from the Northern Baoji Loess Area, *Advances in Space Research*, 62, 2480–2493, <https://doi.org/10.1016/j.asr.2018.07.030>, 2018.
- 680 Härmä, P.: Natural Stone Exploration in the Classic Wiborg Rapakivi Granite Batholith of Southeastern Finland – New Insights from Integration of Lithological, Geophysical and Structural Data, Ph.D. thesis, Department of Geosciences and Geography, University of Helsinki, 2020.
- [Kirillov, A., Mintun, E., Ravi, N., Mao, H., Rolland, C., Gustafson, L., Xiao, T., Whitehead, S., Berg, A. C., Lo, W.-Y., Dollár, P., and Girshick, R.: Segment Anything](https://doi.org/10.48550/arXiv.2304.02643), <https://doi.org/10.48550/arXiv.2304.02643>, 2023.
- 685 Koike, K., Nagano, S., and Ohmi, M.: Lineament Analysis of Satellite Images Using a Segment Tracing Algorithm (STA), *Computers & Geosciences*, 21, 1091–1104, [https://doi.org/10.1016/0098-3004\(95\)00042-7](https://doi.org/10.1016/0098-3004(95)00042-7), 1995.
- Kovesi, P.: Image Features from Phase Congruency, *Videre: Journal of Computer Vision Research*, 1999.
- Kovesi, P.: Phase Congruency: A Low-Level Image Invariant, *Psychological Research*, 64, 136–148, <https://doi.org/10.1007/s004260000024>, 2000.
- 690 Krieger, M. L. H.: Geology of the Prescott and Paulden Quadrangles, Arizona, Tech. Rep. 467, U. S. Govt. Print. Off., ISSN 2330-7102, <https://doi.org/10.3133/pp467>, 1965.
- Kuş, Z. and Aydin, M.: MedSegBench: A Comprehensive Benchmark for Medical Image Segmentation in Diverse Data Modalities, *Scientific Data*, 11, 1283, <https://doi.org/10.1038/s41597-024-04159-2>, 2024.
- LeCun, Y., Bengio, Y., and Hinton, G.: Deep Learning, *Nature*, 521, 436–444, <https://doi.org/10.1038/nature14539>, 2015.
- 695 Mallat, S. and Hwang, W.: Singularity Detection and Processing with Wavelets, *IEEE Transactions on Information Theory*, 38, 617–643, <https://doi.org/10.1109/18.119727>, 1992.

- Masoud, A. and Koike, K.: Applicability of Computer-Aided Comprehensive Tool (LINDA: LINEament Detection and Analysis) and Shaded Digital Elevation Model for Characterizing and Interpreting Morphotectonic Features from Lineaments, *Computers & Geosciences*, 106, 89–100, <https://doi.org/10.1016/j.cageo.2017.06.006>, 2017.
- 700 Masoud, A. A. and Koike, K.: Auto-Detection and Integration of Tectonically Significant Lineaments from SRTM DEM and Remotely-Sensed Geophysical Data, *ISPRS Journal of Photogrammetry and Remote Sensing*, 66, 818–832, <https://doi.org/10.1016/j.isprsjprs.2011.08.003>, 2011.
- Mattéo, L., Manighetti, I., Tarabalka, Y., Gaucel, J.-M., Van Den Ende, M., Mercier, A., Tasar, O., Girard, N., Leclerc, F., Giampetro, T., Dominguez, S., and Malavieille, J.: Dataset of Manuscript "Automatic Fault Mapping in Remote Optical Images and Topographic Data with Deep Learning", *Journal of Geophysical Research - Solid Earth*, 2021, 2020.
- 705 Mattéo, L., Manighetti, I., Tarabalka, Y., Gaucel, J.-M., van den Ende, M., Mercier, A., Tasar, O., Girard, N., Leclerc, F., Giampetro, T., Dominguez, S., and Malavieille, J.: Automatic Fault Mapping in Remote Optical Images and Topographic Data With Deep Learning, *Journal of Geophysical Research: Solid Earth*, 126, e2020JB021 269, <https://doi.org/10.1029/2020JB021269>, 2021.
- Nordbäck, N. and Ovaskainen, N.: UAV-acquired Orthomosaics of Loviisa Shoreline Outcrops, <https://doi.org/10.5281/zenodo.17878870>, 2025.
- 710 Oliveira, M. J., Savastano, V., Matos, G., Schmitt, R., Valente, V., Araujo, M., and Inocencio, L.: The Use of Drones and Deep Learning to Identify Igneous Rocks and Fractures, in: *Offshore Technology Conference Brasil*, <https://doi.org/10.4043/29829-MS>, 2019.
- Ovaskainen, N. and Nordbäck, N.: Manually Mapped Traces from UAV-acquired Images of Loviisa Shoreline Outcrops, <https://doi.org/10.5281/zenodo.7077846>, 2022.
- 715 [Ovaskainen, N., Skyttä, P., Nordbäck, N., and Engström, J.: Detailed Investigation of Multi-Scale Fracture Networks in Glacially Abraded Crystalline Bedrock at Åland Islands, Finland, *Solid Earth*, 14, 603–624, <https://doi.org/10.5194/se-14-603-2023>, 2023.](#)
- [Palamakumbura, R., Krabbendam, M., Whitbread, K., and Arnhardt, C.: Data Acquisition by Digitizing 2-D Fracture Networks and Topographic Lineaments in Geographic Information Systems: Further Development and Applications, *Solid Earth*, 11, 1731–1746, <https://doi.org/10.5194/se-11-1731-2020>, 2020.](#)
- 720 [Peacock, D. C. P. and Sanderson, D. J.: Influences of Map Resolution, Quality and Interpretation on Fault Network Topology, *Earth-Science Reviews*, 277, 105 461, <https://doi.org/10.1016/j.earscirev.2026.105461>, 2026.](#)
- Peacock, D. C. P., Sanderson, D. J., Bastesen, E., Rotevatn, A., and Storstein, T. H.: Causes of Bias and Uncertainty in Fracture Network Analysis, *NORWEGIAN JOURNAL OF GEOLOGY*, 2019.
- Pola, A., Herrera-Díaz, A., Tinoco-Martínez, S. R., Macias, J. L., Soto-Rodríguez, A. N., Soto-Herrera, A. M., Sereno, H., and Ramón Avel-
725 lán, D.: Rock Characterization, UAV Photogrammetry and Use of Algorithms of Machine Learning as Tools in Mapping Discontinuities and Characterizing Rock Masses in Acoculco Caldera Complex, *Bulletin of Engineering Geology and the Environment*, 83, 260, <https://doi.org/10.1007/s10064-024-03743-5>, 2024.
- [Potts, G. J.: Simple Rule to Assist in the Construction of the Outcrop Trace of an Inclined Surface, *Journal of Structural Geology*, 165, 104 749, <https://doi.org/10.1016/j.jsg.2022.104749>, 2022.](#)
- 730 Prabhakaran, R., Bruna, P.-O., Bertotti, G., and Smeulders, D.: An Automated Fracture Trace Detection Technique Using the Complex Shearlet Transform, *Solid Earth*, 10, 2137–2166, <https://doi.org/10.5194/se-10-2137-2019>, 2019.
- Raghavan, V., Wadatsumi, K., and Masumoto, S.: Automatic Extraction of Lineament Information from Satellite Images Using Digital Elevation Data, *Nonrenewable Resources*, 2, 148–155, <https://doi.org/10.1007/BF02272811>, 1993.

- Raghavan, V., Masumoto, S., Koike, K., and Nagano, S.: Automatic Lineament Extraction from Digital Images Using a Segment Tracing and Rotation Transformation Approach, *Computers & Geosciences*, 21, 555–591, [https://doi.org/10.1016/0098-3004\(94\)00097-E](https://doi.org/10.1016/0098-3004(94)00097-E), 1995.
- 735 Rahnama, M. and Gloaguen, R.: TecLines: A MATLAB-Based Toolbox for Tectonic Lineament Analysis from Satellite Images and DEMs, Part 1: Line Segment Detection and Extraction, *Remote Sensing*, 6, 5938–5958, <https://doi.org/10.3390/rs6075938>, 2014.
- Ren and Malik: Learning a Classification Model for Segmentation, in: *Proceedings Ninth IEEE International Conference on Computer Vision*, pp. 10–17 vol.1, IEEE, Nice, France, ISBN 978-0-7695-1950-0, <https://doi.org/10.1109/ICCV.2003.1238308>, 2003.
- 740 Ronneberger, O., Fischer, P., and Brox, T.: U-Net: Convolutional Networks for Biomedical Image Segmentation, in: *Medical Image Computing and Computer-Assisted Intervention – MICCAI 2015*, edited by Navab, N., Hornegger, J., Wells, W. M., and Frangi, A. F., *Lecture Notes in Computer Science*, pp. 234–241, Springer International Publishing, Cham, ISBN 978-3-319-24574-4, https://doi.org/10.1007/978-3-319-24574-4_28, 2015.
- Saint Jean Patrick Coulibaly, H., Talnan Jean Honoré, C., Naga, C., Claude Alain Kouadio, K., Régis Mailly DIDI, S., Diedhiou, A., and 745 Savane, I.: Groundwater Exploration Using Extraction of Lineaments from SRTM DEM and Water Flows in Béré Region, *The Egyptian Journal of Remote Sensing and Space Science*, 24, 391–400, <https://doi.org/10.1016/j.ejrs.2020.07.003>, 2021.
- Samsu, A., Cruden, A., and Vollgger, S.: Scale Matters: The Influence of Structural Inheritance on Fracture Patterns - Supplementary Material, <https://doi.org/10.26180/5CDCAD0A73FE0>, 2019.
- [Sanderson, D. J. and Nixon, C. W.: The Use of Topology in Fracture Network Characterization, *Journal of Structural Geology*, 72, 55–66, 2015.](https://doi.org/10.1016/j.jsg.2015.01.005)
- 750 <https://doi.org/10.1016/j.jsg.2015.01.005>, 2015.
- Scheiber, T., Fredin, O., Viola, G., Jarna, A., Gasser, D., and Łapińska-Viola, R.: Manual Extraction of Bedrock Lineaments from High-Resolution LiDAR Data: Methodological Bias and Human Perception, *GFF*, 137, 362–372, <https://doi.org/10.1080/11035897.2015.1085434>, 2015.
- Sharma, R., Saqib, M., Lin, C. T., and Blumenstein, M.: A Survey on Object Instance Segmentation, *SN Computer Science*, 3, 499, 755 <https://doi.org/10.1007/s42979-022-01407-3>, 2022.
- Smeraglia, L., Mercuri, M., Tavani, S., Pignalosa, A., Kettermann, M., Billi, A., and Carminati, E.: 3D Discrete Fracture Network (DFN) Models of Damage Zone Fluid Corridors within a Reservoir-Scale Normal Fault in Carbonates: Multiscale Approach Using Field Data and UAV Imagery, *Marine and Petroleum Geology*, 126, 104902, <https://doi.org/10.1016/j.marpetgeo.2021.104902>, 2021.
- Soto-Pinto, C., Arellano-Baeza, A., and Sánchez, G.: A New Code for Automatic Detection and Analysis of the Lineament Patterns for 760 Geophysical and Geological Purposes (ADALGEO), *Computers & Geosciences*, 57, 93–103, <https://doi.org/10.1016/j.cageo.2013.03.019>, 2013.
- Steck, A., Epard, J.-L., Escher, A., Gouffon, Y., and Masson, H.: *Carte tectonique des Alpes de Suisse occidentale 1:100 000*, Office féd. Eaux Géologie (Berne), ISBN 978-3-906723-44-0, 2001.
- Sumi, M. R., Das, P., Hossain, A., Dey, S., and Schuckers, S.: A Comprehensive Evaluation of Iris Segmentation on Benchmarking Datasets, 765 *Sensors*, 24, 7079, <https://doi.org/10.3390/s24217079>, 2024.
- swisstopo: *Tectonic Map of Switzerland 1: 500 000*, Federal Office of Topography Swisstopo, Wabern, 2024.
- Thiele, S., Vollgger, S., and Anindita Samsu: *GeoTrace and Compass Rapid Trace-Mapping (Example Data)*, <https://doi.org/10.4225/03/5981B31091AF9>, 2017a.
- Thiele, S. T., Grose, L., Samsu, A., Micklethwaite, S., Vollgger, S. A., and Cruden, A. R.: Rapid, Semi-Automatic Fracture and Contact 770 Mapping for Point Clouds, Images and Geophysical Data, *Solid Earth*, 8, 1241–1253, <https://doi.org/10.5194/se-8-1241-2017>, 2017b.
- Twiss, R. J. and Moores, E. M.: *Structural Geology*, W. H. Freeman, New York, NY, second edition edn., ISBN 978-0-7167-4951-6, 2006.

- Vasuki, Y., Holden, E.-J., Kovesi, P., and Micklethwaite, S.: Semi-Automatic Mapping of Geological Structures Using UAV-based Photogrammetric Data: An Image Analysis Approach, *Computers & Geosciences*, 69, 22–32, <https://doi.org/10.1016/j.cageo.2014.04.012>, 2014.
- 775 Vasuki, Y., Holden, E.-J., Kovesi, P., and Micklethwaite, S.: An Interactive Image Segmentation Method for Lithological Boundary Detection: A Rapid Mapping Tool for Geologists, *Computers & Geosciences*, 100, 27–40, <https://doi.org/10.1016/j.cageo.2016.12.001>, 2017.
- [Villarreal, C. A., Garzón, C. G., Mora, J. P., Rojas, J. D., and Ríos, C. A.: Workflow for Capturing Information and Characterizing Difficult-to-Access Geological Outcrops Using Unmanned Aerial Vehicle-Based Digital Photogrammetric Data, *Journal of Industrial Information Integration*, 26, 100 292, <https://doi.org/10.1016/j.jii.2021.100292>, 2022.](#)
- 780 Wang, Y., Khodadadzadeh, M., and Zurita-Milla, R.: Spatial+: A New Cross-Validation Method to Evaluate Geospatial Machine Learning Models, *International Journal of Applied Earth Observation and Geoinformation*, 121, 103 364, <https://doi.org/10.1016/j.jag.2023.103364>, 2023.
- [Weismüller, C., Prabhakaran, R., Passchier, M., Urai, J. L., Bertotti, G., and Reicherter, K.: Mapping the Fracture Network in the Lilstock Pavement, Bristol Channel, UK: Manual versus Automatic, *Solid Earth*, 11, 1773–1802, <https://doi.org/10.5194/se-11-1773-2020>, 2020.](#)
- 785 Xie, E., Wang, W., Yu, Z., Anandkumar, A., Alvarez, J. M., and Luo, P.: SegFormer: Simple and Efficient Design for Semantic Segmentation with Transformers, <https://doi.org/10.48550/arXiv.2105.15203>, 2021.
- Yaqoob, M., Ishaq, M., Ansari, M. Y., Konagandla, V. R. S., Tamimi, T. A., Tavani, S., Corradetti, A., and Seers, T. D.: GeoCrack: A High-Resolution Dataset For Segmentation of Fracture Edges in Geological Outcrops, *Scientific Data*, 11, 1318, <https://doi.org/10.1038/s41597-024-04107-0>, 2024.
- 790 Zhang, R., Yi, X., Li, H., and Lu, G.: Automatic Extraction of Geological Discontinuities of a Tunnel Surface by Integrating Multiple Features, *Tunnelling and Underground Space Technology*, 154, 106 072, <https://doi.org/10.1016/j.tust.2024.106072>, 2024.