Deep Convolutional Autoencoders for reconstructing MRIs of the healthy brain

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Problem overview

Neuroimaging: study of morphological features of the human brain and its correlations with neurological disorders to improve medical systems

Brain MRI enhancement	Disease Detection	Improvement of Data Acquisition	Data Augmentation

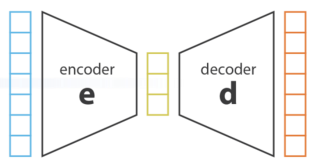
→ **Image Reconstruction** (information compression)

Objective: **capture the representation of the underlying structure of healthy brains in a lower-dimensional space and reconstruct from this under-sampled data.**

Representation Learning approach: We will not only be able to reconstruct a corrupted image, but also, we are going to learn the representation of a healthy brain MRI in the latent space.

ML Topics: Representation learning, dimensionality reduction, Normative model, information compression, latent spaces...

Convolutional AutoEncoder



- Train with disease-free neuroimaging data
- This autoencoder, would define a normal range for the neuroanatomical variability for the illness absence
- It learns the brain structure representation
- Once trained, it encodes an MRI and reconstructs it without corruptions such a noise, artifacts or injuries

SoTA

Architectures

Residual Networks
- *F(x) = H(x) – x*
- ✓Less complexity by learning residuals

Skip Connection CAEs
- Encoder to decoder connections
- ✓Better low-detail reconstruction

U-Net and V-Net
- 3D convolutional "AE" networks
- Symmetric skip connections
- V-NET adds RES building blocks

MRI Preprocessing

Intensity Normalization
Downsampling
Data Augmentation

Profile and relevant slice selection

Profile Selection
Non-isotropic MRI
Relevant Slice Selection
Slices with some amount of brain
- Middle Slice [3]
- Fixed Range

Applications

FastMRI, 2020 [7]
- FAIR, New York University
- Accelerate scan process generating MRI from under-sampled data.

BRATS: Myronenko, 2018 [1]
ResVAE to regularize residual brain tumor segmentation network.

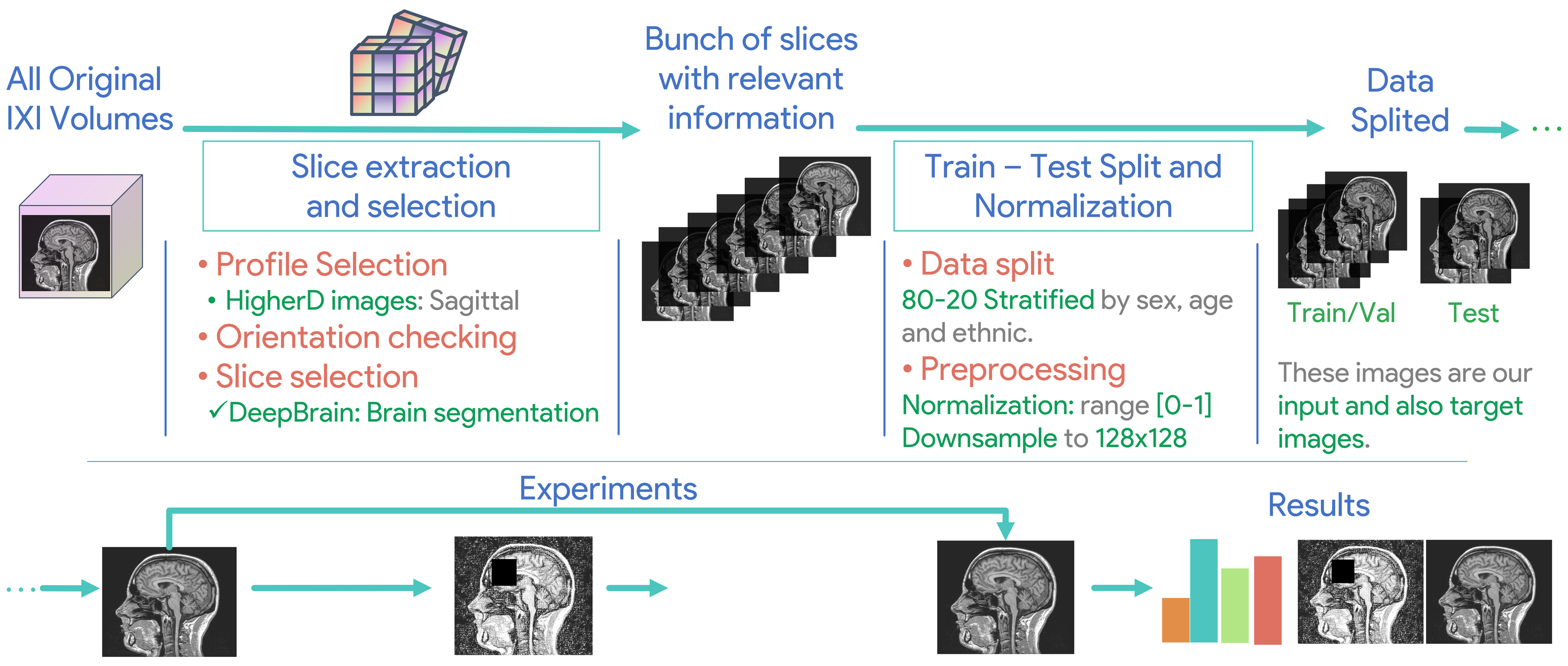
BRATS: T. Estienne et. al., 2020 [6]
V-NET AE for tumor segmentation

C. Bermudez et. Al., 2018 [3]

J. Manjón et. al., 2020 [2]
UNet based lesson inpainting

W. Pinaya et. al., 2019 [5]
Unsupervised anomaly detection

Experiment pipeline at a glance



Slice extraction and selection
- Profile Selection
  - HigherD images: Sagittal
- Orientation checking
- Slice selection
  - ✓DeepBrain: Brain segmentation

Train – Test Split and Normalization
- Data split
  80-20 Stratified by sex, age and ethnic.
- Preprocessing
  Normalization: range [0-1]
  Downsample to 128x128

These images are our input and also target images.

- Training

Data augmentation
- Blank-out regions
- Noise
  - Gaussian
  - Dropout pixels
- Blur images

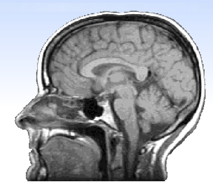
- Architectures
  CAE based on:
  - Resnet-based building blocks
  - Skip-connections

- Regularization
  - L2
  - Batch Norm
- Loss functions
  - MSE
  - DSSIM

Quantitative and Qualitative evaluation
Compare models quantitatively and qualitatively

Dataset and preprocessing

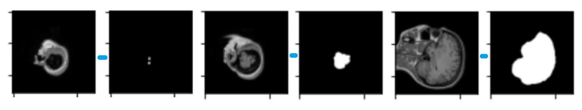
IXI BRAIN T1-Weighted Dataset from Imperial College of London
▶ 584 3D MRI volumes → Nifti Format → 86794 Brain raw Sagittal 2D images

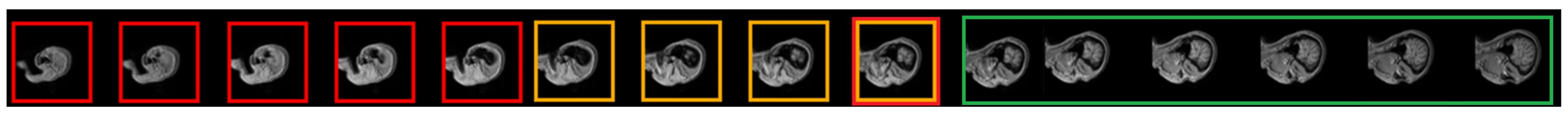


Relevant slices selection

Brain is information: Not every slice has relevant information. Many non-optimal approaches to select relevant 2D images: only middle slice, fixed range, non-0 pixels, mean intensity...

Our approach: DeepBrain [8] → Pretrained CNN for brain segmentation
- Return mask of probabilities of each pixel belonging to brain
- Low-Threshold: 5% of brain pixels → Final relevant slices: 59278



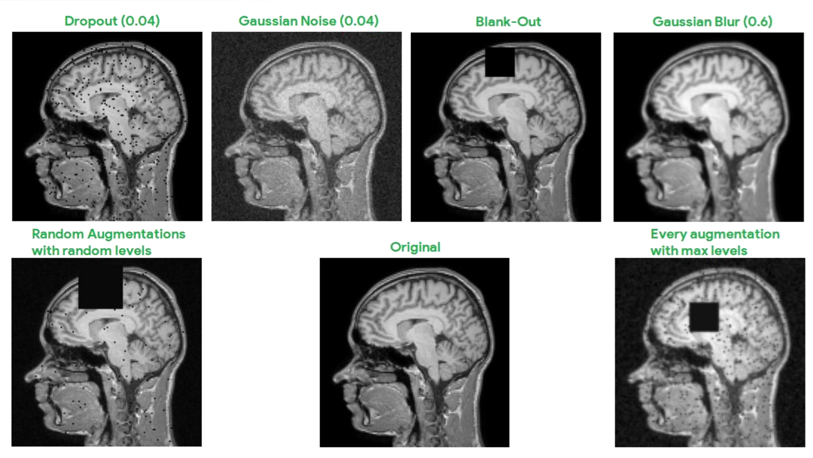


Data Augmentation and split

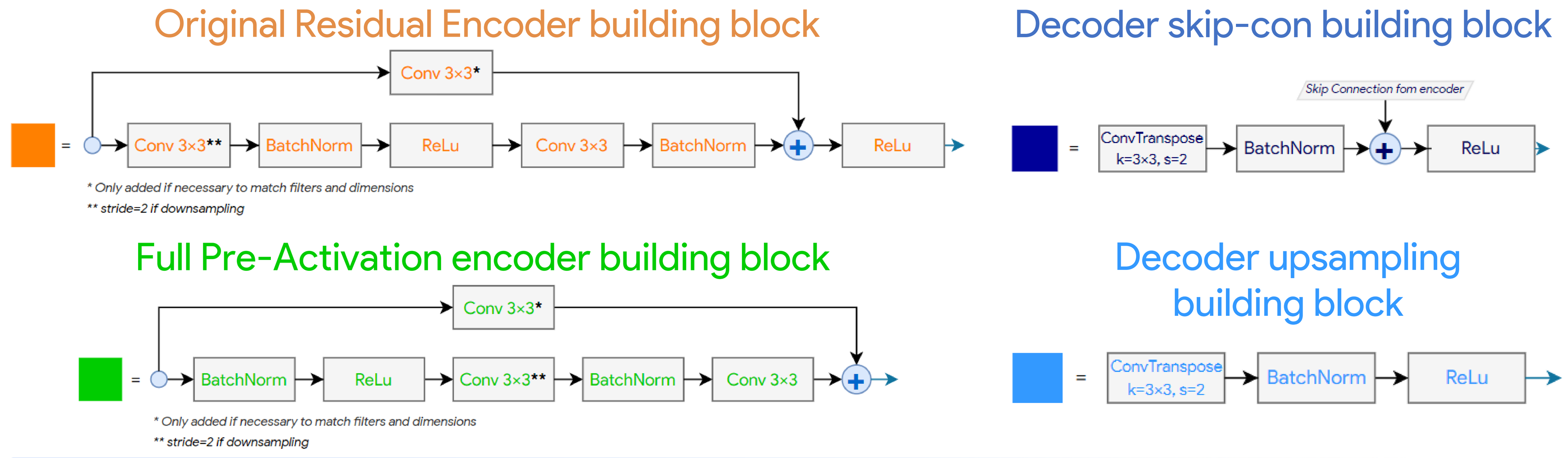
Critical for reconstruction learning: adding variability to input MRIs to enforce the actual brain structure learning

Transformations: Dropout pixels, Gaussian Noise, Gaussian Blur, Blank-out Region (random levels)

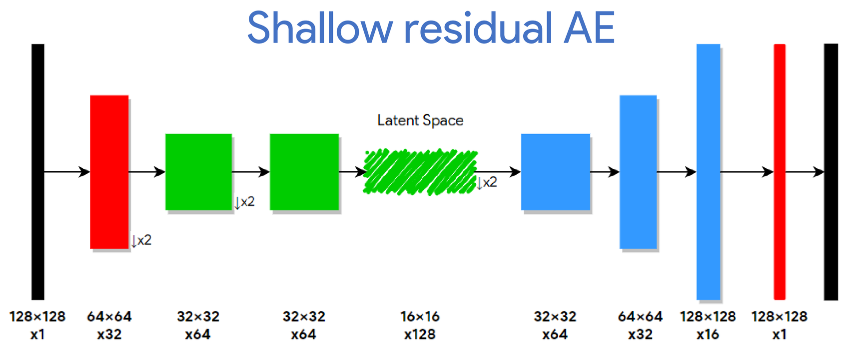
Data i.i.d between splits: [71.8-13.8-8.1]% data split made straight from volumes: every image from one volume in the same split. Stratified by age, sex and ethnic.



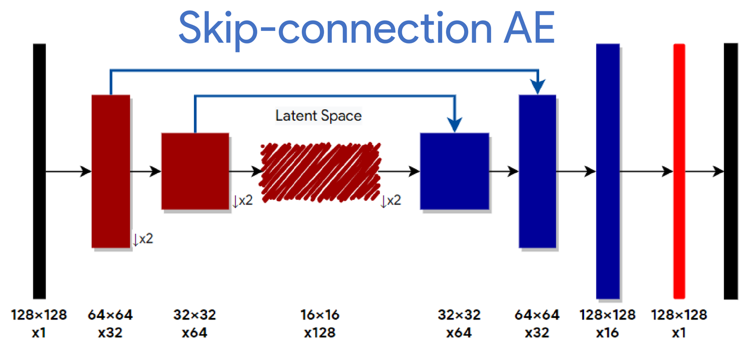
Architectures



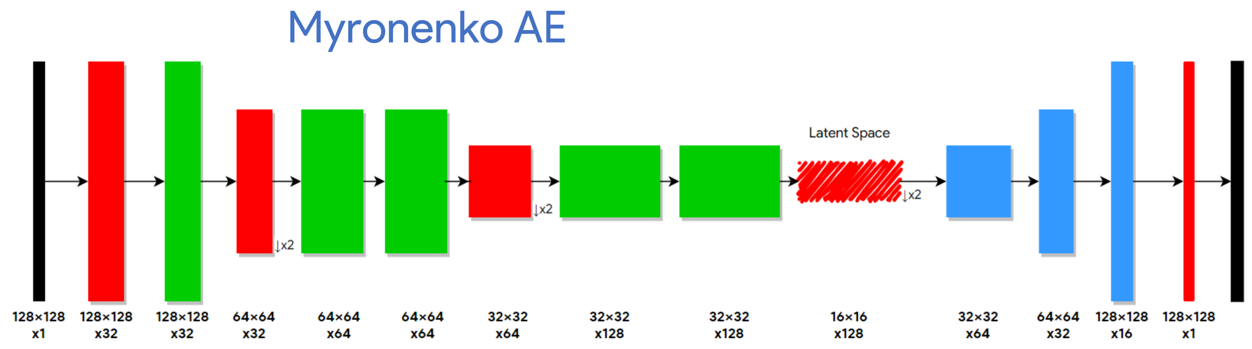
Shallow residual AE



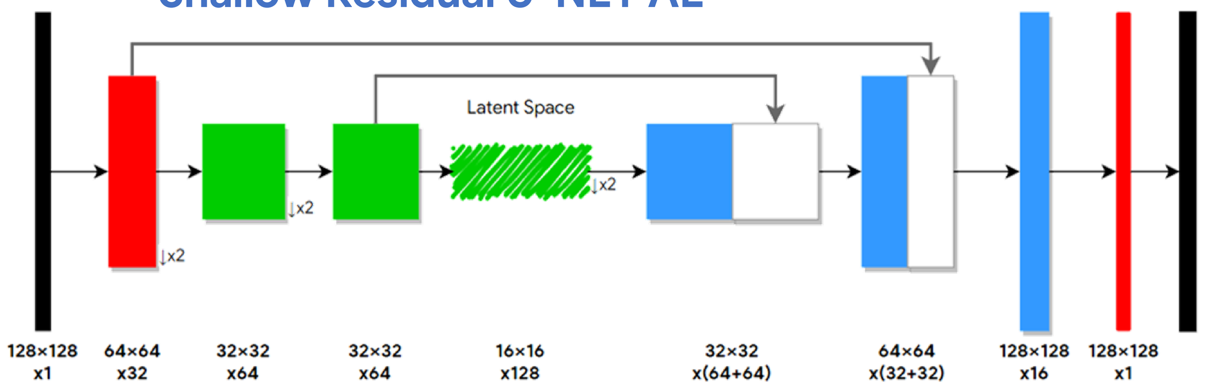
Skip-connection AE



Myronenko AE



Shallow Residual U-NET AE



Loss Functions

$$\mathbf{MSE} = \frac{1}{N}\sum_{i=n}^{n}\left(Y_i - \widehat{Y}_i\right)^2$$

$$\mathbf{PSNR} = 10 \text{ x } \log_{10}\frac{\text{peakval}^2}{\text{MSE(x, y)}}$$

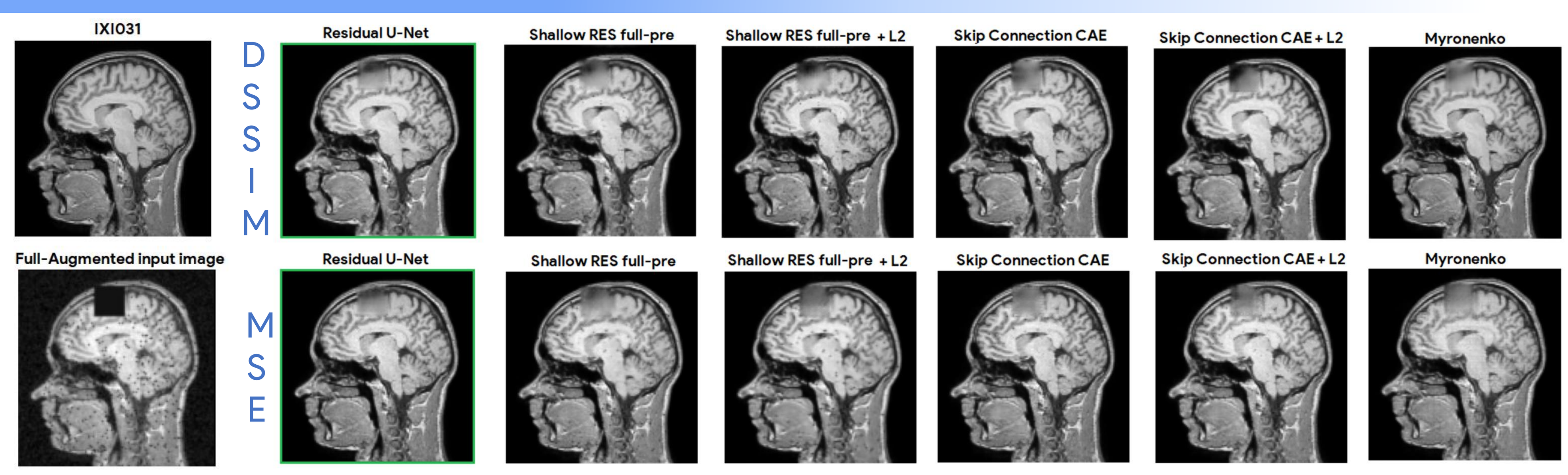
$$\mathbf{DSSIM} = \frac{1 - SSIM(x,y)}{2}$$

$$SSIM(x,y) = \frac{(2\mu_x\mu_y + c_1)(2\sigma_{xy} + c_2)}{(\mu_x^2 + \mu_y^2 + c_1)(\sigma_x^2 + \sigma_y^2 + c_2)}$$

Conv 3x3
Conv 3x3 +BN+ReLu
↓x2:Stride=2

Results

Model	loss	L2	Val loss	MSE	DSSIM	PSNR
Residual U-NET	MSE	No	**3.58e-05**	**3.44e-05**	**2.95e-03**	**44.9**
Shallow RES full-pre	MSE	No	1.55e-04	**1.51e-04**	6.75e-03	38.6
Skip connection CAE	MSE	Yes	2.69e-04	**2.25e-04**	1.65e-02	36.8
Skip connection CAE	MSE	No	3.10e-04	**2.99e-04**	9.36e-03	35.7
Myronenko CAE	MSE	No	3.38e-04	**3.27e-04**	1.57e-02	35.1
Shallow RES full-pre	MSE	Yes	3.72e-04	**3.24e-04**	1.14e-02	35.2
Residual U-NET	DSSIM	No	**1.50e-03**	**7.49e-05**	**1.44e-03**	**41.8**
Shallow RES full-pre	DSSIM	Yes	4.42e-03	2.34e-04	**3.70e-03**	36.7
Shallow RES full-pre	DSSIM	No	4.19e-03	2.88e-04	**4.14e-03**	35.9
Myronenko CAE	DSSIM	No	4.39e-03	6.69e-04	**4.31e-03**	32.1
Skip connection CAE	DSSIM	Yes	4.82e-03	4.08e-04	**4.38e-03**	34.2
Skip connection CAE	DSSIM	No	4.90e-03	4.57e-04	**4.71e-03**	33.7



- Residual U-Net outperforms all methods for both loss functions Qualitatively and Quantitatively
- DSSIM loss models reconstruct better the structure and shape of the brain
- L2 regularization enhance DSSIM-loss models, but decreases MSE-loss ones
- All methods are outstanding reconstructing Gaussian noise and fixing image blur
- Dropped-out pixels are excellent reconstructed by every model but Shallow-Residual ones, which left some little noisy pixels
- Blanked-out regions are better reconstructed by DSSIM models, specifically Res-UNET and Shallow-Residual

AdrianArnaiz/Brain-MRI-Autoencoder
Slides, oficial report and PwC links on Github

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European Laboratory for Learning and Intelligent Systems