Learning class prototypes from Synthetic InSAR with Vision Transformers

Nikolaos Ioannis Bountos*,†, Dimitrios Michail†, and Ioannis Papoutsis*

Abstract—The detection of early signs of volcanic unrest preceding an eruption, in the form of ground deformation in Interferometric Synthetic Aperture Radar (InSAR) data is critical for assessing volcanic hazard. In this work we treat this as a binary classification problem of InSAR images, and propose a novel deep learning methodology that exploits a rich source of synthetically generated interferograms to train quality classifiers that perform equally well in real interferograms. The imbalanced nature of the problem, with orders of magnitude fewer positive samples, coupled with the lack of a curated database with labeled InSAR data, sets a challenging task for conventional deep learning architectures. We propose a new framework for domain adaptation, in which we learn class prototypes from synthetic data with vision transformers. We report detection accuracy that surpasses the state of the art on volcanic unrest detection. Moreover, we built upon this knowledge by learning a new, non-linear, projection between the learnt representations and prototype space, using pseudo labels produced by our model from an unlabeled real InSAR dataset. This leads to the new state of the art with 97.1% accuracy on our test set. We demonstrate the robustness of our approach by training a simple ResNet-18 Convolutional Neural Network on the unlabeled real InSAR dataset with pseudo-labels generated from our top transformer-prototype model. Our methodology provides a significant improvement in performance without the need of manually labeling any sample, opening the road for further exploitation of synthetic InSAR data in various remote sensing applications.

I. INTRODUCTION

The availability of Copernicus Sentinel-1 data, acquired with global coverage on a systematic basis, has spurred the development of new applications in Remote Sensing. The sheer volume of the data generated has allowed the use of scalable deep learning methods that are able to efficiently and accurately automate information extraction from these rich data archives, detect subtle signals hidden in satellite imagery, and predict key environmental variables which in turn can be fed to physical models, e.g. for hazard and risk assessment.

Volcanic hazard in particular, is critical for disaster risk reduction, especially near urban and peri-urban areas, with more than 800 million people living within 100km from an active volcano, while 29 million within 10km [11], posing a valid threat to the population. Direct and severe economic loss is also a direct impact of a volcanic eruption. For example, the 2010 Eyjafjallajökull Icelandic volcano moderate eruption led to the closure of north and central European airspace, the cancellation of ~100,000 flights and the stranding of ~10 million passengers, which according to Oxford Economics [39] resulted to a total global economic impact of ~5bn €, as the major hubs of London, Amsterdam, Paris and Frankfurt were virtually shut down due to the effects of the ash clouds.

In fact, according to Siebert et al. [45], about 1,500 volcanoes are known to have erupted in the last 12,000 years and about 700 of these have erupted at least once in historical times. Currently, worldwide, about 100 volcanic unrests are observed yearly, and about half of them become observable eruptions [15]. However, it is estimated that less than 10% of active volcanoes are monitored on a systematic basis [36], and therefore volcanic hazards are monitored occasionally, or not monitored at all from volcano observatories, such as the Geohazard Supersites and Natural Laboratories initiative [43].

Detecting early signs of volcanic activity can be of paramount importance to promptly mobilise scientific teams, deploy sensing equipment on the ground and alert civil protection authorities. Interferometric Synthetic Aperture Radar (InSAR) products are a rich information source that is used to detect ground deformation associated with volcanic unrest [38]. Such deformation is statistically linked to an eruption [7] and can be detected prior to the event [23]. The deformation appears in the InSAR data in the form of interferometric fringes. Unfortunately, the different atmospheric conditions between the two temporally separated SAR acquisitions that are needed to form an interferogram, can give rise to similar fringe patterns. These patterns are usually correlated with strong topography, and therefore the task of automatically detecting interferograms with fringes attributed to ground deformation and therefore volcanic unrest is challenging.

Recent works, motivated by the advances of computer vision, have attempted to employ convolutional neural networks (CNN) to solve the task of deformation detection in wrapped and/or unwrapped InSAR data. Different CNN architectures have been tested, e.g. AlexNet [2], [3] and VGG-based [24], while custom CNN models have also been designed [53]. A CNN workflow has also been used to detect fringes associated with an earthquake [10]. However, even though CNN methods have proved to be robust and applicable in multiple domains such as medicine [57], remote sensing [41], self-driving cars [18], biology [44] and others, they tend to be exceptionally data-hungry. Deep CNN architectures require large amounts of curated labeled data, however there is no such database for InSAR data. In addition, our problem is inherently unbalanced, since the number of negative samples with no volcanic deformation fringes, surpass the set of positive samples with volcanic deformation fringes, by orders of magnitude. To

*Institute of Astronomy, Astrophysics, Space Applications & Remote Sensing, National Observatory of Athens (e-mail: {bountos, papoutsis}@noa.gr)
†Department of Informatics & Telematics, Harokopio University of Athens (e-mail: michail@hua.gr)
mitigate these problems, researchers have exploited pretrained models from optical datasets [5, 37] such as ImageNet [20] or relied on heavy data augmentation to address the scarcity of labeled InSAR data, as in [2, 3, 24, 53]. However, Bountos et al. [9] showed that training a model with data from a different domain, will incur a drop in classification performance when compared to models trained in the same domain. In fact, the work of Bountos et al. [9] is, to the best of our knowledge, the state-of-the-art for volcanic unrest detection with 91% classification accuracy, by developing a self-supervised pretraining strategy based on unlabeled InSAR data.

In this work we exploit synthetically generated InSAR patches, which we can generate in abundance, and design a training framework based on learning representative class prototypes with vision transformers. Our method is able to generalize well to the real InSAR data domain, contrary to recent works that struggled for a similar task [2, 10, 24]. To summarize, our main contributions are:

- We successfully train both CNNs and visual transformers for the binary volcanic unrest detection problem using only synthetically generated InSAR data.
- We present a novel prototype learning scheme using vision transformers, which significantly surpasses the current state of the art.
- We successfully transfer knowledge from synthetically generated InSAR to real data by designing an unsupervised self-labeling domain adaptation pipeline.
- We provide a framework for robust InSAR data pseudo-labeling and demonstrate its effectiveness.
- We publish all trained models and code used in this work.

II. RELATED WORK

A. Domain Adaptation

Given the lack of labeled InSAR datasets, very few works in literature have attempted to train models using synthetic data. Brengman et al. [10] used synthetic InSAR to classify co-seismic deformation, proposing a CNN architecture called SarNet, and evaluated its performance on real data. The authors report an accuracy of 47.62% on a test set of 32 real InSAR, hence, in order to enhance the generalisation capability of their model, they choose to finetune it by injecting real augmented InSAR data in the learning process. The reported accuracy ranges between 59.22% and 85.22%, but the test set most probably comprises of augmented versions of the real data used during training.

Gaddes et al. [24] use the first five convolutional blocks of a pretrained VGG16 [46] to get an image representation on synthetically generated InSAR data over volcanic areas, and then feed it to a Multi Layer Perceptron (MLP) for the classification task. Their classes include dyke, sill and no deformation. To evaluate their method in the real domain, they generate a set of 52 InSAR and evaluate their model achieving an accuracy of 65%. To improve their results, they finetune on a set of 173 real InSAR, reporting an updated accuracy of 67% for the dyke (3 samples), 82% for Sill (17 samples) and 84% (32 samples) for the no deformation patches, which translates to \( \approx 82.3\% \) accuracy for the binary classification task.

Finally, Anantrasirichai et al. [2] generate synthetic data in order to train an AlexNet for binary classification. They report 41/363 true positives and 0 false negatives. After retraining the network with a combination of real and synthetic data the reported results improve to 41/52 true positives and 1 false negative.

All of the above methods failed to generalize well to the real domain due to the covariate shift. The covariate shift is caused by a change in the distribution of the input samples while the label distribution remains intact. This issue has been studied extensively by the computer vision community. Since we assume no labels from the real domain we focus on the case of unsupervised domain adaptation. In [48] Sun et al. propose a simple framework where they align the second order statistics of the features of source and target domains. CORrelation ALignment (CORAL) was combined with deep neural networks in [49] where they extended the initial method introducing the coral loss that minimizes the distance between the second order statistics of the source and target domains in deep layers, complementing the standard classification loss. In a similar manner, Tzeng et al. [52] proposed to minimize the Maximum Mean Discrepancy [8] of deep representations along with the classification loss. In [26] the authors propose to incorporate a gradient reversal layer along with a domain classifier in order to learn domain invariant features while minimizing a standard classification loss. The gradient reversal layer multiplies the gradient flowing from the domain classifier with a constant negative factor penalizing the feature extractor for the discriminator’s good performance. This “game” results in a feature extractor that can produce domain invariant representations with good classification potential.

Another set of approaches focuses on the style transfer between source and target domain. In that direction Zhu et al. [60] propose a framework that is able to transform images from domain A to domain B and vice versa. Building upon that, Murez et al. [40] propose a methodology for image to image domain adaptation. They enforce the learnt representations to be reconstructable for both domains, while making the latent space domain agnostic via a domain classifier. Furthermore they include a translation loss where an image from the source domain is encoded and then reconstructed as an image from the target domain and vice versa. The translation loss comes from a domain classifier that attempts to identify the domain of the image. Furthermore, they apply a cycle consistency loss where they try to regenerate the original image from its fake opposite domain counterpart. Finally, they integrate a classification loss for the target domain, where source samples are translated to the target retaining their labels. This enables the target domain to be included in the supervised training.

Following a completely different line, self-supervised learning has proved to be very effective on the task of domain adaptation as well [12–14, 16, 32]. Our work is directed towards the creation of a low dimensional space where samples from both source and target domains revolve around the
respective class prototypes. These prototypes are learnable and jointly trained along with the encoder.

B. Prototype Learning

Prototype learning methods have been traditionally used in machine learning for computer vision applications. Typical prototype based methods include the standard k-NN and the learning vector quantization algorithm. However, in modern computer vision there have been only a few works related to prototypes. Yang et al. introduce the general convolutional prototype learning framework that combines the standard convolutional neural network based approaches with learnable prototypes for image classification. In that setting the class of a sample is assigned to the class of its nearest prototype. Li et al. uses prototypes in the setting of self-supervised contrastive learning in order to find embeddings that are able to encode the semantic structure of the data, enforcing samples to have more similar embeddings with their respective prototypes compared to the rest of the prototypes. Moreover, Huang et al. combined graph neural networks with prototype learning for the task of action localization in videos.

Pinheiro et al. address a similar problem to ours for computer vision applications, combining domain adaptation with prototypes. The authors use a domain classifier to discriminate between source and target samples along with a gradient reversal layer, while performing the classification based on similarity with class prototypes. In contrast to our approach, where the prototypes are learnable, in Pinheiro et al. they are defined as the average representation of the source dataset. Furthermore, in our case the classification is based on the distance of samples to the respective prototypes in a space obtained by projecting the learnt representations on a low dimensional prototype space. On the contrary, Pinheiro et al. use a bilinear operation as a similarity measure on which the classification is based.

Prototype learning approaches have also been used in remote sensing. Hua et al. use a prototype learning approach to recognize multiple aerial scenes in an image. They learn prototypes from different known scenes and when a new query image is fed into the network they retrieve the relevant scenes by using a multi-headed attention like mechanism, where the query is the new image and the keys are the known scenes. Then, they combine the results of the different heads and feed it into a fully connected classification layer. Finally, Zhang et al. learn class related prototypes on a feature space obtained from an encoder for the task of hyperspectral image classification. The classification is handled with a nearest neighbor approach. According to the authors this method performed better than other approaches in a limited labeled data regime.

C. Vision Transformers

Transformers have taken the natural language processing (NLP) community by a storm. This success motivated the computer vision community to adapt it to its needs. The resulting vision transformers (ViT) operate by splitting the image into a sequence of patches that are fed to a standard transformer encoder. Given the lack of inductive bias in comparison to CNN’s, training a ViT from scratch is quite challenging. The concept of locality is completely absent even in the presence of positional embeddings since initially they contain no useful information making it extremely difficult to train properly in small datasets, compared to CNNs. Recent works have tried to work around this issue by investigating sophisticated methods to train ViTs or combining them with the inductive bias of CNNs. A standard approach to properly utilize ViTs is to pretrain them in large datasets and then apply them to downstream tasks. We follow this approach throughout this work.

It is not the first time that vision transformers are exploited for remote sensing tasks. Bazi et al. and Papoutsis et al. use them for the task of satellite scene classification, while Horváth address the satellite image manipulation detection problem, in which the authors try to detect satellite images that have been tampered. However, there has been no prior work on synthetic to real satellite data adaptation, let alone the InSAR domain.

III. APPROACH

In this section we discuss the main components of our architecture. We start by defining a Swin Transformer as the backbone of the architecture, adapting it to the needs of a prototype learning approach. Then we introduce a domain adaptation component to further improve the model’s generalization to the real domain. The full pipeline is presented both schematically (Figure 1) and in pseudocode (Algorithm 1).

A. Transformer-based encoder

We utilize a vision transformer as our feature extractor \( f(x) \). We focus on the Swin Transformer but since our framework is encoder invariant, we also report results using other architectures. Swin Transformer builds upon ViTs in order to create a general purpose efficient backbone for computer vision tasks. In contrast with standard ViT, Swin Transformer aims to learn hierarchical features while calculating self-attention in a more efficient manner. It deviates from traditional vision transformers by injecting inductive bias, locality and hierarchy into the transformer architecture. As in standard ViTs, the image is split into a sequence of patches that constitute the input to the Transformer Encoder. Self-attention is computed in local windows in contrast with standard ViTs where self-attention is computed globally. A window is defined as a set of \( M \times M \) patches, where \( M \) is fixed. The fixed size of windows reduces the quadratic complexity to the image size of typical self-attention computation in ViTs to linear complexity to the number of patches for the Swin Transformer. In order to allow communication between windows, a shifting windows approach is used between consecutive transformer blocks. Furthermore, after each set of swin transformer blocks, a patch merging layer is applied to fulfill the promise of hierarchical features. For a more detailed view of the architecture, we refer the reader to [35].
B. Prototype Learning

Instead of classifying using a softmax layer, we feed the encoder’s output to a prototype learning module which learns prototypes of each class during training. We build upon the Convolutional Prototype Learning framework introduced in [58]. In our case the transformer-based encoder is used to extract features. On top of the features we learn prototypes of each class. The classes are assigned via a nearest neighbors approach of the sample’s representation with the class prototypes. Besides the classification loss we add a prototype loss (PL). The PL loss has the tendency to draw samples from the same class closer together and samples from different classes further away. As discussed in Section IV, this results in more robust representations. Furthermore, due to the very nature of the prototype loss, the resulting latent space is more k-means friendly.

Given the binary nature of the problem we use two prototypes, one for each class $m_i$ for $i \in \{0, 1\}$. This can be extended to any number of classes and prototypes for each class. In particular $m_{ij}$ for $i \in \{1, ..., C\}$ and $j \in \{1, ..., K\}$, where $C$ is the number of classes and $K$ the number of prototypes for each class. These prototypes are learnt during training time. The classification is based on a nearest prototype approach using the Euclidean distance. We experiment on different dimensionalities for the prototype space.

We use the distance based cross entropy loss function (DCE) as defined in [58]. Given a distance function $d(f(x), m_{ij}) = \|f(x) - m_{ij}\|_2$ we define the probability of a sample $(x, y)$ to belong to prototype $m_{ij}$ as:

$$p(x \in m_{ij} | x) = \frac{e^{-\gamma d(f(x), m_{ij})}}{\sum_{k=1}^{C} \sum_{l=1}^{K} e^{-\gamma d(f(x), m_{kl})}},$$  \hspace{1cm} (1)$$

where $\gamma$ is hyper-parameter that controls the hardness of probability assignment. We can then define the probability of a sample $x$ belonging to class $y$ as:

$$p(y|x) = \sum_{j=1}^{K} p(x \in m_{yj} | x).$$  \hspace{1cm} (2)$$

The distance based cross entropy loss is then calculated as:

$$l((x, y); \theta; M) = -\log(p(y|x)),$$  \hspace{1cm} (3)$$

where $\theta$ are the parameters of the feature extractor and $M$ the set of prototypes.

Finally we add as a regularizing term a Prototype Loss that attempts to minimize the distance of the representation with the closest prototype of the correct class

$$pl((x, y), \theta; M) = \|f(x) - m_{yj}\|_2^2.$$  \hspace{1cm} (4)$$

The combined loss is then defined as

$$l((x, y); \theta; M) + \lambda pl((x, y); \theta; M),$$  \hspace{1cm} (5)$$

where $\lambda > 0$ controls the effect of the extra prototype loss.

As stated by Yang et al. [58], the PL loss has the ability to pull samples closer to their respective prototypes making the representations of samples from the same class compact and increasing the distance between different classes. Additionally, the classification loss tends to boost the class separation property of the representations. Thus, by combining them we can learn intra-class compact and inter-class separable representations. For low-dimensional prototypes we let both loss terms contribute equally. When we increase the prototype dimension we downscale the PL-loss accordingly.

C. Domain Adaptation Projection Training

An additional boost in performance can be achieved by introducing a supplementary domain adaptation component. The idea is to utilize self-labeling [51] in an effort to improve the model’s adaptation to a new domain in an unsupervised setting. In self-labeling domain adaptation approaches, it is common to use the current model trained under a source domain in order to assign pseudo-labels for all samples to
a target domain. These pseudo-labels are then considered as ground-truth and the model is retrained.

In our case we use an unlabeled, real InSAR dataset and proceed with the pseudo-label generation. Our assumption is that our encoder is generic enough to produce good representations in the real domain too. This is validated in our experiments (see Section IV) and the visualization of the prototype space in Figure 3. Given a good encoder and representative class prototypes, what remains is the projection to the prototype space. Instead of using the projection learnt for synthetic data, we opt to learn a new, non-linear projection tuned from real InSAR patches. We thus, freeze both our encoder and the learnt prototypes and throw away the final layer which projects the encoder’s representations to the prototype space. This last layer is replaced with a 3 × Layer MLP which is trained using the produced pseudo-labels. Besides improving performance on the real domain, the new projection retains the good embeddings learnt for the synthetic domain.

IV. EXPERIMENTS

In this section, we investigate how well we can transfer knowledge learnt on synthetic data to the real domain. Our training set consists of 25,000 synthetically generated InSAR samples created using the generator from [25]. For the validation set we construct a second synthetic dataset containing 3,361 deformation and 5,000 non-deformation patches. To evaluate and compare the performance of our models with the current state-of-the-art, we use as test set the C1 dataset with real InSAR from several volcanoes, used in the work of [9]. The details of each dataset, such as the number of positive and negative samples, can be seen in Table I. Figure 2 contains samples from both the synthetic and the real domain.

The synthetic InSAR data generator we use is SyInterferoPy [25], which produces random interferograms over a collection of subaerial volcanoes. The interferograms arise from the synthesis of i) deformation signals considering simple dyke, sill, or Mogi sources, ii) a topographically correlated atmospheric phase screen (APS), iii) a turbulent APS, iv) phase gradients, and v) the superposition of regions of incoherence. Interferograms without deformation can also be synthesised. In our synthetic dataset, deformation is in the range [10cm 25cm], turbulent APS has on average a maximum strength of 2cm and is correlated on a 5km scale. We also vary the rad/km of delay for the topographically correlated APS. For the Mogi volcanic source the random variables are the expected magma chamber volume change and the source depth, for the sill we vary in addition the depth of its top segment.

As seen in Figure 2 the synthesized interferograms are a very good, but simplified approximation of reality. Interferometric fringe patterns in particular appear in synthetic data to be clearer with respect to real InSAR data. This implies that domain adaptation would be needed to improve classification performance.

A. Investigating the encoder architecture

Our first experiments investigate different encoder architectures. We evaluate the performance of standard convolutional neural network architectures such as ResNet18 [27], VGG16 and DenseNet121 [30] and more recent vision transformer architectures such as ConvViT, DeiT and Swin. In all cases we use a standard softmax layer for the classification. We train all models for 5 epochs with learning rate initialized at $10^{-4}$, batch size equal to 40 and weight decay at $10^{-4}$. The learning rate follows a cosine annealing schedule. We use oversampling for all approaches to create balanced batches as done in [9]. All CNN models were initialized with weights obtained from training on ImageNet. All pretrained transformer models were obtained by the model zoo of [55]. We use the base versions of all vision transformer models. Swin transformer has patch size of 4, while DeiT and ConvViT have 16.

Table II presents the results of the evaluation on the C1 dataset. ACC, FP, TP, FN, TN, stand for overall accuracy, false positives, true positives, false negatives and true negatives respectively. The best accuracy is achieved by the ConvViT (87.7%) architecture. Among CNNs the best one is achieved by the ResNet18 architecture (85%). These results alone are encouraging, taking into account that training has been done only with synthetic data. Nevertheless, the classification accuracy remains lower than the current state of the art on this task (91%). This motivates us to look for more sophisticated methods that are able to overcome the covariate shift.

Table II: Evaluation on the C1 dataset of standard CNNs and ViTs when trained on synthetic data. Classification happens using a softmax layer. ACC, FP, TP, FN, TN, stand for overall accuracy, false positives, true positives, false negatives and true negatives respectively.

| Model       | ACC   | FP    | TP    | FN    | TN    |
|-------------|-------|-------|-------|-------|-------|
| ResNet18    | 85%   | 7     | 296   | 108   | 358   |
| DenseNet121 | 84.3% | 22    | 306   | 98    | 343   |
| VGG16       | 75.2% | 132   | 346   | 58    | 233   |
| ConvViT     | 87.7% | 57    | 367   | 37    | 308   |
| DeiT        | 81.4% | 115   | 376   | 28    | 250   |
| Swin        | 85.4% | 7     | 299   | 105   | 338   |

B. Examining the effect of prototypes

In this section we investigate the effect of replacing the classic softmax classifier by a classifier which uses trainable prototypes as described in Section III-B. Prototype learning architectures allow us to surpass the state-of-the-art despite the fact that we only train on synthetic data.

Table III compares the performance on the C1 dataset of both CNN and Vision Transformer models when they are complemented with prototype learning. In the case of CNNs we see that the addition of class prototypes does not provide the desired performance boost. While the performance of VGG16 slightly improves, the performance of both ResNet18 and

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**TABLE I: Dataset break down.**

| Data Source | Positive | Negative | Purpose |
|-------------|----------|----------|---------|
| Synthetic   | 17976    | 7024     | Train   |
| Synthetic Validation | 3361 | 5000 | Validation |
| C1          | 404      | 365      | Test    |
Fig. 1: This figure depicts the full training procedure. At training time, a synthetic InSAR sample is split in patches and fed to the Transformer Encoder. The output of the encoder is then projected to the prototype space using a learnable linear projection. The prototypes are depicted in the graph with yellow, whereas the two classes with blue and red. The samples are assigned to the class with the closest prototype. At the pseudo training stage, the trained model generates pseudo labels on an unlabeled real InSAR dataset. Then the linear projection module is replaced with a more complex, non-linear MLP for domain adaptation. All parts of the initial model are frozen including the prototypes leaving the MLP the only trainable module. The resulting model retains its classification abilities on the synthetic data while improving on the real domain. In this figure, dashed line boxes correspond to trainable modules, whereas solid line boxes correspond to non-trainable modules.

DenseNet121 degrades. It is interesting that the introduction of prototypes seems to amplify the false negatives considerably.

On the other hand, all tested vision transformer architectures surpass the previously reported state of the art with accuracy > 91%. The boost compared to the corresponding model with a standard softmax layer ranges between 3.7% and 11.3%. This enables us to create robust methods that can transfer knowledge well from the synthetic to the real domain. It is interesting to note that the resulting models achieve their accuracy by balancing the errors between false positives and false negatives.

C. Examination of the Domain Adaptation module

The great boost provided by the use of learnable class prototypes motivates us to look for ways to further improve our model. To this end, we utilize an unlabeled real InSAR dataset as described in III-C. Table III also contains the evaluation of all prototype based transformer models complemented with the additional pseudo-labeled training. We use X-PL-Pseudo to denote the use of both prototype learning and the additional pseudo-training process with an encoder X. The first observation one can make is that the performance of all models increases. Our best model Swin-PL denoted as Swin-PL-Pseudo in this case achieves an impressive 97.1% accuracy.
TABLE III: Evaluation on the C1 dataset of the examined methods using prototype learning and pseudo-labeling and the previous state of the art. ACC, FP, TP, FN, TN, stand for overall accuracy, false positives, true positives, false negatives and true negatives respectively.

| Model                  | ACC | FP  | TP  | FN  | TN  |
|------------------------|-----|-----|-----|-----|-----|
| ResNet18-PL            | 78% | 2   | 237 | 167 | 363 |
| DenseNet121-PL         | 82.4% | 3 | 272 | 132 | 362 |
| VGG16-PL               | 82.9% | 123 | 396 | 8 | 242 |
| ConvViT-PL             | 91.4% | 28 | 366 | 38 | 337 |
| DeiT-PL                | 92.7% | 28 | 376 | 28 | 337 |
| Swin-PL                | 93.8% | 26 | 383 | 21 | 339 |
| ConvViT-PL-Pseudo      | 95.1% | 14 | 381 | 23 | 351 |
| DeiT-PL-Pseudo         | 93.4% | 37 | 391 | 13 | 328 |
| Swin-PL-Pseudo         | 97.1% | 16 | 398 | 6 | 349 |
| ResNet18-Only-Pseudo   | 91.6% | 11 | 351 | 53 | 354 |
| ResNet50-SimCLR [9]    | 91%  | 10  | 347 | 57 | 355 |

Its superiority was expected given its initial 93.8% accuracy on C1. The better the model that generated the pseudo-labels the less the noise it will induce in the pseudo-label training stage.

In order to visually examine how well the two classes are separated, we show the prototype space in Figure 3. We focus on the Swin Transformer model. The top row uses Swin-PL while the bottom row Swin-PL-Pseudo. For the synthetic data there is greater inter-class distance. This is to be expected since the model was trained on this domain. Nevertheless, after the pseudo training process described in Section III-C we can see that the two classes are now more clearly separated in the real domain too. While initially the two classes were blended near their boundary, after the new non-linear projection was learnt via pseudo training the samples surround their respective prototypes and are distinctively separated from samples of the opposite class. Additionally, the performance remains stable on the synthetic domain, solidifying the conclusion on the model’s ability to generalize very well.

D. How does the prototype space dimensionality affect the model?

Finally, in Table IV we examine how the increase of the dimensionality of the prototype space affects the performance of the prototype based models. We notice that increasing the dimensions too much hurts the model massively. This could be attributed to the use of euclidean distance and the problems of distance metrics in high dimensional spaces [1]. The best performance is achieved from our base model with prototypes on a 3 dimensional space.

E. How do prototypes look like?

Learning class prototypes has another obvious benefit besides the improved accuracy. It gives us a direct way to investigate how our model discriminates between the two classes by examining the class prototypes leading to more explainable classifiers. However, since our model is not invertible, we
TABLE IV: Ablation on the effect of prototype space dimension on the C1 dataset.

| Model     | ACC  | FP   | TP   | FN   | TN   |
|-----------|------|------|------|------|------|
| Swin-PL-3d | 93.8%| 26   | 383  | 21   | 339  |
| Swin-PL-100d| 76.46%|105  | 328  | 76   | 260  |
| Swin-PL-1000d| 55.5%| 17   | 79   | 325  | 348  |

cannot directly generate an input sample based on the final 3-d projection in the prototype space. In order to visually inspect how the class prototypes look like we investigate their closest samples. We do that for both real and synthetic domains. Obviously, since the prototypes were found while training on the synthetic data, these samples will be closer and constitute a more realistic representation. However, we find the results from the real domain quite interesting and present them along with the respective figures from the synthetic domain. The prototypes visualization can be seen in Figure 4.

![Figure 4](image1.png)

Fig. 4: Visualization of the closest samples to the prototypes. On the left column, we show the negative patches and on the right the patches that contain deformation. The top row contains the synthetic case where we use the standard Swin-PL architecture. Since the prototypes were learnt for the synthetic domain the synthetic samples are closer to the prototypes. Bottom row presents the real dataset case. Observing that the real samples are better projected to the prototype space after the pseudo projection training, as shown in Figure 3, we use the Swin-PL-Pseudo model to find the closest sample. In both cases the prototypes remain the same. Even though the synthetic set contains mostly larger deformation patterns, our method is able to correctly cluster deformations with smaller intensity at the positive class.

![Figure 5](image2.png)

Fig. 5: Cosine similarity of positional embeddings among patches in DeiT. Each mini patch shows the cosine similarity between its position embedding and the embeddings of the rest of the patches in different positions. The full grid represents the whole image split into 14x14 patches with patch size equal to 16.

**F. How do positional embeddings look like in vision transformers?**

Swin Transformers directly induce locality information in vision transformer architectures. DeiT however, learns positional information from scratch. DeiT had the greatest classification accuracy boost from the use of class prototypes and the second highest accuracy in the simple prototype learning setting. It is worthy to examine what kind of information do the positional embeddings provide and how do they differ between different locations in the image. Figure 5 shows the full 14x14 grid of patches along with their cosine similarity with the rest of the patches. Each patch location is depicted with a mini patch showing the cosine similarity of the specific location in comparison to the rest. It is clear that certain patterns are inferred by the network. The high cosine similarity between close points and low between points that are further away shows that the learnt embeddings encode a notion of distance. Additionally, elements from the same row and column have increased similarity. Dosovitskiy et al. reached to the same conclusions.

**G. Can we extract meaningful insights about the model’s decision from the learnt self-attention?**

We investigate the learnt attention of the top 2 models: Deit-PL and Swin-PL. For Deit-PL we use a gradient attention rollout technique to create class specific visualizations. Figure 4 shows the respective plots. Given the non-global, window based calculation of self-attention and the lack of a classification token in the Swin-Transformer, it is difficult and out of the scope of this work to adapt or create new gradient
Fig. 6: Input sample for self-attention visualization. a) shows the original sample while b) and c) show the respective split in 16x16 and 4x4 patches by DeiT and Swin Transformer respectively.

Based attention visualization methods for it. Instead, for this task we directly explore the self-attention map of the last layer of the swin transformer. As stated in [17], using solely the attention map to explain the model’s reasoning is naive, since there are a lot more layers and processes in a model that contribute to its decisions. However, we can still gain some insights from it. We focus on the middle pixel of the window and visualize where it attends the most. We plot all four attention heads of this layer. Swin Transformer attention can be seen in Figure 8. The patch of Figure 6 was used as an input for Figure 8. Given the different visualization methods a direct comparison between Swin-PL and DeiT-PL is not really possible. In Figure 7 we can see excellent localization to the deformation fringes from DeiT-PL. In Figure 8 we see the 4 attention heads and the self-attention of the middle pixel. Observe that in 3 out of 4 heads the deformation fringe has high attention. In particular head 1 focused more on the core of the deformation. Each head learns different things and their combination leads to good model performance. The most important conclusion from this experiment is the good perception of both models on what constitutes a ground deformation pattern.

H. Can we generate a new trustworthy pseudo labeled InSAR dataset using our models?

In this subsection we discuss whether we can use synthetic data to create new InSAR datasets on the real domain. For this purpose we utilize the great performance of our best model Swin-PL-Pseudo on the real test set (97.1%). Looking at the breakdown of Table III we see that the model produced 16 false positives out of 365 negatives and 6 false negatives out of 404 positives. The low number of false negatives is important for a critical task like that.

Given the above observations, we used Swin-PL-Pseudo to create pseudo labels on a new unlabeled real InSAR dataset with 2272 samples. We then proceed to train a simple ResNet18 CNN for 100 epochs, keeping the training settings as described in Section IV-A, while removing the weight decay since the induced noise of the pseudo-labels can act as a regularizer. The test accuracy of the resulting model (91.6%) on C1 surpasses the previous state of the art (91%) and by far the performance of the ResNet18 model when trained on synthetic data (85%). We denote this model as ResNet18-Only-Pseudo in Table III.

The 91.6% accuracy shows that it learnt quality features in a supervised setting. If the supervision was faulty, with high levels of noise, its accuracy would not be that high, and definitely not higher than the previous state of the art from [9]. However, quantitative evaluation of such a task is not
Fig. 9: Qualitative examination of pseudo labels assigned to the unlabeled dataset using the Swin-PL-Pseudo model. These labels were used to train a ResNet18 with more than 6% higher accuracy in comparison to the respective model trained on synthetic data. We provide 5 challenging samples from each assigned category. The top row shows samples predicted as non-deformation while the bottom shows patches labeled as deformation.

enough. Figure 9 presents a few challenging samples along
with the produced pseudo label. The top row contains non-
decomposition samples while the bottom row patches labeled
as deformation. In the second and fifth column of the first
row, we see patches containing multiple fringes. These fringes
are most likely caused by atmospheric disturbances and were
correctly classified as non-deformation. The most distinctively
encouraging results however, lie on the bottom row. The
easiest example lies in the first column where the deformation
is clearly visible. In the second column, the deformation
on the top right is well identified despite the surrounding
noise. The third and fourth columns show impressive results.
Both patches contain small deformation fringes, especially
the fourth column. Fringes like that are non-existent in the
synthetic dataset and constitute the early stages of volcanic
activity. Furthermore, in the final example we observe fringes
hidden behind noise. This noise could be attributed to the
existence of water or other SAR signal decorrelation factors
that affect interferometric coherence. The ability to identify
the existence of deformation under these conditions is of utmost
importance in this critical task. Hence, considering the great
range of applications of InSAR, and the technology that can
provide us with synthetic data, our proposed method can create
quality labeled datasets that will require minimum to no human
supervision and still be able to train simple models for the task
at hand.

V. CONCLUSION

In this work we systematically tackle the problem of vol-
canic unrest detection using synthetically generated InSAR
data. Our framework, based on prototype learning and vision
transformers, generalizes to the real domain and surpasses
the current state of the art (> 93%). Additionally, given
an unlabeled dataset from the real-domain, we utilize self-
labeling and boost the performance of our model up to 97.1%
without jeopardizing its generalization abilities, retaining its
strong classification performance on the synthetic validation
set. To showcase the robustness of our model, we use it
to pseudo-label a real dataset and train a simple ResNet18
that achieves 91.6% on our test set, higher than the same
architecture when trained using synthetic data. Finally, we
explore the nature of the learnt prototypes as well as the
properties of our encoder, including its self-attention and its
positional embeddings, towards a more interpretable method
for volcanic unrest detection.

Due to the general nature of our methodology and the com-
bined strength of prototype learning and vision transformers,
the approach should be applicable to other downstream tasks
with InSAR data such as localisation of deformation, and
detangling of atmospheric, orbital, Digital Elevation Model
deformation interferometric signals.

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