Anomaly detection for the identification of volcanic unrest in satellite imagery

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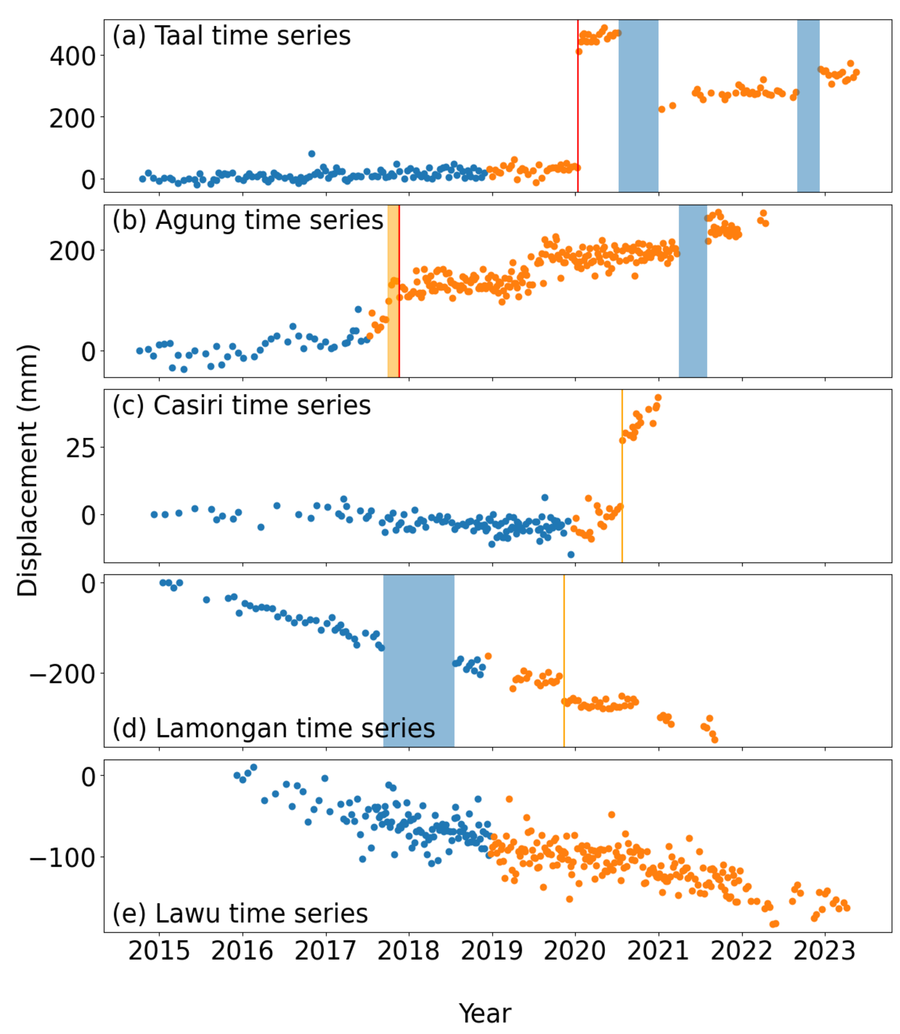
Aim: To study the use of anomaly detection to find deformation in InSAR images of volcanoes

Key Points

- We present an unsupervised machine learning framework to detect volcanic ground deformation as an anomaly in unwrapped interferograms using convolutional neural networks
- We propose a new pre-processing approach to accommodate noise introduced by the atmosphere and vegetation present around the volcanoes
- The final framework was shown to perform better than the existing supervised machine learning system

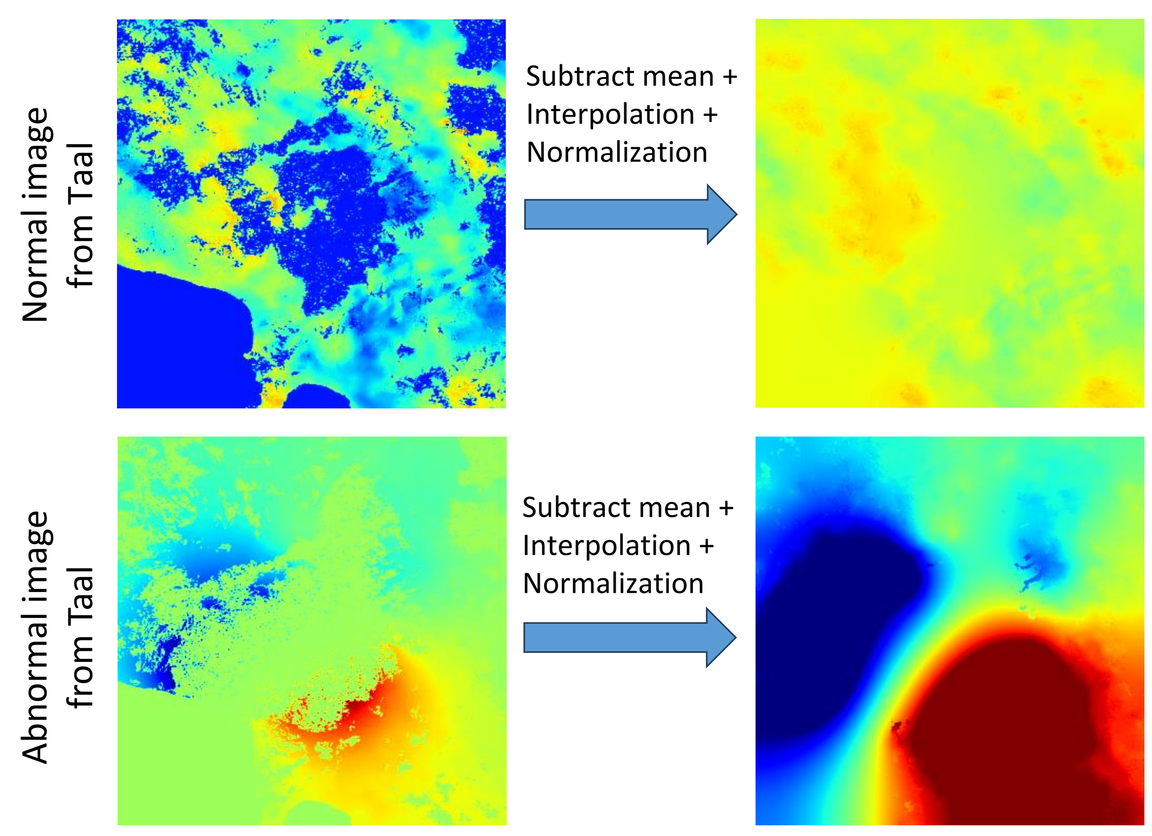
1. Case studies

- Five volcanoes were hand-picked: Taal in the Philippines, Agung, Lamongan and Lawu in Indonesia and Casiri in Peru
- For each volcano, the interferograms were separated into two groups: training (blue) and testing (orange)
- For Taal, Agung, Casiri and Lamongan, training was chosen to extend for 6 months before the deformation event
- For Lawu where no deformation occurred, we use half the images for training

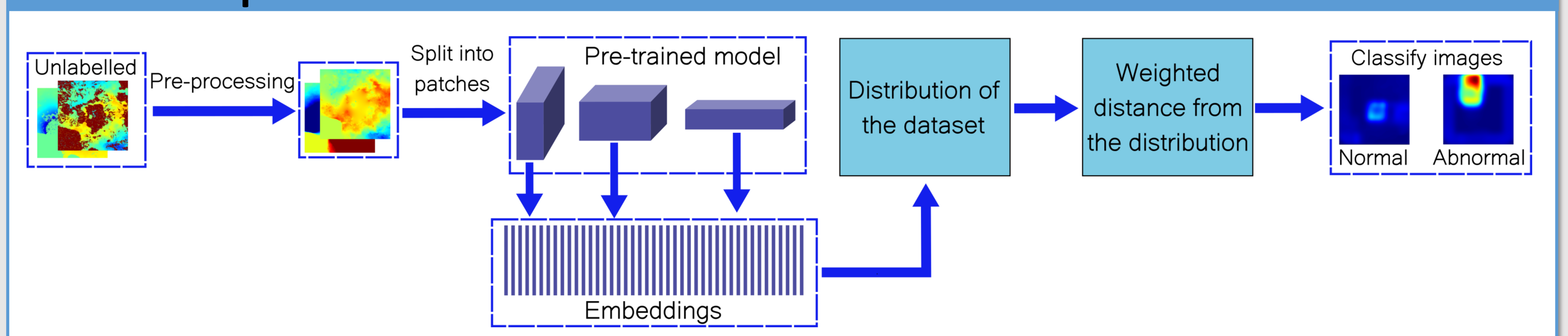


2. Pre-processing

The data is noisy:
- Interferograms contain NaN values
- The range of values varies greatly
- Machine learning models work better with inputs within the range of [−1, 1]



3. Proposed framework

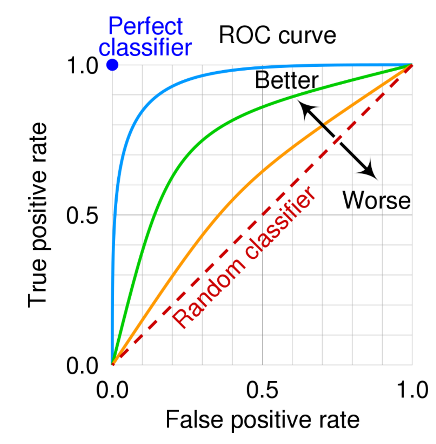


1. The interferograms are split into smaller patches, and embeddings are extracted from these patches using the pre-trained network
2. A distribution of the dataset is created from all the embeddings extracted from the training dataset, and a distance from the learned distribution is calculated for each image
3. The classification of an image is determined based on the calculated distance

- We propose a modified version of Padim[4] where we apply weights to each layer of the network
- The original Padim uses the Mahalanobis distance, we replace it with the weighted Mahalanobis distance[1,2] (wMaha)
- We further improve the model by using the Negative Logarithm of the Matching Likelihood [1,2] (NLML) and the weighted NLML[1,2] (wNLML) to calculate the distance
- We tested our framework against the original Padim[4] model, the existing Supervised machine learning system[3] and two widely used networks: GaNomaly[5] and Diffusion[6]

4. AUROC

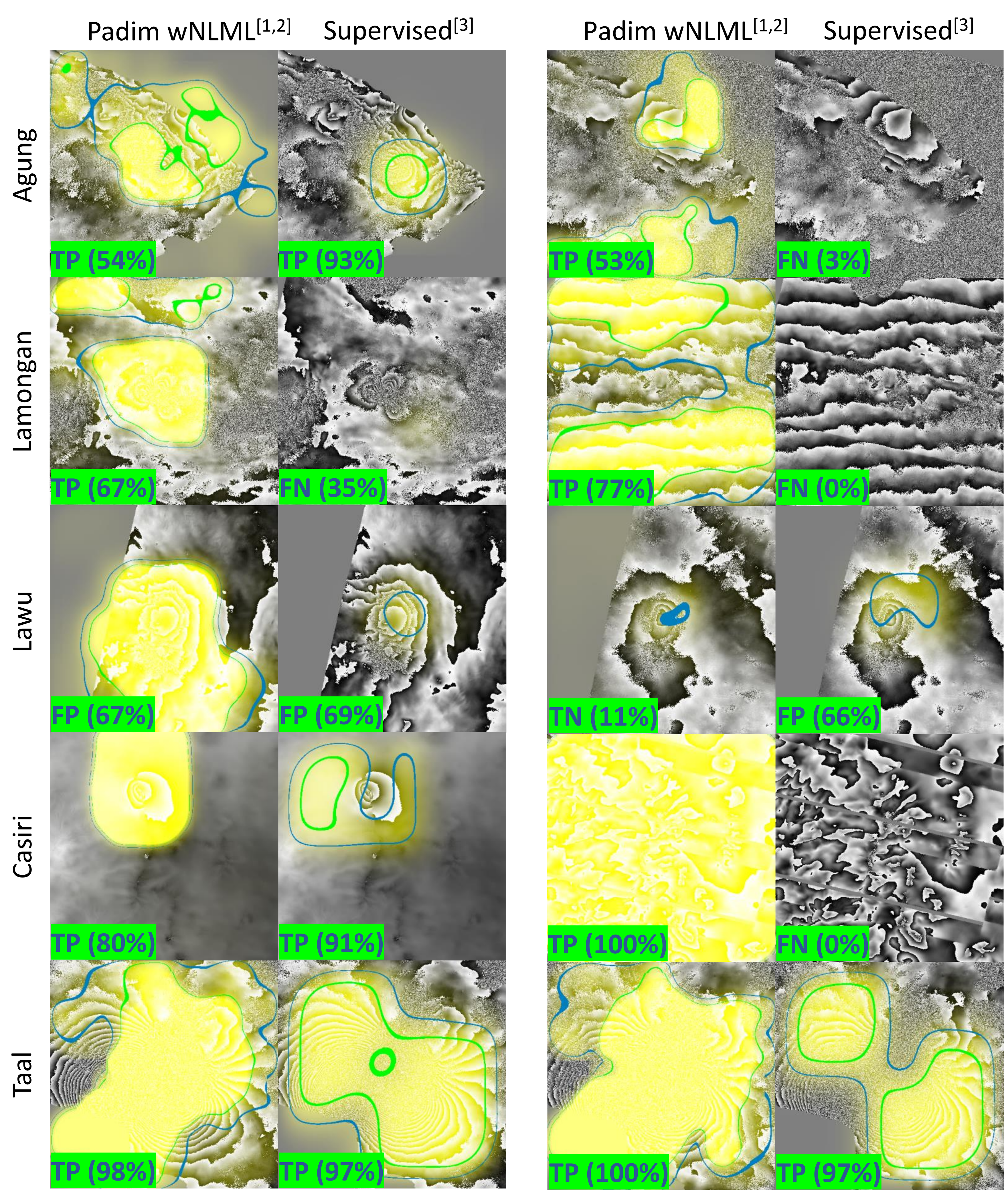
- Unsupervised learning models output the loss value for an image
- We need to choose a threshold to classify images as normal or abnormal. The accuracy of the model relies on the chosen threshold
- We use the Area Under the Receiver Operating Characteristic (AUROC) curve to determine how well a model performs



5. Results

Volcano	Padim[4]	Padim NLML[1,2]	Padim wMaha[1,2]	Padim wNLML[1,2]	GaNomaly[5]	Diffusion[6]	Supervised[3]
Taal	0.96	**0.97**	0.95	**0.97**	0.93	0.90	0.94
Agung	0.90	0.92	0.91	**0.93**	0.73	0.84	0.52
Casiri	0.37	0.44	**0.69**	0.65	0.38	0.35	0.47
Lamongan	0.88	0.89	0.96	**0.97**	0.76	0.86	0.88
Lawu	9 FP*	**7 FP***	9 FP*	8 FP*	11 FP*	12 FP*	**7 FP***

*There are no reported True Positives at Lawu, so AUROC cannot be calculated. We instead report the number of False Positives (FP)



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4. Defard, T., Setkov, A., Loesch, A., & Audigier, R. (2021). Padim: A patch distribution modeling framework for anomaly detection and localization. In Pattern recognition. ICPR International Workshops and Challenges
5. Akcay, S., Atapour-Abarghouei, A., & Breckon, T. P. (2019). GaNomaly: Semi-supervised anomaly detection via adversarial training. In C. V. Jawahar, H. Li, G. Mori, & K. Schindler (Eds.), Computer vision – ACCV 2018
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