





Quantum Machine Learning for Deformation Detection: Application for InSAR Point Clouds

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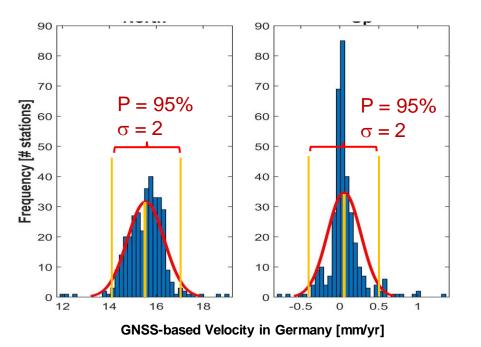
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<u>Le et al (2024), EUG24</u>

Motivation:

Deformation Detection

Using statistical tests





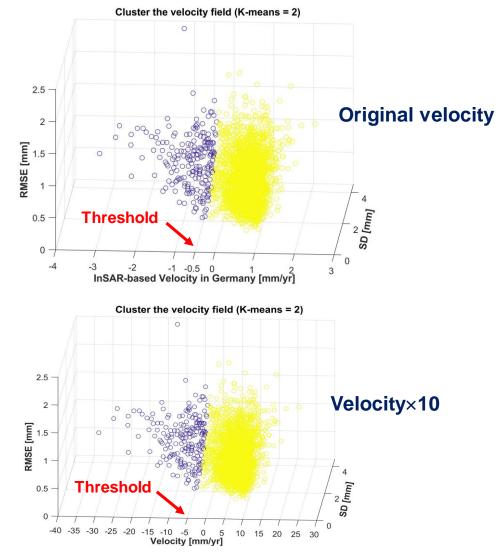
Different datasets/timespans/regions

- → The same statistical threshold but different deformation thresholds
- → Lack consistency



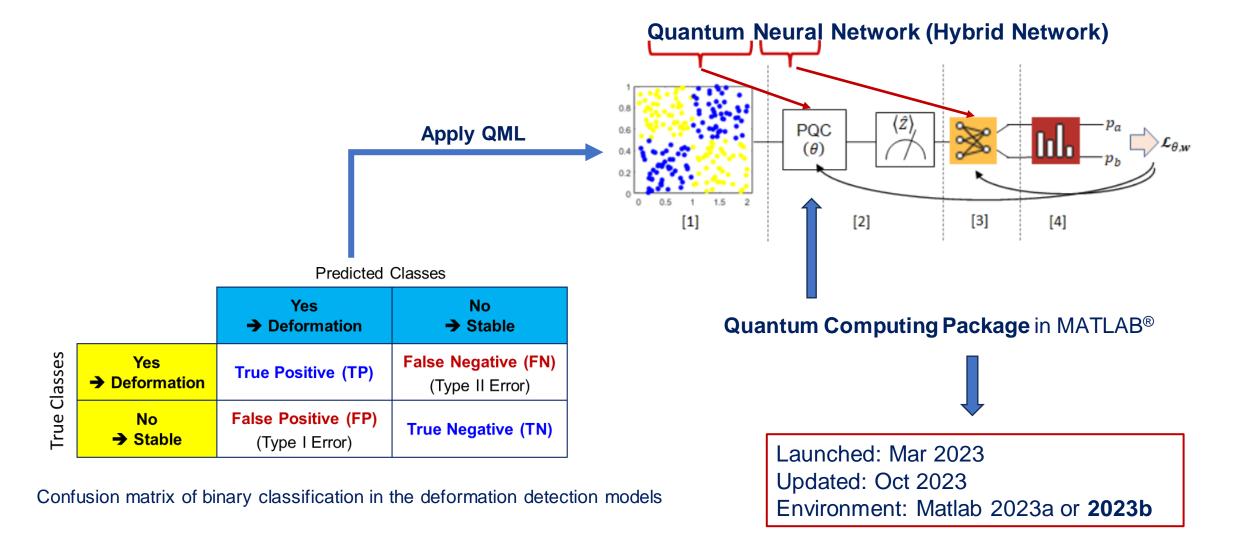
→ Should use the **supervised** ML **models** to detect deformation.

Using unsupervised ML (Clustering ML)



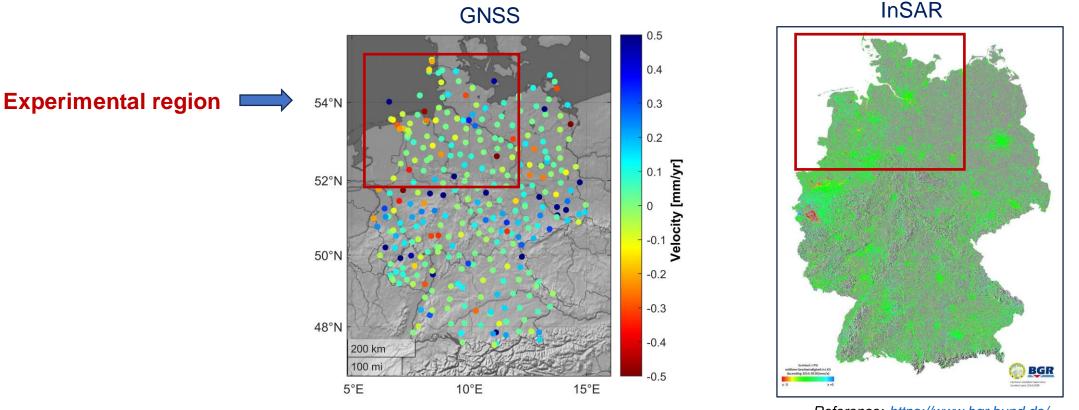


Quantum Machine Learning:



Application:

Detection of surface deformation using GNSS-InSAR and QML



Reference: <u>https://www.bgr.bund.de/</u>

Data:

- ✓ GNSS: 346 monitoring stations (from 1994 to 2020) in Germany → Networks of SAPOS, IGS, and EUREF,...
- ✓ InSAR: 3,500,000 raw time series (from 2015 to 2021) in Northern Germany →BGR



Selecting features for classification

Statistics	RMSE						InSAR time series		
	Median	Mean	Min	Max	Median	Mean	Min	Max	IIISAR LIIIE Series
Clean (mm)	1.33	1.42	0.25	9.21	0.69	0.74	0.13	4.75	
Raw (mm)	1.41	1.50	0.26	9.30	0.73	0.78	0.14	4.79	2,719,002
Improvement (%)	🦸 5.6	5.4	2.1	0.9	1 5.6	5 .4	2.1	0.9	

Statistics	Velocity mm/yr)				Outliers					InSAR time series
	Median	Mean	Max subsi	Max uplift	Median	Mean	Min	Max	Sum	
Clean	-0.07	-0.19	-46.43	33.72						
Raw	-0.10	-0.20	-46.00	32.40	9	9.77	0	55	26,555,233	2,719,002
Changes	🔌 0.03	🖄 0.01	- 0.43	1 .32						

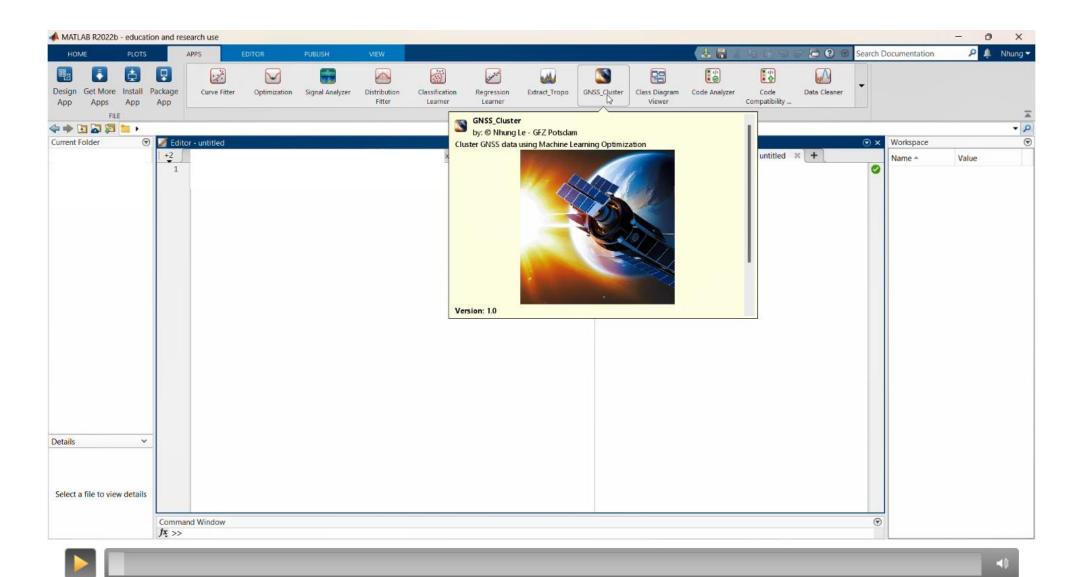
Overlapping/uncertain InSAR grid points have already been removed -



Features: Velocity, Variations, Errors, Outliers, Entropy, Monitoring timespans,...

Create samples for training ML models using the clustering ML App





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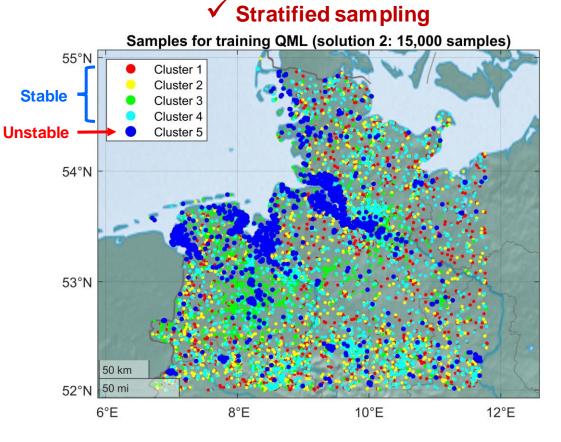


Sampling strategies for training and validating QML

Samples for training QML (solution 1: 10,000 samples) 55°N Cluster 1 Cluster 2 **Stable** Cluster 3 Cluster 4 **Unstable** -Cluster 5 54°N 53°N 50 km 52°N 50 mi 6°E 8°E 12°E 10°E Pick out randomly 2000 samples in each Class from 1 to 5

× Systematic sampling

× Biases due to the samples of stable category



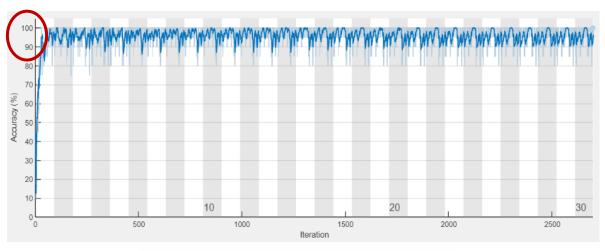
- ✓ 2000 samples in each Class from 1 to 4
 → 8000 samples → Stable category
- ✓ Using all samples of Class 5
 → 7300 samples → Unstable category

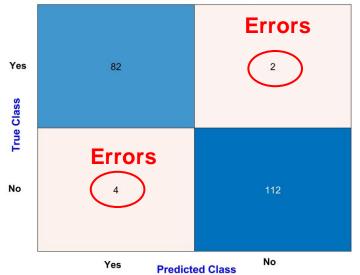


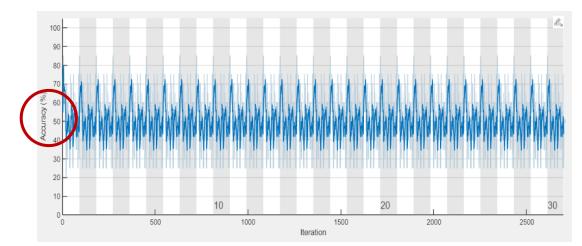
QML vs Pure ML (Hybrid Network vs Neural Network)

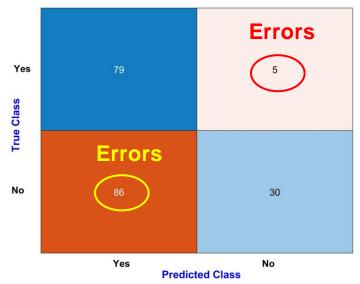


Hybrid Network (QML)







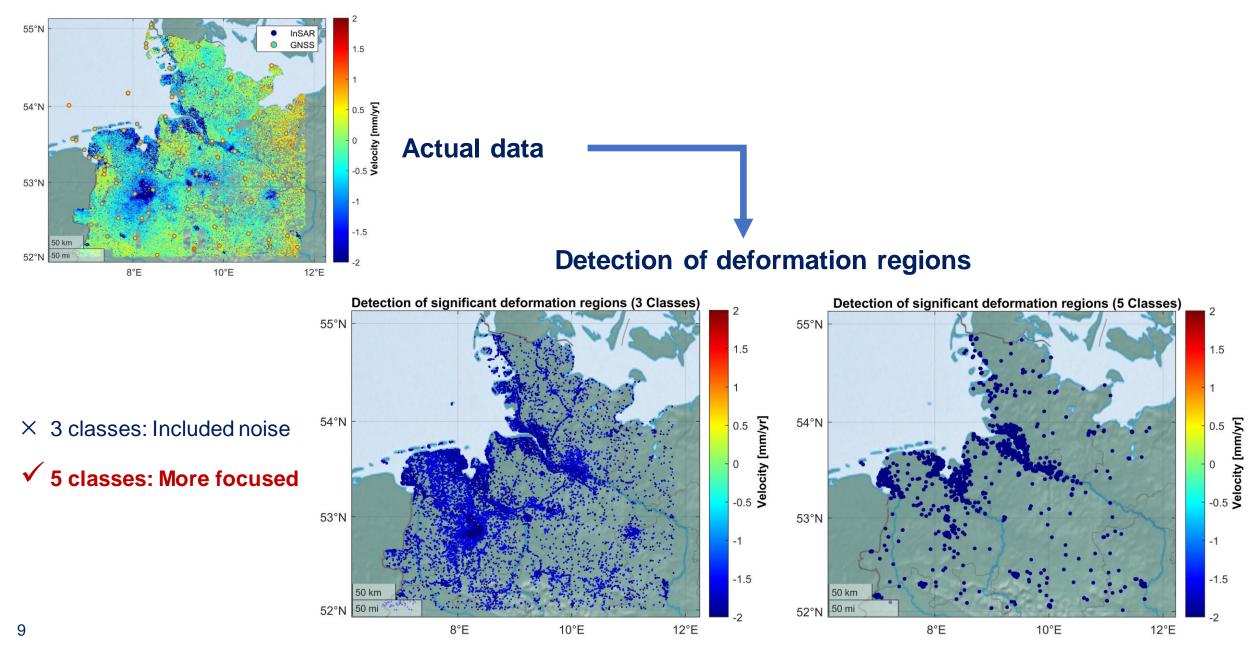


Neural Network (Pure ML)

Detection of significant deformation regions

GFZ

Helmholtz Centre





Conclusions and suggestions

- The QML-based Hybrid Network is recommended for improving the performance of the pure ML-based Neural Network.
- The study suggests a workflow of the Hybrid Network-based binary classification to implement the QML technique for **better sensitivity** of deformation detection.
- > Extend investigations on other ML techniques for a more comprehensive assessment.







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