

# Large-Scale Unsupervised Deep Representation Learning for Brain Structure

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2018

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### Data Preprocessing

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# Data

## Data Preprocessing

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- ▶ A typical sBMRI scan is a 256 by 256 by 256 image containing the subjects head.
- ▶ We crop all the resulting images to the central 200 by 200 by 200 bounding box, using FreeSurfer (current state of art) software to remove isolate just the brain
- ▶ We downsample all the images to 100 by 100 by 100 dimensions to reduce the memory requirement

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# Deep Representation Learning Models

## Convolutional Autoencoders

- ▶ An autoencoder (AE) is a neural network composed of an *encoder* – transforms data into its vector representation – and a *decoder* – reconstructs data from its encoding
- ▶ Minimize loss between original image and reconstruction
- ▶ Capture frequently occurring features through parameter sharing from input to convolution and deconvolution layers

# Deep Representation Learning Models

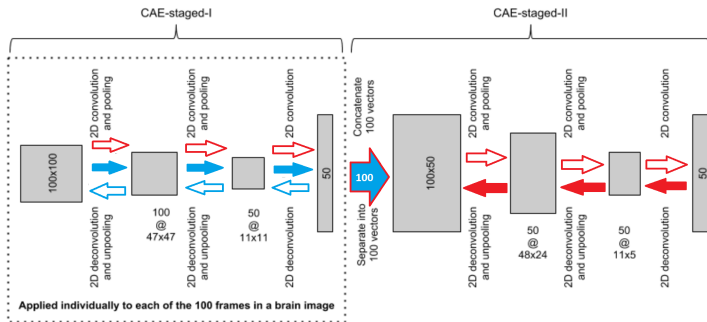
## Convolutional Autoencoders

- ▶ Maxpooling/Unpooling
- ▶ Rectified Linear Activation
- ▶ Batch Normalization

# Deep Representation Learning Models

## Convolutional Autoencoders

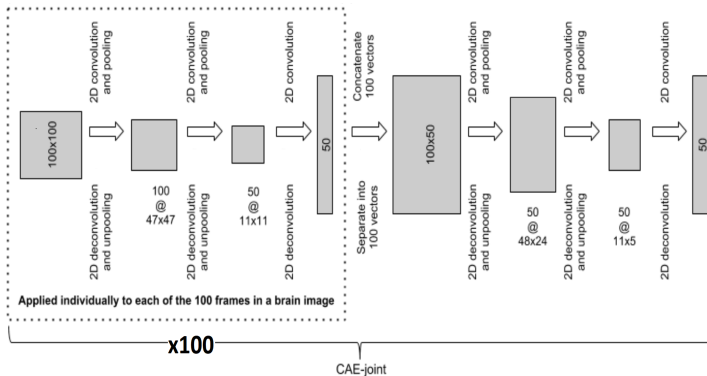
### CAE Staged



# Deep Representation Learning Models

## Convolutional Autoencoders

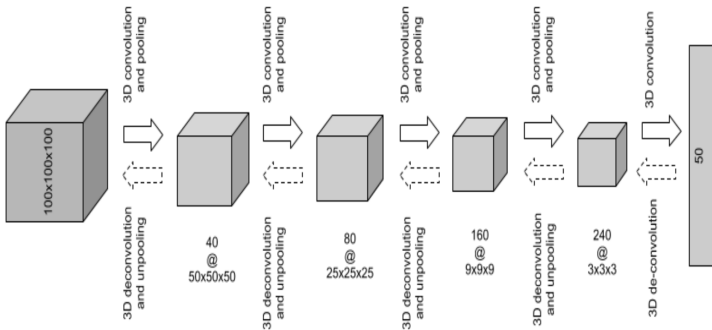
### CAE Joint



# Deep Representation Learning Models

## Convolutional Autoencoders

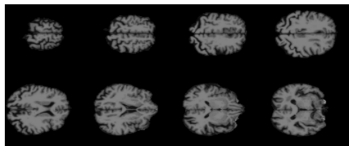
### CAE 3D



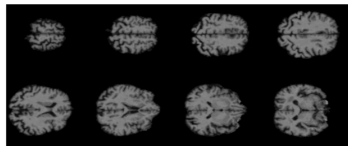
# Deep Representation Learning Models

## Convolutional Autoencoders

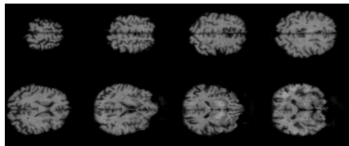
### Reconstructions



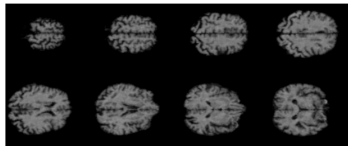
(a) Original brain image



(b) CAE-staged-I reconstruction



(c) CAE-joint reconstruction



(d) CAE-3D reconstruction

**Fig. 3:** 2D frames in original and reconstructed brain images.

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# Experimental Evaluation

## Qualitative Analysis

- ▶ Effect of voxel's perturbation on node's activation
- ▶ Saliency map indicating which voxels present important activation regions for each node



# Experimental Evaluation

## Qualitative Analysis

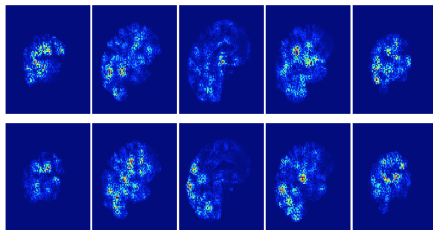


Fig. 4: Saliency map of two nodes in the embedding layer - CAE-staged

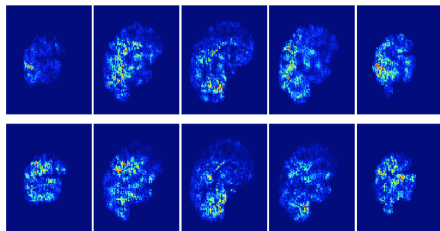


Fig. 5: Saliency map of two nodes in the embedding layer - CAE-joint

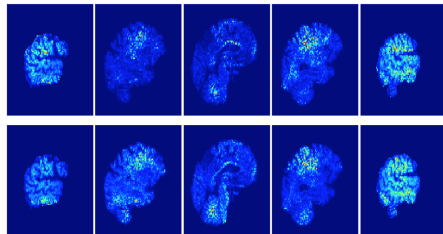


Fig. 6: Saliency map of two nodes in the embedding layer - CAE-3D

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# Experimental Evaluation

## Quantitative Analysis

Classification	Quantitative Analysis							
	Logistic Regression				Random Forest			
	FS	CAES	CAEJ	CAE-3D	FS	CAES	CAEJ	CAE-3D
H-ADNI / AD	0.81	0.67	0.82	0.81	0.86	0.64	0.80	0.83
AD / MCI	0.71	0.67	0.76	0.72	0.77	0.70	0.73	0.73
H-ADNI / MCI	0.77	0.75	0.76	0.76	0.81	0.71	0.77	0.80
H-ABIDE / ASD	0.60	0.57	0.57	0.60	0.65	0.64	0.63	0.66

## Timing Analysis

Feature construction using FreeSurfer takes 2047 hours for each image 10. In contrast, CAE-staged and CAE-joint take 0.55s, and CAE-3D takes 0.45s on average to generate the latent embedding of each brain image

# Conclusion

- ▶ CAE reconstruct brain images with very low error and performance comparable to FS features on classification tasks
- ▶ Less time