

Unbalanced Technics to Improve the Train for ML Models to Detect Earthquake Fringes Bruno Silva | Joaquim Sousa | Milan Lazecky | António Cunha

Abstract

Machine Learning can automatically process large datasets in the most varied areas, including remote sensing data, and it has become an opportunity for earth observation. Recent studies have demonstrated the ability to detect visible fringes deformations in InSAR images. However, InSAR data is frequently unbalanced - deformations are sparse compared to those that do not have deformation, and it needs special attention for training ML models.

In this work, we created two InSAR datasets with 29

Dataset					
	Train	Validation	Test		
Earthquake fringes (deformation)	499	380	252		
No deformation	14979	4051	3826		

Models evaluation

Wrapped interferograms

Unwrapped interferograms

earthquake cases from the LICS database. At start we use Data Augmentation to deal with data unbalanced to detect fringes, but when the data grew, and the unbalancing got bigger DA start to perform worse, so we apply a new technique to deal with the unbalancing.

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Models	Accuracy	F1 Score	AUC	Accuracy	F1 Score	AUC	
InceptionV3	0.952	0.371	0.768	0.938	0.137	0.651	
VGG19	0.971	0.691	0.864	0.951	0.330	0.734	
Resnet50V2	0.960	0.526	0.752	0.943	0.160	0.669	







overlapped ones we can create a well chosen patches to train and improve the results.

Train deep learning models prepare the input data The data will pass for 2.

the layers, resulting a prediction

- Prediction are 3. evaluated through loss function resultin a score.
- The score is used as feedback to adjust model weights 4. throught the optimizer.

Optimizer

Focal Loss compensate data less represented.



Loss function

Data augmentation creates artificial data with small alteration, to balance the data in the same amount.

Objective

Deal with unbalanced data training deep learning models to identify deformation in InSAR images, both is wrapped and unwrapped interferograms.





Methods

Two dataset of InSAR interferograms were created (wrapped)

unwrapped). We cut images into 256x256pixels and overlapped patches. Finally we use the patches to train 3 pretrained models with focal loss and we use the best model to compare focal loss with data augmentation.

