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

Introduction

Being on the Pacific Ring of Fire, New Zealand is particularly vulnerable to earthquake and volcanic hazards. Approximately 14,000 earthquakes occur in the nation annually, of which 150 to 200 are powerful enough to be felt. Communities and infrastructure may be adversely affected by this frequent earthquake activity. Effective disaster predicting techniques are necessary, as demonstrated by the 2011 Christchurch earthquake, which took 185 lives and seriously damaged infrastructure. Another significant risk is volcanic activity. There were tragically 22 fatalities and 25 injuries from the 2019 eruption of Whakaari/White Island. Over the last ten years, the estimated cost of catastrophic earthquake damage in Aotearoa New Zealand has exceeded NZD 10 billion. [1] Volcanic eruptions, like Mount Ruapehu's 1995–1996 eruption, have seriously impacted local transportation and economic infrastructure. [2]

Geophysics, remote sensing, and AI are all integrated in the research area of Deep Learning Approaches for Volcanic and Seismic Hazard Surveillance in Aotearoa New Zealand. At the meeting point of the Pacific and Australian plates is Aotearoa, New Zealand. Because of this, it is vulnerable to active volcanism and frequent earthquakes, particularly along the Alpine Fault and within the Taupō Volcanic Zone. Remote sensing visuals, gas measurements, GNSS equipment, and seismic networking are typically the foundation of hazard surveillance systems. However, human analysts and conventional statistical models are challenged by the growing amount and complexity of data. [3] By automatically finding patterns in diverse and noisy datasets, Deep Learning offers a fresh approach. As a result, analysts experience reduced stress and better real-time monitoring and early-warning systems. This field of study is essential to expanding scientific understanding and strengthening New Zealand's vulnerability to disasters.

A variety of research areas lend support to the application of DL in disaster surveillance. The Earthquake Transformer and other attention-based models have improved seismic monitoring. This model significantly increases catalogue completeness by detecting events and selecting phases in noisy environments [4].Advancements like EdgePhase further improve multi-station phase selecting with high precision, resulting in more dependable early warning for earthquakes [5]. Multi-sensor data analysis has been enhanced by deep learning usages for pattern recognition outside of seismology. For instance, they are employed in gas emission monitoring to detect anomalies and in thermal infrared scans to detect hotspots [6].

In the meantime, convolutional and autoencoder techniques that recognise millimeter scale distortion signals from noisy interferograms have considerably advanced as InSAR (Interferometric Synthetic Aperture Radar) analysis [7]. These days, transformer based models can identify and analyse deformation patterns almost instantly [8]. These developments demonstrate that, even though machine learning offers practical tools for categorisation and forecasting, deep learning continuously provides superior scalability, strength, and accuracy for tracking intricate, multi modal datasets connected to hazards.

InSAR is the most efficient data format for statewide surveillance in New Zealand among the several forms of data used to monitor volcanoes and earthquakes, including seismic waveforms, GNSS, thermal imagery, optical satellite images and gas emissions. [9] InSAR records continuous ground movement across wide areas with millimetre accuracy, in contrast to localised seismic or thermal datasets. [7] It is particularly adept at spotting minute indications of earthquakes or eruptions thanks to its capability. Temporary variations in InSAR time series can be automatically detected by recent deep learning models. These models have produced rapid, unambiguous findings while mitigating the effects of atmospheric noise. [8]

InSAR is being used more frequently in routine surveillance by hazard monitoring organisations like as GeoNet in New Zealand. This change enables wider nationwide coverage, quicker identification of deformation abnormalities, and lower time spent on manually interpretation. It is both scientifically sound and critically necessary to concentrate on studying Associated InSAR Deformation Using Deep Learning. It fills a significant void in the monitoring systems that are in place now [3]

Importance of using Deep Learning for InSAR Deformation

One of the best tools for tracking surface alterations associated with seismic and volcanic activity is Interferometric Synthetic Aperture Radar (InSAR). It is particularly helpful in regions like Aotearoa, New Zealand, where fault movement and volcanic activity present significant concerns, because it can record minute ground movements over wide distances. However, there are disadvantages to using conventional methods for InSAR data analysis. These include problems brought on by air interference, deterioration of clarity, errors in orbit, and the massive volume of data generated by contemporary satellite systems such as Sentinel-1 and the next-generation NISAR project. Algorithms based on preset limitations and manual checks can be subjective, time-consuming, and frequently overlook subtle but significant movement patterns. These issues necessitate more automated and dependable techniques that can successfully distinguish genuine deformation from noise on a broad scale, as [10] note.

For these problems, Deep Learning emerged as a revolutionary solution. It provides a fresh method for identifying InSAR deformation. DL models are capable of independently identifying patterns in time series and interferograms. This eliminates orbital and atmospheric noise and increases responsiveness to weak deformation signals. Convolutional autoencoders, for instance, are able to identify millimetric scale deformation transitions that were missed by classical techniques [7]. Recently, simultaneous detection and interpretation of deformation patterns has been accomplished through the use of vision transformer systems. They deliver results in almost real time and are scalable [8].The requirement for manual interpretation is reduced by these advancements. Additionally, they facilitate the processing of big datasets at both the national and international levels, which expedites the decision-making process in hazard monitoring. DL application to InSAR is essential in Aotearoa, New Zealand. To lower hazards and guarantee population safety, prompt identification of deformation associated with volcanic activity or earthquake preparation is essential. [3] [10]

Related Work

With several architectures designed to handle the particular difficulties of interferometric data, the use of DL for InSAR deformation identification has advanced quickly in recent years. Since they are highly effective at removing air artifacts and detecting localized ground movement, Convolutional Neural Networks have been frequently used for pixel-wise segmentation of deformation in interferograms [10]. By independently identifying faint transient signals from distorted time series, automatic encoder and noise reduction frameworks expand this capability and reveal deformation precursors to earthquake and volcanic eruption scenarios [7]. Generative adversarial networks (GANs) has been researched for producing realistic training datasets in addition to CNNs. This mitigates the lack of identified deformation events and their unequal distribution. Concurrently, transformer-based techniques are gaining attention.To identify long-term dependencies in interferometric data, they employ attention mechanisms.This makes it possible to identify and comprehend patterns of deformation [8]

The process of integrating DL with national surveillance systems has been making headway in operational environments. In New Zealand, for example, the GeoNet program has begun to employ InSAR more in its earthquake and volcanic monitoring procedures. This change demonstrates the necessity of automated methods capable of handling the growing volume of data [3].Around the world, DL models and conventional InSAR analysis techniques have been contrasted. Particularly in regions with strong ambient noise or complex deformation signals, they continuously demonstrate superior speed, precision, and scalability [10].This body of work collectively demonstrates that Deep Learning offers distinct practical advantages, even while conventional methods for machine learning and statistical analysis are still helpful. It can automate large-scale procedures, is more resilient to noise, and is more sensitive to weak signals. These characteristics demonstrate why deep learning based InSAR deformation recognition is currently regarded as a crucial avenue for enhancing seismic and volcanic hazard monitoring.

Comparative Discussion on Research Opportunities

Recent advancements in deep learning for InSAR deformation detection point to a number of unexplored research areas. First, due to the scarcity of real InSAR datasets containing annotated deformation related to earthquakes or volcanoes, there are good opportunities for domain modification and transfer learning. For example, Ioannis Bountos et al. [11] looked at the application of Vision Transformer architectures and synthetic interferograms.By using domain adaptation approaches, they were able to obtain great precision even on real, unlabeled data.This suggests that more research is required to develop deep learning methods that can apply knowledge from artificial or semi-supervised environments to actual InSAR data, especially in the volcanic regions of New Zealand.

Second, there is a chance to enhance detection robustness and lower false positives by combining multi-modal datasets, such as InSAR with seismic, GNSS, thermal, topography, and gas emission data. For example, the review by Liu et al. [10] talks about how to build datasets and how adding more data, including atmospheric and elevation models, enables the DL model remove noise and perform better in various geographical areas.

Third, there is a chance to increase sensitivity to gradual, long-term deformation. According to studies like InSAR Recognition of Slow Ground Deformation, [12] velocity detection thresholds can reach roughly 2-3 mm per year in difficult scenarios if time and space choices are optimized, such as using lengthy time frames with short perpendicular baselines. It may be possible to further reduce thresholds and identify early indications of deformation sooner by using deep learning to these longer time series.

Fourth, zero-shot and few-shot learning frameworks present an opportunity. Zero-shot identification for InSAR-driven land displacement [13] investigates the use of model prototypes and prompt-based methods to identify deformation zones without a large amount of labeled training data. By using these techniques for earthquake and volcano deformation detection, New Zealand's dataset labeling problems may be lessened.

Compared to conventional incremental enhancements like minor adjustments to phase unwrapping or filtering, these opportunities are more important. They address fundamental constraints such as the lack of labels, generalization, sluggish signals, and operational scalability.

Application of the Research Area

There are numerous specific applications for the suggested method, Deep Learning for Automatic Detection of Volcanic and Earthquake-Related Deformation from InSAR. First is monitoring of volcanic systems in real time or nearly in real time. Monitoring organizations in Aotearoa, New Zealand, could identify early indicators of volcanic activity by employing a DL approach that is constantly fed fresh InSAR interferograms, like those from Sentinel-1. [14] Systems that identify, locate, and interpret deformation, such as the MT-ViT modeling, could be included into GeoNet's workflow to provide alerts or result in more thorough studies.

Second, hazard classification and risk evaluation: For volcanoes like Taupō, Ruapehu, and Taranaki that have several vents or calderas, automatically produced deformation mapping and patterns over time can help with hazard models. [15] These maps could be used to modify potential impact zones, direct the planning of infrastructure, or have an impact on land-use regulations.

Third, prioritization of field inspections and resources: Automatic detection aids in identifying which volcanoes or fractures to target when ground resources are scarce. [16] In remote volcanic regions, for example, we might be able to identify minor ground deformation early on, which would allow us to use field instrumentation, gas analysis, or drone surveys.

Fourth, incorporating early warning systems for several hazards: DL-InSAR deformation detection may help trigger warnings from several sensors, including gas emissions and seismic tremor. [17] By integrating deformation with other signals, false alarms can be decreased and confidence raised.

Impacts Analysis of the proposed approach

The way New Zealand manages hazards may alter if deep learning is used to automatically recognize deformation from InSAR caused by earthquakes and volcanoes. Early warnings are a significant advantage. By identifying minor signs that conventional approaches might miss, DL models allow communities and emergency agencies more time to get ready. According to recent research, automated anomaly identification can increase the precision of surface movement mapping [18] and reveal early volcanic developments [19]. This could be the difference between a delayed response and a quick, efficient one in places such as the Taupō Volcanic Zone.

Additionally, the method delivers efficiency and scale. DL may automated recognizing, extraction, and interpretation for big datasets, eliminating the need for teams of analysts to sort through interferograms. Continuous, countrywide monitoring is becoming possible thanks to new approaches including the FLM classifier [20] and multi-task InSAR synthesizers [21].In New Zealand, where numerous active volcanoes are far away and challenging to observe from the ground, this is crucial.

Accuracy enhancement and decision assistance are other important outcomes. According to [22], DL frameworks are now better able to distinguish between actual deformation and disturbances brought on by the weather, snow, or atmosphere. As a result, there are lower false alarms and more people trust monitoring organizations. When compared to prior techniques, case studies like landslide detection using InSAR [23] demonstrate that DL lowers false positives. This translates into more lucid and reliable alerts for emergency management in New Zealand.

In terms of science, DL will result in new findings. Deformation that could otherwise go undetected can be detected by automated InSAR analysis. For instance, subseismic faults have been identified with the aid of displacement gradients calculated from InSAR [24]. By applying these approaches locally, we may be able to improve hazard models by better understanding how magma moves and how earthquakes are prepared.

Lastly, there are obvious social and economic advantages to the strategy. Improved monitoring lowers post-disaster recovery costs, saves lives, and safeguards infrastructure. Improved detection provides greater protection and more intelligent long-term planning for towns around Rotorua, Ruapehu, or Taupō, where farming, tourism, and daily living coexist with volcanic risk. To put it briefly, DL applied to InSAR is a useful step toward enhancing resilience throughout New Zealand, not merely a research breakthrough.

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