Evaluating the Fidelity of Explanations for Convolutional Neural Networks in Alzheimer's Disease Detection

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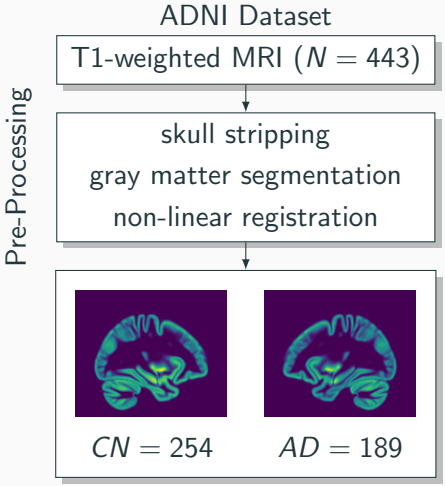
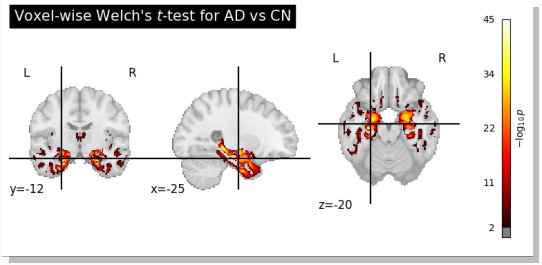
2025-03-09

University of Rostock

Motivation

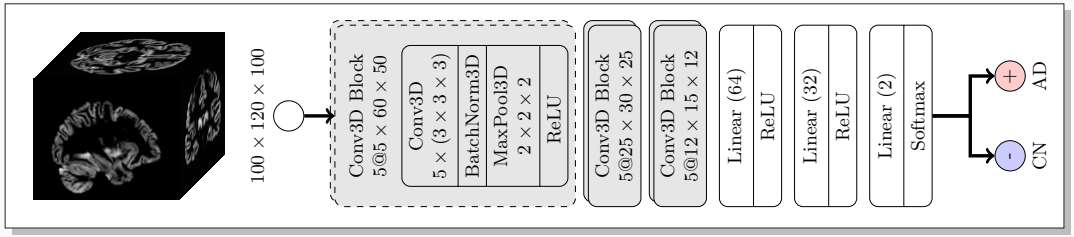
Data and Preprocessing





Voxel-wise Welch's t-test ($\alpha = 0.01$)

A CNN Model for AD vs CN Classification



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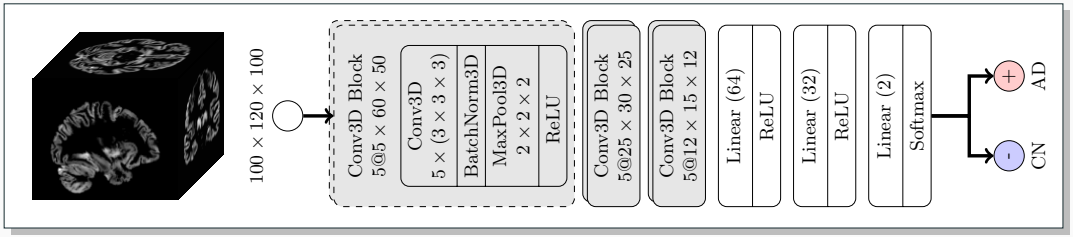

AUC ROC	Accuracy
0.95 ± 0.02	87.64%

5-fold Cross Validation Results

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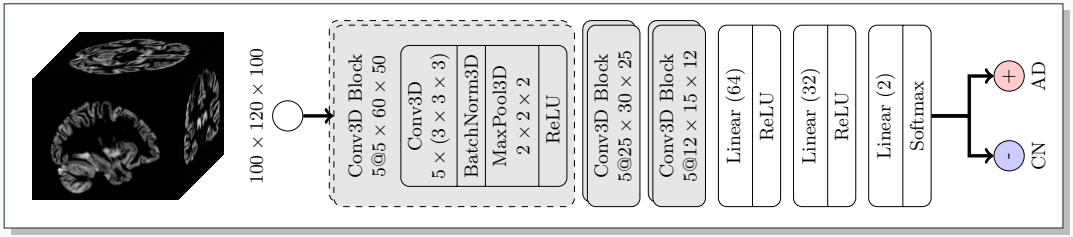

AUC ROC	Accuracy
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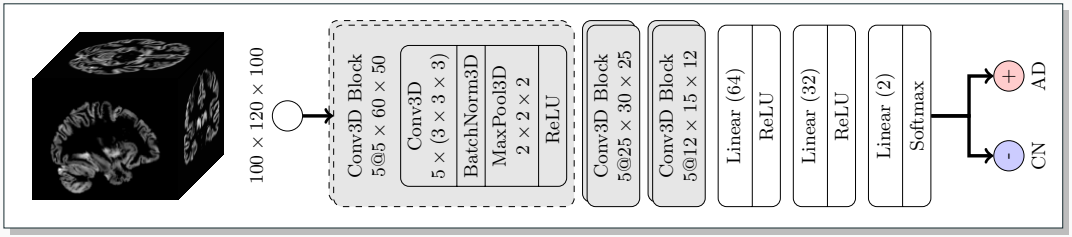
5-fold Cross Validation Results

Acceptable Performance...

...but can we **trust** the model?

Attribution Maps: What did the network look at?



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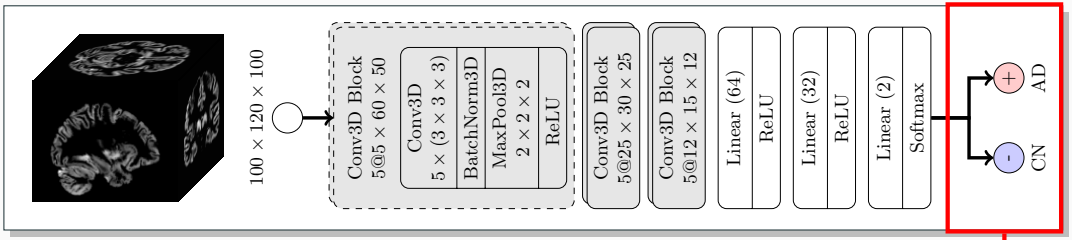
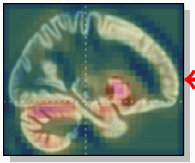
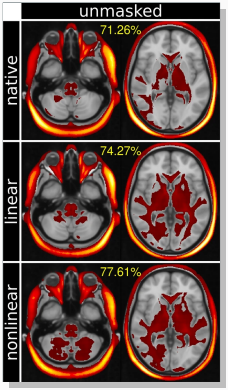




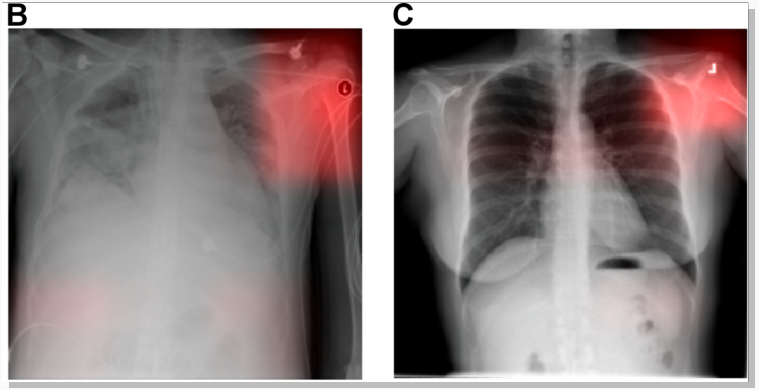
relevance map

Propagation of Relevance

Why should I care?



(a) From: Tinauer et al. [1]



(b) From: Zech et al. [2]

Attribution maps can reveal **shortcut learning**: Neural Networks can use features outside of the brain parenchyma (a) or X-ray side marker tokens (b) for classification.

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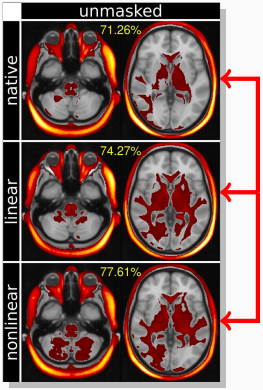

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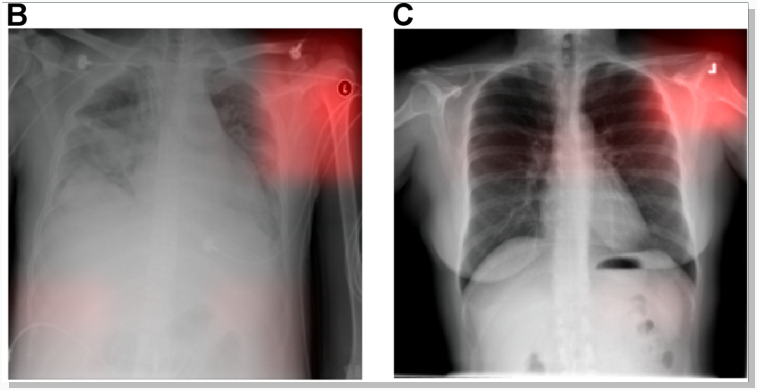

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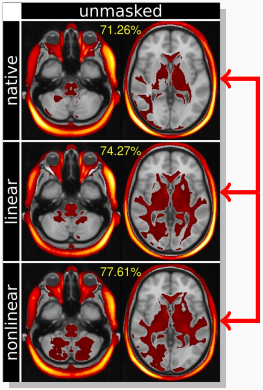

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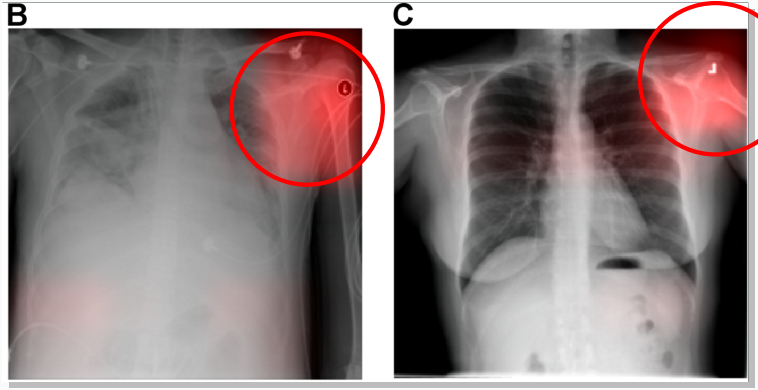

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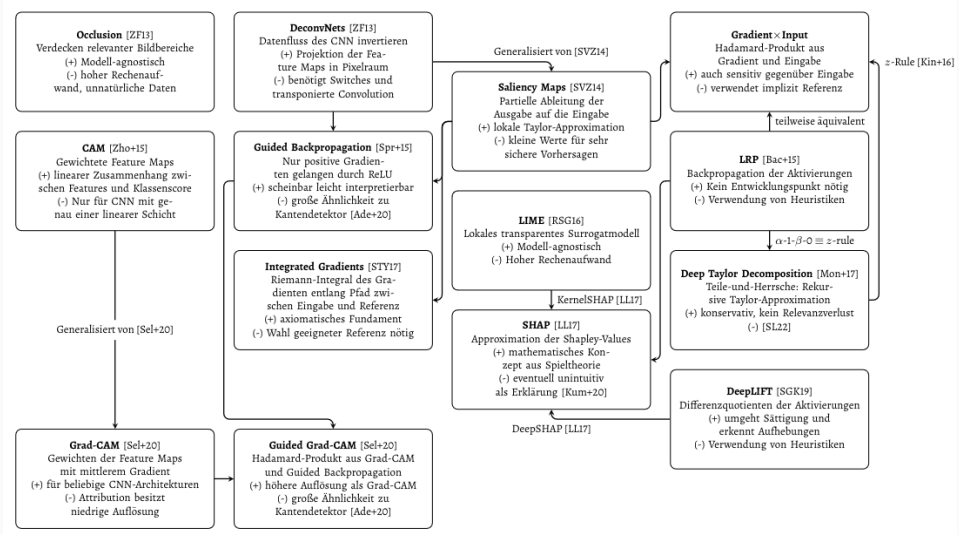
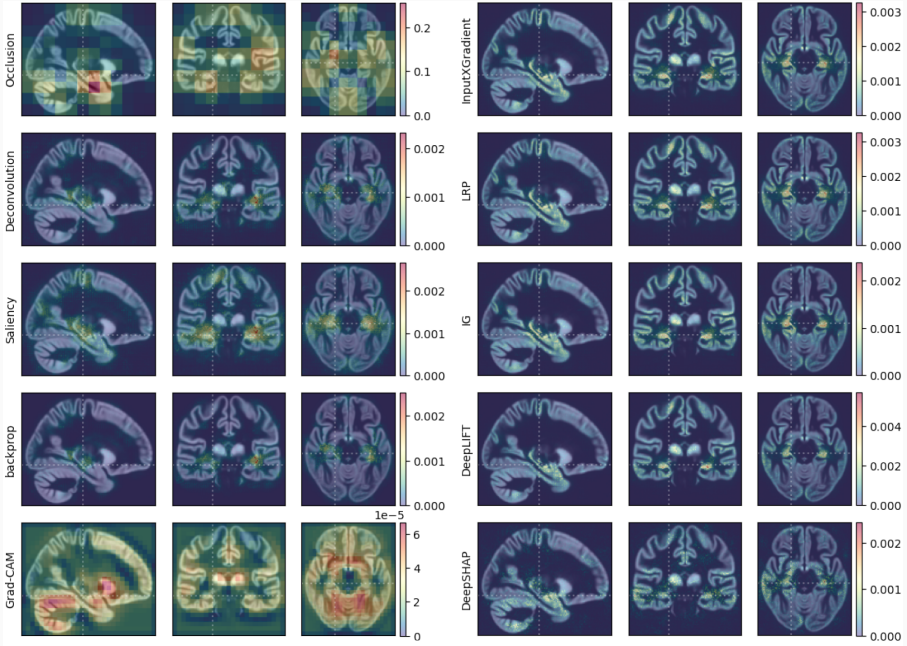


Popular feature attribution methods for Deep Neural Networks and their Relationships


Occlusion
0.2
0.1
0.0
InputXGradient
0.003
0.002
0.001
0.000
Deconvolution
0.002
0.001
0.000
LRP
0.003
0.002
0.001
0.000
Saliency
0.002
0.001
0.000
IG
0.002
0.001
0.000
backprop
0.002
0.001
0.000
DeepLIFT
0.004
0.002
0.000
1e−5
Grad-CAM
6
4
2
0
DeepSHAP
0.002
0.001
0.000

Total Relevance per ROI

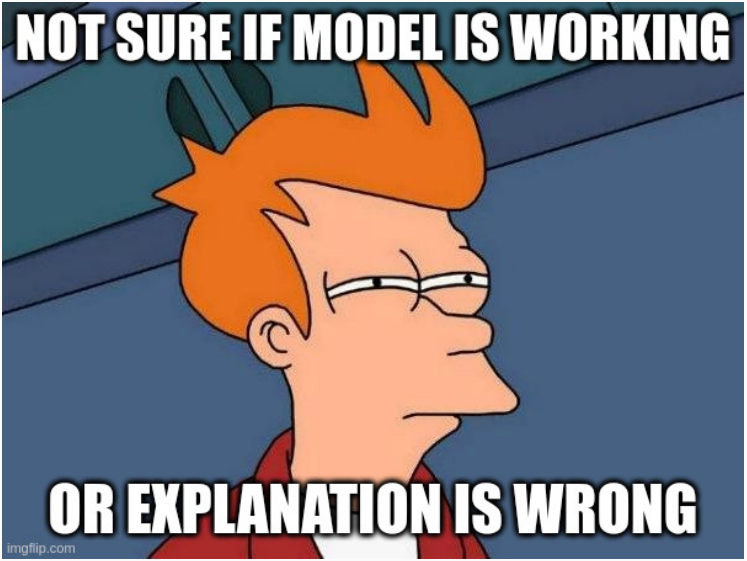
	Occlusion	IG	DeepLIFT	DeepSHAP
1.	Precuneus_L	Temporal_Mid_L	Temporal_Mid_L	Calcarine_L
2.	Precuneus_R	Temporal_Mid_R	Temporal_Mid_R	Precentral_R
3.	Postcentral_L	Temporal_Inf_L	Temporal_Inf_L	Calcarine_R
4.	Supp_Motor_Area_L	Precentral_R	Precuneus_R	Cerebelum_6_R
5.	Supp_Motor_Area_R	Postcentral_L	Precuneus_L	Precentral_L
6.	Postcentral_R	Frontal_Mid_L	Temporal_Inf_R	Lingual_L
7.	Precentral_L	Postcentral_R	Parietal_Inf_L	Postcentral_R
8.	Cingulum_Mid_R	**Hippocampus_L**	Frontal_Mid_L	Postcentral_L
9.	Frontal_Sup_Medial_L	Temporal_Inf_R	**Hippocampus_L**	Lingual_R
10.	Cingulum_Mid_L	Parietal_Inf_L	Supp_Motor_Area_R	Cuneus_L

Top 10 AAL ROIs by total relevance for class AD

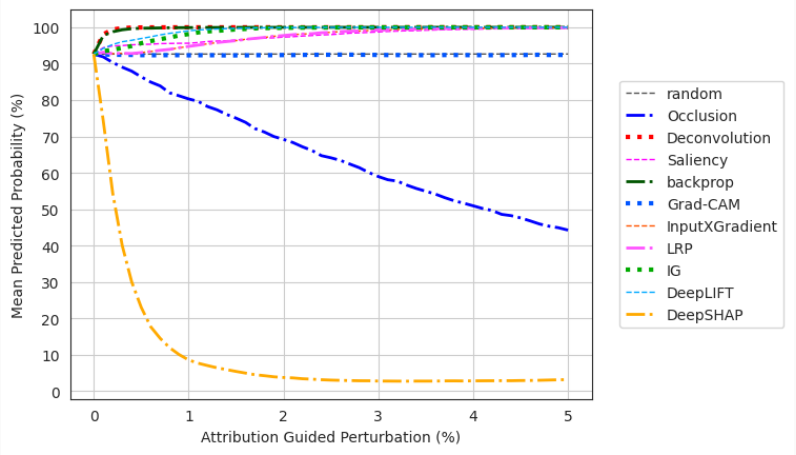
Mean Relevance per ROI

	Occlusion	IG	DeepLIFT	DeepSHAP
1.	Supp_Motor_Area_L	**Hippocampus_L**	**Hippocampus_L**	Calcarine_L
2.	Supp_Motor_Area_R	**Hippocampus_R**	**Hippocampus_R**	Calcarine_R
3.	Rolandic_Oper_L	ParaHippocampal_R	Parietal_Inf_R	Vermis_10
4.	Cingulum_Mid_L	Heschl_L	Amygdala_L	Vermis_7
5.	Cingulum_Mid_R	Parietal_Inf_L	ParaHippocampal_R	Vermis_6
6.	Paracentral_Lobule_R	Thalamus_R	Parietal_Inf_L	Vermis_9
7.	Precuneus_L	Rolandic_Oper_L	Calcarine_R	Vermis_8
8.	Precuneus_R	Temporal_Inf_L	Supp_Motor_Area_R	Cuneus_R
9.	Heschl_L	Temporal_Mid_L	Temporal_Inf_L	Cerebelum_6_R
10.	Frontal_Med_Orb_R	Supp_Motor_Area_R	SupraMarginal_L	Precentral_R

Top 10 AAL ROIs by mean relevance per voxel for class AD



But can the **explanation** be trusted?

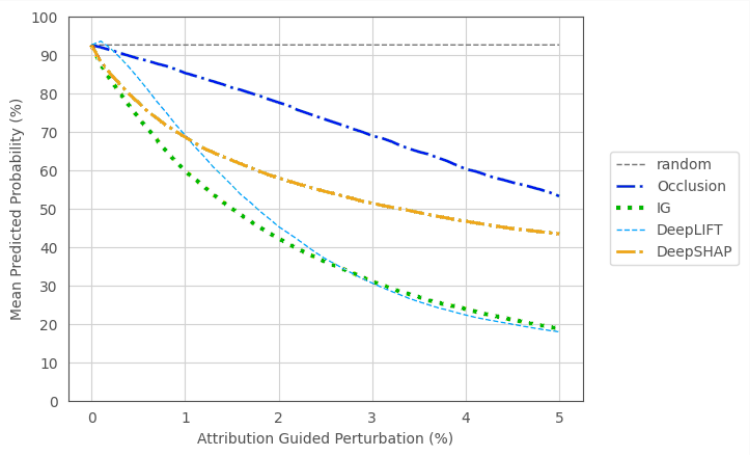


Mean Predicted AD Probability when replacing voxels by the null image baseline

Hypothesis

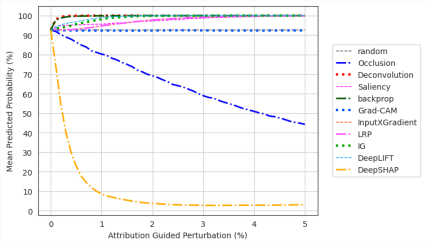
Null image corresponds to "maximum attrophy".

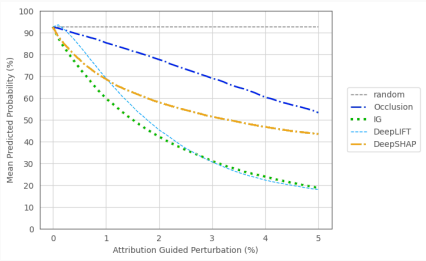
AD to CN Perturbation: Using the CN mean as Attribution Baseline



Mean Predicted AD Probability when replacing voxels by the CN mean

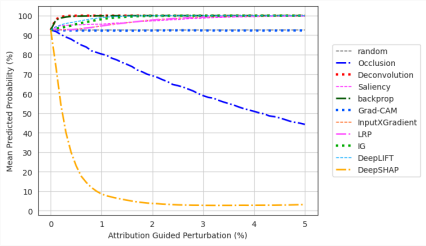
Conclusion

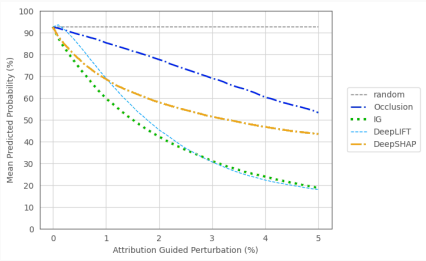




Take-Aways

Conclusion

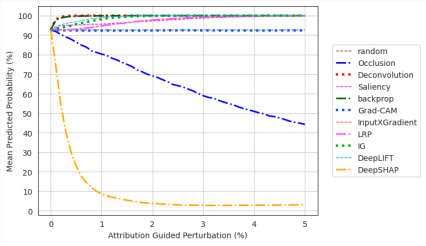


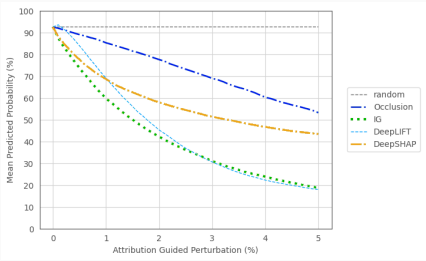


Take-Aways

1. Perturbation tests offer a **model-agnostic fidelity metric**.

Conclusion





Take-Aways

1. Perturbation tests offer a **model-agnostic fidelity metric**.
2. The **attribution baseline** should be chosen carefully.

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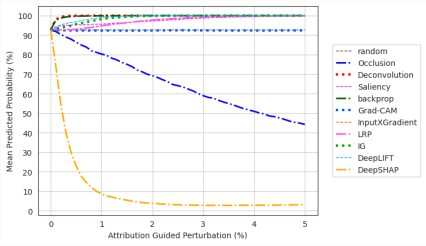

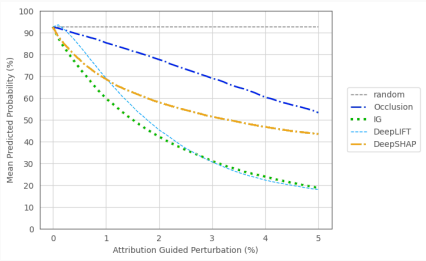

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2. The **attribution baseline** should be chosen carefully.
3. Attribution Maps **need interpretation** to actually explain anything.

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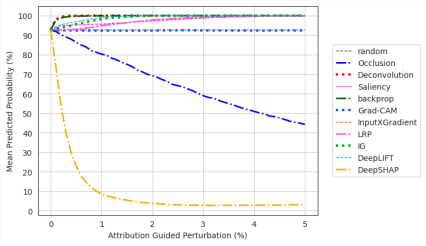

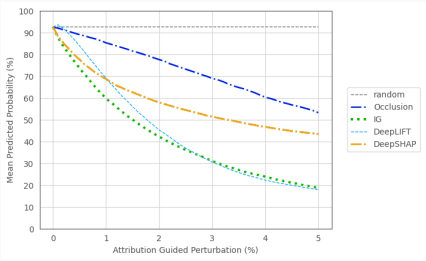

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Meet the Team

University of Rostock


Thomas Kirste


Martin Becker


Sebastian Bader


Bjarne Hiller

DZNE

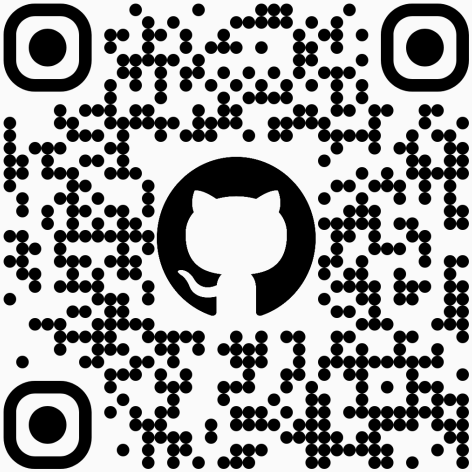

Martin Dyrba


Devesh Singh

Thanks for your Attention!

See you on GitHub!

bckrlab/ad-fidelity



References i

[1] Christian Tinauer et al. "Interpretable brain disease classification and relevance-guided deep learning". en. In: **Scientific Reports** 12.1 (Nov. 2022). Publisher: Nature Publishing Group, p. 20254. ISSN: 2045-2322. DOI: 10.1038/s41598-022-24541-7. URL: https://www.nature.com/articles/s41598-022-24541-7 (visited on 10/12/2024).

[2] John R. Zech et al. "Variable generalization performance of a deep learning model to detect pneumonia in chest radiographs: A cross-sectional study". en. In: **PLOS Medicine** 15.11 (June 2018). Publisher: Public Library of Science, e1002683. ISSN: 1549-1676. DOI: 10.1371/journal.pmed.1002683. URL: https://journals.plos.org/plosmedicine/article?id=10.1371/journal.pmed.1002683 (visited on 10/12/2024).