DZNE

Das Deutsche Zentrum für Neurodegenerative Erkrankungen

Explainable Differential Diagnosis of Dementia via Contrastive Self-supervised Learning

16.02.2022

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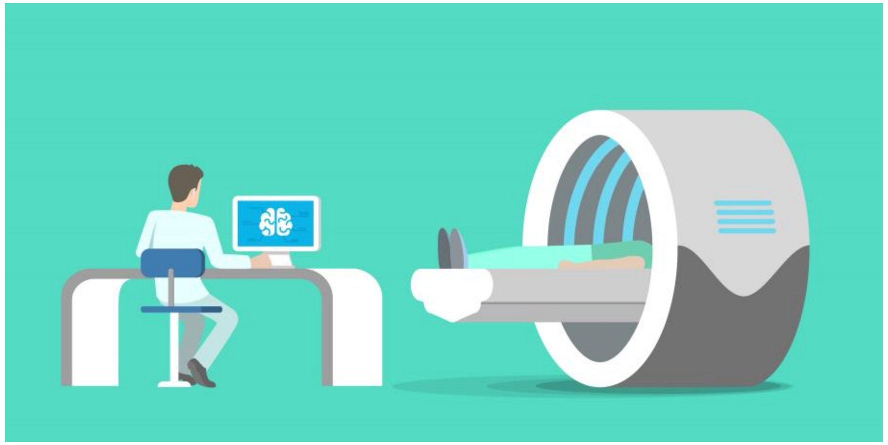
Motivation

- Early recognition of dementia

Source: http://adni.loni.usc.edu/, ADNI_941_S_6581

- Assistive technology for doctors



Source: https://de.freepik.com/sentavio, Designed by sentavio / Freepik

Outline

- Background
  - Contrastive Self-supervised Learning
  - Representation of MRI Data
- Goal
- Architecture
  - Approach
  - Evaluation
- Intermediate Results
- Conclusion & Future Steps

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What is Self-supervised Learning?

- Learns rich representations from data without any labels/annotations

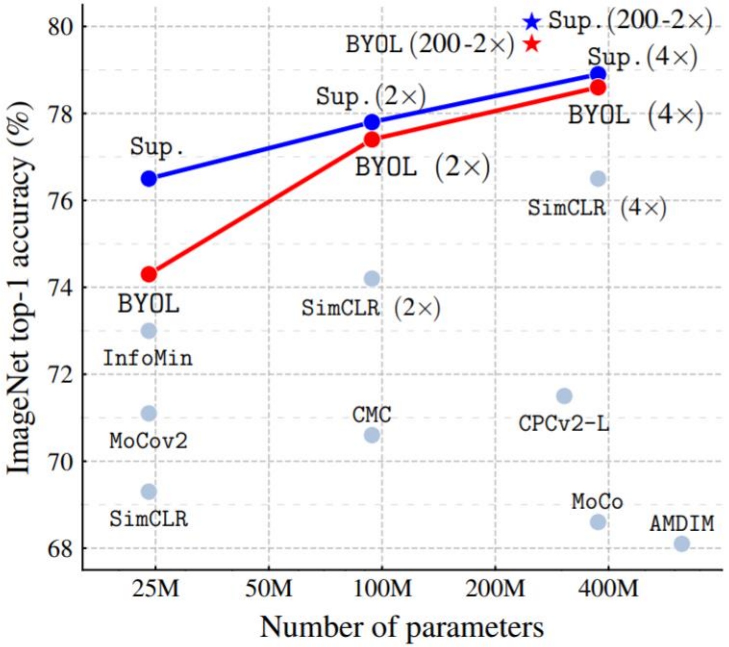
Source: https://www.freeimages.com/photo/horse-1393073

Source: https://www.freeimages.com/photo/goat-1375679

Source: https://www.freeimages.com/photo/sandpiper-going-1373066

Why Self-supervised Learning?

- Competes with supervised learning



Source: Grill et al., 2020

- Imitates the learning process in humans
- A form of common sense
- Data itself is a signal for learning
- Annotated data is not always available

What is Contrastive Self-supervised Learning?

- A paradigm for self-supervised learning of data representations from similar and dissimilar pairs

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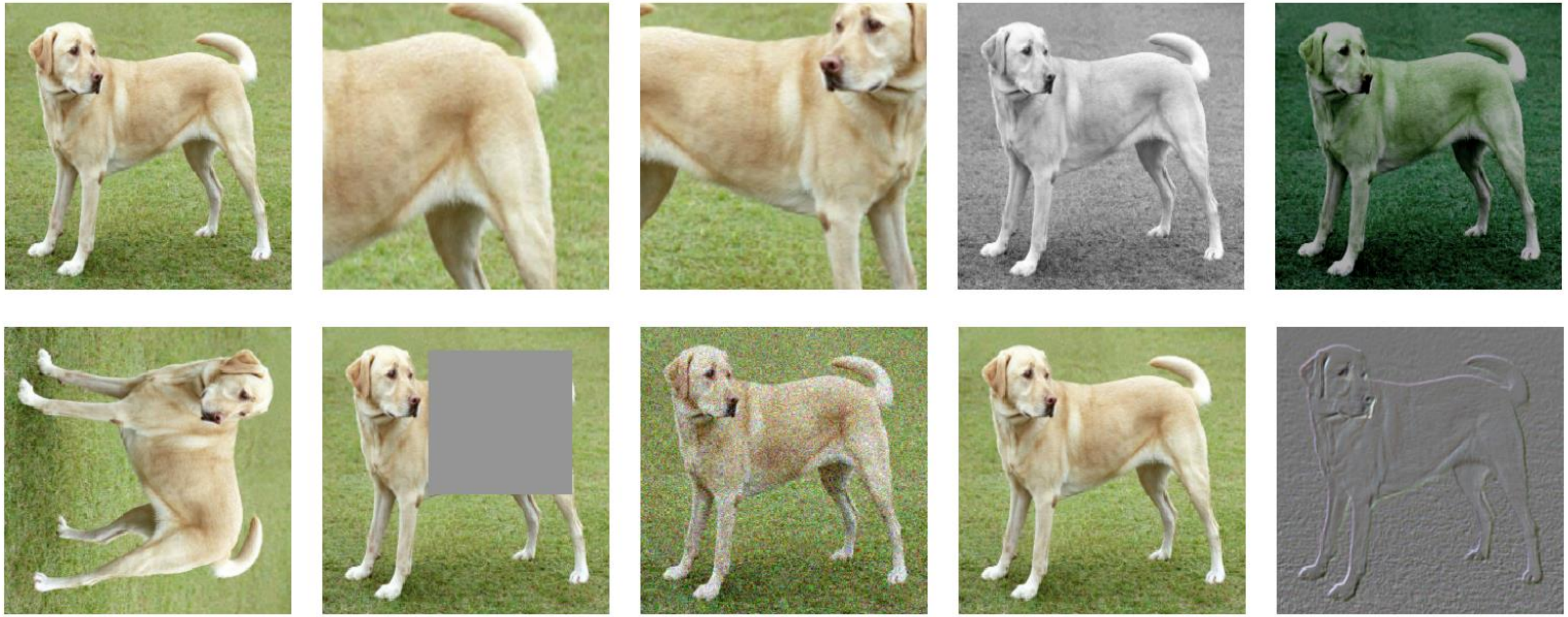
Source: https://www.freeimages.com/photo/goat-1375679

How to Create Similar Pairs?

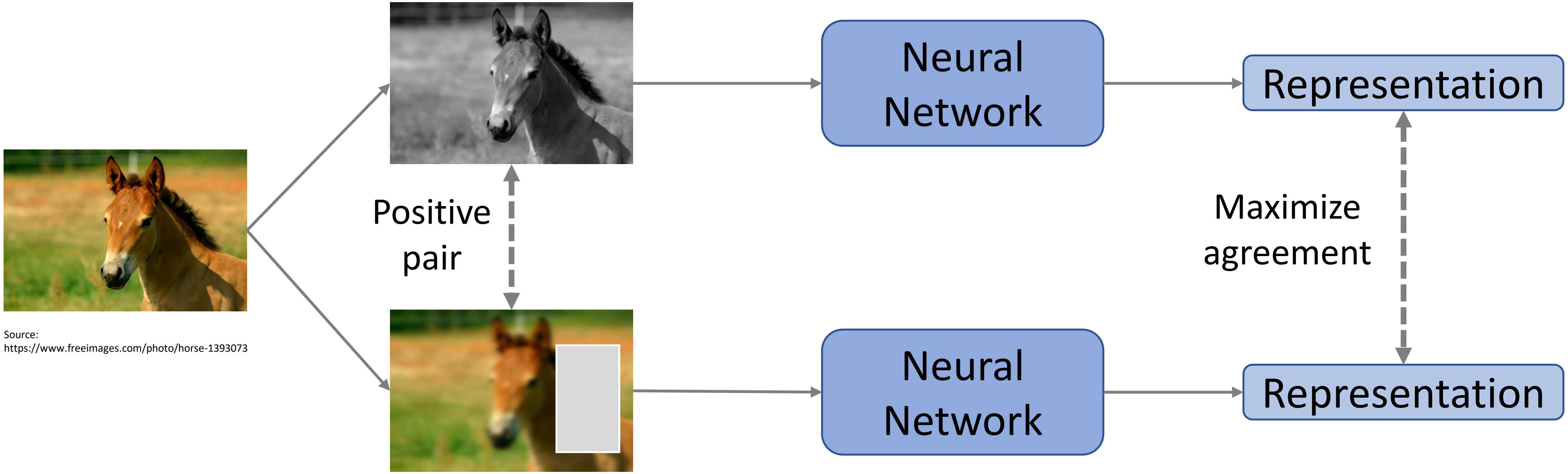
- Data augmentation



Source: https://arxiv.org/pdf/2002.05709.pdf

How to: Contrastive Self-supervised Learning?

- Reduce the distance between the representations of positive samples while increasing the distance between negative pairs



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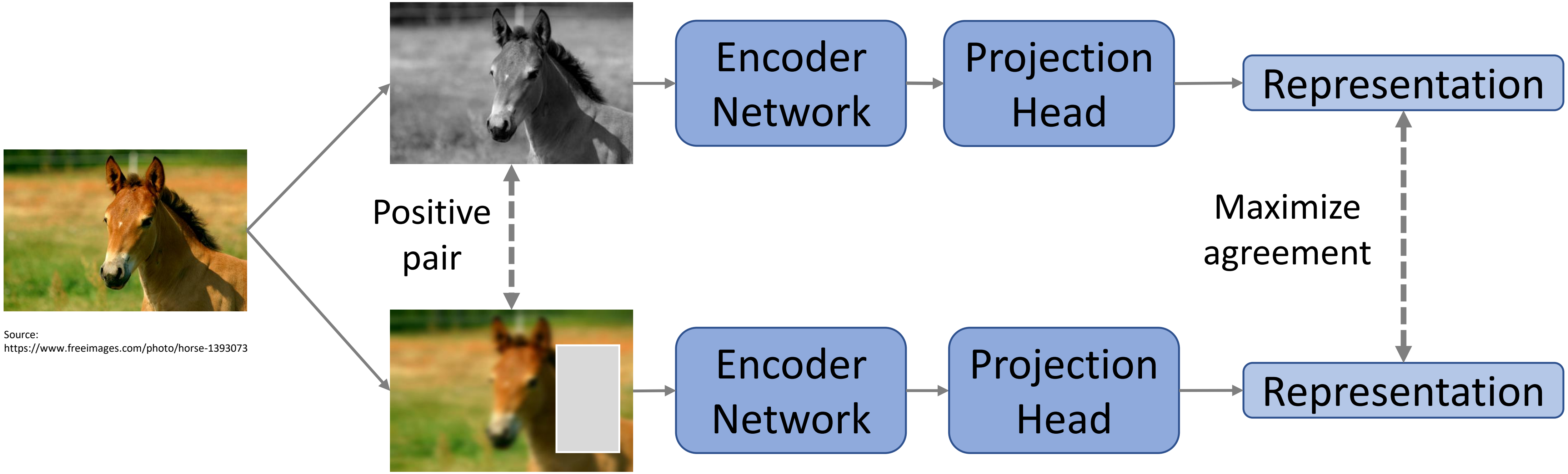

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Based on the method by Chen et al., 2020

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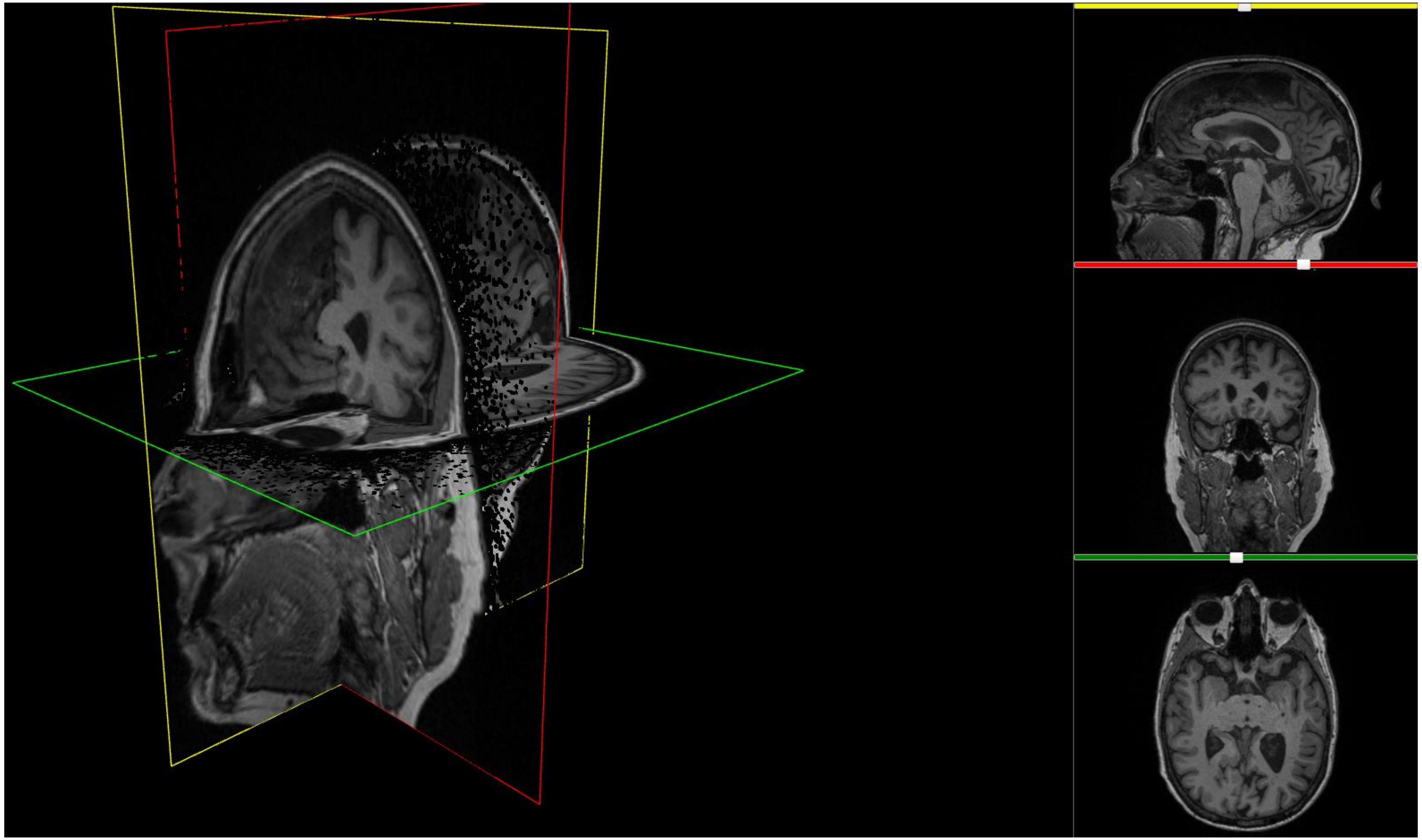
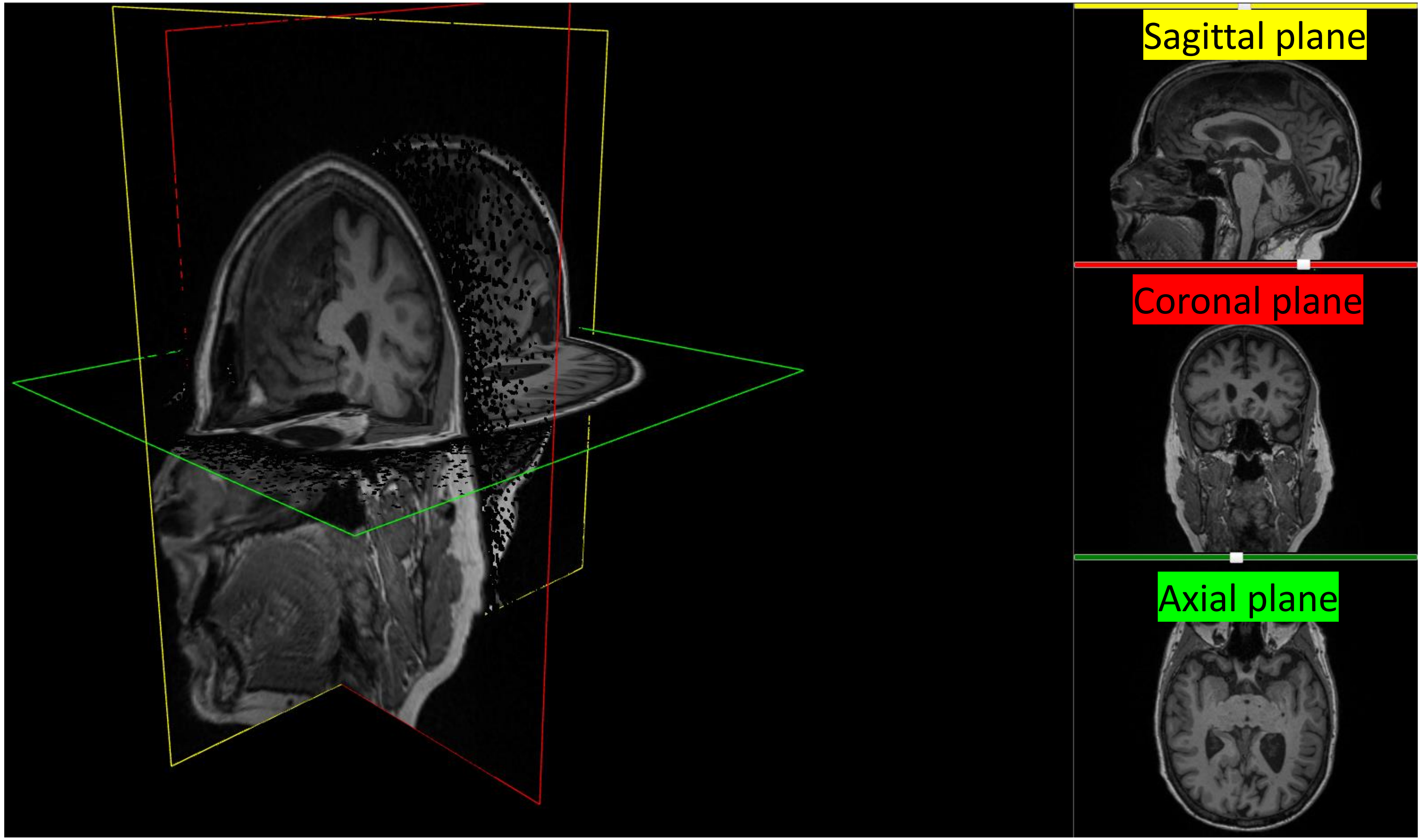
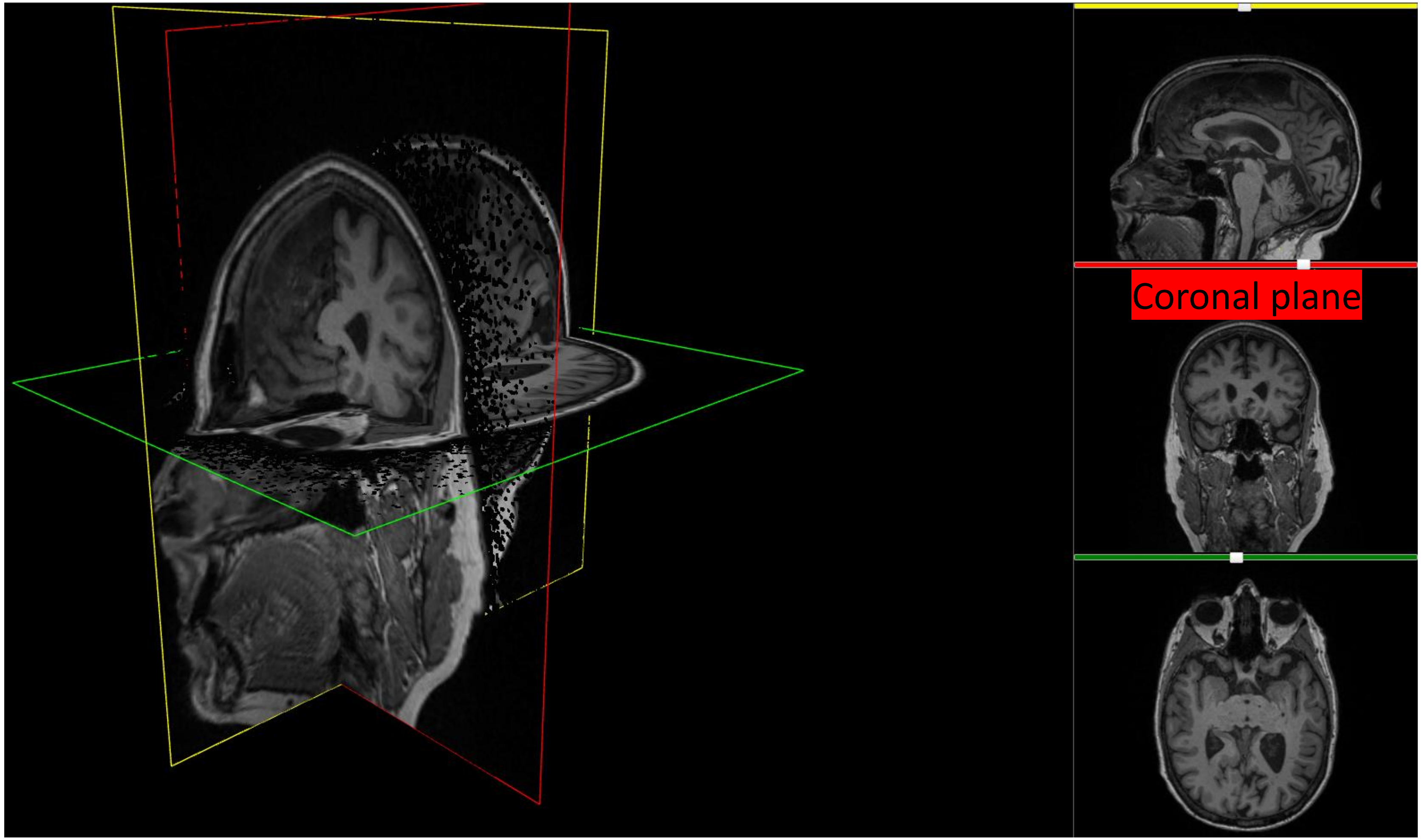
Representation of Data: Structural Magnetic Resonance Imaging



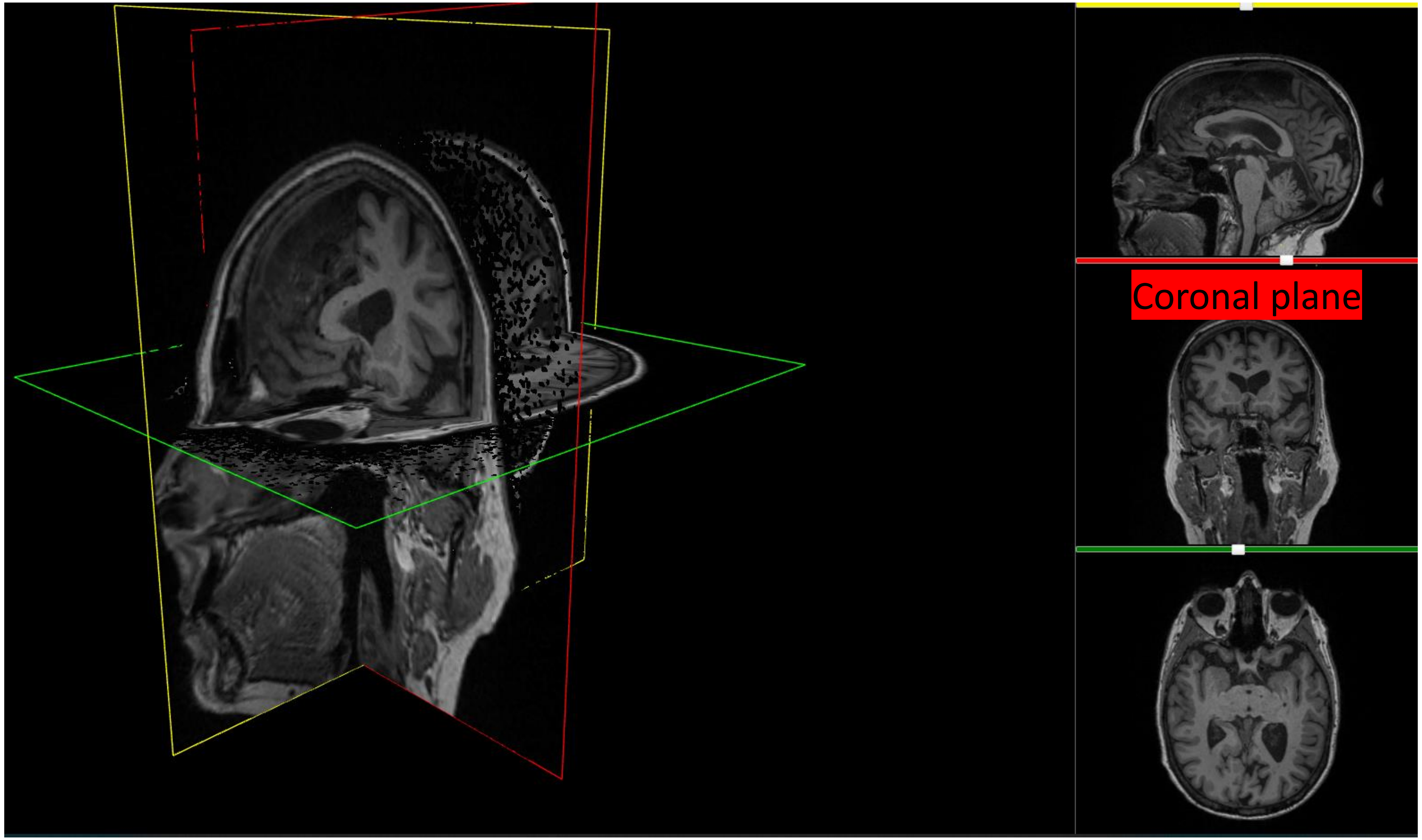
Representation of Data: Structural Magnetic Resonance Imaging



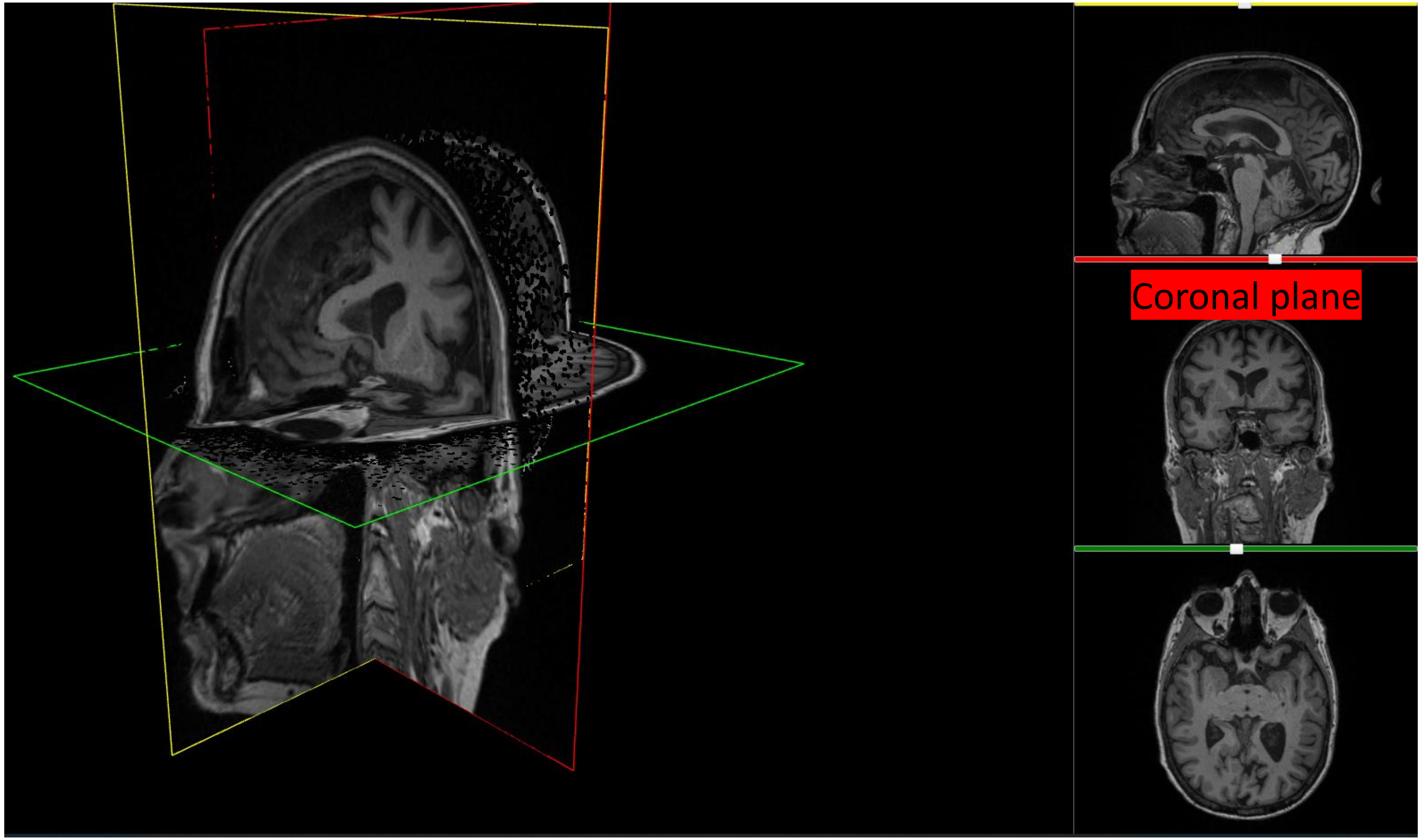
Representation of Data: Structural Magnetic Resonance Imaging



Representation of Data: Structural Magnetic Resonance Imaging



Representation of Data: Structural Magnetic Resonance Imaging



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Goal

Mild Cognitive Impairment

Alzheimer's Disease

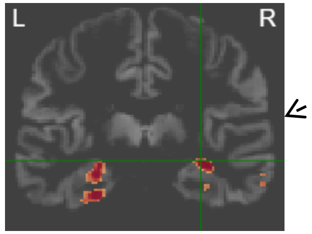
Textual explanations

MCI

AD

Diagnosis System

Relevance attribution



Source:
https://explaination.net/InteractiveVis

DLB

FTD

Source:
https://pixabay.com/vectors/boy-cartoon-chart-checkup-clinic-2027615/

Dementia with Lew bodies

Frontotemporal dementia

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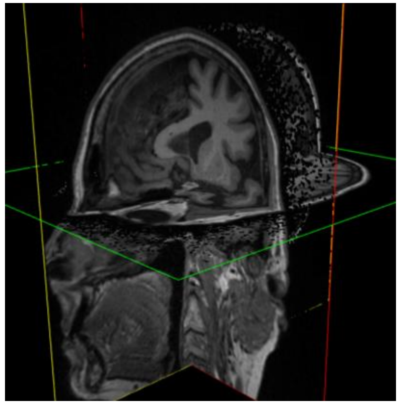
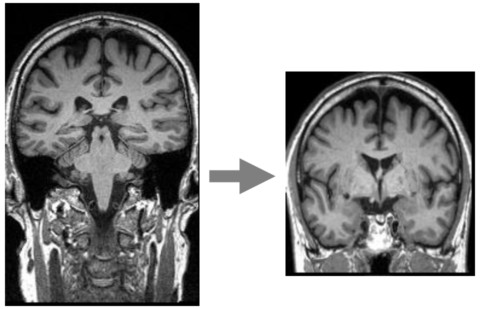
Architecture: Approach

- Extract 2D coronal slices from MRI data
- Use the slices to train a neural network via contrastive learning



MRI data

→ Bias field correction, affine registration, and cropping → Extraction of 2D coronal slices → Contrastive Self-supervised Learning



78.32327	60.70236	95.05656	106.72037	136.54128	156.79462
86.53662	136.37695	232.52194	234.12428	228.66685	178.54318
127.54239	266.55896	280.66675	189.34052	104.67844	64.05920
146.46339	276.26804	199.20343	64.16311	43.32655	49.41847
144.81705	215.30659	196.31628	55.42023	53.54706	51.57083
163.41368	154.62160	201.05951	103.72393	65.26355	45.21485
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207.74698	203.88586	156.68529	155.91566	112.22115	113.25051
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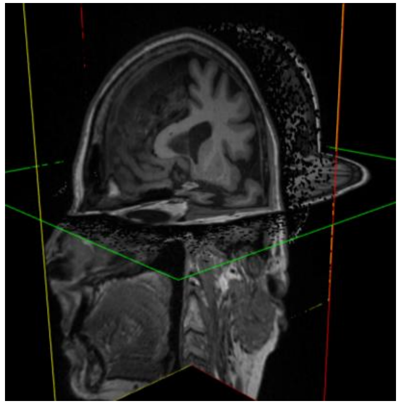
216.74501	208.51189	225.25679	150.88251	54.68575	47.40908
198.07919	212.03587	218.06310	163.92529	63.50377	64.11846
[illegible]	[illegible]	[illegible]	[illegible]	[illegible]	[illegible]

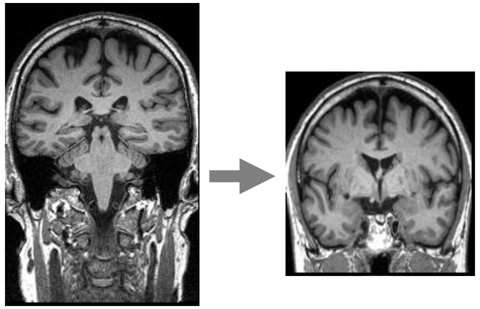
Architecture: Approach

- Extract 2D coronal slices from MRI data
- Use the slices to train a neural network via contrastive learning



MRI data

Bias field correction, affine registration, and cropping



Extraction of 2D coronal slices

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Contrastive Self-supervised Learning

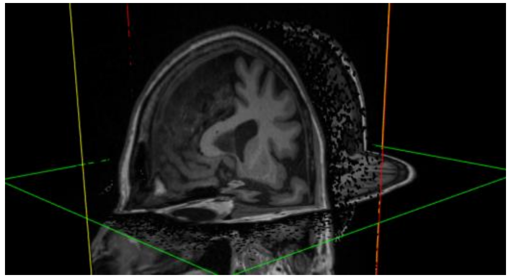
?

Architecture: Contrastive Self-supervised Learning from MRI Data

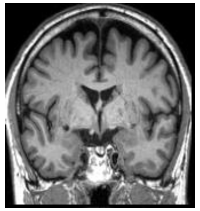
- An MRI scan contains many coronal slices

Source:
https://www.freeimages.com/photo/horse-1393073

vs



- What augmentation techniques can we apply?



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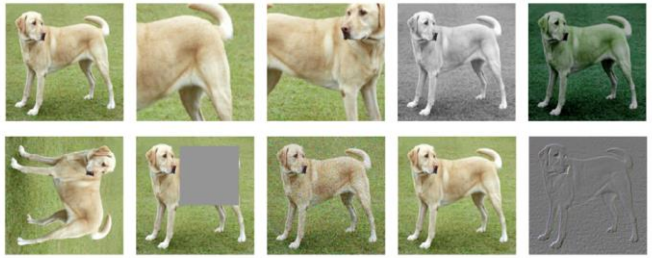
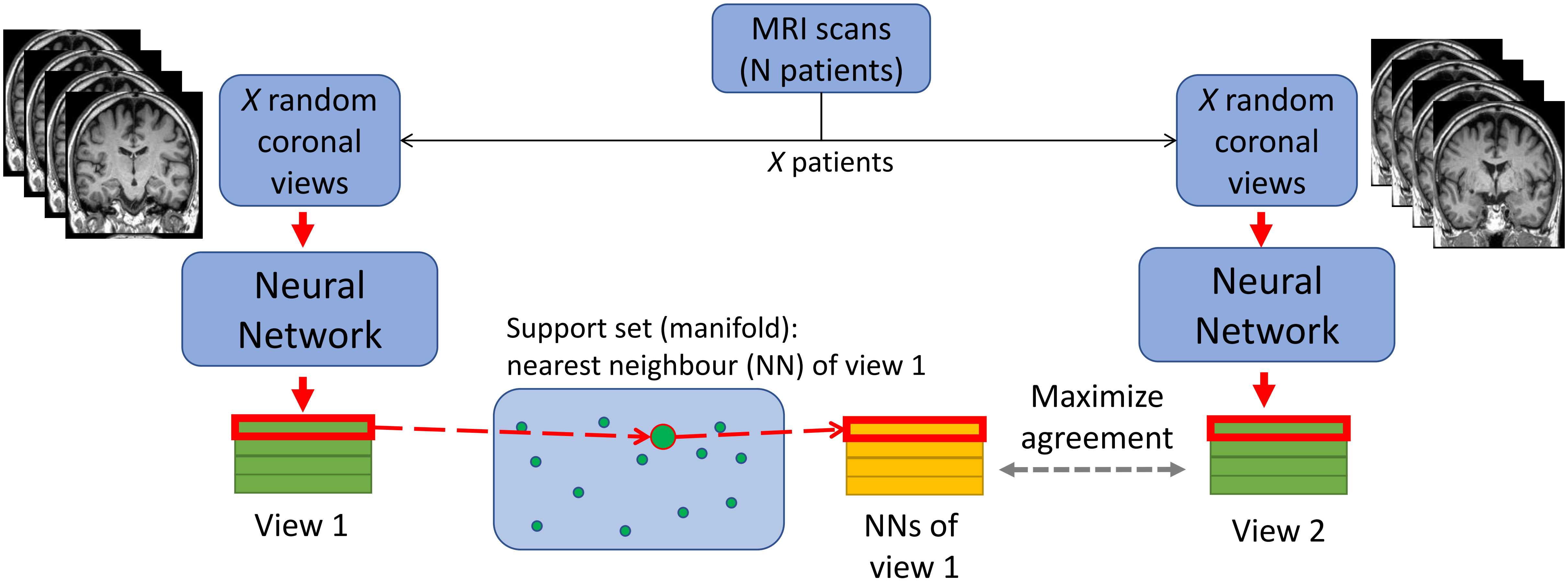


- How do we train a neural network then?

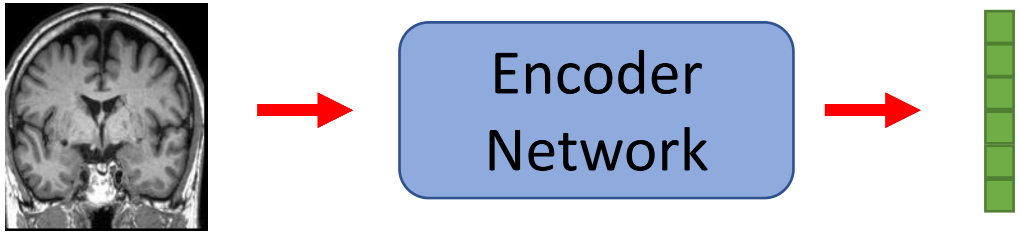
Architecture: Contrastive Self-supervised Learning from MRI Data



Based on the method by Dwibedi et al., 2021

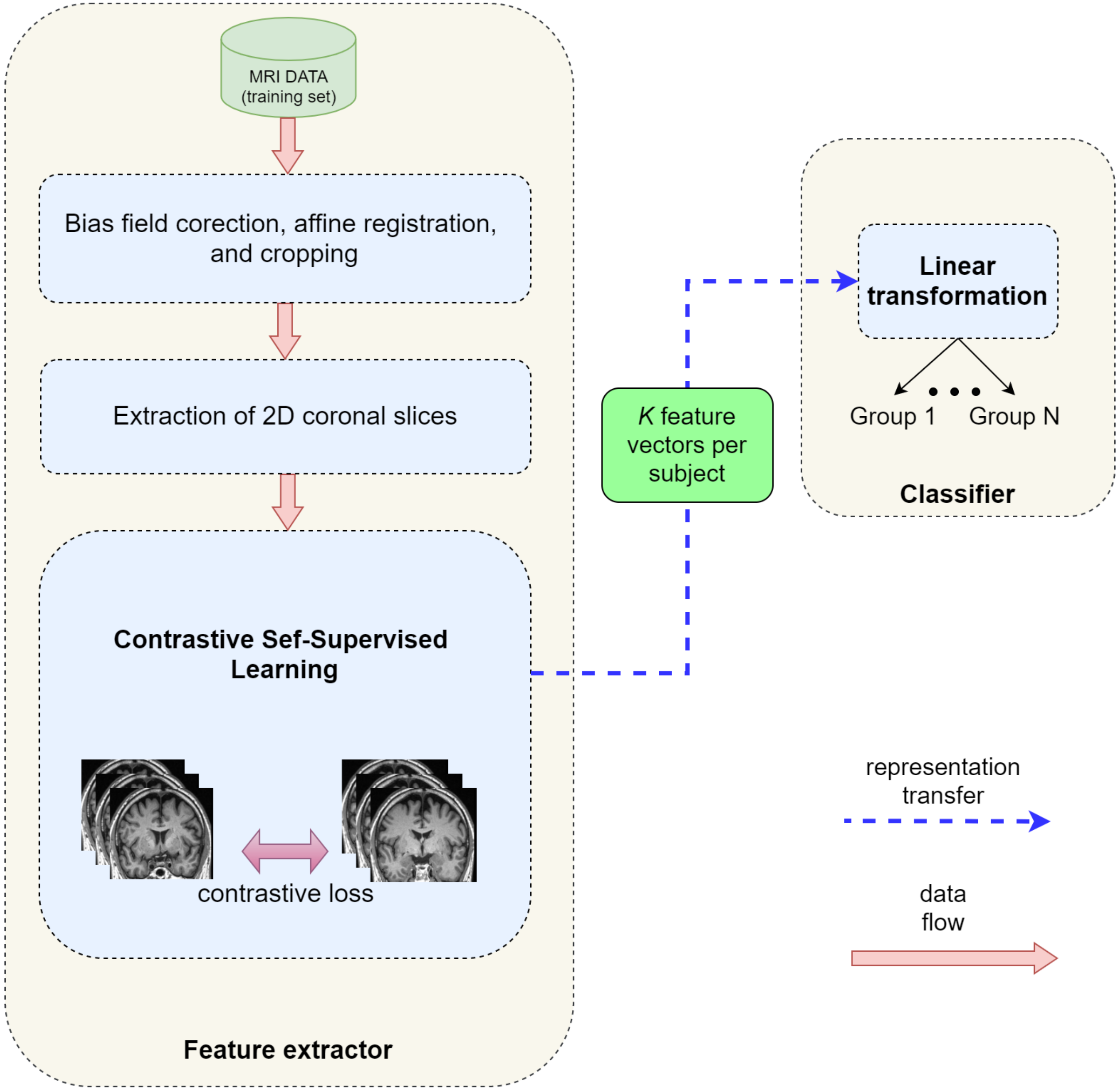
Architecture: Disease Classifier

- An encoder network serves as a feature extractor for MRI data (coronal slices)



- *K* coronal slices are queried and respectively *K* feature vectors are extracted for each subject
- These feature vectors are used then to train a disease classifier (e.g. control vs patient)

Architecture: Disease Classifier



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Planned Evaluation

- MRI Data (training and evaluation):
  - ADNI (Alzheimer's Disease Neuroimaging Initiative), N=2622
  - NIFD/NIFD (Neuroimaging in Frontotemporal Dementia), N=346
  - OASIS (Open Access Series of Imaging Studies), N=1098
  - MIRIAD (Minimal Interval Resonance Imaging in Alzheimer's Disease), N=69
  - PPMI (Parkinson's Progression Markers Initiative), N=1841
  - AIBL (Australian Imaging, Biomarkers and Lifestyle), N=852
  - DELCODE (DZNE Longitudinal Cognitive Impairment and Dementia Study), N=1000

- Quantitative approach
  - Precision & Recall, F_{β} scores
  - Matthew's Correlation Coefficient

- Qualitative approach

Source: https://pixabay.com/vectors/boy-cartoon-chart-checkup-clinic-2027615/

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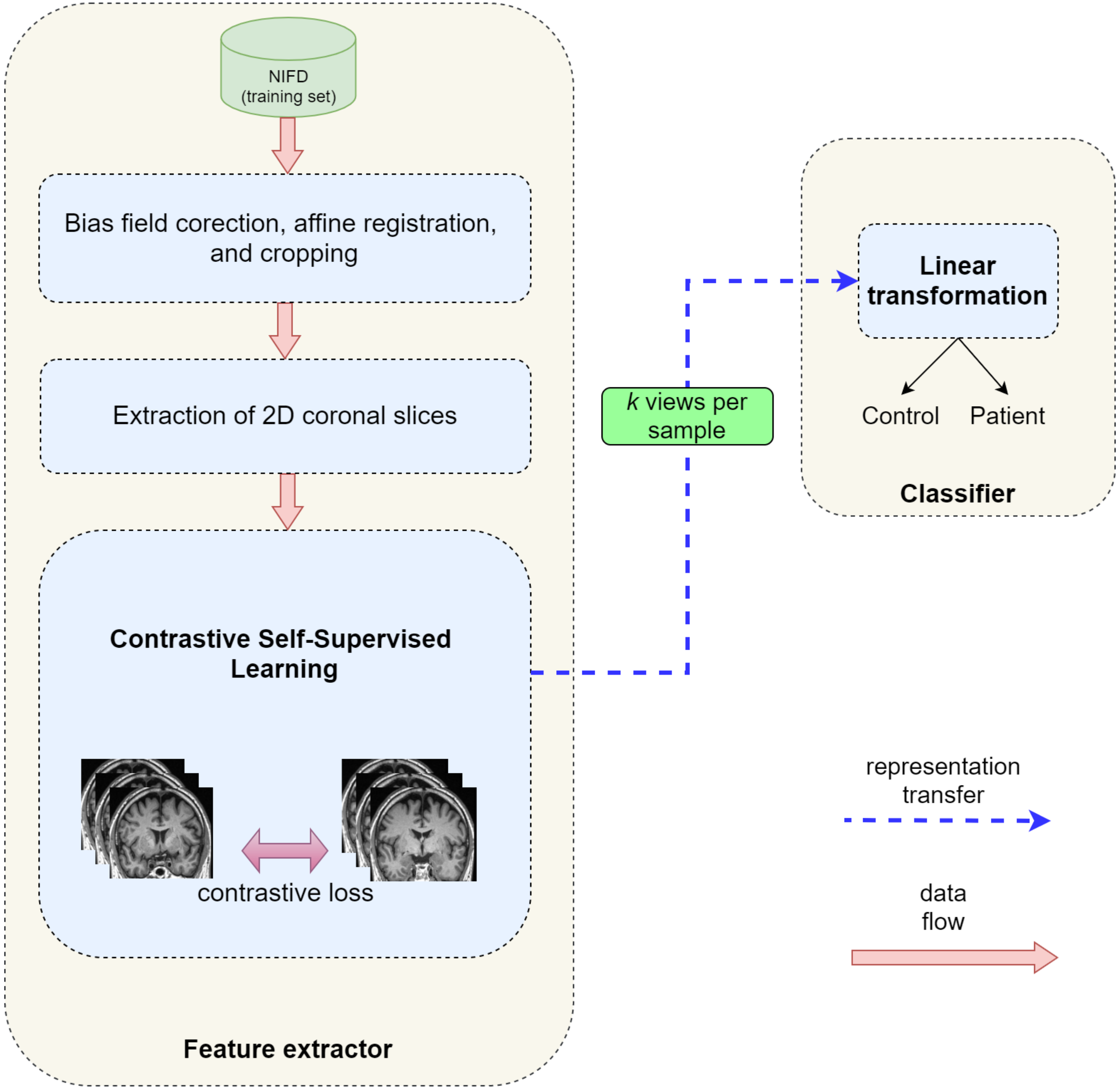
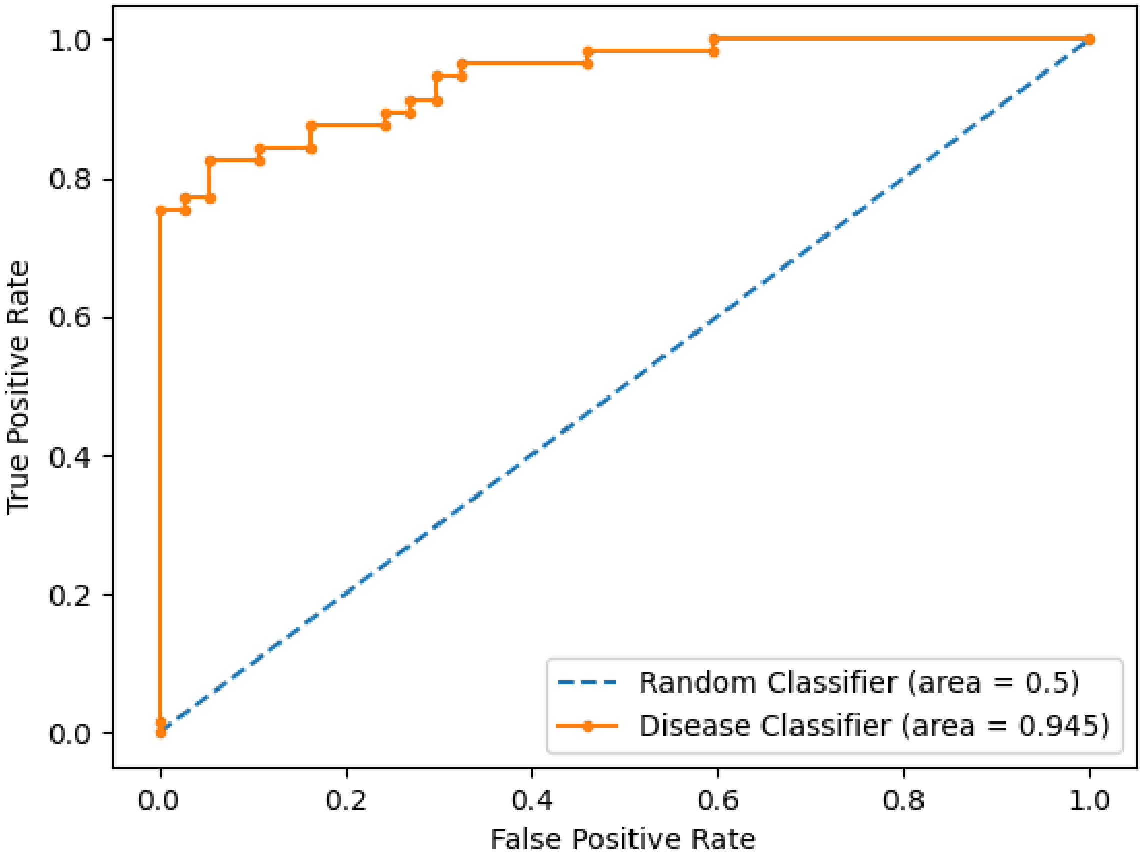
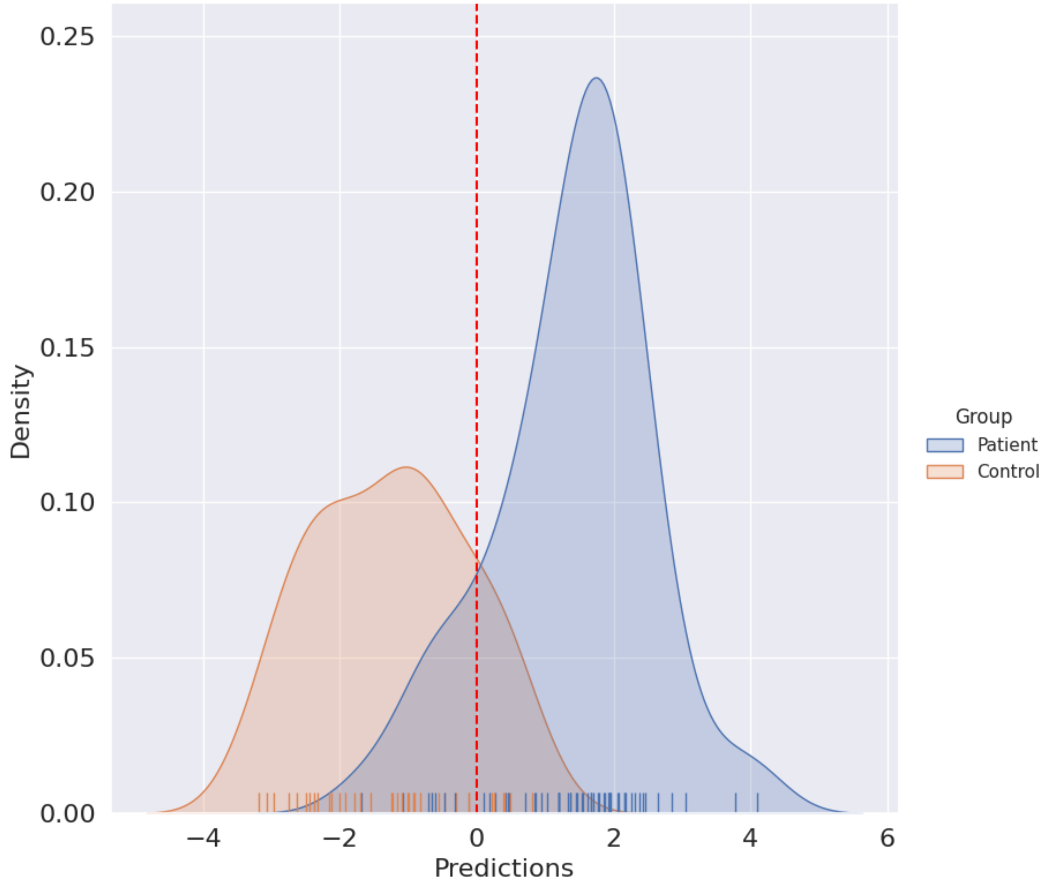
Intermediate Results

- NIFD (Neuroimaging in Frontotemporal Dementia)
  - Training samples: 680
  - Test samples: 94
- Binary classification
  - Control: 379
  - Patient: 395
- Evaluation
  - MCC: ~0,71
  - F1: ~0,88
  - Accuracy: ~0,86



Intermediate Results: Receiver Operating Characteristic and Group Likelihood Estimation





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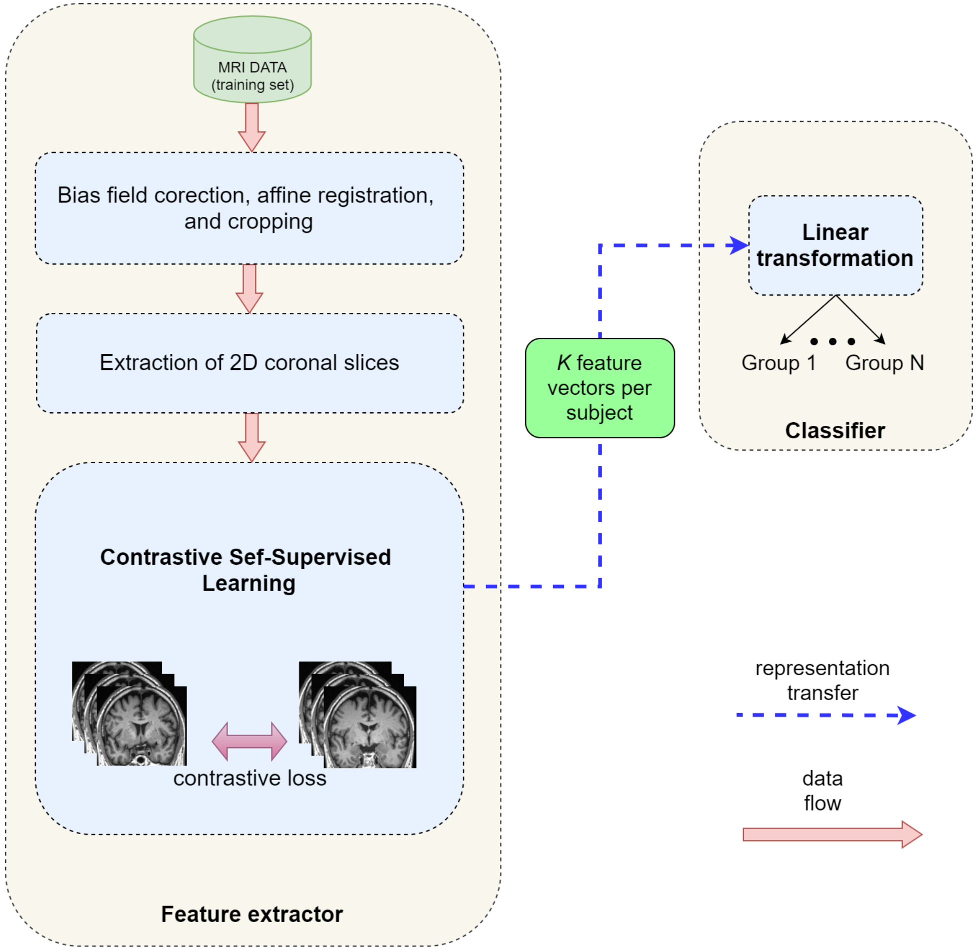
Conclusion & Future Steps

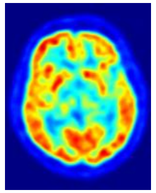
- A system for learning representations from MRI data
- Contrastive learning
- Aim:
  - A self-explanatory assistive system as a support for radiological examination and evaluation
  - Explanations and visualizations as a step to explainable AI (XAI)



Conclusion & Future Steps

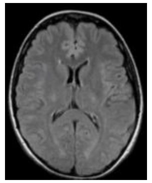
- Multi-Classifier
- Relevance attribution
- Integration of other sources
  - Age, gender, and other tabular data
  - Volumes of the brain regions
- Textual explanations
- Multimodal input

PET



Source: https://commons.wikimedia.org/wiki/File:PET-image.jpg

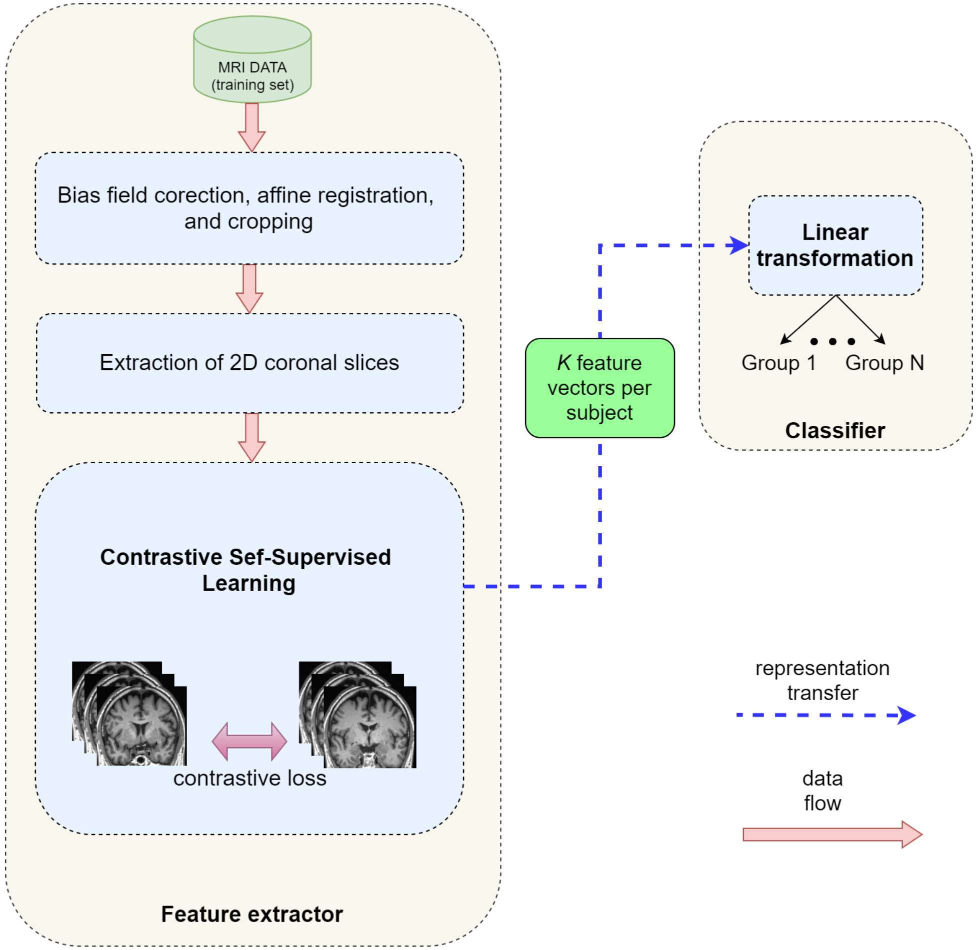
FLAIR



Source: https://case.edu/med/neurology/NR/MRI%20Basics.htm

Source: https://pixabay.com/vectors/boy-cartoon-chart-checkup-clinic-2027615/

- Evaluation by doctors



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