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How Artificial Intelligence and Earth Observation Satellites are re-shaping volcano monitoring

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Abstract

A growing number of satellite missions offer data at various spatial resolutions and revisit times. There are plans for new missions to maintain near-continuous monitoring of volcanic activity globally. Artificial Intelligence (AI) techniques, particularly Machine Learning (ML) and Deep Learning (DL) models, offer distinct advantages in extracting information and knowledge from these vast datasets. Here, the potential of Artificial Intelligence techniques, satellite data, and cloud computing in addressing some of the most critical challenges and questions related to volcanic hazards is shown. A description of how the data-driven science paradigm is used to solve volcanic hazard problems is provided highlighting how earth observation satellite data are able to drive the entire estimation process through advanced AI techniques. An overview of the most important concepts and techniques to assist in interpreting satellite data for volcano monitoring is provided. From feature engineering methods enhancing the input signal for AI models, to convolution filters that can strategically be used in Convolutional Neural Network (CNN) architectures to find patterns, to the concept of "attention" in neural networks and the powerful abilities it brings to briefly discuss strategies from unsupervised, self-supervised and transfer learning to reduce the need for large labeled datasets. The objective of this work is dual, providing the basic concepts of Earth Observation (EO) and AI and showing how they have re-shaped volcano monitoring.

Keywords: Artificial intelligence; Satellite remote sensing; Volcano monitoring; Machine learning; Cloud computing

1. Introduction

Volcanic eruptions have the potential to become major social and economic disasters. To reduce the impact of volcanic eruptions on humans and the environment, scientists must be able to forecast when, where and how volcanoes are going to erupt. The prompt detection of the eruption starting, tracking the evolution of the volcanic activity and nowcast, i.e. short-term forecast, how it will evolve in space and time (Poland et al., 2020). Forecasting volcanic eruptions allows people to be alerted so they can evacuate, reducing the negative impact of eruptions on human populations. However, in order to forecast eruptions, volcanologists should understand volcanoes mechanisms and have enough long term data in order to not only differentiate between normal and "unusual" behavior preceding eruption but also to know what to expect. When the volcano passes to an "unusual" phase, called unrest, volcanoes can give warning signs such as changes in degassing stage and ground deformation from days to months' prior the eruption's start (Kilburn and Bell, 2022; Martí, 2024). Therefore, eruptions can be preceded by unrest and its appearance is the main clue for volcanologists to forecast eruptions. Therefore, they must understand what exactly happens during unrest by looking at the measured volcanic signals in order to make a reliable eruption forecast. Then, when a volcano erupts, the first critical objective is promptly characterizing the hazardous phenomena related to the volcanic activity taking place in time and space. Volcanic processes, such as lava flows or ash plumes, are multi-parametric, which must be accurately derived in order to determine the potential hazard footprint of the phenomenon being studied. Active volcanoes are continuously monitored by several ground based instruments to observe, measure, and analyze various signals of volcanic activity and behavior. However, ground-based volcanic monitoring remain sparse and exposes the volcanologist to high risk. Nowadays, large amounts of data are acquired daily on board of satellites addressing the challenge of monitoring the entire Earth surface including the most remote volcanic areas. Satellite data offer synoptic views of the Earth at a variety of resolutions and across a range of electromagnetic frequencies, providing a critical value to volcanology (Ramsey et al., 2021), especially when considered holistically instead of as independent (Brodtkorb et al., 2024). Over the years, satellite observations have provided great contribution to advance general understanding of volcanic processes and monitor volcanic activity globally (Thompson et al., 2023). Combining multiple satellite dataset allows to observe volcanic activity manifestations, namely thermal anomalies, deformation, gas emissions and ash plume (Poland et al., 2020) through multi-parameter analysis and it can provide insights into the complex, interconnected processes driving volcanic activity. For instance, the global scale monitoring of SO_2 satellite data has allowed as to have an inventory of volcanic degassing over years that permitted to distinguish and quantify the volcanic contribution to the SO_2 in the atmosphere respect to the anthropogenic sources (Carn et al., 2017). However, extracting meaningful information and gaining new insights from such a large volume of data is a challenging task. For example, (Reath et al., 2019) conducted a manual investigation of thermal anomalies using ASTER data for 330 volcanoes in Latin America and identified 16 volcanoes that exhibited thermal features not documented before. The large volume of data can be somewhat handled by automated detection algorithms, which might utilize relatively straightforward thresholds tied to spectral properties or changes in image characteristics over time. For example, MODVOLC uses a specific threshold value to count pixels as thermal anomalies or not, and has the issues with this have been well-described in the literature (Wright et al., 2004). A clear limitation of the thresholds approach is that they are based on expert centric models that are insufficient for effectively learning representations from such vast amounts of data and therefore to extract knowledge and gaining mining capabilities from massive satellite data (Biggs et al., 2022). Volcanology is fundamentally an observational science, with many modern monitoring techniques collecting quantitative data. Therefore, data-driven approaches are arguably the best way to solve problems that arise in estimating the evolution of volcanic hazards, with the data driving this process (Cariello et al., 2024a; Corradino et al., 2022). Nowadays, the technological advancements and the increase in the data volume have pushed the scientific community to the transition from Empirical Science, Theoretical and Computational Science to Data-driven Science, facilitated by the increase in data availability and advancements in computing resources (Pyzer-Knapp et al., 2022). Data-driven approaches naturally began to develop due to the discovered potentiality within vast volumes of data containing valuable information. Advanced data-driven techniques emerged from the necessity to retrieve accurate information and, ideally, knowledge from the data. From this perspective, Machine Learning (ML), a type of AI in which computers learn from data, plays a key role. ML alleviates the limitations of knowledge-based algorithms by discovering rules and patterns from the data without explicit supervision (Lary et al., 2016). One of the first uses of ML for volcano monitoring through Earth Observations (EO) data-driven approaches has been proposed in (Piscini and Lombardo, 2014) where Neural Networks (NNs), a type of ML algorithm able to model complex nonlinear relation, were trained to detect thermal anomalies in AVHRR scenes. However, due to limited computing capabilities, the model was trained and tested using a very small dataset with acquisitions covering the area around Mt Etna, Italy, implying low accuracy and generalization capabilities. Thanks to technological advancements, combining AI techniques and satellite data with advanced computing significantly has been shown to have the potential to enhance our ability to monitor volcanic activity on a global scale. On one hand, ML can be employed in an unsupervised manner to uncover new patterns and relationships between the extracted volcanic variables, which may otherwise remain partially or totally unknown and are not easily revealed using traditional approaches. Thus, one of the primary uses of ML with satellite datasets is data-driven discovery, enabling the extraction of knowledge from data to improve our understanding of hidden dynamics of the volcanic system through pattern discovery (Popescu et al., 2024). On the other hand, ML is utilized to automate the analysis of satellite data, performing complex tasks such as pattern identification/classification that cannot easily be described by a set of explicit commands. Several studies have been devoted to detect specific phenomena that could signal unrest (Caudron et al., 2021), the eruption onset (Amato et al., 2023a) and track the evolution of volcanic phenomena through ML algorithms (Torrisi et al., 2024, Rey-Devesa et al., 2024). Among the first use of Convolutional Neural Networks (CNN) to capture context from infrared data is presented in (Corradino et al., 2023) where subtle thermal changes are detected thanks to accurate detection of thermal emission overcoming limitations of purely intensity-based approaches. Satellite SAR data have widely adopted to monitor deformation globally developing global deformation monitoring systems based on SAR deformation and advanced ML models to automatically identify pre-eruptive deformation changes (Biggs et al., 2022; Gaddes et al., 2024).

At a global scale, heavy computational resources are needed to manage massive satellite datasets and perform complex operations requiring a fundamental shift in how computational resources are utilized, optimized, and made more accessible, alongside the integration of these technologies with Cloud Computing, and the emerging area of Quantum Computing (Rane et al., 2024). Cloud Computing provides a valuable solution with big data storages and state-of art computing resources to ML developers. Among the advantages of cloud computing, algorithms are executed on cloud servers using the most advanced and updated hardware, including GPUs, TPUs (Sether, 2016). In recent years, cloud computing has become the cornerstone for AI and ML applications due to its ability toprovide on-demand processing power and storage (Mungoli, 2023). Nevertheless, issues such as latency, bandwidth limitations, and privacy concerns have led to the use of hybrid solution combining on premises computing, i.e. the decentralized structure allows for more efficient data processing and significantly reduces latency, particularly for applications requiring immediate responses. Quantum computing present solutions that could revolutionize processing speed, scalability, and efficiency, traditional centralized cloud systems often experience pressure as organizations seek to handle increasingly larger data volumes (Ramesh, 2025). It holds the promise of tackling complex challenges that exceed the capabilities of conventional computers, potentially resulting in a dramatic speed-up of machine learning algorithms. Although still in its early stage, the influence of quantum computing on AI and ML is beginning to attract considerable interest from researchers, given the potential breakthroughs it might bring. These advancements create new opportunities for AI, ML, and Deep Learning (DL) algorithms, facilitating quicker data processing, improved problem-solving capabilities, and real-time decision-making that was previously unattainable (Rane et al., 2024).

Here, the potential of AI techniques, satellite data, and advanced computing technologies in addressing some of the most critical challenges and questions related to volcanic hazards is shown. A description of how the data-driven science paradigm is used to solve volcanic hazard problems is provided highlighting how earth observation satellite data are able to drive the entire estimation process through advanced AI techniques. An overview of the most important concepts and techniques to assist in interpreting satellite data for volcano monitoring is provided. From feature engineering methods enhancing the input signal for AI models, to convolution filters that can strategically be used in CNN architectures to find patterns, to the concept of “attention” in neural networks and the powerful abilities it brings to briefly discuss strategies from unsupervised, self-supervised and transfer learning to reduce the need for large labeled datasets. The objective of this work is providing the basic concepts of AI and ML, i.e. a pipeline that can be followed the volcanological community to use these algorithms, and showing how they have re-shaped volcano monitoring from space.

2. Earth Observation satellites for volcano monitoring

Combining multiple satellite data observing thermal anomalies, deformation, gas emissions and ash plume through multi-parameter analysis can provide insights into the complex, interconnected processes driving volcanic activity offering an excellent possibility for forecasting, detecting, and tracking eruptive activity (Genzano et al., 2021; Corradino et al., 2023). Following the fast technological advances in satellite sensors (higher temporal and spatial resolution), several research activities have been aimed at improving the technique for satellite data analysis with the goal to have a faster and high quality response in order to have the opportunity to track volcanic events with fast dynamics. These data facilitate short-term forecasting of intense events, estimation of eruptive parameters such as effusive rate, erupted volume and volcanic cloud tracking. Satellite monitoring of volcanic activity allows near-real time detection and tracking of both ash plume (Pavolonis et al., 2006; Prata, 1989), and thermal anomalies associated with lava flow field through multispectral data (Negro et al., 2013; Steffke and Harris, 2011).

2.1 Satellite sensors

Satellite remote sensing has emerged as a promising tool for monitoring volcanic activity due to several advantages over ground-based methods. These advantages include global coverage, low costs for the users, timely and continuous observations, and integration of multiple sensors. Satellite sensors are deployed on both geosynchronous and polar satellites. Polar satellites usually orbit Earth from north to south, passing roughly over Earth's poles. Satellites in a polar orbit do not have to pass the North and South Pole precisely; even a deviation within 20 to 30 degrees is still classed as a polar orbit.

Polar orbits are a type of low Earth orbit (LEO), as they are at low altitudes between 200 to 1000 km. Sun-synchronous orbit is a particular kind of polar orbit which allows the satellite to be synchronous with the Sun, this means that the satellite always visits the same spot at the same local time.

Satellites in geosynchronous orbit (GSO) circle Earth from west to east following Earth's rotation, taking about 24 hours – by travelling at exactly the same rate as Earth. In order to perfectly match Earth's rotation, the speed of GSO satellites should be about 3 km per second at an altitude of 35786 km. This is much farther from Earth's surface compared to many satellites. A geostationary satellite (GEO) is a GSO satellite orbiting with zero inclination to the equatorial plane. This makes satellites in GEO appear to be 'stationary' over a fixed position. Therefore, geostationary satellites monitor the same area continuously, and offer higher temporal resolution but lower spatial resolution with respect polar satellites. For instance, the Spinning Enhanced Visible and Infrared Imager (SEVIRI) instrument, on board the Meteosat Second Generation (MSG) geostationary provides one image at 3000 m spatial resolution at the equator every 15 minutes (or 5 minutes in rapid scan mode) (Di Bella et al., 2024; Ganci et al., 2011). Both types of satellites are valuable for volcano monitoring based on the specific task to solve. Satellite sensors suitable for volcano monitoring cover the entire electromagnetic spectrum, from ultraviolet (UV) to microwave wavelengths. In particular, passive and active sensors are placed on board of satellites. Passive sensors detect energy when it is naturally available therefore either provided by the sun during the day or naturally emitted (such as thermal infrared) anytime. Active sensors emit radiation towards the target that is reflected back and measured by the sensor. Advantages for active sensors include the ability to obtain measurements anytime and the possibility to investigate wavelengths that are not sufficiently provided by the sun, such as microwaves. A list of widely used satellite sensors at different spectral, spatial and temporal resolution is shown in Table 1. Therefore, EO datasets themselves are complex heterogeneous image datasets characterized by so-called 4V features comprising volume, variety, velocity, and veracity (Guo et al., 2015). Volume refers to big EO datasets (e.g., terabytes of data per day collected, for instance, by the European Space Agency); variety refers to distinct spectral data, such as multispectral and hyperspectral pixel data; velocity refers to the speed of change on the Earth's surface; and veracity refers to imperfect datasets, such as noisy images or remotely sensed images, partly covered by clouds.

Sensor	Satellite	Spectral range	Spatial resolution	Revisit time	Orbit
Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)	NASA TERRA	VNIR-SWIR-TIR	15, 30 and 90 m	10 days	Polar
Advanced Baseline Imager (ABI)	NASA Geostationary Operational Environmental Satellite (GOES)	VNIR-MIR-TIR	500, 1000, 2000 m	5 minutes	Geostationary
Moderate-resolution Imaging Spectroradiometer (MODIS)	NASA TERRA and AQUA	VNIR-MIR-TIR	250, 500, 1000 m	daily	Polar

Sensor	Satellite	Spectral range	Spatial resolution	Revisit time	Orbit
Sea Land Surface Temperature Radiometer (SLSTR)	SENTINEL-3	VNIR-MIR-TIR	500, 1000 m	daily	Polar
Operational Land Imager (OLI)	NASA Landsat-8	VNIR-SWIR	15-30 m	10 days	Polar
Thermal Infrared Sensor (TIRS)	NASA Landsat-8	TIR	100 m	10 days	Polar
Spinning Enhanced Visible & Infrared Imager (SEVIRI)	ESA Meteosat Second Generation (MSG)	VNIR-TIR	1000-3000 m	5/15 minutes	Geostationary
Visible Infrared Imaging Radiometer Suite (VIIRS)	NASA Suomi National Polar-Orbiting Partnership (S-NPP)	VNIR-SWIR-TIR	375-750 m	daily	Polar
Multi Spectral Instrument (MSI)	ESA Sentinel-2A and Sentinel-2B	VNIR-SWIR	10-20 m	2 days	Polar
TROPOspheric Monitoring Instrument (TROPOMI)	ESA SENTINEL-5 Precursor	UV	3500 × 7000 m	daily	Polar
Synthetic Aperture Radar (SAR)	SENTINEL-1	RADAR C band (5.405GHz)	10 m	10 days	Polar

Table 1. Main satellite sensors features.

2.2 Volcano monitoring from space

Several works have been focused on satellite monitoring of volcanic activity using multispectral data (Harris et al., 1995; Pergola et al., 2004). The spectral response of a variety of satellite sensors can be used to observe volcanic activity manifestations, namely ground deformation and surface changes, thermal anomalies, gas emissions and ash plumes. From ultraviolet (UV), visible (VIS), infrared (IR), and microwave data on both polar and geostationary satellites recording information at different spatial, temporal, and spectral features (Cigna et al., 2020). Visible (VIS) bands play a crucial role to characterize volcanic deposits (composition, properties, and age (Corradino et al., 2020; Manley et al., 2022). In fact, every object has its own chemical composition and each composition has its own spectral signature, i.e. variation of reflectance or emittance of a material with respect to wavelengths. With lava flow age, an increase of reflectance is observed in the visible giving rise to a clear feature in this spectral region. The peak in the visible region is mainly due to the weathered surfaces (oxydation). Infrared radiation proves invaluable in characterizing thermally active volcanic phenomena and extracting crucial insights about ongoing volcanic activity (Corradino et al., 2020) thanks to the wide range of thermal features exhibited. The predominant radiant emissions fall within the near-infrared (NIR), the shortwave infrared (SWIR), middle infrared (MIR), and thermal infrared (TIR) portions of the spectrum, from the hottest to the coolest emitting surface respectively. TIR bands are particularly effective for the lower-temperature volcanic emissions (e.g to detect lava flows even for days after the end of the effusion, as cooling lava radiation). In contrast, SWIR band is primarily emitted by extremely hot surfaces such as fires and incandescent lava (Cariello et al., 2024b; Kato et al., 2021). The Ultraviolet band (UV) bands are useful to characterize volcanic clouds in atmosphere. In particular, the UV bands have a great sensitivity to the Sulphur dioxide, aerosol and ash particles that absorb and scatter the sunlight (Taylor et al., 2018). Finally, the micro-wave band (SAR imagery), creating high-resolution images of Earth's surface allows monitoring topographic change, the distribution of eruptive products and surface displacements (InSAR) at subaerial volcanoes. The InSAR using the change in phase between time-separated radar images allows to measure displacements of the Earth's surface on a centimeter to millimeter scale (Albino et al., 2020). Therefore, a multi-band analysis can provide insights into the complex, interconnected processes driving volcanic activity. As previously stated, these sensors are placed on board of satellites that orbit the Earth at either low (polar) or high (geostationary) altitudes providing either high spatial resolution with lower revisit time or low spatial resolution with higher revisit time respectively.

Thermal anomalies are observed using all the available optical bands from MSI, OLI-TIR, ASTER, MODIS, VIIRS, SLSTR, SEVIRI, ABI. IR radiation, for instance, proves invaluable in characterizing thermally active volcanic phenomena and extracting crucial insights about ongoing volcanic activity (Amato et al., 2023b). According to Wien's Law, the peak of emission surface depends on its temperature, higher temperatures corresponding to shorter wavelengths of peak emission. During volcanic activity, thermal features exhibit a wide range of temperatures. Fresh basaltic lava, for instance, typically ranges between 1073 and 1273 K, with temperatures measured in lava lakes reaching as high as 1473 K, while cooler active surfaces may register around 673 K (Pinkerton et al., 2002; Spinetti et al., 2009). High spatial resolution data collected by Landsat and ASTER have been employed for the thermal analysis of active lava flows, lava lakes (Harris et al., 1999), and fumarole fields (Pieri and Abrams, 2004), subtle thermal anomalies (Corradino et al., 2023). Lower spatial, but higher temporal, resolution sensors, such the Advanced Very High Resolution Radiometer (AVHRR) and the MODIS, have also been used for infrared remote sensing of volcanic thermal features, as has GOES (e.g. Harris et al., 2001). The high temporal resolution (15 minutes) offered by the Spinning Enhanced Visible and Infrared Imager (SEVIRI), already employed for the thermal monitoring of effusive volcanoes (Di Bella et al., 2024), has recently been exploited to estimate lava discharge rates for eruptive events of short duration (a few hours) at Mt Etna (Bonaccorso et al., 2011).

Gas emissions are observed using TROPOMI SO_2 Vertical Column Density (VCD) input measurements at 1 km, 7 km and 15 km altitude data integrated with the TROPOMI CLOUD altitude product and thermal infrared bands from MODIS, SEVIRI and ABI data spectral bands centred around 8 and 10 µm highlighting the presence of SO_2. Attention has been posed on volcanic SO_2 monitoring, that is a clear indicator of the unrest condition of one volcano, could be determined both in UV band and also in thermal infrared band (Kearney et al., 2009). The SO_2 can be quantified not only during the more intense eruptive phase (huge of emitted quantity) but also during the quiescent stage of a volcano.

Ash plumes can be observed using thermal infrared bands from MODIS, SEVIRI and ABI spectral bands centred around 10 and 12 µm highlighting the presence of volcanic ash (Prata, 1989; Pavolonis et al., 2006). In fact, distinctive features in the TIR spectra of SO_2, silicate ash, and ice crystals allow to discriminate volcanic SO_2 and ash from icy meteorological clouds. When extracting information from satellite images, a key question is what kind of context is required to perform the desired task among spatial, temporal and spectral contexts. For instance, rapidly evolving volcanic activity such as lava fountains requires data at high temporal resolution, therefore geosynchronous satellite sensors will be needed. Once the required context has been identified, the appropriate satellite sensor can be selected based on its spatial, temporal and spectral resolution.

Deformation is observed using S1-InSAR (interferometric synthetic aperture radar) – the interferometric combination of synthetic aperture radar (SAR) scenes that are acquired from approximately the same point in space at different times. The SAR signals are used to monitor resurfacing processes such as lava flows and ash deposits and in particular, to detect surface changes. The complementary information provided by SAR and multi-spectral sensors can be exploited for an effective and accurate extraction of volcano-related features.

High spatial resolution satellite sensors play a crucial role in closely monitoring changes with exceptional sensitivity. This capability makes them well-suited for capturing pre-eruptive trends that may herald an eruption and accurately characterizing the spatial extent of lava flows at the moment of satellite passage. These data enable the recognition of ongoing volcanic activity, localization of active vents, and characterization of lava flow geometries and spatial-thermal distributions.

On the other hand, high temporal resolution satellite sensors are essential for tracking volcanic activity in near-real-time, providing continuous monitoring throughout the entire duration of a volcanic eruption. These data facilitate the assessment of volcanic activity status, estimation of Time-Averaged Discharge Rate, determination of erupted volume, and tracking the evolution of volcanic activity over time. Specifically, by estimating the released volcanic radiative power (VRP), eruptive parameters such as effusive rate can be derived. Therefore, for rapidly evolving eruptive phenomena this kind of data is fundamental for near-real time monitoring. In general, focusing on volcano monitoring, satellite sensors can be classified into two big categories based on their spatial and temporal resolutions: high spatial/low temporal resolution and low spatial/high temporal resolution sensors (Fig. 1).

By combining satellite sensors with different temporal, spatial, and spectral characteristics, it is possible to overcome individual sensor limitations, providing a comprehensive understanding of the volcanic phenomena (Corradino et al., 2021; Ganci et al., 2020). Depending on the time, spatial and spectral scale of the volcanic phenomena, the sensor with the appropriate temporal, spatial and spectral features should be used. Finally, it is worthy to highlight the importance of the relative time passing between the eruption date and the satellite sensors acquisition time. In fact, this time interval will influence the choice of the spectral bands and satellite sensor to use, e.g. if the goal is mapping a lava flow after the end of the eruption, either thermal infrared band at higher wavelengths will be needed (lava flows keep high temperature for long) or ML learning lava flow spectral signatures (Corradino et al., 2019; Spinetti et al., 2009) or active sensors highlighting the presence of volcanic deposits (Kyriou and Nikolakopoulos, 2022; Orynbaikyzy et al., 2023).

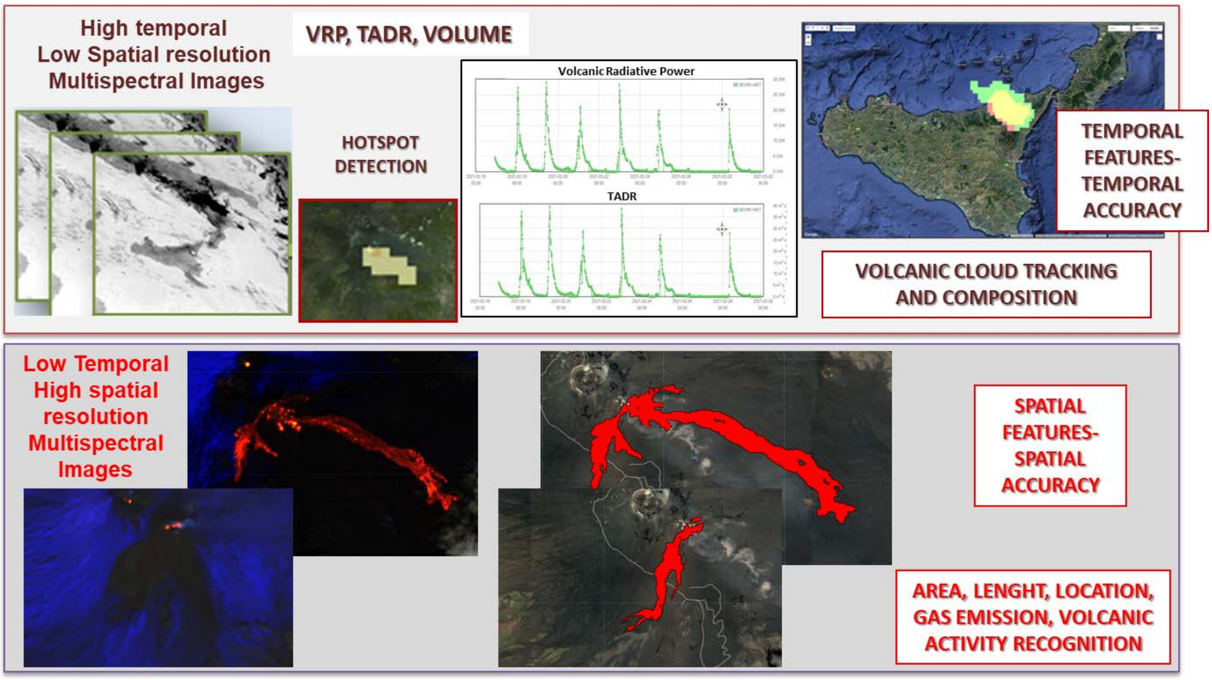

Figure 1. Volcanic features and parameters derived by satellite sensors at different temporal and spatial scale.

2.3 Cloud-Computing

Cloud computing is the on-demand access of computing resources – physical servers or virtual servers, data storage, networking capabilities, application development tools, software, AI-powered analytic tools and more – over the internet with pay-per-use pricing. Multi-petabyte catalog of satellite imagery and geospatial datasets already stored in public data archive and readily accessible. The images are daily made available for global-scale data mining. Cloud computing provides the vast computing power and other resources needed to take advantage of cutting-edge technologies like generative AI and quantum computing. For satellite image processing, providers like Google and Amazon allows for easy access to satellite data, integration with external satellite data through API, algorithm execution on cloud servers using their hardware including GPUs and TPUs. For instance, Google Earth Engine (GEE) is a platform for scientific analysis and visualization of geospatial datasets hosting satellite imagery and storing it in a public data archive that includes historical earth images going back more than forty years. The images, ingested on a daily basis, are then made available for global-scale data mining. Earth Engine also provides APIs and other tools to enable the analysis of large datasets (Amani et al., 2020; Gorelick et al., 2017). Google Colab is a hosted Jupyter Notebook service that requires no setup to use and provides free access to computing resources, including GPUs and TPUs (Carneiro et al., 2018). Cloud computing has become the cornerstone of many AI applications due to its ability to offer scalable and flexible computational resources. AI tasks, particularly those leveraging deep learning models, demand considerable processing power, storage space, and access to large datasets. The cloud provides the necessary infrastructure for training and deploying AI models, alleviating concerns related to on-premises hardware limitations. The combination of AI and cloud computing has led to the rise of AI-as-a-Service (AIaaS), a model where AI capabilities are delivered via the cloud (Rane et al., 2024). This allows to take advantage of powerful AI tools and frameworks without requiring extensive understanding of the underlying algorithms. Major cloud providers, such as Amazon Web Services (AWS), Microsoft Azure, and Google Cloud, offer services like natural language processing (NLP), image recognition, and predictive analytics through their platforms. These offerings democratize access to artificial intelligence, allowing businesses of all sizes to leverage sophisticated machine learning models. A significant area within AI and cloud computing is the development of federated learning frameworks. Federated learning is an approach that enables the training of AI models on various dispersed devices while keeping raw data localized (Rane et al., 2024).

3. An overview on Artificial Intelligence: from traditional ML to Generative AI

AI is the science of enabling computers and machines to simulate human learning, comprehension, problem solving, decision making, creativity and autonomy. Applications equipped with AI can see and identify objects learning from new information and experience. One of the early approaches to AI was to create knowledge-based approaches requiring expert input to define the rules and associations. Volcanic phenomena have widely been monitored using expert-centric approaches typically relying on predefined rules based on a priori knowledge. While these methods perform well in the most trivial cases, e.g. detection of intense thermal anomalies during a volcanic eruption, they may fail when observations conditions are not optimal, e.g. volcanic activity is low and hard to detect. Sensor limitations, such as limited spatial, temporal, or spectral resolution, can hinder the capability to discriminate thermal anomalies below a certain intensity or dimensions. ML alleviates the limitations of the knowledge-based approach to artificial intelligence and discovers rules and patterns from the data without explicit supervision. ML models have demonstrated the ability to surpass traditional approaches by learning the best decision rules from data (Bonaccorso, 2017; Goodfellow et al., 2016). In essence, ML models learn decision rules during the training phase using historical data, without external bias. Traditional ML algorithms mainly rely on structured input data, i.e. raw data undergoes a feature engineering phase in order to extract the main discriminative features for the problem to solve (Mumuni and Mumuni, 2025). Human experts determine the hierarchy of features to understand the differences between data inputs, usually requiring more structured data to learn. The computational advancements have allowed to move to Deep Learning (DL) where models are able to mimic human brain functions such as how human process visual information to understand what is happening in the scene. These models can ingest unstructured data in its raw form (e.g. text, images), and it automatically determines the hierarchy of features which distinguish different categories of data from one another (Yang et al., 2022). Deep Learning led to a big paradigm change in Computer Vision, the field of AI that teaches computers to interpret and capture information from images (Rosso et al., 2021). By applying ML and DL models to images, computers can classify objects and gain valuable insights from the massive amounts of data overcoming limits due knowledge-based approaches. This has represented a great step forward into volcanic activity monitoring using satellite multispectral images. Advanced AI techniques exploit not only spectral intensities but also spatial and temporal features of volcanic phenomena. By learning spatial and temporal features from satellite images, automatic interpretation of data becomes possible, allowing for meaningful insights to be drawn from the images.

Recently, a new step has been performed towards general artificial intelligence, Generative AI, i.e. models are able to build knowledge similarly to how human being does and create new contents. At a high level, generative models encode a simplified representation of their training data, and then draw from that representation to create new work that's similar, but not identical, to the original data. In general, generative AI operates in three phases: Training, to create a foundation model-Tuning, to adapt the model to a specific application-Generation, evaluation and more tuning, to improve accuracy. Specifically, a Foundation Model is a large-scale neural network architectures pre-trained on vast amounts of unlabeled data through self-supervised learning. This models, are then fine-tuned on downstream tasks, e.g. image segmentation and image classification, for which a far smaller size of labeled datasets are needed. Earth Observation Foundation models have been used in several fields such as climate and weather (Nguyen et al., 2023). One of the best performing generative AI foundation model for Earth observation that has been developed by IBM and ESA is TerraMind combining insights from nine types of Earth observation data to provide an intuitive understanding of our planet (Jakubik et al., 2025).

Generative Deep Learning has only been started to be applied in the field of natural hazard (Ma et al., 2024). Although a deep description of these techniques is out of the scope of this paper, the main ingredients of ML will be highlighted, namely unsupervised and supervised learning, input selection and features extraction, modeling, and evaluation (Bansal et al., 2022).

3.1 Unsupervised VS Supervised Learning

In the field of ML, it is possible to distinguish two learning approaches, namely supervised and unsupervised (Fig. 2). In unsupervised approaches, users input unlabeled data into the algorithm, which then endeavors to extract common patterns autonomously based on data similarity. Specifically, unlabeled input dataset selected as significant for the problem under investigation, are given as input to the unsupervised algorithm (step 1) that will cluster data based on similarity criteria. Identified patterns can then be investigated and knowledge can be extracted. The types of problems to which unsupervised learning is suited to are clustering and anomaly detection. Clustering aims at identifying similarities inside groups, while anomaly detection aims at identifying abnormalities in data. Supervised learning techniques train ML algorithms using labeled datasets, which consist of sample data tagged with a target parameter. The algorithm utilizes this target parameter to evaluate its accuracy in interpreting the training data. In this case, labeled data are given to the algorithm, i.e. coupled input and desired output dataset, from which it learns from (step 1). New data will be tagged accordingly to the learned function (step 2). The types of problems to which supervised learning is suited to are classification and regression. Classification and regression aim at predicting discrete and continuous values, respectively.

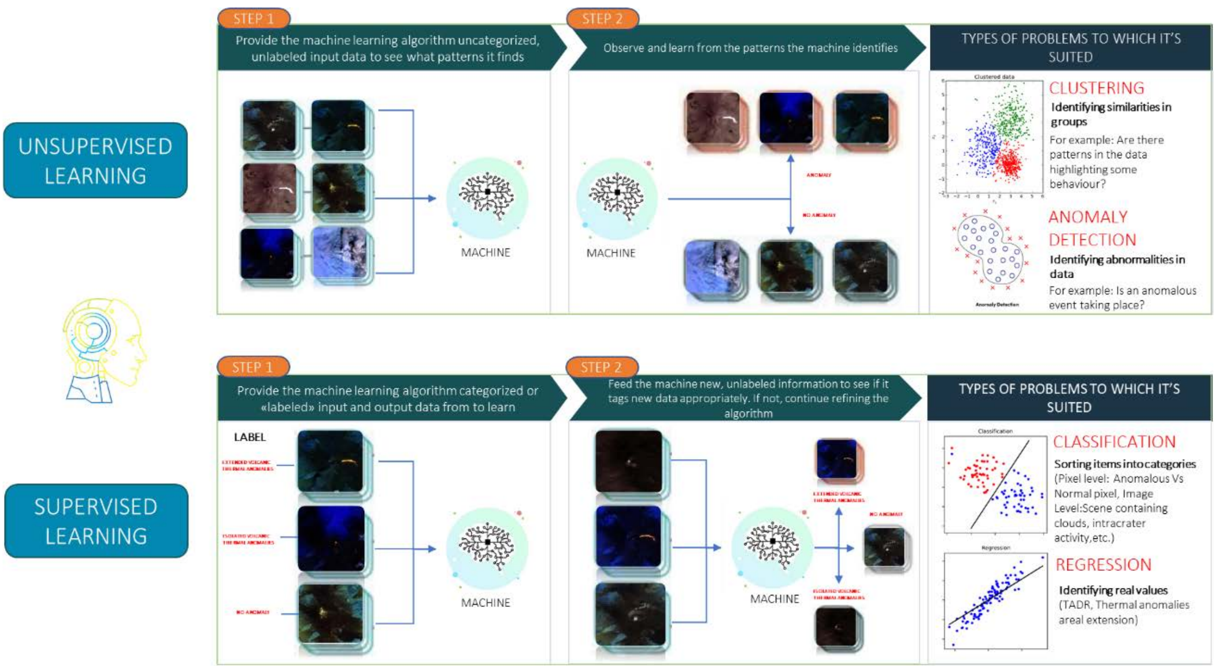

Figure 2. Unsupervised VS Supervised Learning.

3.2 Input selection and features extraction

The algorithm needs data to learn from. Input selection, e.g. appropriately selecting the bands to use for the specific problem, and features extraction are fundamental step. Data needs to be clean, i.e. noise and data artefacts should be removed, and representative for the problem to solve covering the entire learning domain. Experts will select as model input, data that are relevant to the problem based on their knowledge. This is achieved by considering the information discussed in Section 2.2. Coupled input and target dataset need to be collected.

Based on the number of classes (discrete problems) or behaviours/ranges (continuous problems), it is important to use a balanced dataset, i.e. approximately the same number of samples belonging to different class should be considered when training the model. In fact, unbalanced data tend to create polarized model driven towards the most abundant class. Although strategies exist to reduce this effect, it is better to opportunely prepare the data. The dataset will be splitted in Training-Validation and test sets, where the training is used for learning, validation for hyperparameters tuning and test for the final evaluation. This division is usually based on random selection and a splitting ratio of 60-20-20 or 80-10-10. Since the single random spit could bias the model prediction, strategies such as Cross-Validation (CV) could be used. In the basic approach, called k-fold CV, the training set is split into k smaller sets and the model is trained k times using each time k-1 of the folds as training data and validated on the remaining part of the data. The performance measure reported by k-fold cross-validation is then the average of the values computed. This approach is particularly useful in problems where the number of samples is very small.

Then, features need to be extracted to feed the model. As previously stated, while DL model may be fed with raw data and its architecture will allow for automatic feature extraction, traditional ML algorithms rely on a Feature Engineering step where input is mapped into a new representation space that will allow the model to learn and achieve the task. Finally, features with different scales should be normalized in order to improve accuracy.

3.2.1 Features extraction based on Feature Engineering

Feature engineering is the process of using domain knowledge to extract features (characteristics, properties, attributes) from raw data. This task is achieved using a variety of approaches. For satellite image processing, extract spatial information is fundamental in several applications. Traditional methods for satellite data retrieval often consider satellite pixels as separate entities or rely on basic spatial information, such as the neighborhood's standard deviation (Grecu and Anagnostou, 2001). Classic image processing techniques can effectively extract spatial details (Ramsey et al., 2023; Corradino et al., 2024a). For instance, significant spatial information can be derived (1) through the use of predefined filters that highlight specific image characteristics, like the local mean or image gradient; and (2) via image pyramids, which depict images at various resolutions, thus offering a multi-scale perspective of the images. Numerous ML algorithms could be enhanced to be simpler, more resilient, and more understandable by leveraging these traditional methods for feature generation, particularly by utilizing image pyramids along with classic filters to create more robust features suitable for simpler ML techniques, such as support vector machines or random forests instead of CNN.

3.2.2 Feature extraction based on ML models

Unstructured data in its raw form (e.g. text, images) can be ingested into ML models to automatically determines the hierarchy of features. In this case, features are learned by ML models during the training phase. DL algorithm creates its own features during the training process, e.g., CNN learns its own spatial filters, rather than using pre-defined convolution filters from classic image processing. CNNs are a class of NNs that leverage deep locally connected layers to extract discriminative features and classify input data through training. When applied to images, a CNN assigns importance (learnable weights and biases) to various features and captures spatial and temporal dependencies by applying relevant filters (convolutions).The information content in spatial patterns is an important factor in the ability of CNNs to outperform traditional methods (Guilloteau and Foufoula-Georgiou, 2020). The main constituents of a CNN are shown in the representative basic scheme for image classification task in Fig. 3, namely convolution, pooling and classification. The Convolution block reduces the size of the input by applying a spatial filter (usually 3x3) keeping only features that are important in classifying an image. It performs an element-wise multiplication of the kernel with the input image and summing the values, outputs the extracted feature map by sliding the filter on the input image. The Pooling block reduces the size of the feature map further. A common adopted technique is the max-pooling, i.e. the filter slides over the feature map and picks the largest value in a given box. The Classification block, a fully connected layer, receives the flattened extracted map and outputs the prediction.

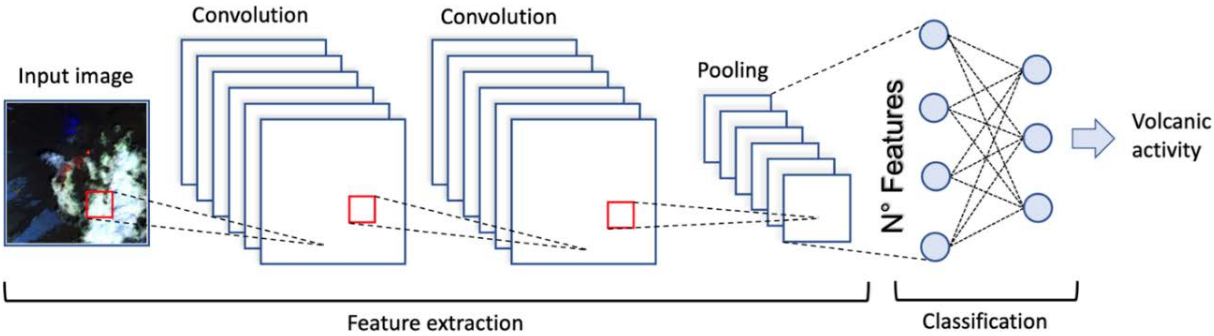

Figure 3. CNN representative basic scheme for image classification task.

Since CNNs use many layers of filters stacked on top of each other that in combination extract patterns, it is not interpretable. Therefore, depending on the needs of the specific application the use of classical approaches rather than CNN can be maximized by using volcanological and mathematically motivated image features first when higher standard of transparency is required or small number of available training samples are available.

3.2.3 Normalization

Normalisation involves rescaling features to a standard range finding a common scale for the data while maintaining the intrinsic variations. It is essential for datasets with different units or magnitudes across different features. Finding a common scale for the data while maintaining the intrinsic variations in value ranges is the main goal of normalization. Z-Score Normalisation (Standardisation) and Min-Max Scaling are two commonly used normalisation techniques adjusting the features to have a mean of 0 and a standard deviation of 1 or 0 and 1 respectively (Henderi et al., 2021). Normalisation is essential to ML for a number of reasons.

Throughout the learning process, it guarantees that every feature contributes equally, preventing larger-magnitude features from overshadowing others. It enables faster convergence of algorithms for optimisation, especially those that depend on gradient descent. Normalisation improves the performance of distance-based algorithms like k-Nearest Neighbours. Normalisation improves overall performance by addressing model sensitivity problems in algorithms such as Support Vector Machines and NNs. Because it assumes uniform feature scales, it also supports the use of regularisation techniques like L1 and L2 regularisation.

In general, normalisation is necessary when working with attributes that have different scales; otherwise, the effectiveness of a significant attribute that is equally important (on a lower scale) could be diluted due to other attributes having values on a larger scale.

3.3 Modeling

The purpose is to teach a ML algorithm to make predictions given the provided training data. Mathematically it means finding the parameters of the model by optimizing an objective function. Therefore, the ML model learns the optimal parameters by minimizing a loss function. The procedure used to carry out the learning process is called the training (or learning) strategy. The learning strategy is applied to obtain the minimum loss possible. This is done by searching for parameters that fit the ML model to the data set. Therefore, the main ingredients for modeling are: training strategy, loss index and optimization algorithm.

3.3.1 Training Strategies

The training datasets must closely resemble the actual problem in terms of feature space and data distribution, as the algorithm can only learn from the effects represented in the training data. This requirement means that training datasets must be large and varied enough to capture even rare occurrences. In practice, acquiring such datasets becomes more challenging as the complexity of problems increases. These challenges can be alleviated through 'transfer learning' (Weiss et al., 2016) which encompasses a range of strategies designed to lessen the required quantity and quality of data while also enabling the utilization of previously gained knowledge rather than starting each learning process from the beginning. While research on the transfer of knowledge for ML is ongoing, the study of continual learning largely operates independently from transfer learning, possessing distinct terminology and methodologies that allow for intriguing comparisons. 'Continual learning' (Wang et al., 2024) is centered on addressing multi-task classification issues with established source and target labels through the use of deep learning methods. In cases of multi-tasking with consistent label spaces, the terms 'incremental learning' or 'lifelong learning' are applied. The objective for both is to learn tasks sequentially without forgetting previously acquired tasks, a challenge referred to as 'catastrophic forgetting,' enabling all tasks to eventually be addressed by a singular deep learning algorithm.

3.3.2 Loss Index

The loss index is essential in the application of NNs. It specifies the task that the NN needs to perform and offers a metric for assessing the quality of the representation necessary for learning. Selecting an appropriate loss index is contingent on the specific application. When defining a loss index, it is important to select two distinct components: an error term and a regularization term (Ciampiconi et al., 2023).

The error term is the most important term in the loss expression. It measures how the NN fits the data set. All those errors can be measured over different subsets of the data, namely training validation and test. There are several different error types that can be used, such as Mean squared error (MSE), normalized squared error, weighted squared error, Minkowski error, Cross entropy error and focal cross entropy. In particular, focal cross entropy loss function addresses class imbalance during training in tasks like object detection. This term is a scaling factor that automatically down-weight the contribution of easy examples during training and rapidly focus the model on hard examples.

The regularization term is added to the error term in order to manage the effective complexity of the NN. This goal is achieved by modifying the contribution of some input variable to get the output.

3.3.3 Optimization algorithm

As said, the learning problem for NNs consists of searching for a set of parameters at which the loss index takes a minimum value. The necessary condition states that the gradient is zero when the NN is at a minimum of the loss index. The loss index is generally a non-linear function of the parameters. Consequently, finding closed optimization algorithms for the minima is impossible. Instead, we consider a search through the parameter space consisting of a succession of steps or epochs, namely an iterative approach. The loss will decrease at each epoch by adjusting the NN parameters. In this way, to train a NN, we start with some parameters vector (often chosen at random). We generate a sequence of parameter vectors to reduce the loss index at each algorithm iteration. The optimization algorithm stops when a specified condition is satisfied. Some stopping criteria commonly used are: the loss improvement in one epoch is less than a set value, loss has been minimized to a goal value, a maximum number of epochs is reached, the maximum amount of computing time has been exceeded, the error on the selected subset increases several epochs, the optimization algorithm determines how the adjustment of the parameters in the NN takes place. Many different optimization algorithms have a variety of additional computation and storage requirements. Moreover, there is no one best suited to all locations. The most used optimization algorithms are: Gradient descent (GD), Conjugate gradient (CG), Quasi-Newton method (QNM), Levenberg-Marquardt algorithm (LM), Stochastic gradient descent (SGD), Adaptative linear momentum (ADAM). For small data sets (10 variables, 10,000 samples), the LM algorithm is recommended due to its high speed and precision. For intermediate problems, the QNM method or the conjugate gradient will perform well. For big data sets (1000 variables, 1000000 samples), the SGD or ADAM methods are the best choices.

3.4 Performance evaluation

In ML, model performance evaluation assesses how well a model is performing at the specific task it was designed for. Performance evaluation can identify things like data drift and model bias, allowing models to be retrained for improved performance. Evaluating model performance is essential to ensure that ML models are both accurate and robust, i.e. models need to generalize well to new data for reliable predictions.

3.4.1 Performance metrics

Different types of ML models use specific metrics for evaluation, depending on the task (regression, classification).

Classification metrics are generally used for discrete outcomes. In order to clearly show how the model predicts each class, a confusion matrix for the model is created. It is made by TP – true positive (the correctly predicted positive class outcome of the model), TN – true negative (the correctly predicted negative class outcome of the model), FP – false positive (the incorrectly predicted positive class outcome of the model), FN – false negative (the incorrectly predicted negative class outcome of the model). This matrix makes clear not only how often the model predictions were correct, but also in which ways it was correct or incorrect. These are some of the most commonly useful classification metrics that can be calculated from the data contained in a confusion matrix.

Performance metrics	Description	Formula
Accuracy	% of the total variables that were correctly classified	(TP+TN) / (TP+TN+FP+FN)
False Positive Rate (FPR)	How often the model predicts a positive for a value that is actually negative	FP / (FP+TN)
Precision	% of the positive cases that were true positives as opposed to false positives	TP / (TP+FP)
Recall	% of the actual positive cases that were predicted as positives	TP / (TP+FN)
F1-score	Harmonic mean of the precision and recall, often used when the class distribution is uneven (where one class significantly outnumbers the other)	2 Precision Recall / (Precision + Recall)
Receiver Operator Characteristic (ROC) and Area Under the Curve (AUC)	It summarizes the trade-off between the true positive rates (sensitivity) and the false-positive rates for a predictive model. ROC yields good results when the observations are balanced between each class	

Table 2. Performance metrics for Classification.

Regression metrics are techniques generally better suited to be applied to continuous output of a ML model. Some of the most useful regression metrics include:

Performance metrics	Description	Formula
Coefficient of determination (or R-squared)	It measures the variance of a model compared to the variance of actual data. It reflects how much of the error is a result in variation in the data rather than of the poor fit.	$\frac{Var(\hat{y})}{Var(y)}$
Mean Squared Error (MSE)	It measures the amount of average divergence of the model from the observed data	$\frac{\Sigma(yi - \hat{y}i)^2}{n}$
Mean Absolute Error (MAE)	It measures the vertical and horizontal distance between data points and a linear regression line to illustrate how much a model deviates from observed data	$\Sigma\frac{\|yi - \hat{y}i\|}{n}$

Table 3. Performance metrics for Regression.

3.4.2 Overfitting and Underfitting

Overfitting occurs when the model works well with the training dataset while it fails to generalize with input data never seen before. This can be observed looking at the score of models on the validation data that would peak after training for a number of epochs and then stagnate or start decreasing. You only get accurate predictions if the ML model generalizes to all types of data within its domain. Overfitting occurs when the model cannot generalize and fits too closely to the training dataset instead. Overfitting happens due to several reasons, including small training data size not accurately representing all possible input data values, noisy training data, long training time on a single sample set of data, too high model complexity leading to learn the noise within the training data. Therefore, overfitting can be prevented accordingly by

- using a bigger and more complete training data covering the full range of inputs
- reducing noise in data and selecting only the most important features within the training set (Pruning)
- pausing the training phase before the ML model learns the noise in the data (Early stopping),
- reducing the model complexity by grading features based on importance (Regularization)
- combining prediction from several separate ML algorithms (Ensemble). Ensemble methods can combine all the weak learners to get more accurate results.
- using data augmentation, a ML technique changing the sample data slightly every time the model processes it, e.g. applying transformations such as translation, flipping, and rotation to input images.

Underfitting occurs when the model can be improved further. Reasons include a too simple model, over-regularization, or it has simply not been trained long enough. Therefore, the relevant patterns in the training data have not been learnt. Finding the right number of epochs is fundamental to avoid under and overfitting.

4. AI-powered volcanic hazard monitoring from space

We are continuously acquiring a variety satellite data to improve our understanding of volcanic processes and our ability to assess hazards. Managing such a massive data set is a challenge. Many automated techniques have been designed to process geospatial data sets with minimal human interference (previously reliant on a-priori defined explicit rules). Extracting meaningful information and gaining new insights from such a large volume of data is a challenging task. Therefore, AI play a key role to gain knowledge from data and extract information on volcanic activity from data. Below applications of ML applied in volcanic hazard monitoring from space are described.

4.1 AI for knowledge retrieval

The vast amount of satellite data available contains valuable information that can be unearthed using ML techniques. This includes uncovering relationships between variables or identifying recurrent behaviors. Unsupervised approaches are particularly suitable for this task as they are not biased by any prior information about the phenomena being investigated. Pattern discovery techniques can be applied to both raw satellite data and processed satellite data, such as extracted volcanological signals. In the following examples, we will showcase the application of AI for pattern discovery in volcano hazard monitoring from space. These approaches leverage the wealth of satellite data to identify patterns and trends that can enhance our understanding of volcanic activity and improve hazard assessment and mitigation efforts.

4.1.1 Investigation on explosive activity on Stromboli

In (Corradino et al., 2021) Paroxysms and Major events at Stromboli volcano are investigated using a clustering technique. Paroxysmal events are rare, occurring approximately five times in the last 20 years. Consequently, the size of the training dataset would be insufficient to employ any supervised technique for their classification. Moreover, some of the major events are not definitively classified by humans. Therefore, a multivariate unsupervised classifier was developed to objectively identify events as either major explosions or paroxysms. The rationale for utilizing a multivariate approach lies in the fact that even seemingly less relevant features can become significant when combined with others, potentially leading to better class separation. For example, even an uncorrelated feature to the target may improve separability between classes. An unsupervised k-means classifier was proposed to automatically differentiate explosive events as either paroxysms or major explosions based on information related to surface temperature of the summit area, plume height, and magnitude of explosive deposits, including pyroclastic flows, ballistics, and tephra fallout. Centroids are defined for both clusters, providing the main values of features characteristic for each class of explosive eruption. These results demonstrate that ML algorithms, when combined with satellite data, have the potential to create an automated system for detecting the intensity of explosive eruptions, even in remote and inaccessible volcanoes. The varying sizes and broad range of intensities observed in the most intense explosive eruptions at Stromboli volcano from January 2018 to April 2021 were classified by combining satellite imagery and ML techniques.

4.1.2 Investigation on volcanic unrest thermal conditions worldwide

The main idea behind anomaly detection through unsupervised learning relies on the fact that the behavior of an observed variable is defined as anomalous when it deviates from its usual behavior. Therefore, by modeling the behavior of an observed variable during normal conditions it is possible to detect anomalies when observations greatly deviate from the model prediction. This approach is unsupervised because anomalies emerge automatically from the incapability of the model fitted on normal data to reproduce the observed anomalous behavior. The choice of the model to fit the data and the criteria to assess how much the anomaly deviates from data depend on the specific application. In (Corradino et al., 2024b) an example of anomaly detection using thermal infrared data is provided. Specifically, Land Surface Temperature (LST) data from MODIS have been used to thermally monitor volcanic activity spanning from pre-eruptive thermal changes due to increasing degassing for instance, to eruption and to erupted deposits. In order to only detect LST anomalies, an unsupervised learning algorithm has been proposed. Specifically, the normal trend has been fitted using Ordinary Least Square algorithm, therefore the difference between the simulated normal trend and the measured one provided a measure of thermal activity being normal when the error was close to zero and high when the error was high. How much high? In order to automatically identify anomalies, an isolation forest was used to isolate anomalous pixels that are easily to be isolated because farer from the nearby observations, thus corresponding to the shorter branch of the tree. This approach intrinsically account for the local relative features since a point is isolated if it deviates from the closer ones that are observed in the same time interval. This method has been shown to be effective in detecting pre-syn and post eruptive volcanic activity.

4.2 AI for automatic data interpretation

Advanced AI techniques exploit not only intensities but also spatial and temporal features of volcanic phenomena to automatically classify satellite images either at image level (classification task) or at pixel level (segmentation task). By learning spatial and temporal features from satellite images, automatic interpretation of data becomes possible, allowing for meaningful insights to be drawn from the images.

4.2.1 Thermal emissions

An example of application in volcanic hazard monitoring from space is the use of CNN to segment thermal images to detect subtle to high thermal anomalies. In fact, Anomaly detection algorithms typically rely on intensity, yet they face challenges in detecting subtle thermal anomalies that may signal changes from steady-state conditions. While high thermal anomalies indicative of intense volcanic activity are easily discernible, subtle thermal changes often blend with the background. The averaging of volcanic thermal emissions over pixel areas often results in values comparable to those of non-volcanic thermal sources. However, volcanic features exhibit distinct spatial characteristics from non-volcanic sources, such as solar radiation. Replicating the mechanisms of the human visual system, which can detect volcanic features by accounting for spatial features like shape and texture in addition to intensity, offers a promising approach. In (Ramsey et al., 2023), Gabor features were employed to replicate this mechanism, achieving impressive performance. This algorithm successfully detected pre-eruptive changes within one week of eruption in 81% (13 out of 16) of known eruption dates. However, explicit rules may struggle to generalize across different scenarios. In this context, CNNs offer a promising approach. In (Corradino et al., 2023), a UNET model was trained with a learning rate of 1e-3, a mini-batch size of 128, four encoder depths, for 100 and 300 epochs using the Adam optimizer to minimize mean square error. The model was also trained to identify clouds and solar radiance as background. The results showed high accuracy (93%) with excellent generalization capabilities. The effectiveness of the model in detecting the full range of thermal emissions was demonstrated across volcanoes with diverse activity styles. Notably, the DL model successfully detected subtle thermal increases in the crater area of Vulcano (Italy) during the 2021 degassing crisis. The qualitative assessment of volcanic threats worldwide is paramount for expediting responses to hazardous events. High spatial resolution satellite sensors offer a means to monitor volcanic features of various sizes and temperatures, providing finer spectral and geometric details of observed phenomena. Different types of volcanic hot spots exhibit distinct spatial and spectral attributes, such as shape, size, brightness, and texture, which can be used to categorize them. This information enables the interpretation of ongoing volcanic activity and allows for the rapid assignment of each condition to a unique category by visual inspection of the scene. The application of CNN models on Sentinel-2 MultiSpectral Instrument (S2-MSI) infrared images proves effective in automatically interpreting volcanic areas in a short timeframe. This approach, as demonstrated by (Cariello et al., 2024b), enables the discrimination among categories such as “No Volcanic Activity,” “Cloudy-Sky Condition,” “Isolated Volcanic Thermal Anomalies,” and “Extended Volcanic Thermal Anomalies.” By leveraging CNN models on satellite imagery, researchers and responders can swiftly assess volcanic conditions and make informed decisions to mitigate risks and ensure public safety. To enhance accuracy, a top-down approach based on a cascading scheme has been adopted. This ML approach combines the strengths of both scene-level deep learning (DL) classification models and pixel-level ML semantic segmentation models. The scene classifier is an ensemble model consisting of 11 SqueezeNet models, each trained using a transfer learning approach. Transfer learning allows for the adaptation of pretrained models’ weights to a new data domain, reducing both training times and data size. When the reliability of a scene prediction falls below a given threshold, a segmentation model is applied. This segmentation model, namely a random forest already trained in (Corradino et al., 2022), is used to verify the reliability of the SqueezeNet outcomes and quantify any thermal anomalies spatially. The cascading ensemble model demonstrates higher performance compared to single ML models, achieving an accuracy of 95%. This improvement results in better and more powerful predictors, rendering the tool suitable for operational use. The model’s high level of accuracy enables the detection of thermal signals that are often challenging to detect with current detectors, thus revealing hidden volcano dynamics.

4.2.2 Ash emissions

During explosive volcanic events, volcanic clouds containing ash and sulfur dioxide (SO_2) are ejected into the atmosphere, posing risks to public health and aviation. It is crucial to track the dispersion and composition of these volcanic clouds for effective risk management (Poland et al., 2020). Geostationary satellite missions currently provide thermal infrared data with high revisit times, enabling the monitoring of volcanic clouds generated during violent explosive eruptions. However, the large volume of satellite data requires automatic and accurate processing algorithms, especially when dealing with observations every 5 minutes on a global scale. The use of ML approaches to identify and track volcanic clouds using EUMETSAT MSG SEVIRI (Meteosat Second Generation – Spinning Enhanced Visible and InfraRed Imager) images has proven to be effective for volcanic cloud segmentation. This approach allows for the automatic and accurate detection of volcanic clouds in satellite imagery, facilitating timely responses to volcanic hazards and enhancing public safety. In (Torrisi et al., 2024), a DL model was developed using a hybrid architecture known as VGG16-UNet, which combines the strengths of a VGG16 model (reduced complexity, fewer parameters, and easy access to parameter weights) with the benefits of a traditional UNet, particularly in image segmentation tasks. This model leverages spatial and spectral intensity information primarily from SEVIRI Ash RGB images to segment volcanic clouds, achieving an impressive F1-score of 91%. Once the volcanic cloud is identified, a supervised ML model can be employed to discriminate pixels containing ash or sulfur dioxide (SO_2). In (Torrisi et al., 2022), a support vector machine (SVM) was trained on a set of SEVIRI Ash RGB samples to classify the main components of a volcanic cloud, distinguishing between ash-rich, SO_2-rich, or mixed-component pixels. By combining the detection DL model and the characterization ML model, entire volcanic events can be detected and tracked using SEVIRI high temporal resolution satellite images. This approach enables the monitoring of volcanic cloud evolution in near real-time, allowing for a better understanding of which regions may be most affected by its impact. Emissions of ash and SO_2 can pose significant hazards to public health, making it crucial to monitor their dispersion. Moreover, this ML approach facilitates the retrieval of important parameters essential for characterizing volcanic cloud evolution, such as the cloud's area coverage, travel distance, spread direction, propagation speed, and height. Applied on a global scale, this approach can efficiently track the evolution of volcanic clouds in near-real-time, processing extensive satellite datasets to provide rapid availability of results. As a result, valuable insights can be derived regarding the dispersion of volcanic clouds, aiding in the understanding of their potential impact on the surrounding environment and climate.

4.2.3 Gas emissions

Magmatic gases, particularly sulphur dioxide (SO_2), play a crucial role in influencing eruptive styles, making the monitoring of SO_2 emissions essential. Recent advancements in satellite remote sensing technology, including higher spatial resolution and sensitivity, have enhanced our ability to detect SO_2 emissions from volcanoes worldwide. Recent technological advancements have significantly enhanced the capability to identify SO_2 emissions through satellite remote sensing, thanks to the introduction of sensors with higher spatial resolution and sensitivity. These improvements have enabled the detection of previously undetectable SO_2 emissions and the global monitoring of volcanoes, proving particularly crucial in areas that lack ground-based instruments. Numerous studies have demonstrated the potential of ML for SO_2 detection, including approaches involving NNs (Piscini et al., 2014). Accurately quantifying SO_2 is not a trivial task because of the strong dependence on plume height, especially when it reaches high altitudes. In (Corradino et al., 2024a) an AI algorithm is applied to TROPOMI (Tropospheric Monitoring Instrument) satellite UV data that uses a Random Forest (RF) model for near real-time identification of volcanic SO_2 plumes, followed by the integration of the TROPOMI Cloud Top Height product to quantify SO_2 masses within the plumes. The RF model was trained using satellite images of SO_2 emissions from Mt. Etna. The model was applied to the entire period from 2019 to 2023 and compared our results with published data for Mt. Etna volcano. Furthermore, to assess the reliability of our RF approach, it was tested on other volcanoes (Villarrica, Cumbre Vieja, Fuego, and Pacaya), characterized by different volcanic cloud geometries and amounts of emitted SO_2. The proposed AI approach is fully developed in Google Earth Engine (GEE), a cloud-based geospatial analysis platform that enables users to visualize and analyze satellite images at a planetary scale.

4.2.4 Deformation

Interferometric Synthetic Aperture Radar data can detect surface deformation strongly linked to eruptions. In (Anantrasirichai et al., 2018), a ML algorithm is applied to short-term interferograms from Sentinel-1SAR at over 900 volcanoes to automatically detect volcanic ground deformation. A CNN is used to classify interferometric fringes in wrapped interferograms with no atmospheric corrections. A transfer learning strategy is adopted and different pretrained networks are tested with the AlexNet being the best one. The positive results are checked by an expert and fed back for model updating. Following training with a combination of both positive and negative examples, this method reduced the number of interferograms to ~100 which required further inspection, of which at least 39 are considered true positives. ML can efficiently detect large, rapid deformation signals in wrapped interferograms. This study was the first to use ML approaches for detecting volcanic deformation in large data sets and demonstrates the potential of such techniques for developing alert systems based on satellite imagery. In (Beker et al., 2023), subtle volcanic deformations are automatically detected using interferometric Synthetic Aperture Radar (InSAR) from Sentinel-1SAR and a deep learning model discriminating them from other deformation types in five-year-long InSAR stacks. Models are trained on a synthetic training set. A CNN has been trained to perform InSAR analysis differentiating also between different styles of volcanic deformation, and by determining the spatial size of a deformation signal (Gaddes et al., 2024).

5. Discussion and conclusions

5.1 Challenges and Opportunities

Satellite data provide synoptic views of volcanic activity that might not otherwise be possible due to location, hazards, and/or environmental conditions. These data support such societally important applications as tracking ash clouds, recognizing eruption precursors (like thermal or deformation anomalies), and assessing variations that might indicate changing hazard conditions in ongoing eruptions. These advantages are best displayed at volcanoes where ground-based monitoring is limited or nonexistent – a condition that is more common than not (Poland et al., 2020). However, sensor technology, human, and data volume limitations represent the main challenges to a greater exploitation of satellite data in volcanology. The transition to data-driven science has revolutionized our ability to extract valuable insights from vast volumes of satellite data, enabling us to better understand volcanic dynamics and improve hazard assessment and mitigation efforts. While in the past significant barriers to the acquisition and analysis of satellite remote sensing data limited their potentiality for volcano monitoring, the advent of advanced computing resources and AI techniques allowed a significant boost on a global scale. Cloud-computing has allowed to facilitate free access to satellite imagery and analysis of different types of imagery requiring knowledge of numerous data formats and expertise. Open access data archives through cloud services allow for readily access to massive volume of satellite data being acquired over volcanoes. Whereas examining this quantity of data is difficult, or perhaps impossible, with traditional approaches, the use of ML has allowed to retrieve information from such volume of data through the combined use of advanced computational resources that, when not available locally, are provided by cloud computing platforms. The use of unsupervised algorithms allows to discover volcanic behaviors from data without explicit expert supervision paving the way towards better understanding of volcanic processes. As regard sensor technology limitations, ML has shown to be valuable in taking the most from data overcoming intrinsic limitations due to data in some cases. For instance, even though limited pixel sizes make the detection of low-level thermal anomalies during passive degassing challenging, the use of CNN allows to exploit complex spatial features allowing discrimination from same-intensity artefacts like solar radiation. Accurate detection of such signals allows for the emergence of pattern otherwise never seen using traditional approaches (Corradino et al., 2023). Nevertheless, sensor technological barriers are still present such as thermal and visible sensors that cannot see through thick cloud cover and have limited spectral resolution, InSAR data suffering with artifacts caused by atmospheric water vapor and coherence loss. New missions aim to reduce these physical limitations, e.g. Surface Biology and Geology (SBG) (Ramsey et al., 2022). Differently from the past when volcanology took advantage of any space-based resources to detect volcanic eruptions since no satellites sensors were designed with volcano surveillance in mind, the SBG team has designed Orbiting Terrestrial Thermal Emission Radiometer (OTTER) sensor considering volcano monitoring as one of the scientific objective (Thompson et al., 2023). This has been highlighted by the NASA Decadal Survey, where the future of volcano monitoring from space as part of the objectives is outlined. An elevated temperature product and a volcanic product have been planned whose running algorithm candidates also include ML models (Ramsey et al., 2023). Finally, remote sensing data from volcanoes must ultimately be considered in combination, rather than independently. Attempts in this directions have been performed combining infrared and radar data to map lava flows and to assess explosive eruption magnitude. However, a further step needs to be performed in this direction by combining satellite sensors with different temporal, spatial and spectral resolution. The use of ML will be fundamental to efficiently merge them representing a new integrated frontier in volcano science and surveillance. The use of 4D input datasets, namely spatial along two dimensions, temporal, and spectral will be fundamental for a synoptic interpretation of the monitored volcanic activity. The creation of innovative data fusion methods and the adjustment of AI frameworks that can efficiently utilize this data, like transformers, presents new possibilities. The "attention-based mechanism" related to the idea of contextual temporal-spatial information will allow to highlight behaviors previously missed. ML technology used in the field of volcano monitoring from space will explore the possibility of predicting volcanic behavior by merging satellite temporal-spatial-spectral information. Additionally, the constraint caused by the absence of a method to guarantee the physical consistency of ML models will be tackled by Physics-Informed NNs, which allow for the integration of physical laws into the learning procedure.

5.2 Future frontiers: Quantum Computing and Quantum ML

In response to the need for advanced processing techniques to manage high-resolution Big Data, EO is now exploring novel computational technologies. Certain AI challenges that involve large, complex, and diverse EO datasets present insurmountable computational issues for traditional high-performance computing (HPC) systems. This is where quantum computing (QC) is set to be essential by utilizing the distinct characteristics of quantum mechanics to carry out specific calculations at an exponentially faster rate than classical computers (Ramezani et al., 2020; Steane, 1998). The computational complexity conjecture establishes distinctions among computational problems based on their difficulty, considering the necessary resources for both classical and quantum computation. In particular, the "polynomial time" (P) computational problem is easy to solve for both quantum machines and classical computers, the "Bounded error, Quantum, Polynomial time" (BQP) computational problem is easy for quantum machines with a bounded probability of error but hard for classical machines, and the "nondeterministic polynomial time" (NP) computational problem is hard for classical computers as well as quantum machines. Therefore, merging the computational capabilities of quantum computing with the learning abilities of AI will elevate the potential of AI to unprecedented heights. The fundamental unit of information that represents data in quantum computing is called a qubit, which is one of the simplest quantum entities that exhibit the unique characteristics of quantum mechanics (Sakurai et al., 2020). Essentially, it operates as a two-state quantum system, such as an electron that can occupy two energy levels (spin up and spin down) or a photon that may be in one of two polarization states (vertical and horizontal). Unlike a classical system where a bit can exist in only one state at a time, a qubit is capable of existing in a coherent superposition of the two states at the same time, a key feature of quantum mechanics. For n qubits, it is possible to represent 2^n different states, which represents an exponential advantage compared to classical systems that can only represent n states using n bits. Quantum registers are capable of managing significantly more data than their classical counterparts; while a classical bit register can store a binary string of size n, a n-qubit register can store a binary string of size 2^n by representing information in amplitudes, which offers inherent parallelism and a substantial speed advantage over classical algorithms. Therefore, QC offers unprecedented levels of parallelization, exponential speedup and enhanced AI capabilities, i.e. ML tasks require the capability to process vast amounts of data as efficiently as possible. Realizing this advantages typically necessitates the effective loading of classical data into quantum states. Since quantum machines operate only with data encoded in quantum states, classical data must first be transformed into this quantum format. In (Zoufal et al., 2019), a hybrid quantum-classical algorithm is used for efficient, approximate quantum state loading, namely a quantum Generative Adversarial Networks (qGANs) facilitating efficient learning and loading of generic probability distributions – implicitly given by data samples – into quantum states. Therefore, Quantum ML (QML) algorithms manipulate the quantum states in order to understand the underlying patterns and learn about the data. The application of quantum technology for remote sensing has been considered for at least last 20 years including studies solving challenging EO problems with QML. In (Sebastianelli et al., 2022) quantum computers are used to enhance the performances of ML algorithms when applied to land-use and land-cover classification, where quantum CNNs (QCNNs) are considered for accelerating geospatial data processing. Unlike traditional CNN architectures, the chosen QCNN updates the standard NN with a quantum layer and the hybrid QCNN has proven to be effective in terms of multiclass identification and computing efficiency. Applications of QML in the volcanology field has not been shown yet and will surely represent a steps forward in EO data-driven discovery for volcanic hazard problems. Although the promising capabilities of QC for EO that will advance, lots of research and work need to be done to face QC technological limitations including noise and limited error correction.

6. Conclusions

The potentiality of AI and innovative technologies to process satellite data to address critical challenges in volcanic hazard monitoring has been explored. The combination of advanced AI techniques, satellite data, and cloud computing has significantly enhanced our ability to monitor volcanic activity on a global scale. The next research frontiers will be focused on exploiting the power of generative AI to better understand volcanic hazard problems from space. Building knowledge from the heterogeneous big EO dataset to better understand volcanic systems will be one of the main objective of the volcanology communities. The development of ever more efficient High Performance Computing (HPC) systems, the advent of Quantum Computing (QC), the rapid progress in satellite on-board processing capabilities all present an indisputable opportunity to push the boundaries of AI applications in the Earth system sciences. By automating data analysis and pattern discovery, we can better understand volcanic mechanisms, enhance early warning systems, improve hazard assessment, and mitigate the impacts of volcanic eruptions on society and the environment.

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