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CHAPTER 5.5 - Methodological Advances in Volcanology: The Role of Artificial Intelligence in Volcano Monitoring, Modelling, and Hazard Assessment – PART 1: Tectonics and plumbing systems

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Abstract

This chapter explores the opportunities and challenges of using Artificial Intelligence (AI) and Machine Learning (ML) in volcanology. It starts by introducing the basic concepts of AI and ML. Then, it discusses the current and potential applications of AI and ML in volcanology, including recent advances in petrology, geophysics, remote sensing, and ground monitoring. We highlight that AI and ML can potentially have a transformative effect in understanding volcanic systems, from deciphering the architecture of magma feeding systems and pre-eruptive processes to eruption forecasting. However, the success of AI in volcanology relies heavily on having access to extensive, cohesive, and high-quality data sources for both training and testing models. Data scarcity, noise, and interpretability remain key challenges. Furthermore, many volcanoes lack comprehensive and multi parametric monitoring networks, limiting AI's full potential. Education also needs to evolve, with universities offering curricula that include AI and ML skills to prepare future researchers for an AI-aware future. Understanding the limitations of and pitfalls associated with these tools, will be important.

SGDs: (a) Good Health and Well-being by providing tools for volcanic hazards and risk assessment; (b) Quality Education by making the volcanological community aware that the development of interdisciplinary courses in Earth Sciences, including programming and data science skills, is now imperative; and (c) Partnerships for the Goals since the effective application of the concepts reported in the present chapter in volcanology requires collaboration across multiple sectors, scientific disciplines, and countries.

Keywords (5-10 words)

artificial intelligence; machine learning; volcanology; petro-volcanological applications; remote sensing; volcano monitoring; plumbing system imaging.

Introduction and State-of-the-art

Volcanology is the study of all processes and dynamics that govern the behaviour of a volcanic system. It is a complex and multifaceted discipline that requires contributions from many scientific fields, including geology, physics, chemistry, mathematics, and computer science. The intersections between volcanological, statistical and computing techniques is not new, and they have already been reported in the past editions of the Encyclopaedias of Volcanoes [1]. Volcanology is a living discipline, evolving constantly. Many researchers are involved in developing new methods and techniques for data acquisition, processing, and modelling to achieve discovery in volcanology with the main objective of protecting civil society.

The application of Artificial Intelligence (AI) and Machine Learning (ML) techniques to volcanology is emerging rapidly, drawing the attention of volcanologists to exciting new opportunities and stimulating perspectives. In principle, AI and ML can support volcanologists in many different ways, including process automation, for direct and inverse modelling, and to drive discovery (Fig. 1)[2]. Automation involves the use of ML to perform complex and repetitive tasks with large datasets, using a sequence of instructions that are challenging to be undertaken by humans. For modelling, ML can efficiently solve problems that involve complex mathematical formulations like systems of differential equations. For example, ML can support numerical simulations by speeding up computationally heavy processes and providing solutions for direct and inverse problems. Finally, data-driven discovery derives new insights, patterns, or knowledge by analysing large data sets, even if researchers cannot provide explicit physical constraints or laws to achieve the solution. Data-driven investigations complement the model-driven approach, where researchers use the observed data to either support or contradict one or more physical laws. A basic example of data-driven investigation is to perform a regression task (e.g., thermo-barometric investigations based on chemical exchanges among melts and crystals) without providing an equation to fit the sample data. Examples of AI and ML applications in volcanology include the capability of identifying patterns in the data from seismographs, GPS stations, satellite imagery, and gas sensors, all of which are associated with volcanic behaviour and, by extension, eruptions.

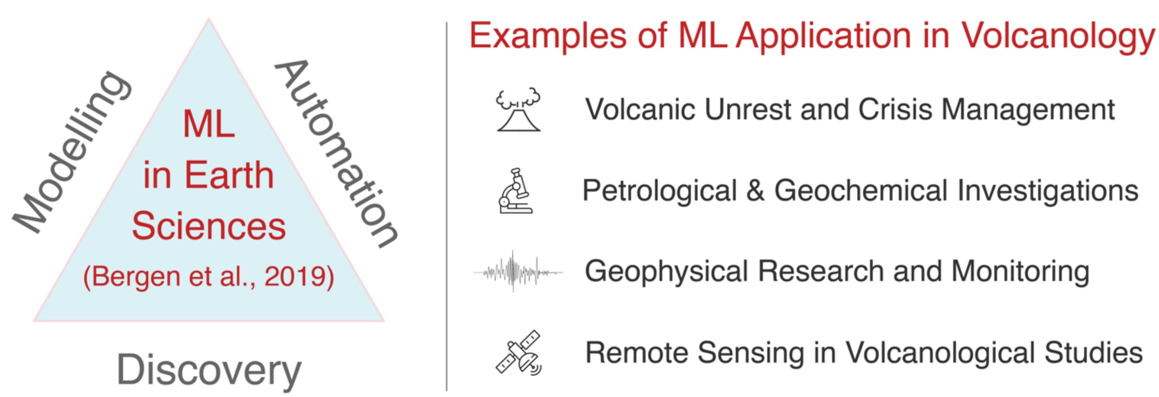

Figure 1: Applications of ML in Earth Sciences. In agreement with ref. [2], the left panel highlights the three main scenarios for the application of ML in Earth Sciences: automation, modelling, and discovery. The left panel reports a list of application cases of ML in Volcanology.

Table 1: A showcase of various ML applications in volcanology using supervised and unsupervised methods. The cited references are listed in the further readings section online, along with additional case studies.

ML Method and Acronym	Type	Brief Description	Example in Volcanology
Logistic Regression (LogR)	Supervised	Used for binary classification by modeling the probability of a class using the logistic function.	Thakur et al. (2020) investigated the evacuation behavior under an imminent threat of volcanic eruption using a LogR-based approach.
Support Vector Machines (SVM)	Supervised	Finds the hyperplane that best separates different classes in the feature space.	Petrelli et al. (2017) utilized a SVM model in a tephrochronological investigation to provide new age constraints for the Pleistocene magmatism of central Italy.
K-Nearest Neighbors (KNN)	Supervised	Classifies data based on the majority class among the k-nearest samples.	Hajian et al. (2019) reported two ML approaches, i.e., DT and K-NNN, to classify volcanic activity at Mount Etna (Italy), in the period 01 January 2011 – 31 December 2015, encompassing lava fountain events and intense Strombolian activity.
Decision Trees (DT) and ensembles of trees, e.g., Random Forests (RF), Extremely Randomized Trees (ERT), Extreme Gradient Boosting (XGBoost)	Supervised	Ensemble of decision trees are typically used for classification and regression.	Benet et al. (2024) investigated the use of XGBoost to classify volcanic ash particles since they can support the understanding of volcanic activities during the early stages of a crisis and possible transitions toward different eruptive styles.
Gaussian Process Classifiers (GPC)	Supervised	Uses a probabilistic approach to predict classes. Effective in high-dimensional spaces and where uncertainty quantification is crucial.	Manley et al. (2020) investigated the timing of eruption end using different machine learning approach to classification of seismic time series. The utilized ML were Gaussian Process Classifiers, Random Forest, Logistic Regression, and Support Vector Machine
Bayesian Belief Network (BBN)	Supervised/Unsupervised	Graphical model representing variables and their conditional dependencies via a directed acyclic graph for probabilistic inference.	Aspinall et al. (2003) advocated the use of Graphical Bayesian Belief Networks (BBNs) for making informed decisions during volcanic crises. The text highlights a retrospective analysis of the 1993 Galeras volcano eruption.
Principal Component Analysis (PCA)	Unsupervised	Reduces dimensionality by transforming features into fewer non-correlated variables.	Unglert et al. (2016) evaluated the performance of Self Organizing Maps and PCA on synthetic volcano seismic spectral data constructed from observations of two eruptions at Klauea Volcano (Hawai'i, USA).
K-Means Clustering (K-Means)	Unsupervised	Partitions n observations into k clusters in which each observation belongs to the cluster with the nearest mean.	Watson (2020) applied K-means clustering to identify changes in eruptive behavior at Mount Etna (Italy).
Hierarchical Clustering (HC)	Unsupervised	Builds a tree of clusters and can be visualized as a dendrogram.	Musu et al. (2023) investigated the use of HC to unravel the magmatic evolution at Mt. Etna Volcano during the February–April 2021 sequence of lava fountains from a mineral chemistry perspective
Manifold Learning (ManL)	Unsupervised	Seeks a lower-dimensional representation of the data that preserves certain relationships in the high-dimensional space.	Bernal-Oñate et al. (2024) reported a novel approach employing audio features and psychoacoustic scales to represent micro-earthquakes at Cotopaxi and Llaima Volcanoes using ManL. They also developed a multi-class classification system for events generated by these volcanoes, incorporating feature selection techniques based on audio-inspired features. The aim is to enhance the detection of volcanic phenomena triggering eruptions and improves interpretability.

Table 1 reports a few applications of different ML techniques in volcanology, covering a broad spectrum of challenges that volcanologists face. These applications, to cite a few, include: exploring evacuation behaviour in response to an impending volcanic eruption; the use of ML to support tephrochronological studies; unravelling and classifying volcanic activities; estimating eruption timing; supporting volcano monitoring (Tab. 1 and Fig. 1; please refer to further readings for a complete list of references). The progressive incorporation of AI and ML techniques in volcanological investigations is an engaging and attractive prospect. However, it also comes with new challenges. They include producing more robust predictions and making the volcanological community aware of the possibilities, strengths, and limitations of ML. Finally, the growing use of AI and ML techniques in volcanology comes with some potential drawbacks, such as the introduction of processing and modelling tools that can be opaque to human understanding. Proper application of these tools also requires a baseline level of understanding that is outside of the traditional training experiences of volcanologists.

The present chapter aims to: (a) provide the basic concepts and introduce the jargon of AI and ML to volcanologists; (b) highlight the potential of AI-related techniques and ML in volcanology; and (c) emphasize the challenges and limitations of ML and AI. The chapter is divided into two main parts: the first it is generically devoted to introducing AI and ML to the volcanological community; the latter reporting relevant study cases in the fields of igneous petrology, remote sensing, and volcano monitoring. Specifically, we start by providing the fundamentals definitions of AI and ML, including the concepts of ML tasks, training approaches, ML algorithms, workflows, generalization capability and FAIR data principles. Then, we report on key current volcanological applications of AI and ML in igneous petrology, remote sensing, seismology, ground monitoring, and forecasting.

The fundamentals of Artificial Intelligence & Machine Learning

Artificial intelligence (AI) is a scientific field that encompasses a broad range of studies and research areas focused on creating systems and algorithms able to perform tasks that usually require human intelligence [3]. Typically, AI algorithms are iteratively improved (or trained) to produce models with abilities similar to some form of intelligence on defined tasks. In sciences, AI is mostly used for robotics, smart devices, object recognition and segmentation, chatbots, and, of course, scientific automation, modelling, and discovery [4](Fig. 1).

Current AI approaches are mainly based on Machine Learning (ML): a subset of AI producing data-dependent models. ML models are designed to fulfil specific tasks [5] including classification, regression, clustering, and dimensionality reduction. Classification assigns a new observation to a specific category, given a set of possible categories. These categories are taught to the ML model by providing several known examples (labelled observations in the ML jargon). However, a typical ML model won't be able to define new categories by itself. For example, we can develop an ML classification model to correlate distal tephra samples to a labelled volcanic source or, possibly, to a specific labelled eruption (Tab. 1). Regression aims to predict continuous quantities. For example, we can develop ML models to estimate clinopyroxene crystallization temperature and pressure without providing an explicit equation describing the changes in entropy and volume occurring in equilibrium reactions between melts and crystals, as in the case of traditional thermo-barometric investigations [6].

ML regression is a powerful and flexible tool; however, current models mostly rely on previously observed data, lacking extrapolation capabilities. For example, an ML barometer that has been trained with observations in the range of 0-12 kbar won't ever predict a pressure of 13 kbar. Clustering consists of separating a set of observations into various groups (named clusters) depending on their similarities. Clustering techniques may allow the discovery of hidden patterns within data, boosting discoveries. Finally, dimensionality reduction, or data representation, aims to reduce the number of variables used to represent a dataset.

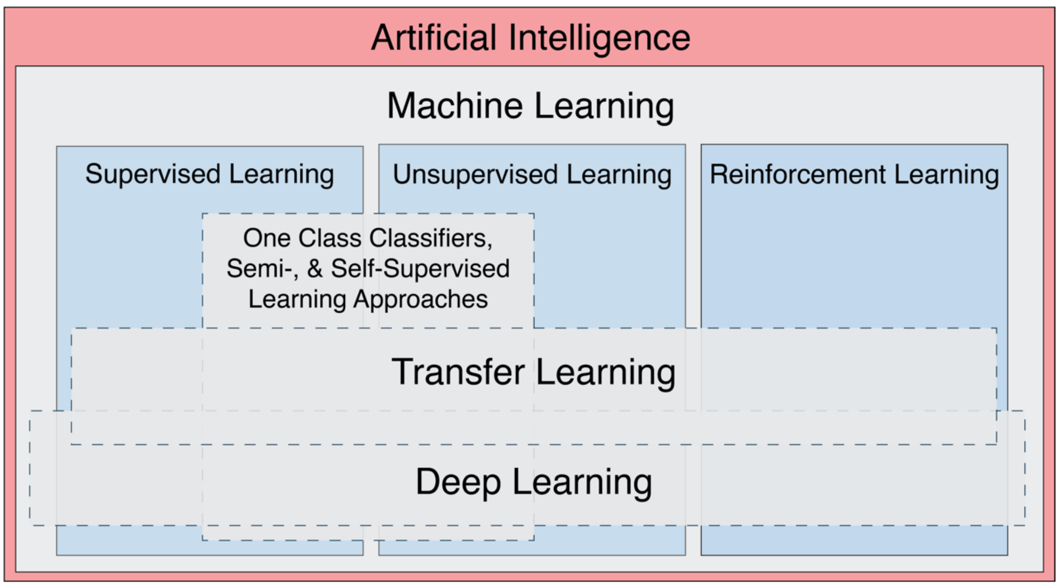

Figure 2: Venn Diagram highlighting the relationships among Artificial Intelligence (AI), Machine learning (ML), and the different learning approaches used to train ML algorithms. Training paradigms in ML include supervised, unsupervised, and reinforcement learning. Supervised learning uses labelled observations (i.e., known solutions) to train the model by example, unsupervised learning seeks to discover patterns in unlabelled data, and reinforcement learning trains agents through feedback from their actions. Newer approaches like one-class classifiers, semi-supervised, self-supervised, and transfer learning blur these lines. One-class classifiers focus on specific classes, semi-supervised learning uses both labelled and unlabelled data, self-supervised learning extracts features without labels, and transfer learning leverages knowledge from pre-trained models (see text for further details).

The reduction process learns the relevant variables needed to summarize the properties of the data that are useful for the task of interest. Such variables are often referred to as features or embeddings in the ML jargon. The main objective is to maintain meaningful information from the data while either allowing their visualization in a lower dimensional space, or developing models that only incorporate significant features. The concept of learning or training describes a general process through which a model gains knowledge from the data and enhances its ability to perform specific tasks. Training allows ML models to adjust and refine their internal parameters where knowledge is typically stored, depending on the input data (referred to as the training data). The model evolves throughout the training stage, learning how to identify patterns, relationships, and trends within the training data. After training, the final model is set and can be put to use.

Practically speaking, the training is based on an algorithm, named a training algorithm, that attempts to find the optimal model parameters to dynamically converge toward an optimized solution: the model. Different types of learning algorithms, or learning paradigms, are currently used and they can be categorized depending on their constraints and objectives. Figure 2 shows some learning paradigms in use during the writing of the present chapter. They provide a foundation from which to start understanding AI in volcanology. However, new learning methods will likely emerge in the future. Among the historical and still widely used training paradigms, we highlight supervised, unsupervised, and reinforcement learning. Supervised learning emulates the idea that a tutor trains the machine to fulfil a specific task by providing the correct solutions. These solutions are called labels in ML terminology. Typically, supervised learning allows the development of classification and regression models. In contrast, unsupervised learning aims to solve tasks without explicit external instructions, focusing on discovering intrinsic data structures. Finally, Reinforcement Learning (RL) is a significantly different training paradigm, where no dataset is initially needed to train the model. RL uses agents—entities (like a robot or software program)—that make decisions by interacting with their environment. The agent learns from the feedback it receives after each action, aiming to achieve a specific goal. Typical examples of RL models involve game development, where agents try to maximize the score by making the best decisions. While supervised, unsupervised, and RL learning are well-defined, the definitions of newer methods are more blurred than in the past, often with strongly overlapping boundaries (Fig. 2). Among them, we recognize the following: One-class classifiers, self-supervised, semi-supervised, transfer, and deep learning. One-class classifiers focuses the training on a specific class. They are often applied to binary classification problems, i.e., the model can distinguish the known class from unknown events. Typically, such models are applied in anomaly and novelty detection. Semi-supervised learning utilizes both labelled and unlabelled data for training a model. The use of such models is like supervised ones, but the constraint for the training is lowered, i.e., not all the data need a label. Self-supervised learning aims at training a representation model (i.e., a conceptual framework or mathematical structure used to describe, interpret, or simulate a system, phenomenon, or process) to extract relevant and complex features or embedding (i.e., the process of mapping data from a high-dimensional space into a lower-dimensional space while preserving important relationships or properties of the original data). In detail, during the training, the model uses a form of supervision that comes intrinsically through the data, without using pre-defined labels. The main interest in this learning paradigm is to use the capabilities of some ML algorithms for feature extraction, even when the data have not been labelled manually. Autoencoders are a well-known structure of self-supervised learning. In the case of transfer learning, researchers leverage a model that was previously trained on a large dataset and possibly for a distinct purpose to extract features or embeddings on a different data set and use case. Both transfer and self-supervised learning are particularly effective when data is scarce, a common condition in Earth Sciences. Finally, deep learning approaches rely on neural networks, which we will discuss in more detail in the "Deep Learning" section.

An interesting angle to keep in mind when facing an AI or ML model is the data-driven versus physics-informed paradigm (Fig. 3) [7]. Though both approaches are not completely unrelated, most traditional ML models are purely data-driven, and therefore, do not use any pre-defined physical constraint during the modelling. Data-driven approaches have been demonstrated their power over big data, defined as extremely large and complex datasets that are difficult to process, analyse, and manage using traditional data processing tools. These datasets are typically characterized by the "3 Vs": Volume (large amounts of data), Variety (different types of data, such as structured, semi-structured, and unstructured), and Velocity (high speed at which data is generated and must be processed). However, purely data-driven models are much less explainable than physics-informed ones. This leads to a common limitation of many ML models which is a lack of explainability. In other words, they behave as ‘black boxes.’ However, current research in ML is attempting to moderate this limitation with an increasing interest toward interpretable and explainable AI. This goal can be achieved by developing methods to understand how 'black box' models achieve a solution and embedding a physical guidance to the modelling (i.e., introducing observational, inductive or learning biases; Fig. 3). A current recommendation to be kept in mind would be a parsimonious and mindful use of purely data-driven approaches and use them only in situations when physics-informed models reach limited performance.

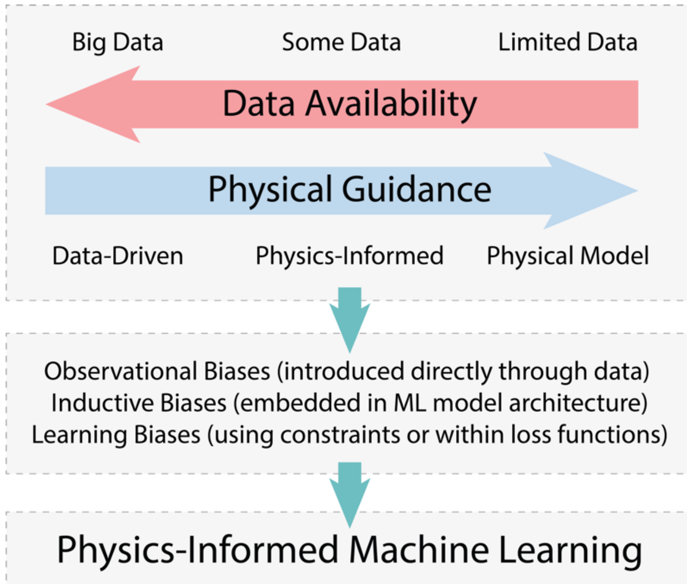

Figure 3: Data and physics scenarios in ML (modified from ref. [7]). The figure depicts three scenarios for the modelling of physical processes. The limited data (i.e., a few focused observations are available) domain assumes a complete knowledge of the physics behind the investigated problem. On the contrary, in the big data (i.e., a large amount of complex and heterogeneous data) regime, physical laws may be entirely unknown, and data-driven methods become particularly useful. A common scenario in volcanological applications is the intermediate one, where some physical knowledge and some data are available. However, there may be missing parameters or even unknown forms of entire terms in the system of equations describing the physical process under investigation. Indeed, physics-informed machine learning aims at merging data with governing physical laws, even in models where some physics is missing.

Machine Learning Workflows and Algorithms

Figure 4 illustrates a characteristic workflow to perform machine learning investigations [8]. Typically, the process begins with data collection. In volcanology, this step might include gathering field observations, remote sensing acquisitions, and the collection of geophysical, geochemical, or petrological data. Data preprocessing is typically the second step of the workflow. This stage prepares the data for the subsequent steps, and involves data inspection, cleaning, scaling, engineering, selection, and maybe augmentation to improve the training process. The heart of each ML workflow is the training process, aimed at developing a model to perform a specific task. The training phase is closely tied to the validation phase, which includes fine-tuning the model's hyperparameters (i.e., parameters that govern the configuration of the model and are not involved during the training phase). Hyperparameters are pre-defined to control the behaviour of the training algorithm. Validation helps in selecting the most effective model based on performance metrics such as accuracy, loss, or other relevant evaluation criteria. These stages may be iterated to refine the model's accuracy. The subsequent step consists of model assessment using the test data set, used as a proxy for new and unseen data.

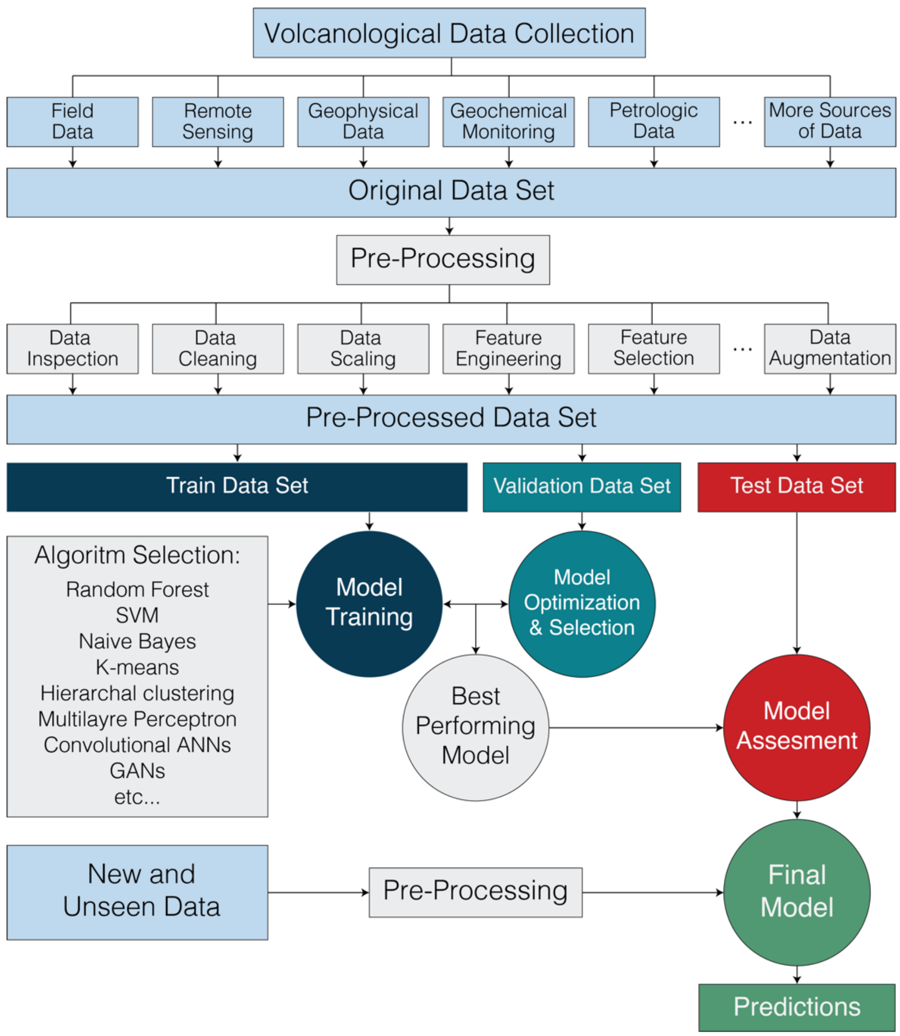

Figure 4: A workflow for the application of ML in Volcanology. It consists of 1) acquiring volcanological data; 2) preprocessing raw data; 3) performing the training and validation of one or more ML algorithms; 4) model assessment using a test data set; and 5) deploying the final model and making predictions on new data.

The performance of the model applied to test data defines the accuracy and precision of the model. After the performance assessment, the model is ready to process new real-world data, with user awareness of its performance and limitations. Machine Learning algorithms span a wide range of logic and implementations. Most ML methods require manual feature selection before the training, typically through statistical analysis or predefined filters. The selected features are subsequently employed to tackle specific tasks using, for example, ML algorithms such as support vector machines and decision-tree-based methods (Fig. 5). Support Vector Machines (SVMs; Fig. 5a) are a group of supervised machine learning algorithms that excel in classification tasks. The core concept behind SVMs is that input observations are transformed into a higher-dimensional feature space through a nonlinear mapping process. Within this transformed space, a linear decision boundary is then established (Fig. 5a). In volcanology, SVMs have been successfully used in tephra correlations to infer the timing of eruptions (Tab.1), as well as to classify satellite images [9] and seismic signals [10].

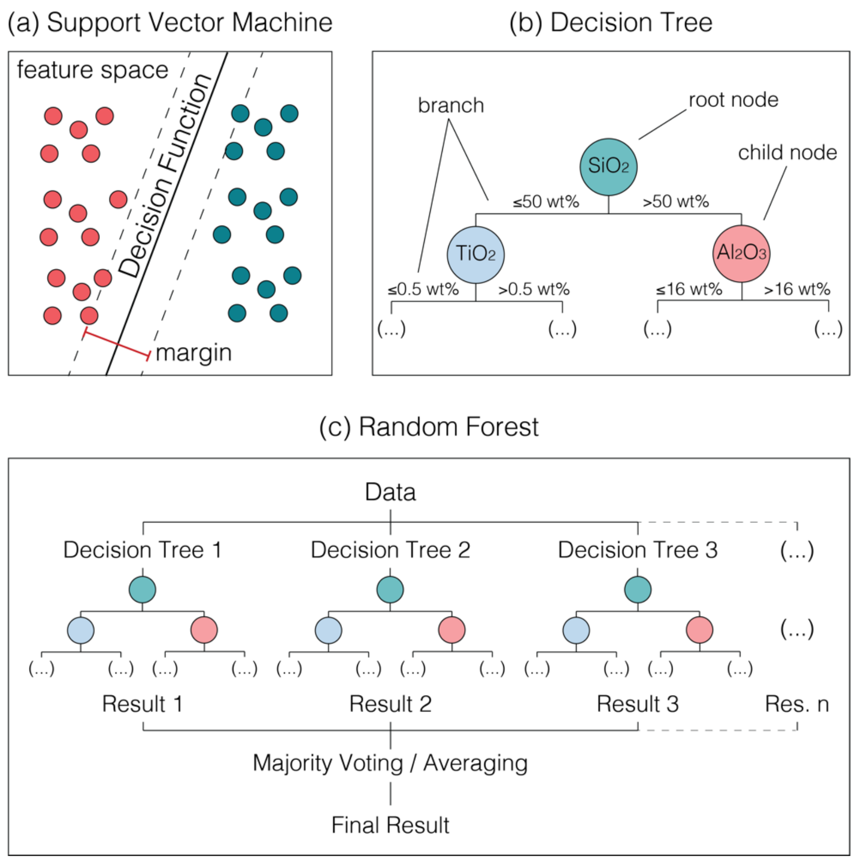

Figure 5: Typical ML algorithms: a) Support Vector Machines; b) Decision Trees; c) Random Forests. Modified from [8]. For a gentle introduction to ML for Earth scientists please refer to [8].

The decision tree algorithm (Fig 5b) and its extensions such as Random Forests (RF; Fig 5c), Extremely Randomized Trees (ERT), and Extreme Gradient Boosting (XGBoost) segment the input space into distinct sub-regions to fulfil both regression and classification tasks. Specifically, each node of a tree corresponds to a specific region of the input space and subdivides it into smaller sub-regions based on established splitting criteria. Consequently, the process of a decision tree involves a systematic division of the input space through a series of decisions or splits, resulting in a set of non-overlapping regions, each uniquely associated with a leaf node of the tree. In volcanology, decision-tree-based methods have similar uses to SVM and have been successfully applied to the development of geo-thermo-barometers and to classify volcanic ash particles to support the understanding of volcanic activities. Please refer to further readings for a full list of references.

Deep Learning

The introduction of deep learning algorithms [11], based on artificial neural networks (ANNs; Fig. 6), marked a paradigm shift in the development of ML and their applications to real-world scenarios. Unlike classical ML methods that mostly require manual feature extraction, deep learning algorithms attempt to learn relevant features directly from data. This approach is called feature or representation learning [12]. ANNs are ML algorithms that are inspired by the structure and function of biological neural networks in the human brain (Fig. 6a-b). Within ANNs, the input data is fed into the network, and computations are performed layer by layer through a process called forward propagation. In the attempt to mimic biological neurons (Fig. 6a), each artificial neuron (Fig. 6b) in the network receives input signals from the previous layer, multiplies them by their corresponding weights, adds a bias term, and applies an activation function to produce an output. This process continues until the output layer is reached, generating the network's predictions. During the training process, once the predictions are generated, a loss function is used to quantify the difference (i.e., loss or risk in the ML jargon) between the predicted outputs and the actual outputs (ground truth). The goal of training an ANN is to minimize this loss, which indicates how close the network's predictions are to the actual targets. After calculating the loss, the network adjusts its parameters, which is achieved through a process called backpropagation. Backpropagation helps a neural network to learn by adjusting its weights. It calculates how much each weight contributes to the error (i.e., the loss). This is done step by step, starting from the output and moving backward through each layer. The weights are then changed to reduce the error. This process repeats until the error gets reasonably small. The overall process of adjusting the weights is called optimization.

The multi-layer perceptron (MLP; Fig. 6c) serves as a fundamental form of ANN, comprising multiple hidden layers of neuron assemblies, thus earning the designation 'deep learning'. Typically, these neural layers exhibit full connectivity to adjacent layers. However, this approach carries the drawback of potentially having a vast number of parameters, which could make the models susceptible to learning meaningless information or even noise, introducing biases. When the data have multiple dimensions, like images, convolutional neural networks (CNNs; Fig 6d) are often employed. CNNs are inspired by the human visual system, where the visual cortex contains neurons arranged in layers, with each layer responsible for detecting specific features such as edges, textures, shapes, and more complex patterns. Similarly, in CNNs, convolutional layers apply specific operations (named convolutions) to input data, aiming at extracting from them specific features (e.g., edges, textures, shapes, in the case of images, or more complex patterns). Moreover, CNNs are organized in layers, with each layer detecting more complex features than the one before, similar to how our brain processes visual information. This structure allows CNNs to learn complex patterns by building up from simpler ones found in earlier layers.

Generative adversarial networks (GANs; Fig 6e) are a type of Generative AI. Generative AI refers to a class of artificial intelligence models and algorithms designed to create new content, data, or solutions that resemble existing patterns in a given dataset.

Unlike traditional AI, which focuses on recognizing patterns or making predictions based on existing data, generative AI attempts generating novel outputs—whether it's text, images, music, code, or even 3D models—based on the learned patterns from the training data. GANs consist of two neural networks, called the generator and discriminator. For example, if the inputs are images, such as satellite images, we could use CNNs for both the generator and the discriminator. The generator and discriminator are trained in a competitive manner, where the generator produces synthetic data that appears real, and the discriminator attempts to determine whether it is real or fake. In this way, the generator continuously improves its ability to create synthetic data that closely resembles reality. When working with the sequential data, e.g., time series, we could use specialized types of ANN named Recurrent Neural Networks (RNNs; Fig 6f).

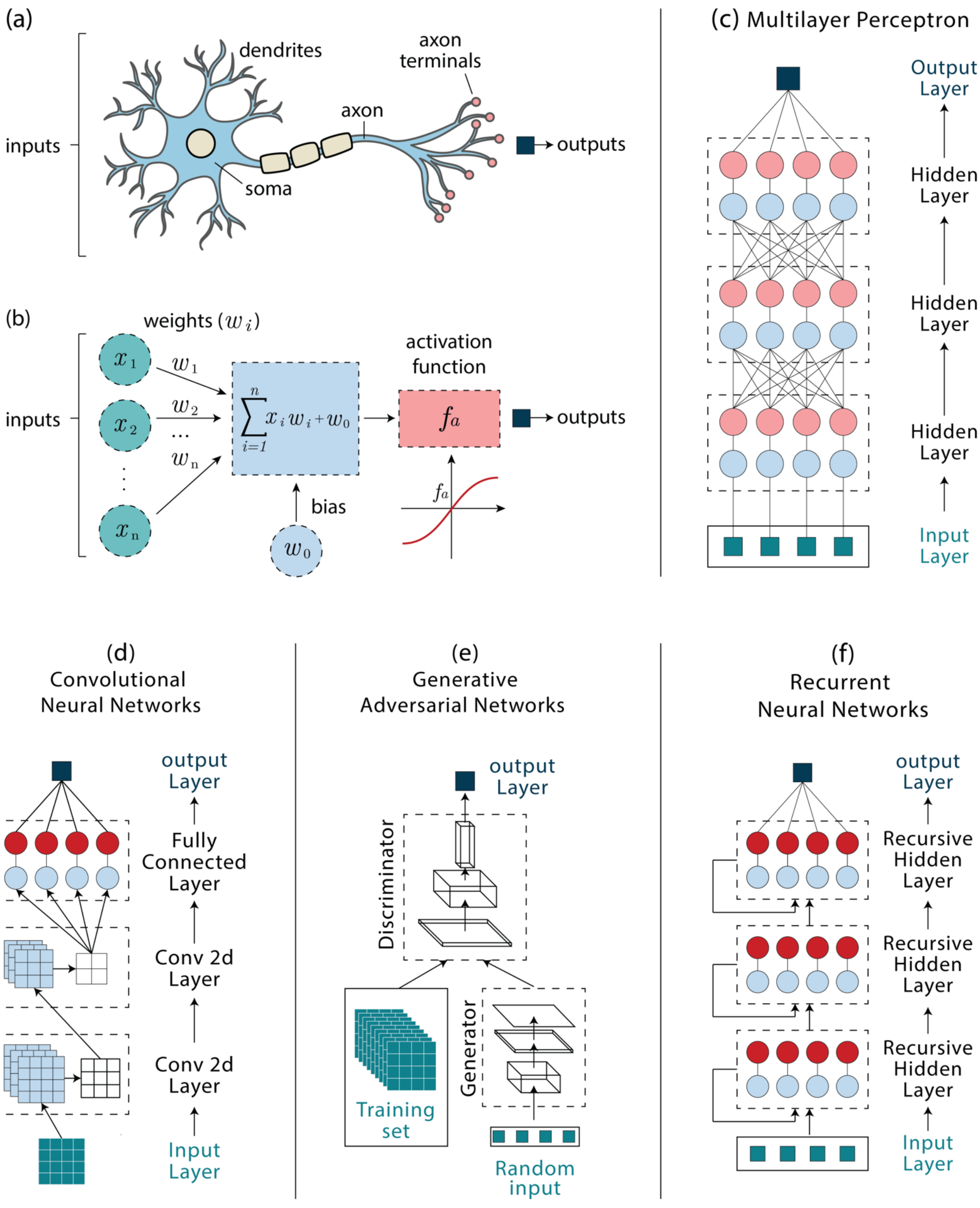

Figure 6: Deep Learning Principles and Algorithms (from ref. [11, 12]): (a) Biological neuron, (b) Artificial neuron, (c) Multilayer Perceptron (MLP), (d) Convolutional Neural Network (CNN), (e) Generative Adversarial Network (GAN), (f) Recurrent Neural Network (RNN). A neural network (NN) is a computational algorithm structured to simulate the architecture and functioning principles of the human brain. The fundamental unit of a NN is the artificial neuron (b), which draws inspiration from the operational characteristics of biological neurons (a). Adapted from ref. [17].

Unlike standard ANN, RNNs have a 'memory' that allows them to remember information from previous steps, making them well-suited for tasks where the order of data matters, like predicting the next value in a time series.

At the time of writing this chapter, the most modern ML methods have adapted the architectures originally developed for large language models (LLM), called Transformers, to capture long-range dependencies in data sequences. The key innovation of transformers is the attention mechanism, which allows the model to weight the importance of features, capturing more contextual information. In volcanology, transformer architectures have been used, for example, to characterize fringes in InSAR (Interferometric Synthetic Aperture Radar) images that are produced during volcanic deformation [13].

Generalization Ability of a Machine Learning Model and FAIR principles

The capability of an ML model to perform successfully with new and unseen data is referred to as the generalization ability [14]. In other words, the generalization capability of an ML model refers to its ability to perform effectively in real-world scenarios, i.e., outside the dataset used during training. To better define the concept of the generalization capability of an ML model, it is useful to discuss risk and risk minimization. As reported in a previous section, in ML the risk (or loss) quantifies the expected errors of a model across a range of observations. Specifically, the true risk is a theoretical error, calculated across the entire population being studied, which ideally includes every possible observation. Therefore, the true risk measures how well a model is expected to perform on all the potential data it might encounter. A model that minimizes true risk effectively is thus considered to have excellent generalization capabilities.

However, accessing true risk is often impractical because we typically deal with a limited sample ('empirical distribution' in the ML jargon) of the whole data domain. This limitation forces us to rely on the so-called empirical risk, calculated using the training data set only. Most supervised ML models are trained by minimizing the empirical risk (i.e., Empirical Risk Minimization, ERM; Fig. 7)[15]. The underlying assumption behind the ERM is that reducing the empirical risk will also decrease the true risk, supposing that a model performing well on the training data should also perform well on new, unseen data. This assumption comes with specific requirements for training data sets and challenges encountered during the minimization process.

The requirements of the training data include diversity, coverage, representativeness and volume, ensuring that it spans a broad spectrum of cases from the problem space. The achievement of diversity coverage, representativeness, and volume means including data from different scenarios, allowing the model to explore all the situations it expects to handle in the real world. For example, many learning algorithms in volcanology are based on supervised learning to solve classification tasks. Despite the large amount of data generated during volcanic monitoring, there are significantly fewer instances of volcanic activity (i.e., unrest or eruptions). This imbalance in the data could lead to bias in the ML algorithm toward the majority category (i.e., baseline activity). In these cases, data augmentation or data synthesis strategies may be employed to improve the number of training samples. Data augmentation involves modifying existing data samples to create new, artificial observations through various transformations. In image analysis, data augmentation may involve rotations, scaling, translations, flipping, adding noise, and changing brightness or contrast. Data synthesis, on the other hand, involves creating entirely new data sets, often using so-called generative models. Please note that, after data augmentation or data synthesis, ML models might still face problems with generalization. Dealing with the assumption that minimizing Empirical Risk will also deliver low True Risk also comes with challenges (Fig 7). These challenges include avoiding under and over-fitting issues [14, 15]. Under-fitting arises when an ML model is too simplistic, and not able to capture the complexity of the investigated phenomena. This often occurs when the model does not have enough capacity (i.e., it incorporates too few parameters or features) to learn from the data. Over-fitting, on the other hand, happens when an ML model learns the training data set too well, focusing on its noise and outliers and starting to learn patterns that are specific to the training data; the trained model will then fail when attempting to model new and unseen data. To prevent under- and over-fitting, researchers should ensure that the model's complexity aligns with the size, heterogeneity, and variability of the analysed dataset.

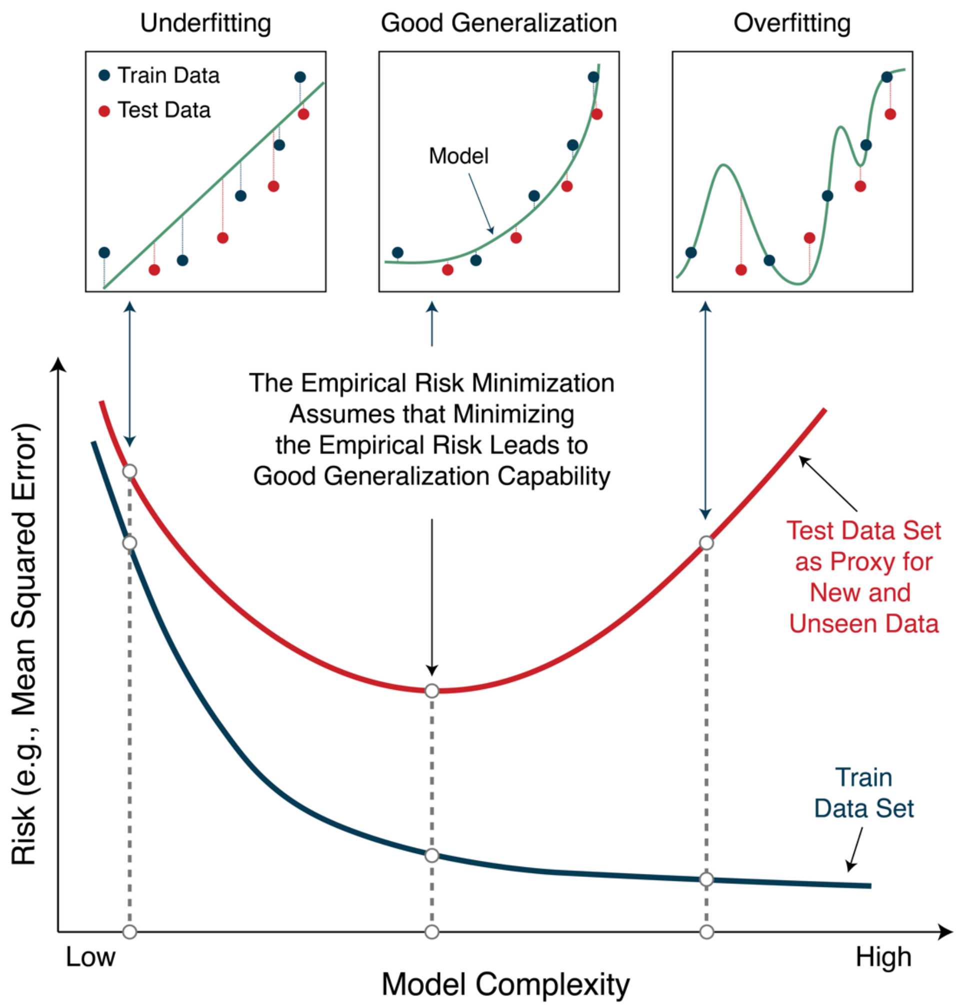

Figure 7: Generalization Ability of a ML model as a function of model complexity (modified from ref. [15]). Overly simplistic models will lead to an inability to minimize the risk for both the train and test data sets, leading to underfitting. On the contrary, extremely complex models will be prone to overfitting. In this case, the model will start learning the noise in the train data set where the risk minimization will achieve exceptionally low values, but the model will fail with new and unseen data.

Implementing FAIR (Findable, Accessible, Interoperable, and Reusable) and Open Science principles to volcanological data could significantly support researchers to access, reproduce, and test existing models, also allowing a better assessment of model generalization capabilities. Moreover, implementing Open Science and adhering to FAIR principles [16] is crucial to develop rigorous volcanological investigations relying on analytical, statistical, and numerical methods, including AI and ML. Open science fosters transparency, collaboration, and the free exchange of research outcomes, which are critical for progressing knowledge in volcanology. Moreover, following FAIR principles will allow volcanological data to be readily discoverable and accessible to other scientists [16].

Machine Learning Advances in Petro-Volcanological Applications

Figure 8 reports the state-of-the-art of ML in petrology as reported by [17]. All the tasks reported in Figure 8 also find application in volcanology. Established ML applications reported in Figure 8 mainly concern data-driven studies in the fields of clustering, dimensionality reduction, classification, and regression. Among them, the clustering and dimensionality reduction could support volcanologists in unveiling hindered chemical patterns within the crystal and melt record of volcanic products. For example, some authors (ref. [17] and references therein) reported intriguing examples of unsupervised ML investigations on the crystal cargo belonging to different volcanic systems (e.g., Villarrica's recent activity and Mt Etna).

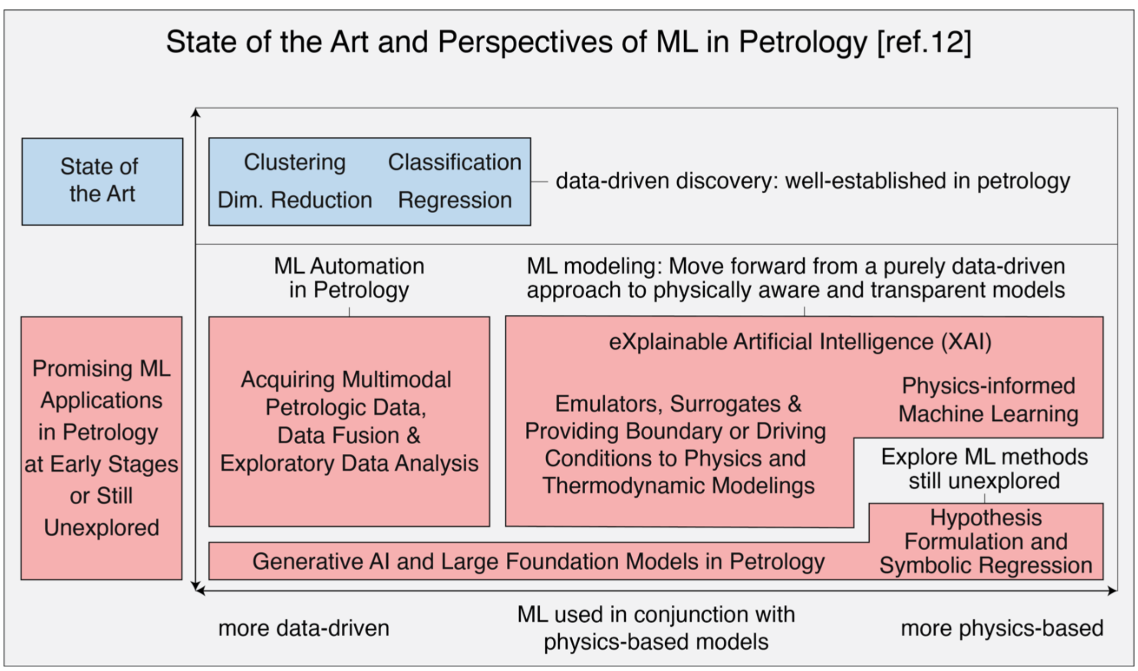

Figure 8: A scenario depicting the application of ML in petrology as reported by ref. [17]. The figure illustrates the dichotomy between data-driven and physics-based modelling in igneous petrology, as shown in Fig. 3. Current ML applications (state of the art) in igneous petrology are mainly data-driven (upper-left, in light blue). The lower portion highlights promising ML applications in igneous petrology that are either in early stages or still unexplored. Applications on the left are primarily data-driven, while those moving towards the right increasingly incorporate physical foundations.

Petrological and geochemical classification tasks have been widely applied in tephra correlation studies. For example, ML-based methods have been used as classifiers to successfully correlate distal tephra samples to their proximal counterparts. In the field of ML automation, some authors investigated the use of deep convolutional neural networks for the automated segmentation of olivine phenocrysts in volcanic rocks. ML Regression in volcanology has been used to calibrate liquid-only, single-crystal, and liquid-crystal thermometers and barometers. The lower portion of Figure 8 highlights several additional fields of investigation. They include the development of automated workflows for the acquisition and fusion of petrological data from multiple and heterogeneous (i.e., multimodal) sources (including chemical analyses, modelling, literature data, etc.). Overall, the coupling of fundamental laws of physics (Fig 6) with ML to move beyond the purely data-driven approach is one of the main challenges for the future applications of AI-based methods in petro-volcanological applications. This may also include the development of surrogate models (i.e., models that learn how to solve time expensive and computationally intensive tasks) to speed up numerical simulations and modelling. Exploring foundation models, formulating scientific hypotheses by ML, and applying symbolic regression certainly merit attention, as they could lead to exciting and challenging results.

Machine Learning Remote Sensing Advances in Volcanology

A major challenge in volcanology, particularly for eruption forecasting, is that few volcanoes have good ground-based monitoring networks, and most have no permanent ground-based instrumentation. For example, in the United States, less than half of potentially active volcanoes have a seismometer, and only a few percent have continuous gas measurements. Our current understanding of the life cycles of volcanic systems is biased by an emphasis on a small number of recent, well-studied eruptions, which do not fully represent the range of volcanic plumbing systems and so may not scale to the largest eruptions. Satellites offer the unique potential to globally monitor all of the ~1,400 subaerial Holocene volcanoes using a common set of sensors that span the electromagnetic spectrum—ultraviolet, optical, infrared, and microwave. Between them, the rapidly growing international constellation of satellites are able to image: 1) surface deformation and topographic change; 2) the emissions of SO_2 and ash into the atmosphere; and 3) thermal emissions from lava flows and fumaroles. The growing archive of satellite imagery has the potential to help us understand the architecture of magmatic systems as well as the links between unrest and eruption, while real-time data acquisitions have enormous potential for forecasting activity. However, AI-based approaches are needed to tackle the new challenges of visualisation, interpretation, and timely dissemination that the enormous datasets represent. AI approaches to satellite datasets can be divided into those designed for detecting unrest signals, those used for classifying the signals, and those used for forecasting future activity.

The vast majority of satellite images do not contain any signal related to volcanic activity, and the challenge of detection is to flag those that need further analysis. Examples include searching for deformation signals in InSAR images or thermal anomalies in infrared data. Supervised-learning methods are designed for detecting signals whose characteristics are well-known and for which labelled datasets are available. For example, simple models of deformation processes and atmospheric artefacts can be used to adapt pre-trained Convolutional Neural Network (CNN) to identify deformation signals in InSAR images via transfer learning (Fig.9) [9]. This approach has the advantage that, while training the network is computationally expensive, the trained model can rapidly appraise large datasets and flag images that need expert analysis (typically <1%). Unsupervised methods have the advantage that they can require no prior knowledge of the signal characteristics, instead learning the characteristics of 'normal' behaviour during a training period. For example, time series of interferograms can be separated into component parts using Independent Component Analysis (ICA). This can be used to detect changes in a component that was present during the training phase, or the addition of new components that were not present during training. Deep learning techniques, including CNNs, GANs, and Variational Autoencoder (VAEs), can also be used for image anomaly detection by using un-labelled training data to learn to generate normal samples and identify anomalies by comparing the generated image with the original one.

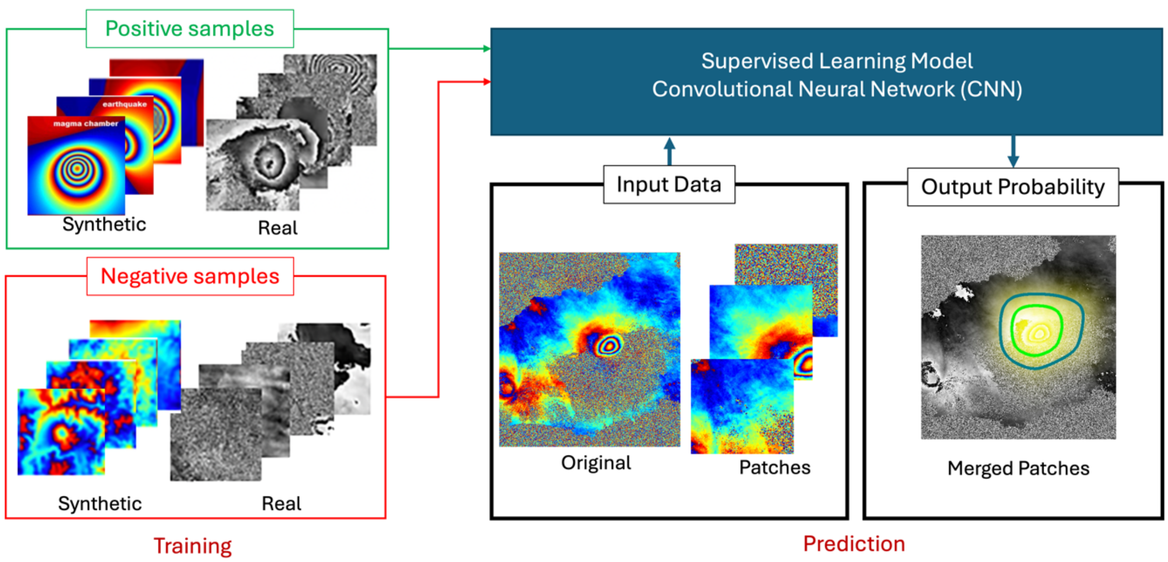

Figure 9: Application of Supervised Machine Learning via a Convolution Neural Network to the detection of volcanic deformation in routinely generated satellite images. Modified from ref. [9]. The model is trained using both positive and negative samples, with real examples taken from previous satellite missions and synthetic examples generated using models of source processes and atmospheric artefacts. The input data is divided into overlapping patches and the model assigns each patch a classification probability. The probabilities of each patch containing deformation are then merged into a map.

Accurate and rapid mapping of lava flows and ash plumes is critical both for managing crises and calibrating models for hazard mapping. Satellite data is better suited to lava flow mapping than ground- or aerial methods which suffer when access is limited, and the availability of multiple bands and types of satellite data lends itself to AI approaches. Unsupervised clustering methods (such as k-means or SVM) can be used to separate pixels into classes, but are easily confused by environmental factors such as snow, cloud, or vegetation cover, or when distinguishing a recently cooled lava flow from older lava flow fields [18]. Supervised methods such as ANNs or expert system classifiers have been shown to be well-suited for complex data classification and can learn the non-linear relationship between the input and target variables based on a labelled training dataset. Both these approaches have the potential not only to map the extent of volcanic products, but to distinguish between different lava flow morphologies, and between the SO_2 and ash components of volcanic plumes.

AI approaches to time series forecasting are increasingly used across a wide range of applications, and perhaps this is the most exciting potential application of AI technology in volcanology. Will AI enable us to use the vast archive of satellite data to forecast the onset of volcanic eruptions, or the trajectory of volcanic flows and plumes? If so, combining the recent technological advances in AI and satellite technology has the potential to transform the ways in which volcanic crises are managed.

Machine Learning Support for Seismic Imaging of Volcanic Plumbing Systems

Mapping the distribution of magma beneath a volcano is important for understanding a volcano's structure, magma supply, and eruptive potential. Seismological analysis can provide insight into a volcano's subsurface structures; as earthquakes spatially cluster around magma chambers, catalogues of precisely located earthquakes can add spatial information to the geometry of a volcano's plumbing system. Changes in the magma system, like dike intrusions or rapid pressurization of a magma chamber, can generate earthquake sequences that spatially migrate over time or suddenly increase in rate. By capturing these sequences, earthquake catalogues can additionally provide temporal information about the magmatic plumbing system. Discrete magma reservoirs can also be identified using secondary products derived from earthquake catalogues. The most prominent such technique is travel-time tomography, in which the travel times of seismic waves between earthquake hypocentres and the seismic instruments are used to map out spatial variations in seismic velocity beneath a volcano (Fig. 10, modified from ref. [19]). Spatially coherent anomalies in the mapped velocity structure can indicate regions of probable magma storage, but individual feeder dikes usually fall below the resolution of this tomographic method.

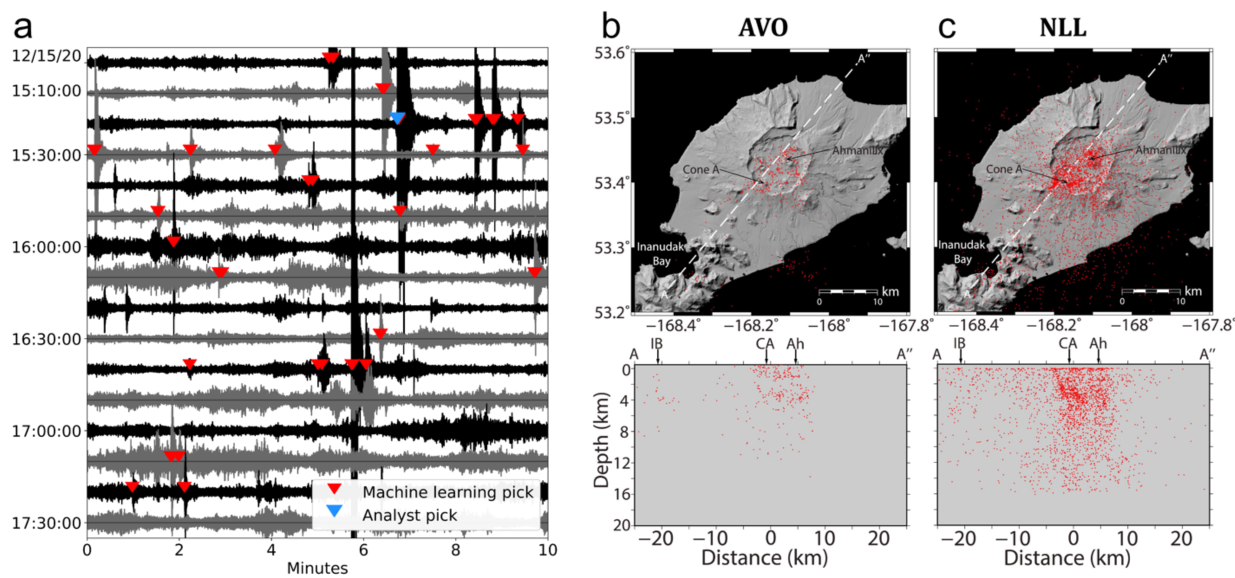

Figure 10: (a) Noisy seismic data from a pre-eruptive earthquake swarm at Kilauea volcano recorded by station RIMD in the Hawaiian Volcano Observatory network. In this 160-minute window, only one analyst phase pick (blue) was made, while a deep learning phase picking algorithm automatically detects many more phase picks (red) despite significant noise contamination. (b-c) A comparison of earthquake catalogues developed at Okmok volcano using (b) analyst-picked data and (c) automatic picks including contributions from a deep learning picking algorithm. Top panels show the map view, and bottom panels are depth cross-sections along the A-A' profile. The incorporation of machine learning increases the number of documented earthquakes by a factor of 8. Adapted from ref. [19].

Compiling these earthquake catalogues at volcanoes requires the detection of many earthquakes using ground motion data recorded by seismic instruments. Earthquake detection and localization is a two-step process (Fig. 10). In the first step, called phase picking, incoming seismic waves (phases) generated by earthquakes are detected on seismic sensors and each phase's time of arrival is typically recorded to centisecond precision. In the second step, called phase association, phases are identified as belonging to discrete earthquakes and grouped together. The timing of the arrivals of an earthquake's phases can then be used to estimate the earthquake's hypocentre.

This catalogue-building process is typically undertaken by teams of qualified analysts who systematically review seismic data for evidence of earthquakes. At volcanoes with large seismic networks (>10 instruments), this task is time-consuming (Fig. 11). During periods of heightened volcanic unrest, some volcanoes might generate hundreds of earthquakes per day, further complicating the catalogue-building process. Because of these factors, the time and effort required to build earthquake catalogues can serve as a major barrier to scientific analysis. Automatic earthquake monitoring systems designed for tectonic earthquakes are commonly used for monitoring volcanic earthquakes. However, the high frequency and elevated background noise make comprehensively detecting small volcanic events challenging. In the past five years, volcanology has benefited from the use of ML to facilitate earthquake detection, specifically through increased automation and augmenting detection of small earthquakes that had previously gone undetected.

Supervised ML algorithms have shown great promise in automating phase picking. In recent years, neural networks have been frequently employed for this purpose; the convolutional neural network is the most widely adapted architecture. Such a network can be trained on hundreds of thousands of labelled waveforms to recognize arriving phases, even when data are noisy or low-quality. This network can then be used to process seismic data from the volcano and automatically pick seismic phases, often achieving accuracy rivalling that of expert analysts. Due to their robust performance in noisy environments, these picking networks are effective at detecting small earthquakes that analysts might miss; by detecting these earthquakes, ML-assisted catalogues could increase the number of catalogued earthquakes at a volcano by a factor of 10 or more, thus providing more detailed spatio-temporal information about the volcanic plumbing system. Additionally, because these automated phase pickers require minimal user input, their application to seismic data can speed up the phase picking process by orders of magnitude relative to expert analysis, all while ensuring consistent picking standards. In addition to the advancements in phase picking, phase association has also benefited greatly from the introduction of unsupervised machine learning techniques. Clustering techniques, when applied to sets of seismic phases, can automatically and accurately assign phases to earthquakes [20]. This efficiency is particularly desirable in volcanic settings, where waveform recordings are frequently contaminated with noise sources (e.g., tremor, rockfall, or weather events) that can complicate the association process.

Although these algorithms are recent developments in seismology, having been introduced in the last five years, their benefits have led to their rapid proliferation in volcano research. Contributing to their popularity, many ML phase-picking algorithms have been shown to generalize, or perform well on data from regions that were not included in their training data. This property allows users to apply automated phase pickers that have been trained on particular volcanic (or tectonic) settings to data from other regions [21]. The high-resolution catalogues that have been produced with these algorithms can directly provide improved spatial and temporal information about magma in the subsurface. For instance, ML-enhanced catalogues have been used to identify correlations between eruptive activity and increased magma supply in the mantle [21] and image magma intrusions in remote, poorly instrumented settings [22]. Data derived from ML-generated catalogues have also been used as inputs for high-resolution tomographic models. This approach has already shown promise in imaging complex geometries of grouped, interconnected magma chambers [23], improving constraints on the melt fraction of magma storage chambers [24], and differentiating between hydrothermal fluids and melt in the subsurface [25]. Novel deep learning schemes may also offer future applications in directly imaging fine scale sub-surface volcanic structure. Trained using vast quantities of seismic wavefield simulations, Fourier Neural Operators (FNOs) have recently been shown to recover detailed structural information from small quantities of input data [26].

Machine Learning in Real-Time Volcano Monitoring and Forecasting

Traditionally, machine learning and AI approaches have been used to analyse previously collected data. Therefore, data acquisition and data analysis are usually distinct steps. In these cases, the obtained results aim to better understand volcano dynamics and, eventually, mitigate related risks. The previous sections have illustrated such use of AI.

An alternative paradigm consists of using machine learning techniques on real-time incoming data streams (Fig. 11). As detailed in the chapters belonging to Part 6 of the present edition of the Encyclopedia of Volcanoes [27, 28, 29], these data may encompass different sources such as seismic, geodetic, gravimetric, and geochemical monitoring networks. By doing so, the two stages of data acquisition and data processing are no longer separated. In this latter case, the main aim is to produce monitoring tools to facilitate the day-to-day work of surveilling a volcano. To illustrate such use of AI tools, we take the example of volcano-seismic monitoring. As stated in the previous section, a given volcano can be equipped with a rather large number of seismic sensors. As the number of seismic sensors significantly increases, the manual processing of the incoming data streams is not feasible anymore. In such situations, AI becomes of great interest, allowing for effective real-time analyses that are impractical by manual processing.

Among them, we can mention: (i) the automatic detection of events in a continuous stream of data, as reported in the previous section [30]; and (ii) the automatic classification of the events, either in the continuous data stream [31], or once they have been detected [10]. Both analyses can be conducted by ML or AI models trained in a supervised way: the idea is to replicate and automate an analysis that is usually manually done by an expert and to provide operational tools [32]. For example, Figure 11 reports a case study on the analysis of different classes of volcano-seismic signals.

We strongly stress the point that automating expert analysis does not mean replacing expert knowledge. Such models need labelled data to be trained: they can only be trained thanks to human expertise and supervision. Their main interest is to allow continuous analysis of a larger number of stations for a given volcano, real-time analysis in crisis periods, or the monitoring of a larger number of volcanoes. We also stress a current limitation of AI: prediction reliability. Current models output probabilities of a given data belonging to a given class. However, it has been shown that those probabilities are often over-estimated and that current models are often poor at saying: "I don't know". Moreover, if a volcano's behaviour changes or evolves into a state not represented in the training data, the ML model is likely to fail in making accurate future predictions. Please refer to the “Generalization Ability of a Machine Learning Model” section for further details on the current limitations of ML models. Also, AI predictions are valuable and extremely potent on average, but the reliability of a single given prediction is, today, still 'unsafe'.

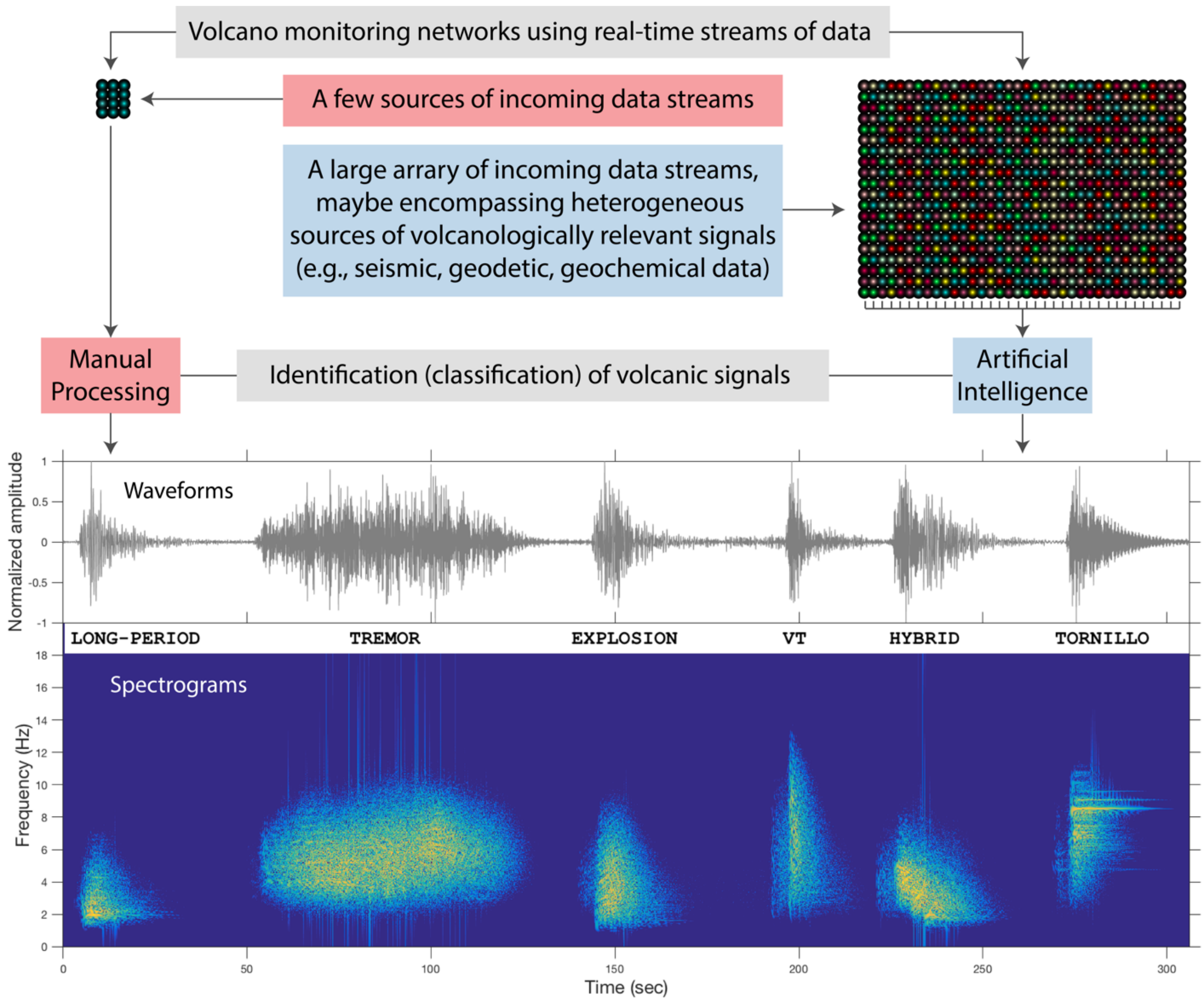

Figure 11: ML support to real-time volcano monitoring and forecasting. AI and ML tools can support volcanologists in the real-time analysis of data streams from large arrays of monitoring stations (upper portion of the diagram). For example, they found application in the processing of Volcano-seismic signals, as in the case reported by ref. [10] for the Ubinas volcano (bottom portion of the diagram), where ML tools supported the classification of different classes of volcanic signals (e.g., long period, tremor, explosions, etc.).

Perspectives and Challenges of AI and ML in Volcanology

From the data perspective, future developments of AI and ML, in volcanology will heavily depend on the quality, volume, and integration of available datasets for training, validation, and testing. Remote sensing investigations are already mature, indeed, they can access diverse, well-covered, representative, and large datasets [33]. In petro-volcanological investigations, experimental (labelled) data is typically scarce, with datasets often limited to ~10^3 observations. However, there is a plethora of geochemical data already available on natural samples covering both whole-rock and microanalytical investigations. As a drawback, these data are often sparse and noisy, with restricted groups of researchers that have been working, continuously, to make them FAIRly available for the research community (e.g., GEOROC and PETDB). Regarding the ground monitoring, only a few volcanoes have been equipped with large arrays of monitoring stations, hindering the ability of AI tools to correlate the learned knowledge across different volcanic systems. One of the most transformative skills of AI is its ability to uncover patterns in big data. Therefore, combining multiparametric (e.g., geophysical, geochemical, and multispectral) observations is one of the main challenges for a widespread success of AI in volcanology. In this case, the main challenge will consist of developing multimodal (i.e., able to store information derived from different sources) datasets to be easily accessible by ML. A few multiparametric monitoring networks recording high-quality data already cover some volcanoes over long periods. However, most volcanoes still lack a robust network of multimodal monitoring sources.

Moving from pure data driven modelling tools that behave as black boxes to transparent models is another challenge. As these challenges are overcome, it will allow stakeholders and decision makers to better rely on AI tools and start systematically adopting such approaches in hazard assessment, risk mitigation, and crisis management. The application of explainable AI techniques to unblur deep learning algorithms, the adoption of hybrid modelling strategies that include physical guidance into the ML model, and incorporation of domain-specific knowledge in the decision process are all critical strategies that can enhance transparency, build trust, and ultimately drive a broader adoption of AI in Volcanology.

Overall, the main limitation that is currently inhibiting the development of AI and ML in volcanology, and more broadly in Earth Science, is the lack of educational curricula that include fundamental AI and ML skills. As proposed by [34], universities need to revise their core curricula to prepare graduates for an AI-enabled future. Enhancing collaboration between Earth and data scientists is also a crucial challenge.

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