Unsupervised Anomaly Detection of Paranasal Anomalies in the Maxillary Sinus

D.Bhattacharya et al.

Iagaru David
david.iagaru@student-cs.fr
Durand–Janin Louise
louise.durand–janin@ens-paris-saclay.fr

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Introduction

Paranasal sinus anomalies are frequently diagnosed during neuroradiological assessments. These incidental findings present clinical challenges, yet their significance in the general population remains unclear. To face the high misdiagnosis rate associated with these anomalies, **Deep Learning methods** have been explored to **automate paranasal anomaly detection** in Magnetic Resonance Images (MRI)

Position regarding the SOTA

Traditionally, supervised Deep Learning was the predominant approach for classifying maxillary sinus (MS) anomalies. It however has limitations such as the **large necessary labelling effort and the possibility to only detect a single anomaly at a time.**

Main contributions

In this study, the authors provide an unsupervised Deep-Learning-based method to detect any anomalies on the Maxilliary Sinus from MRI images. It uses **3D-Auto-encoders trained only on healthy MS volumes** thus reducing the labelling task to the acquisition of normal volumes. Based on the voxel's reconstruction error, they are able to display a heatmap allowing to **locate the anomaly.**

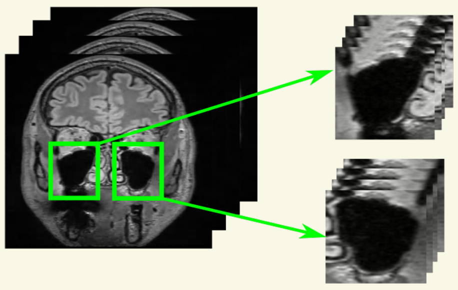
Methods

Dataset

- 499 MRI MS volumes (269 Normal ,130 annomalous)

Preprocessing

- Resampling of the global volume
- Sub-Volumes extraction
- Reshaping and normalization of the subvolumes



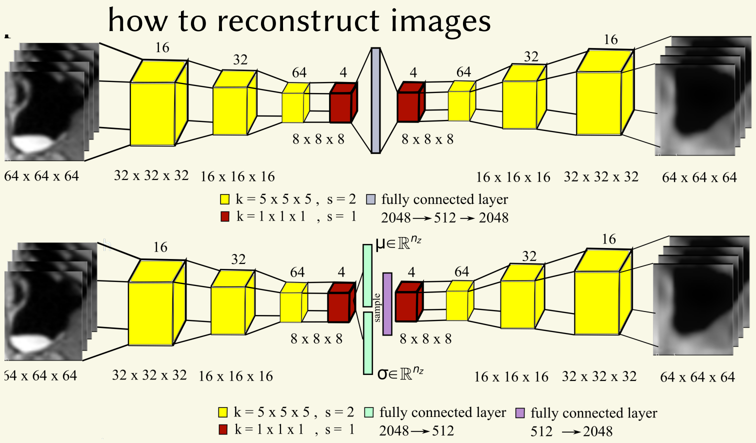
Extraction of left and right MS from head and neck MRI

Data split

Training : 172 Normal Volumes (NV)
Validation : 43 NV, 52 AV
Test : 54 (NV), 78 AV

Architectures : 3D Auto-Encoders

- Train 2 independent Auto-Encoders only on healthy MS volumes.
  - Convolutionnal (cAE)
  - Variationnal (VAE)
- They are designed with different architectures, leading to distinct ways of learning how to reconstruct images



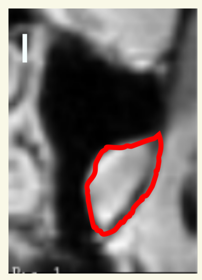
Architectures of the considered 3D Auto Encoders

Motivation :

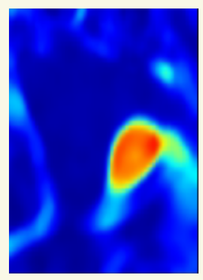
They will fail to reconstruct anomalous MS volumes. A MS volume is considered as anomalous if the reconstruction error (L1 or L2) is higher than a tunned threshold.

Localization of the Anomaly

Visualizing the intensity difference between the original and the reconstructed volume thanks to the voxel-wise absolute difference.



Original image where the anomaly is circled in red.



Heatmap based on the reconstruction error

Validation and results

- **Evaluation metric :** Area Under the Precision Recall Curve (AUPRC) as the test data is imbalanced
- The threshold to consider a volume as unhealthy is selected according to the higher F1-score on the validation set
- Anomaly detection performance on two thresholds L^1 and L^2

Method	Precision		Recall		F1		AUPRC	
	L1	L2	L1	L2	L1	L2	L1	L2
VAE	0.64	0.68	0.76	0.80	0.68	0.72	0.67	0.75
cAE	0.72	0.77	0.73	0.71	0.71	0.74	0.78	0.82

- Accuracy per anomaly on the test set :
  - Normal volume : 0.61 %
  - Polyps : 0.91%
  - Mucosal Thickening : 0.62 %
  - Cysts : 0.80 %

Conclusion

- This unsupervised method opens a new path for paranasal sinus anomalies dectection which requires only healthy data
- Threshold on the L^2 error is more accurate. cAE showed roughly better performance than VAE
- Accuracy on healthy MS volumes needs to be improved.

References

[1] D.Bhattacharya et al. Unsupervised anomaly detection of paranasal anomalies in the maxillary sinus. 04 2023