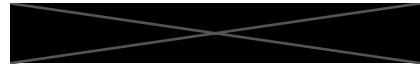# Autonomous Detection of Volcanic and Seismic Hazards Associated with InSAR Deformation Using Deep Learning

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Abstract

As New Zealand has multiple active volcanoes and is located near a tectonic plate boundary, therefore it is important that ground deformation is monitored effectively to reduce both volcanic risk and seismic risk. Satellite radar imagery (InSAR) is the primary tool for measuring millimetre level movements over large distances, but there are several challenges that limit the ability to use this tool operationally. First, the quality of the images can be affected by atmospheric effects; second, the amount of data that must be processed is large; and third, the interpretation of the data requires trained experts. At the same time, there is evidence that using artificial intelligence (AI) can be used effectively to identify patterns and anomalies within complicated datasets (geophysical). This literature review combines several of the available studies regarding the application of artificial intelligence to detect potential volcanic and seismic hazards in New Zealand, as well as some other geographic areas around the world.

The literature search produced over sixty articles, which have been categorized in the following manner: traditional InSAR processing, deep learning algorithms (supervised and unsupervised), the generation of synthetic datasets, multi-temporal analyses using InSAR, and the combination of InSAR with other types of geophysical data such as seismic, GNSS, thermal imagery, and gas emissions. Comparative tables are provided for evaluating different types of AI algorithms (convolutional neural networks, autoencoders, recurrent and transformer network models) and platforms that allow for continuous operational monitoring. In addition, this review suggests that there has been a gradual shift from conventional supervised classification of images to an emphasis on detecting anomalies using hybrid models developed from large datasets containing both real and synthetic data.

Keywords: AI (Artificial Intelligence); DL (Deep Learning); CNN (Convolutional Neural Network); GAN (Generative Adversarial Network); XAI (Explainable Artificial Intelligence); GNSS (Global Navigation Satellite System); TVZ (Taupō Volcanic Zone); NZ (New Zealand).

Chapter 1

Introduction

As a result of being located on an active boundary between the Australian and Pacific tectonic plates, New Zealand is subjected to frequent seismic activity and high levels of volcanic activity. Approximately 14,000 earthquakes occur each year, and of these, approximately 150–200 are large enough for people on the surface to feel them [1], [2]. Although many of the earthquake events are minor in magnitude, large earthquakes such as the Christchurch Mw 6.2 earthquake on February 22nd, 2011, which caused 185 fatalities and severe damage to infrastructure, illustrate New Zealand's susceptibility to seismic hazards [3].

New Zealand also has a significant risk of volcanic hazard due to the concentration of most recent volcanic activity in the Taupō Volcanic Zone (TVZ). Within this zone is a number of major caldera systems, including Taupō and Okataina, numerous active volcanoes including the cone volcanoes Ruapehu, Tongariro/Ngauruhoe and Whakaari/White Island [4], and a recognised difficulty in providing timely warnings to communities at risk from volcanic eruptions. The most recent major volcanic eruption was that of Whakaari on December 9th, 2019; the eruption resulted in the deaths of 22 people, including both tourists and guides [5].

Through the GeoNet programme, New Zealand has developed a sophisticated operating system to collect and distribute data from multiple national sensor networks (seismic and GNSS/GPS) in addition to visual cameras for monitoring activity along fault lines and volcanoes [6]. In the past few years, there has been a rapid increase in satellite remote-sensing data being generated from missions [7], including Sentinel-1 and other Synthetic Aperture Radar (SAR) platforms, which produce large volumes of global, oppositely-arranged interferometric synthetic-aperture radar data (InSAR) time series that allow for the detection of millimetre-scale ground movement over large geographical areas [8]. However, converting these cluttered and extensive datasets into accurate near real-time hazard information continues to be a substantial operational and scientific challenge to overcome.

In light of these factors, this study reviews the literature to critically assess the use of deep learning and multi-modal methods to autonomously identify volcanic and seismic hazards through analysis of InSAR deformation data and focus on New Zealand's environmental monitoring.

Chapter 2

Background and Review Methodology

The selection and organization of the literature review for determining the Most Relevant Literatur was done using a Structured Search and Selection Process which focused on deep learning-based InSAR deformation detection literature. [6] Given the rapid advancements in AI, the literature review was limited to only Peer Reviewed Journal Articles and Conference Papers published between five years. [9], [10] The selected literature must have included Research Studies from at least one of the following categories [11]: Research on Machine Learning or Deep Learning applications for InSAR-based Deformation Detection [12]; Research on Multi-Sensor and/or Multi-Modeled Volcano and/or Seismic Monitoring that included InSAR as one of the main components [13]; Research Studies from New Zealand or Tectonic and Volcanic Environments that have similarities to New Zealand; and Research on Infrastructure Monitoring Systems, Atmospheric Correction, and/or Synthetic Data Generation design principles that are strongly related to the Construction of DL-InSAR systems [14].

Study were excluded from this literature review if they were theoretical treatments of InSAR processing that did not provide a direct connection with hazard detection data. This included studies that focused only on algorithmic approaches, such as algorithms for phase unwrapping or conventional time series inversion [15], as well as those that presented general computer vision and deep learning architectures with no geophysical or remote sensing application [5], [16]. This ensured that the literature review focused exclusively on works that relate to the autonomous detection of volcanic and seismic hazards.

By using these criteria works were classified into several thematic categories to facilitate the understanding of these works. Background on the types of hazards associated with volcanic and seismic activity, the InSAR process for hazard detection in New Zealand [6] [9], early automated methods of detecting the deformation associated with volcanic and seismic activity [12], deep learning approaches for InSAR image and time series analysis, multimodal fusion of InSAR and seismic, GNSS, optical, thermal, and gas observations [13], operational platforms used to demonstrate the operation of these systems on a large scale and finally, the challenges, limitations and gaps in our understanding of these systems [14] [17]. The thematic classification of these works will serve as the scientific framework of this review and is consistent with the desire to provide a thorough overview of the literature, to provide an evaluative study of the works to assess the appropriateness of using the methods selected from this review as the basis for the proposed research literature.

Chapter 3

Literature Review

3.1 Volcanic and Seismic Hazards, InSAR and the New Zealand Context

3.1.1 Volcanic and Seismic Risk in New Zealand

With eight caldera-type volcanoes and several often active cones (Taupō, Okataina, Ruapehu, Tongariro, and Whakaari), New Zealand's Taupō Volcanic Zone is regarded as one of the world's most active volcanic regions [18].Ashfall, pyroclastic flows, lahars, gas emissions, and ground deformation are only a few of the many possible risks caused by these volcanoes.

New Zealand experiences over 14,000 earthquakes annually, of which between 150 and 200 are felt by the general population [19]. Significant earthquakes, including those in Canterbury (2010–2011) and Kaikōura (2016), have resulted in significant damage, fatalities, and long-term social and economic repercussions. According to the information above, testing sophisticated hazard detection systems in New Zealand is a top priority. An autonomous detection system must work within the context of the New Zealand Volcanic Alert Level system, be compatible with the current GeoNet operation [20], and be resilient to local environmental circumstances (vegetation, snow, and difficult terrain).

3.1.2 InSAR for Ground Deformation Monitoring

InSAR estimates surface changes over wide areas with accuracy ranging from centimeters to millimeters using phase differences from many SAR photos. Early research demonstrated InSAR's capacity to record displacement fields using radar interferometry, such as the mapping of the Landers earthquake [1]. Applications for faults, volcanoes, groundwater extraction, and human-caused land subsidence were later added in this work.

For a large portion of the planet, satellite missions like Sentinel-1, ALOS-2, and other commercial constellations frequently produce InSAR time series. [2] The creation of interferograms, unwrapping stages, [3] filtering, stacking, and time-series analysis (e.g., SBAS and PSI) are all summarized in reviews [4] [5]. Large-scale InSAR processing and automated systems like MOUNTS [6] show how these methods can be extended [8].

However, noise, decorrelation, and air delays frequently outweigh the real ground deformation [9]. Although atmospheric effect correction techniques [10] like weather models, GNSS, and more recently deep learning (TropoDeep) [11] have improved accuracy, they have not entirely eliminated ambiguity. According to certain research, analyzing hundreds of thousands of interferograms [12] is still laborious and subjective.

These difficulties motivate the use of deep learning, which will be discussed in the following sections, to identify patterns and anomalies in InSAR.

3.2 Traditional Automated Detection vs Deep Learning Approaches

3.2.1 Traditional and Classical Machine Learning Methods

Statistical thresholds, clustering, and conventional machine learning methods were the mainstays of early automation attempts. For instance, identified regions of strong gradient in interferograms using region expanding and pixel-wise thresholding [21]. In the meanwhile, used support vector machines with manually created feature descriptors [22], such as phase gradients and texture measurements, to distinguish atmospheric artifacts from deformation. Similar to this, found distinct deformation signals in time-series stacks using principal component analysis [23] and unsupervised grouping. Nevertheless, these techniques mostly relied on meticulous parameter optimization and manually created characteristics. They frequently had trouble with complicated, non-Gaussian noise, particularly tropospheric effects in mountainous regions [24]. They also had to deal with non-linear or multi-episode deformation histories that were difficult for basic time-series models to represent. Global scalability was constrained since decision criteria that were optimized for one volcano typically did not function well for others.

3.2.2 Emergence of Deep Learning for InSAR

End-to-end feature learning is possible with deep learning. [13] Without the requirement for explicit feature engineering, it can automatically identify helpful temporal and geographical patterns. Supervised CNN classification of interferograms [25] and unsupervised autoencoders for anomaly identification [26] were the main focus of the first systematic attempts to apply deep learning to volcano-related InSAR.

Table 1: Traditional vs Deep Learning Approaches for InSAR Deformation Detection

Feature	Conventional ML	Deep Learning
Feature extraction	Manually Crafted(gradients, textures, phase stats)	Automatically learned using Data(CNN filters, embeddings)
Handling of noise	Susceptible to Atmospheric Artifacts	Learns to ignore Many Common Noise Patterns
Temporal modelling	Non or Basic Parametric Models	Recurrent Neural Networks, Long Short Term Memory, Temporal Convolutions, transformers
Data requirements	Small Dataset Supported	Larger, labeled or synthesized datasets required
Scalability / Automation	Limited to Generalization across Volcanic Regions	Demonstrated global frameworks [12]
Interpretability	Rules based on human reasoning	Requires Explainable AI tools(saliency, attention maps)

While deep learning does not eliminate every obstacle, it offers a more adaptable foundation for independent, worldwide InSAR evaluation

3.3 Deep Learning Models for InSAR-Based Hazard Detection

The primary deep learning model families used for InSAR deformation are reviewed in this part, along with their advantages and disadvantages in relation to the research objective.

3.3.1 Supervised CNNs for Interferogram Classification and Localization

Convolutional neural networks, or CNNs, have been used to locate areas of deformation and distinguish between deformation and non-deformation in interferograms.

A thorough study in this field was provided in [13], which created training examples for a CNN by combining realistic air noise with simulated volcano deformation interferograms. By applying these models to actual Sentinel-1 data, the scientists showed that some of the problems caused by a lack of annotated deformation events were lessened by utilizing synthetic training data. Expanding on this idea, [25] talked about using CNNs to detect volcanic deformation in regularly produced Sentinel-1 interferometric photos of several volcanoes. Furthermore, by categorizing and localizing various deformation types discovered in the VolcNet database, [14] enhanced the earlier research. Global ecosystems can benefit from the application of deep learning and machine learning. Large-scale experiments in these sectors have shown their limitations, nevertheless. Over 600,000 Sentinel-1 radar photos from all over the world, including over 1000 volcanoes, were used to test a machine learning classifier [27]. In addition to recognizing some non-volcanic signals among the most likely interferograms, the classifier was able to identify those interferograms that showed possible volcano deformation, as confirmed by expert evaluation, by the volcanic eruptions that came from subliming and slow deformation. Because of air artifacts and unmodeled noise, the results also demonstrate a significant incidence rate of false positives, even though these kinds of automated classification of global data are feasible [12].Similarly, while CNNs (convolutional neural networks) are commonly used to detect slow and subtle movement, research has shown [16] that a deep learning-based method can accomplish this by concentrating on signals with a millimetre of movement per year within a Central Volcanic Zone location, whereas [28] combined CNN and synthetic training sets when applying CNNs to detect slow volcanic deformation with regard to tectonic and anthropogenic signals.

3.3.2 Autoencoders and Unsupervised Anomaly Detection

The absence of labeled data sets makes unsupervised techniques attractive because real deformation occurrences are rare in volcanology.

Cohen and colleagues employed an autoencoder network that was trained on several InSAR time series patches that they described as typical or "normal" behavior. These Deep Autoencoder models demonstrated the ability to detect slow earthquakes with deformations as small as 2mm by automatically identifying deformation signals as reconstruction errors when applied to InSAR data gathered from the North Anatolian Fault and other regions. Building on these findings, [17]suggested an unsupervised anomaly identification framework for volcanic deformations that used a variety of architectures, including PaDiM and Generative Adversarial Models (GANomaly and diffusion models), to model InSAR patches. When used in a volcanic scenario, this method treats deformation as an anomaly in a normal baseline and yields encouraging outcomes.

An alternative method produced time-based embeddings of normal behavior with flags or alerts for any observed transitory anomalies by combining Autoencoder networks (Autoencoders plus LSTM) in the ALADDIn framework. The approach's capacity to detect localized transient deformation in the absence of labeled training data was confirmed by extensive testing employing a noisy processing method to unwrap the InSAR time series [29]. The most recent study expanded the use of this type of unsupervised anomaly identification to include volcanic deformations by incorporating domain knowledge to enhance performance through comparison with extracted deformation catalogs and preprocessing.

As an evaluated Unsupervised methods, are scalable to large datasets (such as global archives) and prevent dependency on labeled deformation occurrences. And intrinsically in line with the NZ monitoring methodology's goal of automated and autonomous anomaly detection. [30] And nevertheless extremely susceptible to variations in the instrument's noise level, changing atmospheric conditions, and prolonged human-caused changes that may also manifest as abnormal behaviors. Unsupervised autoencoders and anomaly approaches are particularly appealing in the context of New Zealand because they require less manual labeling by local experts in order to train on sizable InSAR archival datasets.

3.3.3 Time-Series Models: RNNs, LSTMs and Temporal CNNs

Many scholars have created temporal models as part of their analytical methods since deformation varies throughout time. Examples include the application of [31] recurrent neural networks (RNN), which tackle the problems caused by missing and unevenly spaced data and were utilized to eliminate atmospheric noise from InSAR time series. In a similar vein, [32] created a Deep Learning-based time-series prediction model to forecast mining-related subsidence and demonstrated that it performed better than conventional forecasting techniques. Additionally, [33]created an AL-ADDIn framework that combines an autoencoder with long short-term memory (LSTM) networks to simultaneously predict spatial patterns in interferograms with temporal variations in deformation. These temporal models are especially useful for monitoring extremely sluggish, protracted disturbance (inflation may take months to emerge). [30] Additionally, these temporal models are highly helpful in distinguishing longer-duration trends from shorter-duration deformation events. However, because these temporal models need longer temporal windows to reach high levels of accuracy, they do tend to complicate the mathematical models that researchers utilize and will raise the cost of computing the results. Essentially, a crucial trade-off for researchers creating sufficient prediction capacities for risks related to volcanic instability will frequently be attaining high levels of accuracy while retaining some degree of timeliness in the post-analysis.

3.3.4 Vision Transformers and Prototype-Based Learning

Originally designed to process language, transformers have recently been modified to address a variety of image and geospatial issues: [34] developed a method called Vision Transformer-ViT, which is a model that classifies single wrapped interferograms of volcanic activity using synthetic interferograms. Phase unwrapping, which can result in mistakes, is eliminated by the ViT model, which considers every patch in an interferogram and employs self-attention to encode long-distance spatial relationships.Another innovation presented in [34] was a domain adaptation technique that allowed the researchers to achieve an impressive detection accuracy of roughly 97% on their test set by fine-tuning the prototypes created from the synthetic datasets using pseudo-labels derived from the real data. According to the researchers, this offers intriguing opportunities for New Zealand, where the application of synthetic InSAR may be useful in assessing the probability of volcanic deformation at volcanoes that do not yet exhibit any indications of instability. By utilizing multi-head attention, other researchers [35] have also demonstrated that transformer-based architectures can outperform CNNs on a variety of intricate spatial and temporal patterns [36]. because they are able to comprehend a global spatial structure instead of merely focusing on local areas using CNNs' local filters. Additionally, because there are fewer real-world deformation events accessible, they are probably going to gain more from the use of synthetic training data and Domain Adaptation. Transformers need a lot of computing power and have a voracious thirst for data. By using pre-trained models and creating designs that already exist in a patch format, the latter can be significantly reduced.Taking into account all of these aspects, it is evident that Transformers are excellent options for the detection system's image-related component when combined with anomaly detection techniques or temporal modeling to fully utilize the time-series component.

3.3.5 Generative Models and Synthetic Data

Generative Adversarial Networks (GANs) and related generative models have been widely used in InSAR applications. They can create artificial interferograms to supplement training data [13] [28] [34] denoise or super-resolve atmospheric and InSAR fields (TropoDeep, for instance, employs SRGAN-like architectures for tropospheric corrections [11], and be included into unsupervised anomaly detection frameworks [17]. High-fidelity synthetic data may span a wide range of deformation geometries, source depths, and noise conditions, which is the primary benefit of these techniques. This makes it possible for models to acquire rich feature representations even in situations when there are few actual tagged events. Future hazard-monitoring pipelines are anticipated to include generative AI as a key component, according to reviews of synthetic data generation in remote sensing [37]

Table 2: Comparison of Major Deep Learning Architectures for InSAR Deformation

Architecture Type	Typical Task	Advantages	Limitations / Risks	Key Examples
CNN classifiers	Deformation vs no-deformation, multiclass	Simple, fast; strong spatial feature extraction	Needs labelled data; sensitive to domain shift	[13], [25], [14]
Autoencoders	Unsupervised anomaly detection	No labels needed; good for rare events	Can confuse slow trends/noise with anomalies	[26], [17]
CNN + LSTM (hybrid)	Time-series anomaly detection	Uses spatial + temporal context	Complex training; higher compute	[33], [31], [32]
Vision Transformers	Single-image classification/localisation	Captures long-range interactions; good with synthetic data	Requires large training sets; heavy models	[34], [36]
GANs / generative models	Synthetic training data, denoising	Data augmentation; improved robustness	Training instability; evaluation difficult	[13], [17], [37]

3.4 Multi-Modal Sensor Fusion for Hazard Detection

By itself, InSAR is unable to fully distinguish between atmospheric noise and deformation or collect all pertinent antecedents. Multi-modal fusion tries to mix InSAR with other data sources.

3.4.1 InSAR + Seismic Data

Attention-based architectures are used by deep learning models for earthquake detection, such as the Earthquake Transformer [38], to simultaneously choose phases and identify earthquakes in worldwide seismic datasets. Another neural network approach, EdgePhase [39], selects phases using graph-based multi-station input data. While both models are centered on seismology, they incorporate concepts of design for processing time-series data from many sensors, which could be beneficial for integrated InSAR-burial (Interferometric Synthetic Aperture Radar)-Seismic systems. At volcano locations, seismicity often happens either before or at the same time as deformation. In order to provide a relevant, comprehensive dataset, MOUNTS [6] and other frameworks that synthesize numerous sensors [12] [40] combine a variety of seismic catalogue entries with InSAR, thermal, and gas data. For example, studies [41] [42] demonstrate that combining deformation with seismic swarm features (such as their frequencies, types, and extremes) might improve the classification of different kinds of volcanic unrest.

3.4.2 InSAR + GNSS and Tropospheric Correction

GNSS is used in numerous applications in New Zealand that require accurate point measurements of displacement in both vertical and horizontal directions. Furthermore, in areas where SAR density is high, the GNSS time series can be integrated with InSAR data to give a method for calibrating deformation rates, detecting biases, and validating anomalies. The approach named TropoDeep [11] is the only solution now available that leverages GNSS and WRF Model Output from the weather forecast system as input data to a neural network that will predict tropospheric delays [43] , and hence improve InSAR's capacity to produce displacement estimations. Research has showed that after each of the GNSS stations was adjusted using TropoDeep, the RMSE reduced roughly 10–29% compared to the earlier estimations.

3.4.3 InSAR + Optical, Thermal and Gas Data

Sentinel-2 SWIR pictures (for identifying thermal abnormalities), Sentinel-5P TROPOMI files (for measuring SO_2 emissions), and worldwide seismic catalogues are only a few of the data sources that

are integrated by volcanic monitoring systems like MOUNTS [6] [40]. Thresholding (classically) and deep CNNs [44] are capable of identifying active vents and lava flows as well as temperature anomalies. It is possible to distinguish between non-magmatic subsidence/uplift and magmatic inflation when combined with deformation data.

When accessible, gas measurements can offer more details about the hydrothermal or magmatic genesis of unrest. While machine learning methods and traditional inversion approaches [40] [44] are being used more frequently, deep learning on gas time series data is still in its infancy.

3.4.4   Practical Challenges in Multi-Modal Fusion

Although multi-modal fusion offers enormous potential, it also brings numerous obstacles. Each type of sensor (satellites, GNSS, seismic, cameras, etc.) has a unique sampling frequency and is not always synchronized to the same point in time [45]. Geographically (or spatially), different types of sensors (e.g., cameras, seismic networks, etc.) collect information at varying levels of detail; some may provide measurements at a single point, while others may provide raster images over a broader area. Because of this, data from each type of sensor must be properly time-aligned and spatially co-registered before being integrated.In addition to the challenges of synchronizing several types of sensors, connection and bandwidth limits restrict access to all available data sources (e.g., streaming) when processing data from remote volcanoes in near-real time [6]

When many sources of data are merged without regard for the accuracy and uncertainty of each source, the overall uncertainty associated with the combined data is often greater than if the data from each source were kept separate. The issues discussed here are comparable to those faced when using multi-sensor monitoring in crowds. However, same issues arise in the setting of geophysics. The InSAR-fusion study has yielded new insights into how to create robust, scalable multi-modal fusions, which necessitates robust pre-processing and the development of standardised interfaces for all types of data, as well as the adoption and implementation of cloud-native architectures for multi-modal fusion; these findings have been documented in a recent study on multi-sensor monitoring [11] and other published articles on multi-sensor monitoring and crowd-surveillance [40]

Table 3: Modalities Commonly Fused with InSAR for Hazard Monitoring

Modality	Information Provided	Typical Use with InSAR	DL/ML Examples
Seismic	Earthquake rate, swarms, tremor	Confirm unrest type; trigger targeted InSAR	[38] [39] [41] [42]
GNSS	Precise point displacement	Calibration; tropospheric model training	[11] [40]
Thermal (SWIR/TIR)	Surface temperature anomalies	Identify active vents, lava flows	[44] [6]
Gas (SO_2 etc.)	Magmatic degassing	Distinguish magmatic vs hydrothermal unrest	[6] [40]
Optical imagery	Surface ruptures, landslides, ash deposit	Validate deformation interpretations	[6] [44]
Infrasound/audio	Explosive events, vent activity	Short-term eruption detection	[3] [6]

New Zealand has already set up a GeoNet Network that collects seismic, GNSS, camera, and gas data. The country also has access to satellite data through international programs. As a result, a multi-modal monitoring system using deep learning to monitor all aspects of the country's geology is technically feasible. Organisational and resource restrictions remain important impediments to the implementation of such a monitoring system.

3.5   Large-Scale Platforms and Operational Experience

As demonstrated by a number of initiatives, deep learning and InSAR are already being incorporated into complex real-time monitoring systems. MOUNTS [6] [40] a multisensor platform that

employs AI to monitor hundreds of volcanoes worldwide and generate data on deformation, thermal activity, and gas release in almost real-time, is one example. COMET and other frameworks related to Sentinel-1 Volcano Monitoring [8] [12] [14] automatically construct InSAR time series and utilize machine learning classifiers to detect possible signals of volcanic disturbance.

Among these numerous techniques [8] has created methods that apply simple functional fits to characterize deformation time series as either linear, sigmoidal, or a combination of both methods, making it easier to analyze data on a continental scale. Individual components that could assist the operation of a larger monitoring system have also been developed by other researchers, including [11] [34] and [17]. Examples of such components would include "TropoDeep", for compensating for atmospheric effects in InSAR; ViT based classifiers which enhance classification accuracy and make them easier to use; and Unsupervised anomaly detectors which enable for efficient identification of anomalous data.

The significance of standardised data formats and metadata (VolcNet project [14]) in training, benchmarking, and sharing models will be important for future initiatives. While these efforts resulted in significant automation, the human-in-the-loop review process remains vital, as false positives and other unclear patterns will still require expert judgement to resolve or validate. Similarly, cloud and HPC infrastructure allow for efficient processing of global InSAR archives; a similar architecture could be implemented in New Zealand by leveraging either national or regional computing facilities, with GeoNet serving as the central hub for the integration of InSAR, deep learning models, and complementary data sources

Table 4: Representative Operational or Large-Scale DL–InSAR Systems

System / Study	Scale & Coverage	Key Methods	Strengths	Limitations
MOUNTS [6, 40]	Global, hundreds of volcanoes	Multisensor fusion + AI	Multi-hazard products (deformation, SO_2, heat)	Complex system; requires substantial resources
Biggs et al. 2022 [12]	~600,000 Sentinel-1 images, >1000 volcanoes	ML classifier + expert review	Demonstrated global ML feasibility	False positives from atmosphere
Albino et al. 2020, 2022 [8, 14]	Continental-scale Sentinel-1	Automated time-series fitting	Routine volcano monitoring framework	Limited deep learning; mainly statistical
Gaddes et al. 2019, 2024 [21, 14]	VolcNet database, multiple volcanoes	CNN classification + localisation	Joint type + location detection	Requires labelled database
Popescu et al. 2025 [17]	Benchmark datasets for anomaly detection	Unsupervised CNN & generative models	No labels needed; flexible	Sensitive to preprocessing choices

Chapter 4

Limitations, Research Gaps and Selection of Methods

The key challengers, method selection, and research gap identification components are all directly addressed in this section.

4.1 Trends and Strengths in the Literature

Several themes emerged from the literature review. The first trend is a growing shift away from typical supervised Convolutional Neural Networks (CNNs) and toward more advanced types of CNNs, such as unsupervised and hybrid CNNs. Most earlier studies [13, 25] focused on binary classification (deformed vs. non-deformed) using supervised CNN methods, whereas more recent studies [26, 17, 33, 30] have focused primarily on anomaly detection and self-supervised learning techniques, as deformed events are infrequent and most data represents normal conditions developing. Third, the utilization of synthetic data will have a substantial impact on our current DL-InSAR approaches. The production of Synthetic Interferogram Time Series data has given a mechanism to address concerns related to class imbalance while also creating a greater range of deformation and noise conditions for model training [13, 14, 28, 34]. While this approach addresses the identified issue of a lack of labeled event data, it also raises concerns about the extent to which the generated synthetic training data represents'real-world' scenarios and how well the developed models will perform when tested against real, unpredictable environments. Fourth, in addition to developing new synthetic data solutions for DL-InSAR training, there is an increasing trend toward more advanced designs that give greater flexibility throughout the DL-InSAR workflow. These include transformer-based designs [34] , hybrid CNN-LSTM architectures [33], and graph neural networks [39]. These research findings reinforce the trend toward increasing model design flexibility, allowing models to take into account both global spatial context and dynamic temporal activity, rather than treating these pieces of input data as separate. Finally, emerging studies show that, as a result of DL-InSAR's collective findings and capabilities, they are no longer just the subject of research experiments; rather, they are now being deployed in operational systems capable of deploying on a continent or globally [6, 8, 12, 14].

4.2 Key Limitations and Research Gaps

Despite advancements, a number of enduring issues are apparent.

4.2.1 Atmospheric Noise and Environmental Artefacts

Even complicated models can misinterpret snow-induced decorrelation, model error, or the existence of an unmodeled land cover in the atmosphere as deformational displacements of the earth surface. Many research programs still rely on skilled analysts to manually filter false positive detections [12]. The TropoDeep tool [11] improves the accuracy of tropospheric corrections; nevertheless, the majority of this tool's training dataset was conducted within defined geographic boundaries, making its utility in New Zealand's maritime environment questionable.

4.2.2 Data Scarcity, Imbalance and Representation Bias

There are very few documented incidents of deformation compared to the large amount of no deformation data [46]. This has resulted in a Class Imbalance in our Supervised Models and biases towards certain locations (Europe, Japan, and some parts of South America) since they have been better instrumented than others, whilst more remote places (for example, the offshore volcano regions of New Zealand) are underrepresented. We can generate synthetic data, but it may not accurately reflect local conditions (for example, the complicated geothermal systems in the Taupo Volcanic Zone or snow on Mount Ruapehu).

4.2.3 Domain Shift and Transferability

Models trained on data from a single satellite (e.g., Sentinel-1) or region may not perform well in other places due to differences in orbit geometries, incidence angles, noise characteristics, and even vegetation. Domain adaptation strategies [34, 17] show promise in solving these issues, but they are still in their early stages.

4.2.4 Interpretability and Trust

GeoNet and other operationally focused organisations require interpretability because volcanic scientists want to know why they classified a specific interferogram as unusual. There are few examples of researchers using explainable artificial intelligence (AI), such as saliency maps and attention visualisation techniques [17, 34]. As a result, if the output lacks XAI, decision makers may be hesitant to use deep learning (DL) model outputs to guide a change in alert levels.

4.2.5 Multi-Modal Fusion Complexity

Using InSAR with seismic, GNSS, thermal, and gas data improves robustness but complicates data synchronization, modeling uncertainties, and ensuring appropriate infrastructure to support data fusion [6, 11, 40]. There is currently no defined architecture for such a fusion process.

Table 5: Summary of Major Research Gaps

Gap Category	Description	Consequences for NZ Context
Atmospheric and environmental noise	Limited general corrections for different climates	False positives and negatives in TVZ, snow-covered or coastal areas
Data scarcity and imbalance	Few labelled deformation events and limited NZ-specific data	Models may not perform well on local volcanoes and offshore systems
Domain shift and transferability	Models adjusted for specific satellites or regions	Re-training needed when the mission or monitored area changes
Interpretability XAI	Limited use of explainable methods	Harder to justify alert changes to stakeholders
Multi-modal fusion frameworks	No standard setups for combining seismic, GNSS, and other data streams	Fragmented tools make it hard to maintain complete pipelines

4.3 Selection of Methods for the Proposed Research

After evaluating past work, it was determined that the proposed project "Autonomous Detection of Volcanic and Seismic Hazards Associated with InSAR Deformation Utilizing Deep Learning" can use an anomaly detection strategy rather than a supervised classification approach. The primary

component of the system would be the use of an unsupervised or self-supervised anomaly detection method to distinguish between normal and aberrant behaviour. This may be accomplished by developing an anomaly detection algorithm (an autoencoder or PaDiM-based CNN) and training it on a large dataset of InSAR data from New Zealand and other comparable nations [26, 17, 33].As a result, this is a viable solution for addressing the issues associated with class imbalance and the low frequency of large deformation events, as the model will be able to determine what constitutes normal behavior and then identify deviations from it without requiring a large number of annotated eruptions.

The system will benefit from using either a Vision Transformer (ViT) component [34, 47] or a CNN with attention mechanisms to extract spatial data. The capabilities of such designs are perfect for capturing the spatial structure of interferograms across long distances and are less susceptible to noise from nearby events. A viable implementation strategy would be to pre-train the spatial component of the model using synthetic interferograms representing the projected deformation patterns on New Zealand volcanoes, then apply the model on real Sentinel-1 and future satellite pictures. By doing so, the best elements of synthetic data can be incorporated into the model while remaining backed by actual observations.

To add time to the model, a lightweight temporal CNN or LSTM module will be added on top of the spatial features generated. The temporal block will not operate on the raw phase, rather, it will accept input in the form of either the anomaly scores generated over time or the learnt embeddings of the data over time [33, 31]. Using this temporal block, it will be feasible to distinguish between short-term atmospheric artifacts and multi-episode (or long-term) deformation patterns, all without constructing an unnecessarily complex or onerous system to operate.

These designs also require a basic multi-modal integration layer. This Anomaly Detection Layer (ADL) [48] will combine IN-SAR anomaly scores with features including seismicity rates, GNSS displacement, and thermal or optical indications [6, 38, 39]. Initially, simplified probabilistic or rule-based fusion methods could be used in this layer due to their ease of explanation and maintenance, as more data becomes available, data integration could be investigated using learning-based approaches for late-fusion: such as MLPs that incorporate features from all three modalities.

Explainability and a human-in-the-loop component in the operation of the ADL are critical. As a result, it should construct saliency maps for each interferogram to illustrate which locations had the largest influence on an anomaly score [17, 34], and present them alongside the primary plot outputs from seismicity, GNSS, and thermal/optical activity. The ADL outputs would be shown on summary dashboards for volcanologists and integrated with GeoNet's current workflows, allowing them to assess alerts, provide input, and adjust alert thresholds.

The validity of the chosen methods will be evaluated by contrasting them with real-world situations in New Zealand. Using established, well-documented volcanic eruptions like those that happened in 2019 at Whakaari [49], volcanic activity (unrest) of Mount Ruapehu, seismic activity linked to tectonic plate shifting in the Taupo Volcanic Zone, and earthquake sequences along the Alpine Fault [50], case studies could be used to validate detection, timeliness, and incorrect identifications [3, 12, 40]. The findings of this study will allow us to compare the outputs of the developed anomaly detection method, as well as the lead time and false positive information produced by new methods, to baseline statistical data generated by established analytical methods and manual interpretation [51].In conclusion, the integration of anomaly-detection techniques, attention-based models, lightweight temporal context, multi-modal fusion, and process explanation is well-supported by the literature currently in publication and satisfies the requirements for satisfying New Zealand's particular hazard-monitoring environment through direct comparison and logical justification described in Selection of Methods.

Chapter 5

Conclusion

This literature review delves into the use of deep learning and multi-modal systems to aid in the autonomous identification of volcanic and seismic risks using satellite radar, specifically the analysis of InSAR measurements and deformation. The paper explains why automated detection systems are especially important in New Zealand, which has a high level of volcanic and seismic activity, a large metropolitan area covered by monitoring stations, and significant previous damaging events such as the Christchurch 2011 earthquake and the Whakaari eruption in 2019.The InSAR technique gives a mechanism of detecting subsidence or elevation of the ground in real time over broad geographic regions. Nevertheless, it is not feasible to fully evaluate the data set by hand due to atmospheric noise and the volume of InSAR data.

The literature study also emphasizes the application of several deep learning frameworks, such as CNN Classifiers, Autoencoders, Long Short-Term Memory (LSTM) Neural Networks, and Transformers, to identify deformations from InSAR data. Synthetic training data achieved good outcomes by combining enormous volumes of data into high-performance processing systems. The review points out that unsupervised and semi-supervised anomaly detection approaches are most suited for use in volcanology because the occurrence of continuing geological disturbance is unusual, and therefore, most available data will represent the normal state of a region. Additionally, the capability to identify motions is increased when InSAR is combined with additional monitoring kinds including seismic, GNSS, thermal, and gas detection technologies. This calls for careful data engineering and the application of more sophisticated modeling approaches.

Research has progressed, yet there remain several crucial areas for future research to address. Improving atmospheric correction capabilities for existing satellite data, addressing domain shifts that occur when switching between satellites and across geographical regions, improving the interpretability of existing models, and creating a common framework for combining disparate data streams are some of these challenges. By choosing a hybrid architecture that focuses on anomaly detection and integrates both autoencoder or PaDiM type models with transformers that function as spatial encoders, temporal dataset processors, and multi-modal data fusion components, this suggested study would overcome these shortcomings.In order to develop an efficient way to provide actionable information to support decision-making by GeoNet and the NZ civil defense organizations, a significant emphasis will also be placed on improving the framework's interpretability and testing against actual New Zealand case studies.

The viability of creating autonomous systems based on deep learning (DL) and interferometric synthetic aperture radar (InSAR) technologies is well acknowledged in the literature, as is its potential to greatly lower hazard risks and impacts to people and property in New Zealand. In order to fully realize the promise of these systems, it will be necessary to manage noise effectively, mitigate the consequences of data imbalance, consider local conditions, and continuously analyze and adapt them through human participation. These issues will be addressed by the proposed initiative.

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