Universität Rostock

Traditio et Innovatio

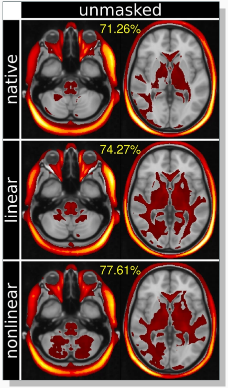
Evaluating the Fidelity of Explanations for Convolutional Neural Networks in Alzheimer's Disease Detection

Bjarne C. Hiller

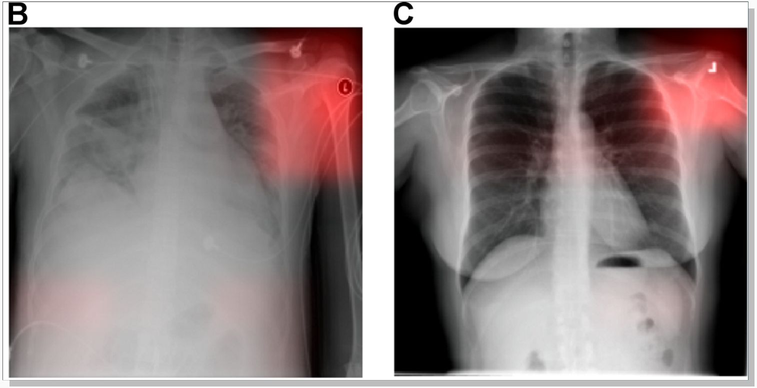
2025-03-09

University of Rostock

Motivation: Can you trust Neural Networks for Medical Image Processing?



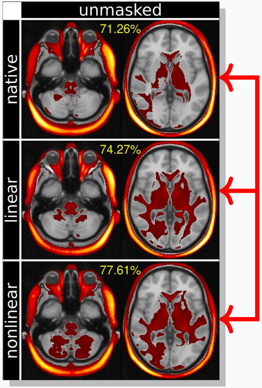
(a) From: Tinauer et al. [2]



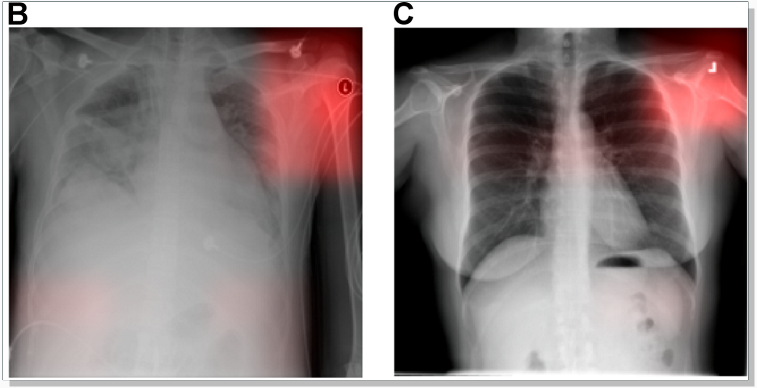
(b) From: Zech et al. [3]

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.

Motivation: Can you trust Neural Networks for Medical Image Processing?



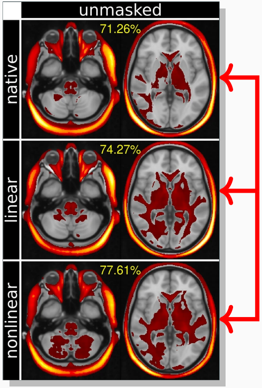
(a) From: Tinauer et al. [2]



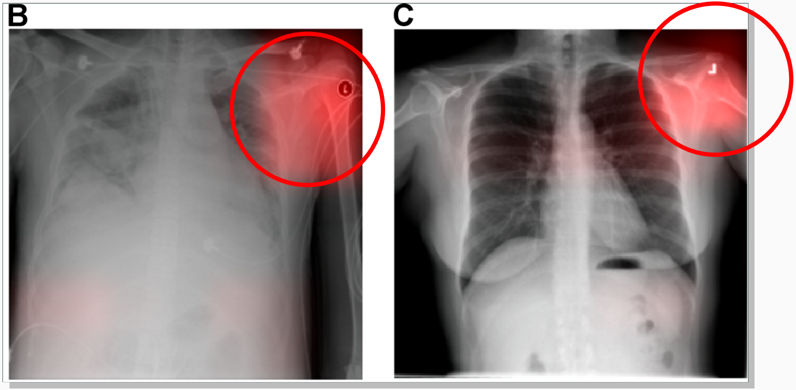
(b) From: Zech et al. [3]

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.

Motivation: Can you trust Neural Networks for Medical Image Processing?



(a) From: Tinauer et al. [2]



(b) From: Zech et al. [3]

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.

Pre-Processing

ADNI Dataset

T1-weighted MRI ($N = 443$)

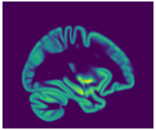
↓

skull stripping

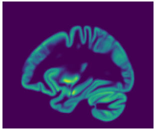
gray matter segmentation

non-linear registration

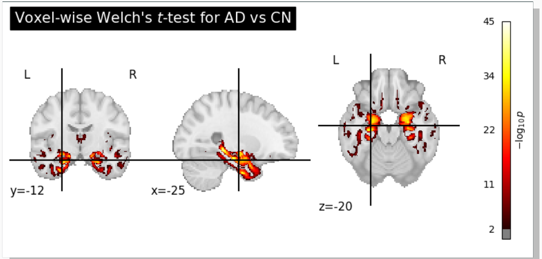
↓



$CN = 254$

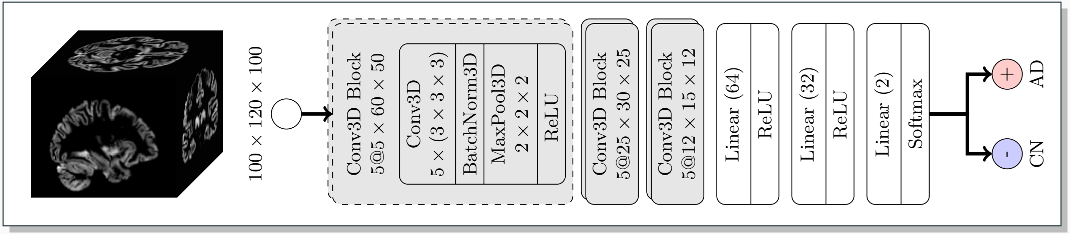


$AD = 189$

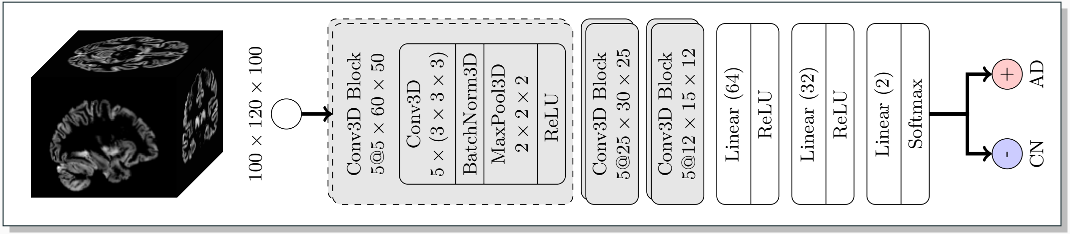


Voxel-wise Welch's t-test ($\alpha = 0.01$)

A CNN Model for AD vs CN Classification



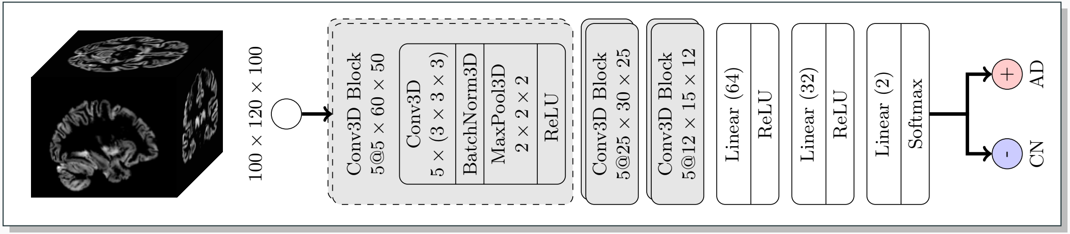
A CNN Model for AD vs CN Classification



AUC ROC	Accuracy
0.95 ± 0.02	87.64%

5-fold Cross Validation Results

A CNN Model for AD vs CN Classification



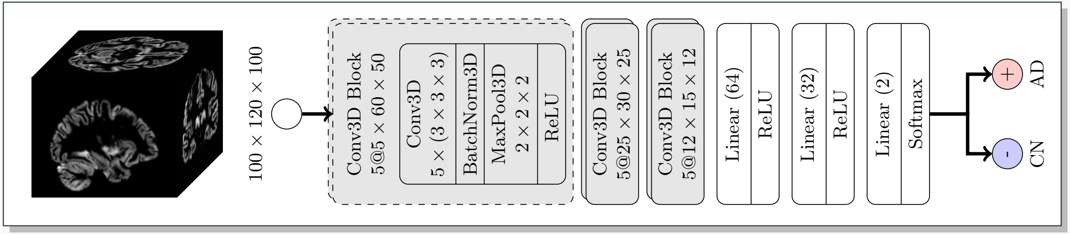
AUC ROC	Accuracy
0.95 ± 0.02	87.64%

5-fold Cross Validation Results

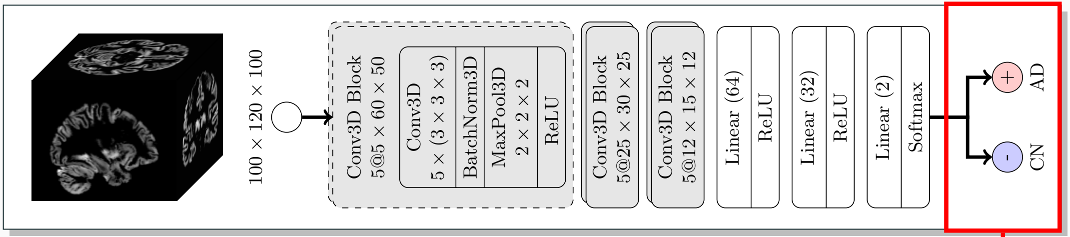
Acceptable Performance...

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

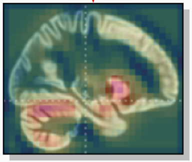
Attribution Maps: What did the network look at?



Attribution Maps: What did the network look at?

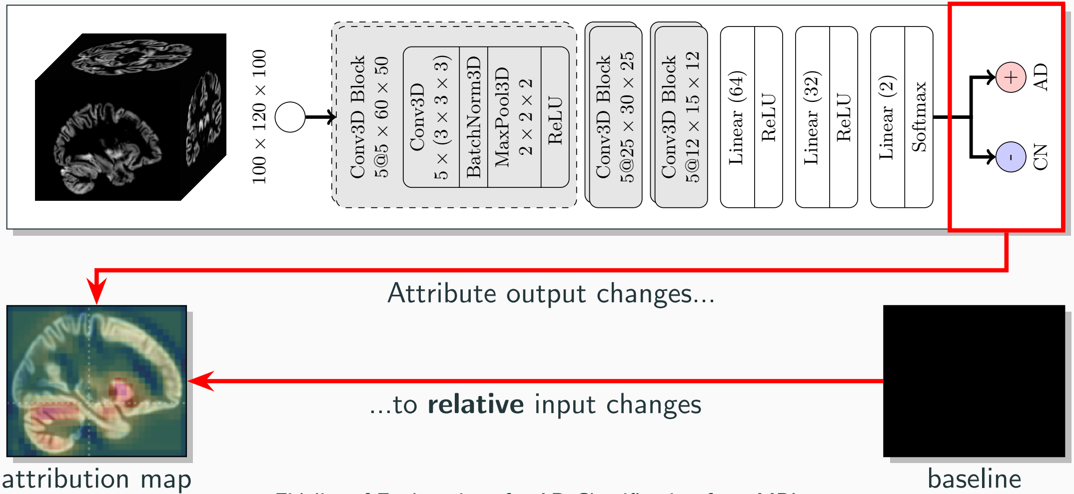


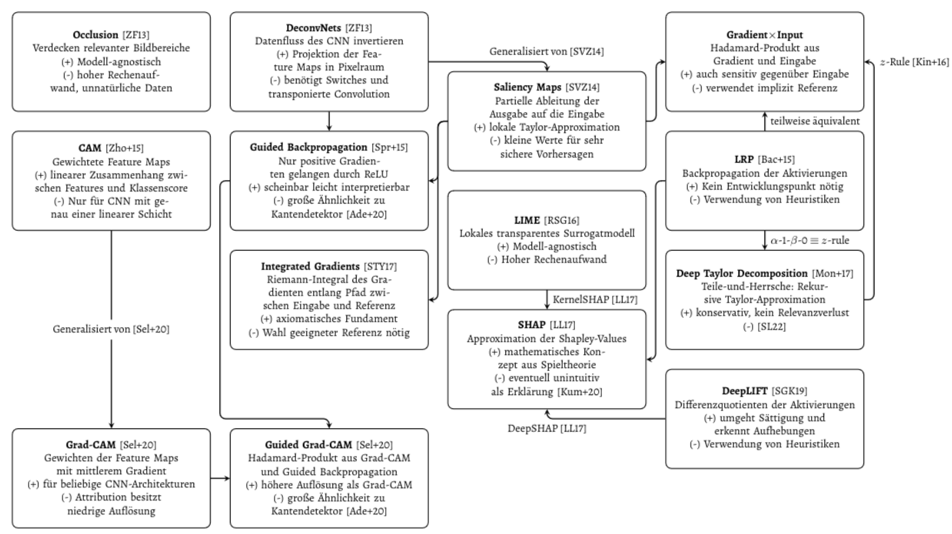
Attribute output changes...



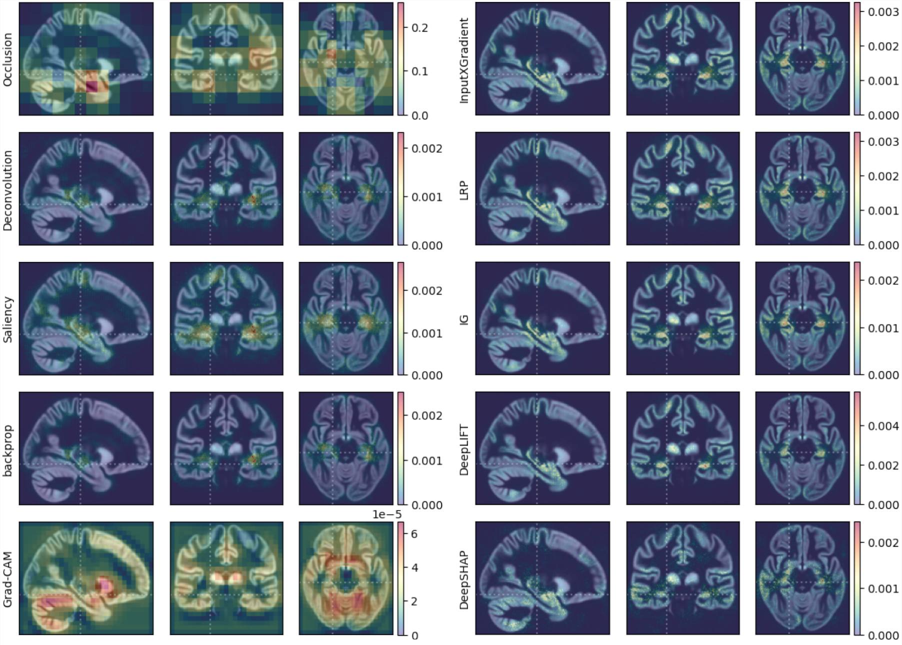
attribution map

Attribution Maps: What did the network look at?





Popular feature attribution methods for Deep Neural Networks and their Relationships



Occlusion
Deconvolution
Saliency
backprop
Grad-CAM
InputXGradient
LRP
IG
DeepLIFT
DeepSHAP
1e−5

Total Relevance per ROI

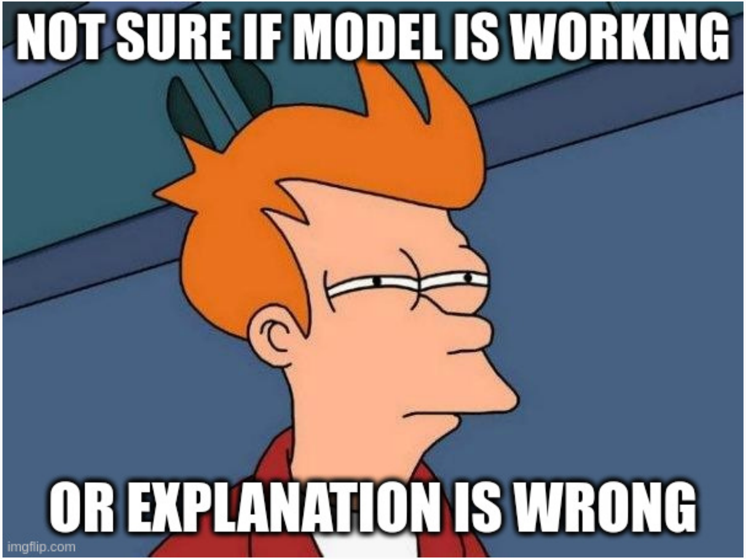
	Occlusion	IG	DeepLIFT	DeepSHAP
1.	Precuneus_L	Temporal_Mid_L	Temporal_Mid_L	Calcarine_L
2.	Precuneus_R	Temporal_Mid_R	Temporal_Mid_R	Precentral_R
3.	Postcentral_L	Temporal_Inf_L	Temporal_Inf_L	Calcarine_R
4.	Supp_Motor_Area_L	Precentral_R	Precuneus_R	Cerebelum_6_R
5.	Supp_Motor_Area_R	Postcentral_L	Precuneus_L	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

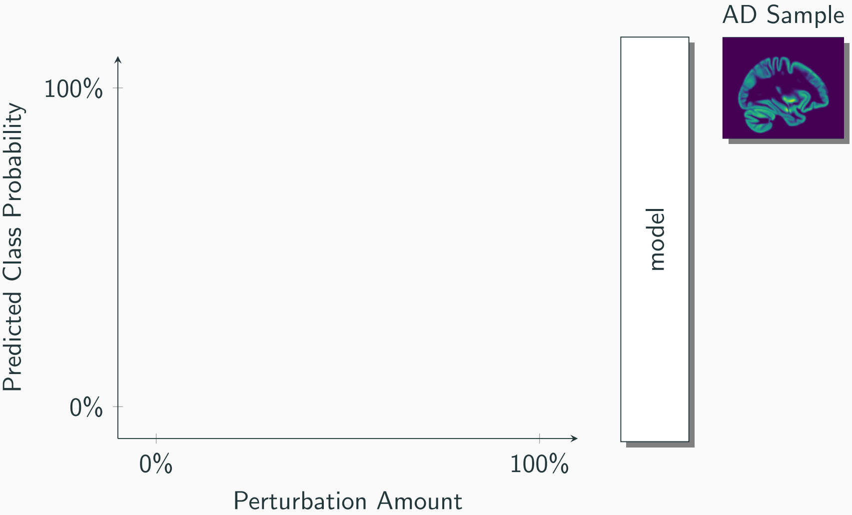
	Occlusion	IG	DeepLIFT	DeepSHAP
1.	Supp_Motor_Area_L	**Hippocampus_L**	**Hippocampus_L**	Calcarine_L
2.	Supp_Motor_Area_R	**Hippocampus_R**	**Hippocampus_R**	Calcarine_R
3.	Rolandic_Oper_L	ParaHippocampal_R	Parietal_Inf_R	Vermis_10
4.	Cingulum_Mid_L	Heschl_L	Amygdala_L	Vermis_7
5.	Cingulum_Mid_R	Parietal_Inf_L	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

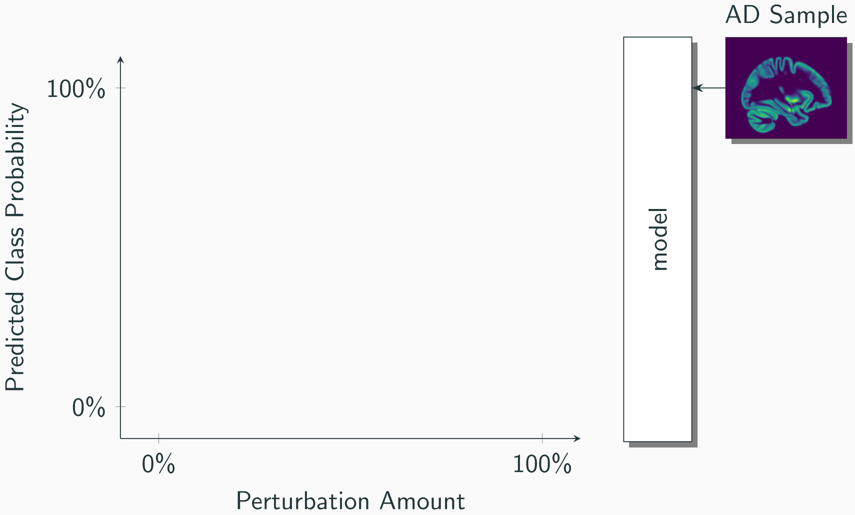


But can the **explanation** be trusted?

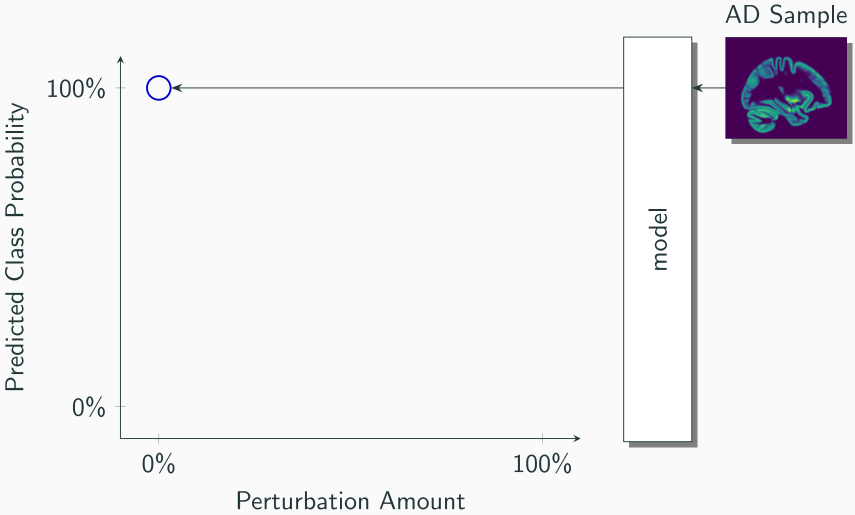
Perturbation Tests: Insertion and Deletion [1]



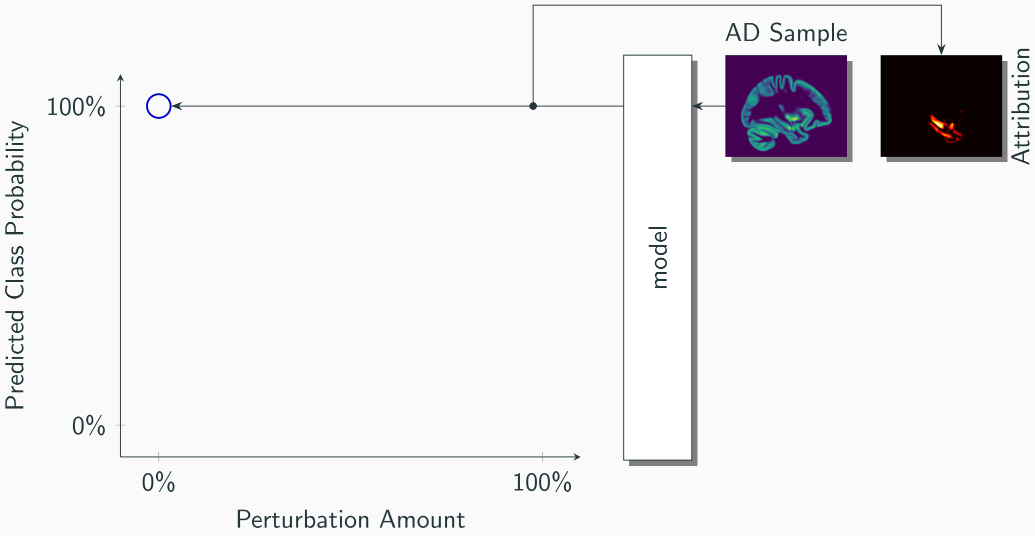
Perturbation Tests: Insertion and Deletion [1]



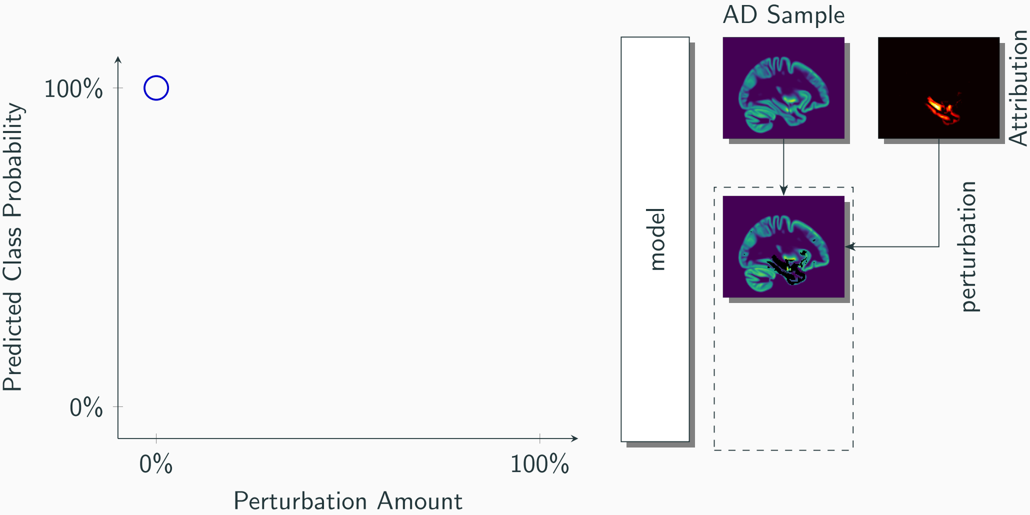
Perturbation Tests: Insertion and Deletion [1]



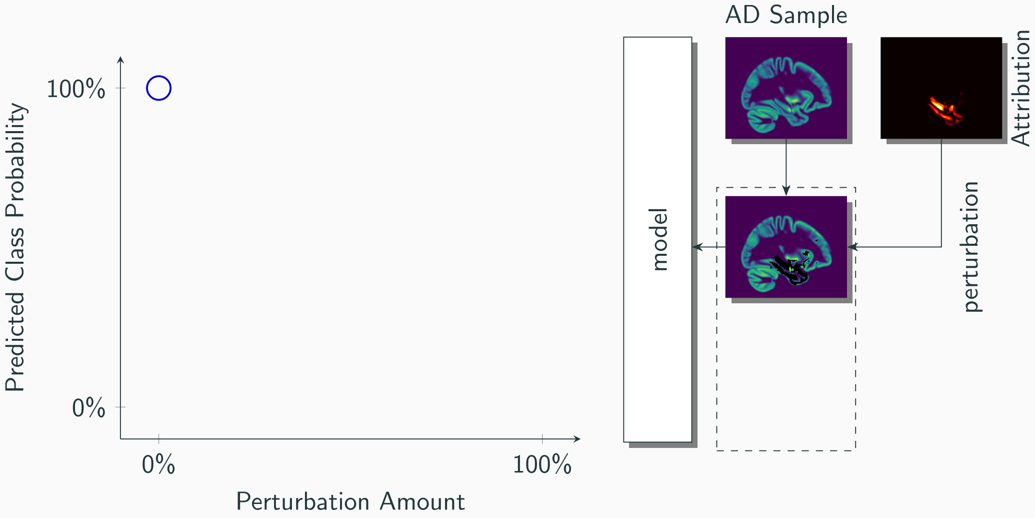
Perturbation Tests: Insertion and Deletion [1]



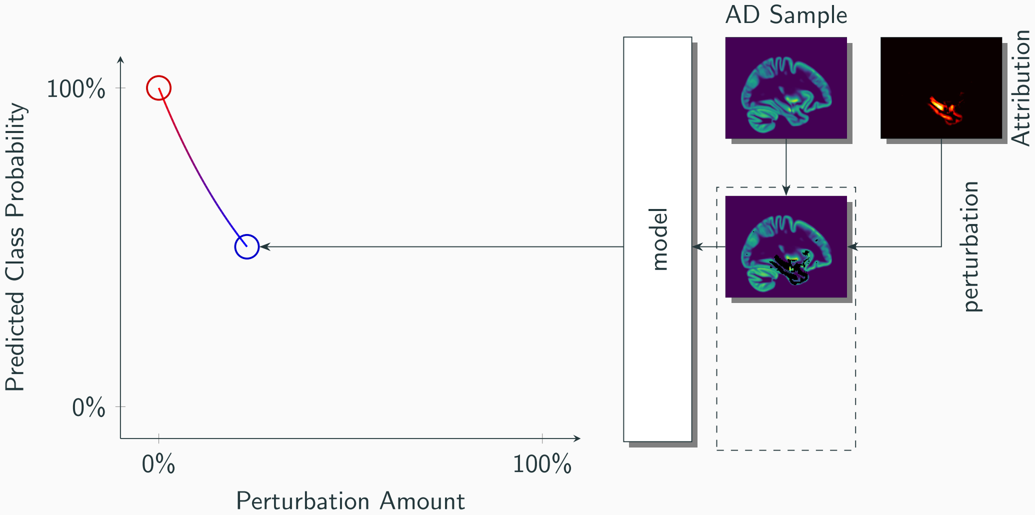
Perturbation Tests: Insertion and Deletion [1]



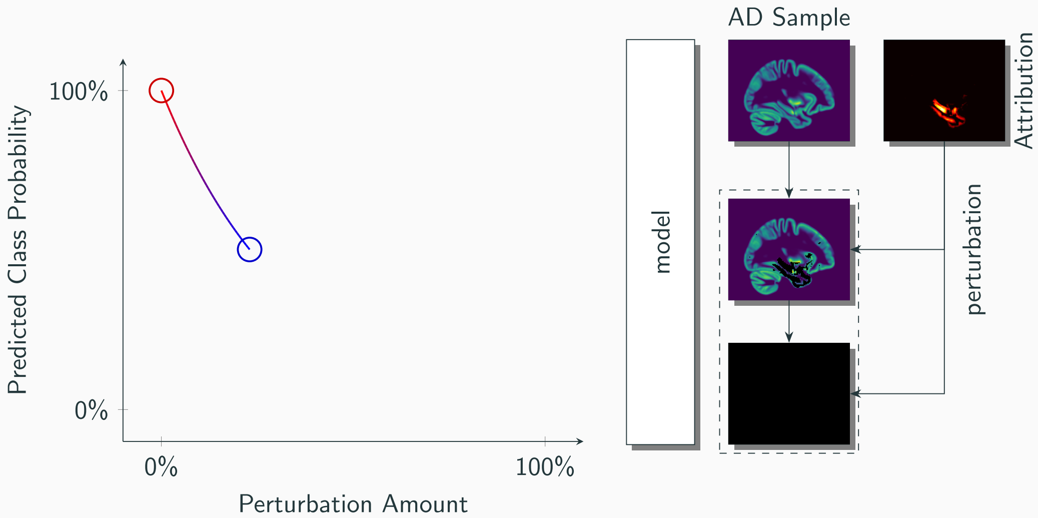
Perturbation Tests: Insertion and Deletion [1]



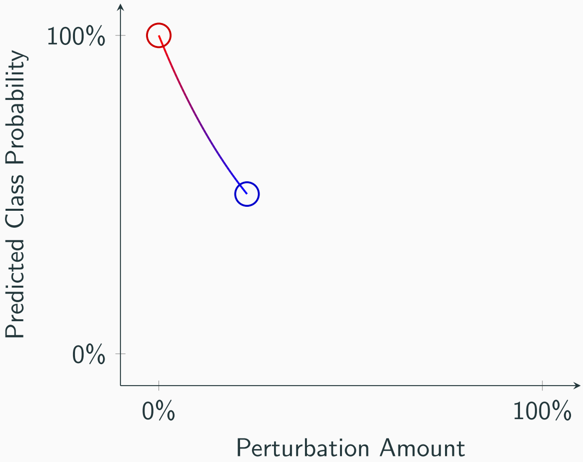
Perturbation Tests: Insertion and Deletion [1]

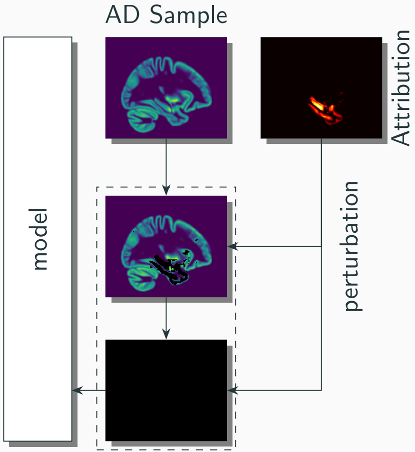


Perturbation Tests: Insertion and Deletion [1]

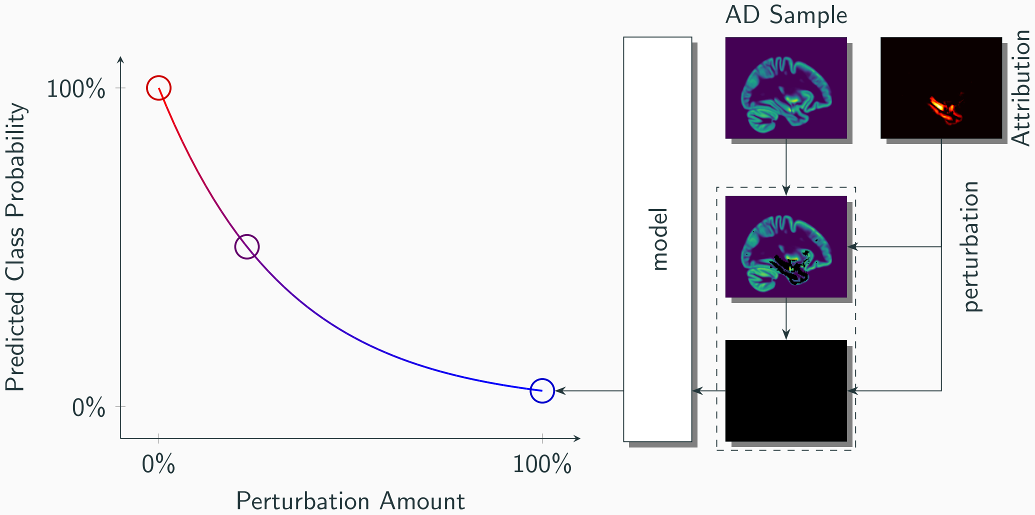


Perturbation Tests: Insertion and Deletion [1]

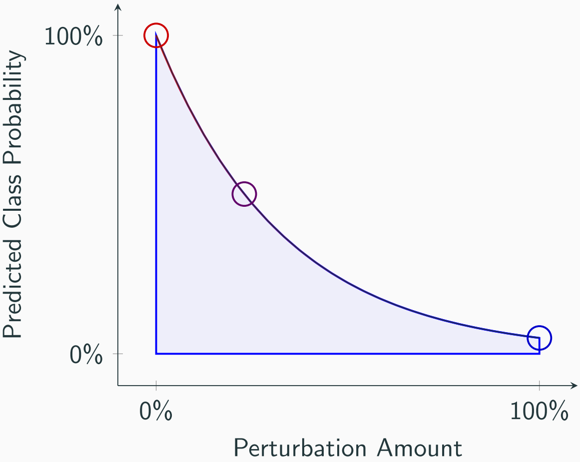


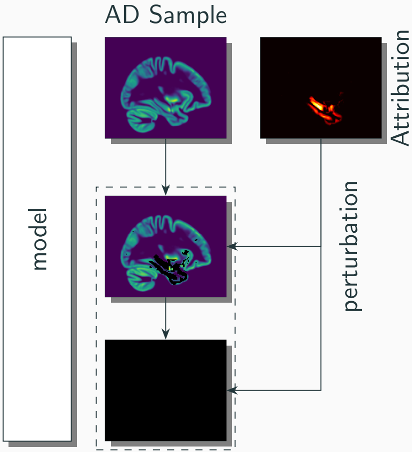


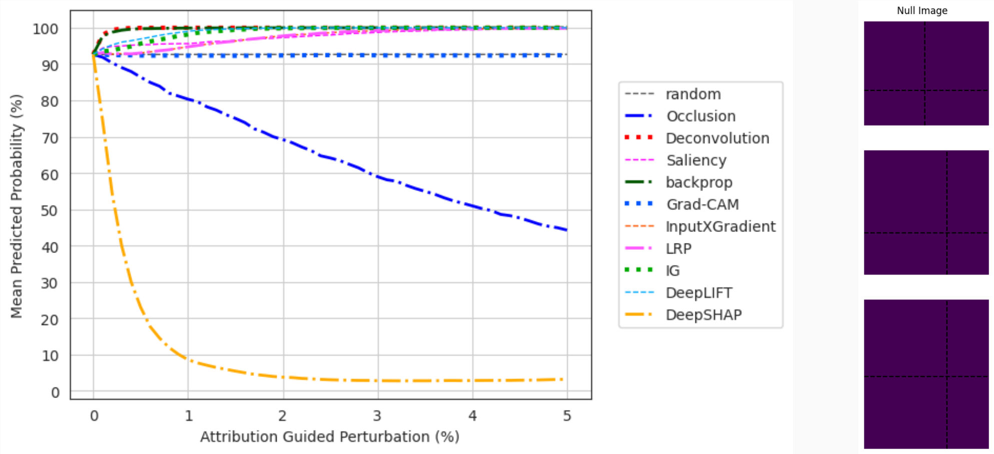
Perturbation Tests: Insertion and Deletion [1]



Perturbation Tests: Insertion and Deletion [1]





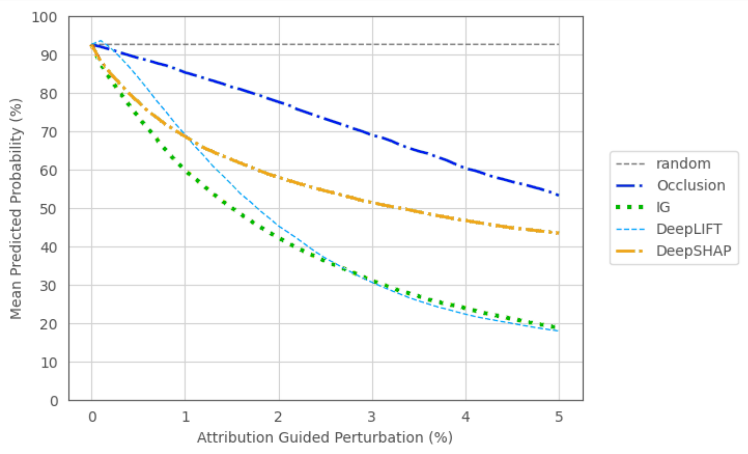


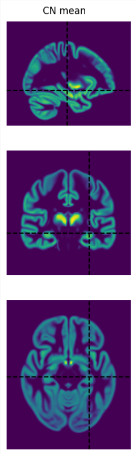
Mean Predicted AD Probability when replacing voxels by the null image baseline

Hypothesis

Null image corresponds to "maximum attrophy".

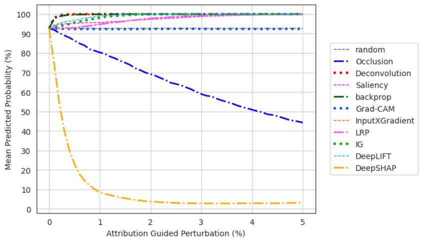
AD to CN Perturbation: Using the CN mean as Attribution Baseline

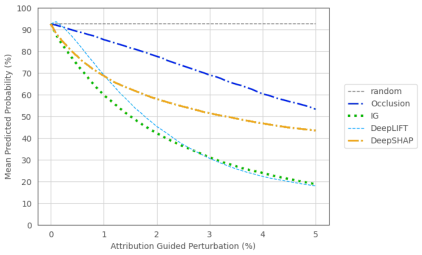




Mean Predicted AD Probability when replacing voxels by the CN mean

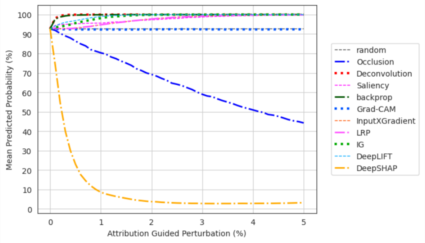
Conclusion

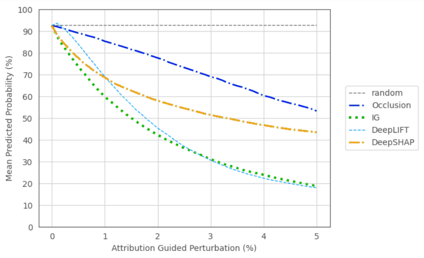




Take-Aways

Conclusion

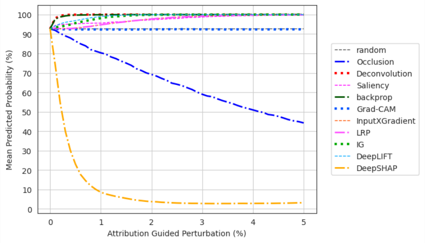


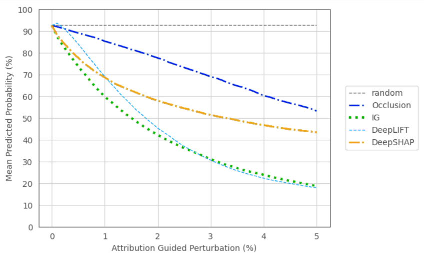


Take-Aways

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

Conclusion

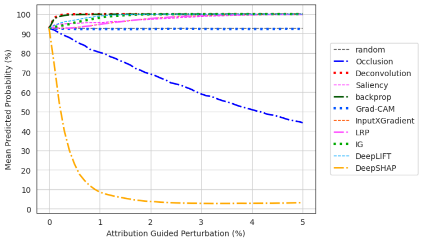


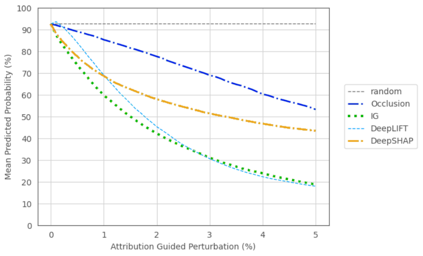


Take-Aways

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

Conclusion

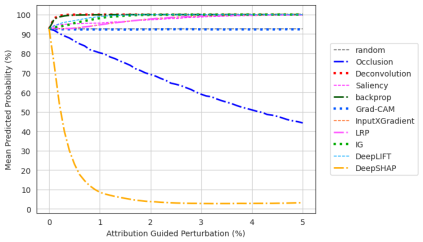


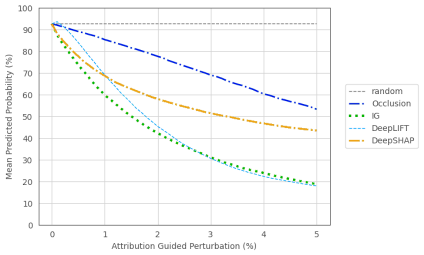


Take-Aways

1. Perturbation tests offer a **model-agnostic fidelity metric**.
2. The **attribution baseline** should be chosen carefully.
3. Attribution Maps **need interpretation** to actually explain anything.

Conclusion





Take-Aways

1. Perturbation tests offer a **model-agnostic fidelity metric**.
2. The **attribution baseline** should be chosen carefully.
3. Attribution Maps **need interpretation** to actually explain anything.

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] Vitali Petsiuk, Abir Das, and Kate Saenko. **RISE: Randomized Input Sampling for Explanation of Black-box Models**. arXiv:1806.07421. Sept. 2018. DOI: 10.48550/arXiv.1806.07421. URL: http://arxiv.org/abs/1806.07421 (visited on 10/22/2024).

[2] 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).

[3] 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).