-Denoising Autoencoder (DAE)

-Variational Autoencoder (VAE)

-Denoising Convolutional Neural Network (DnCNN)

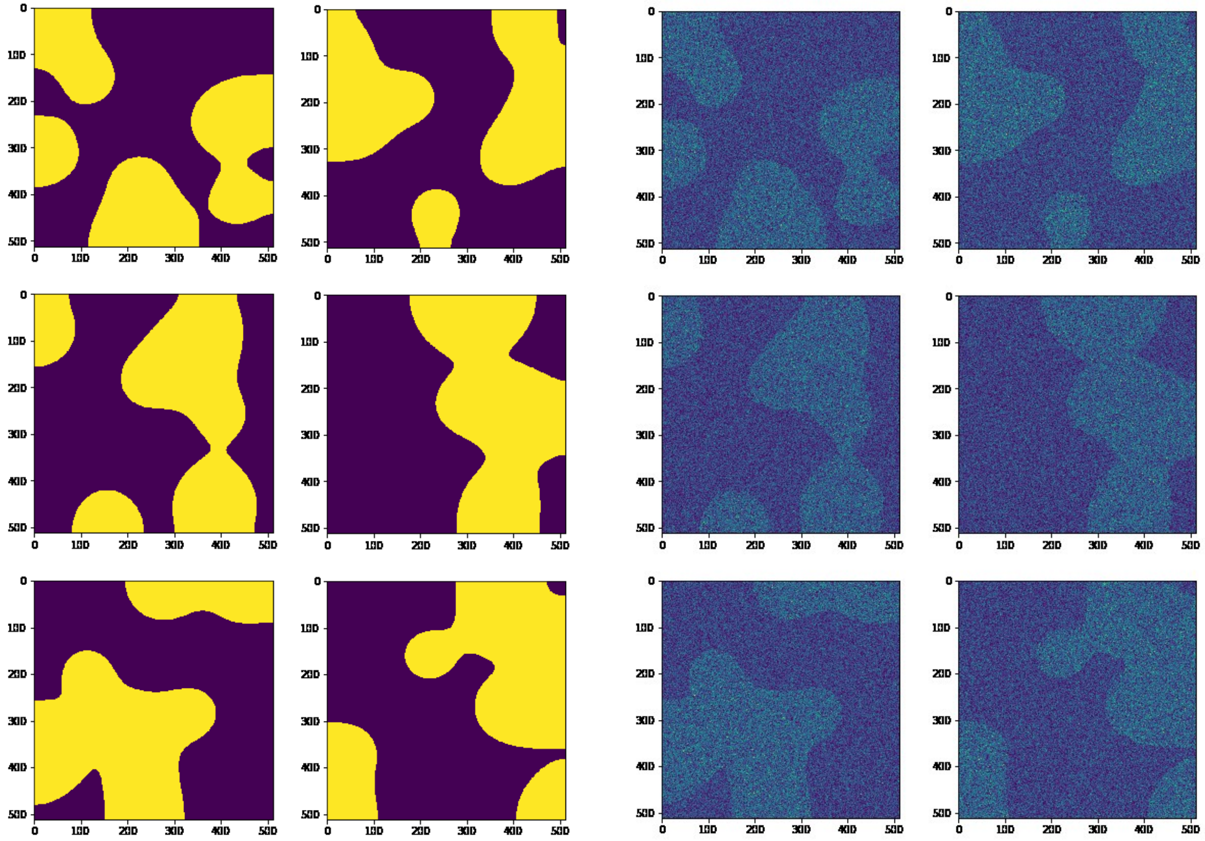
Dataset 1

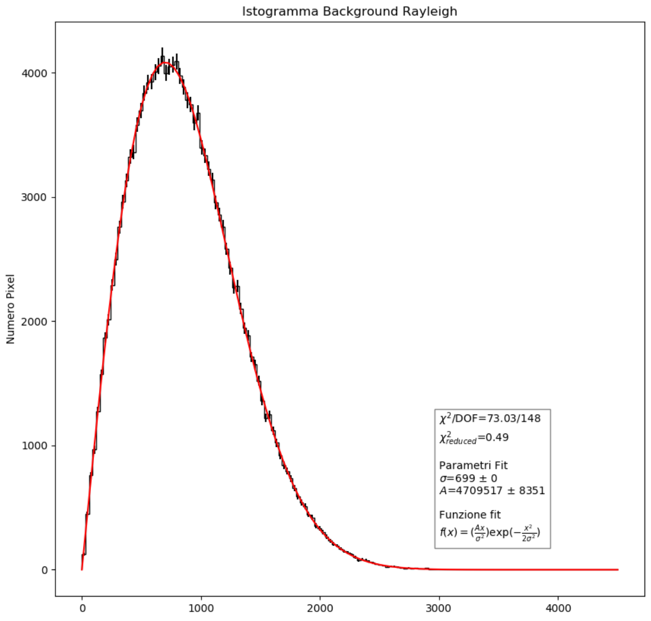
Generation parameters:

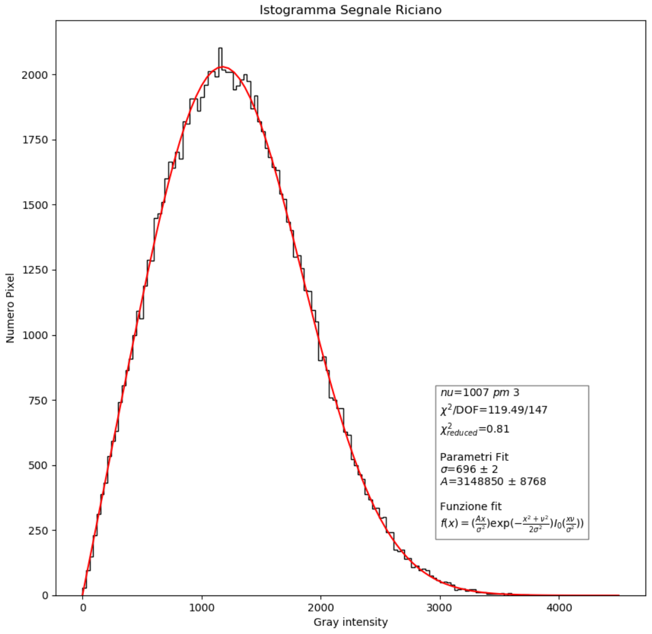
- Signal = 1000
- Sigma = 700
- Image Size = 512x512
- Blobsize = 10.
- Nseeds = 3

Signal

Signal+Rician Noise

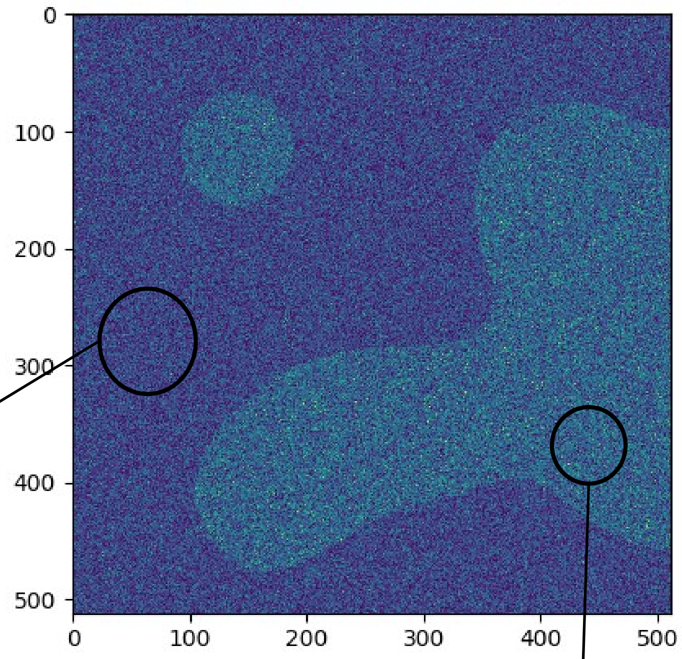






First analysis

$$Rayleigh\colon\ f(x,\sigma) = \frac{x}{\sigma^2}\,\mathrm{e}^{-\frac{x^2}{2\sigma^2}}$$



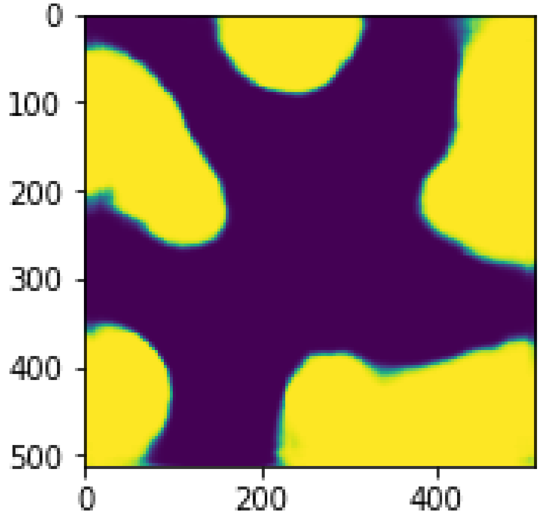
Background

Signal

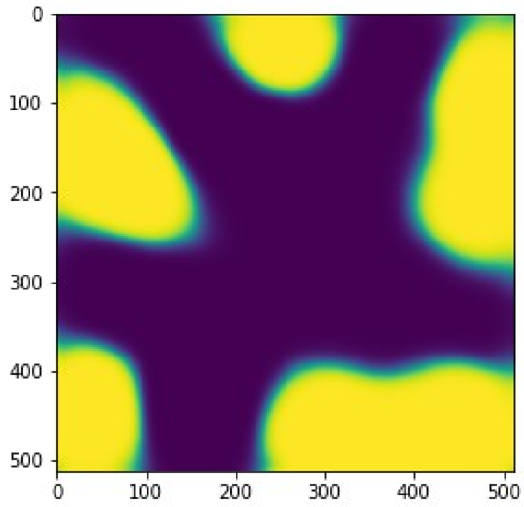
$$Rice\colon\ f(x|\nu,\sigma) = \frac{x}{\sigma^2}\exp\left[\frac{-(x^2+\nu^2)}{2\sigma^2}\right] I_0\left(\frac{x\nu}{\sigma^2}\right)$$

Results dataset 1

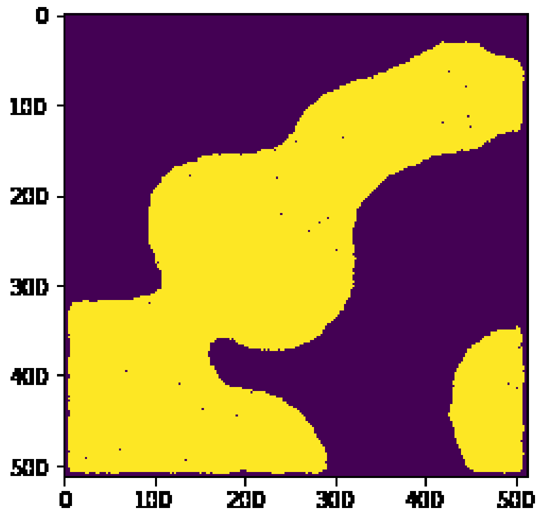
	PSNR (dB)	Dice coefficient
Noised Images	5.863 ± 0.332	0.334 ± 0.008
Denoising autoencoder	17.039 ± 1.433	0.959 ± 0.010
Variational autoencoder	13.989 ± 1.101	0.905 ± 0.018
Wiener filter	16.701 ± 0.875	0.973 ± 0.006



DAE



VAE



WIENER+OFFSET

Results dataset 1

	PSNR (dB)	Dice coefficient
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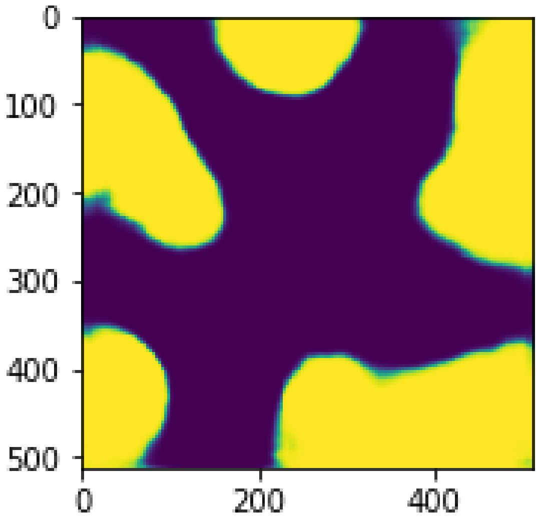
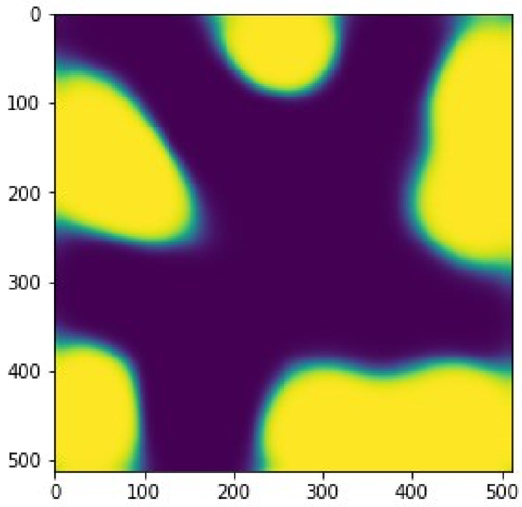
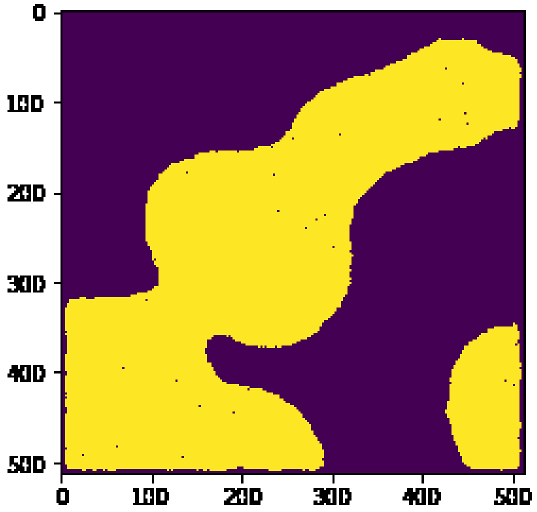
Best performance



DAE



VAE



WIENER+OFFSET

Dataset 2

- Fixed shape and Rician noise
- Can DAE denoise it? Like a Wiener filter?
- Can a generative model (VAE) do the ‘‘same’’ task?

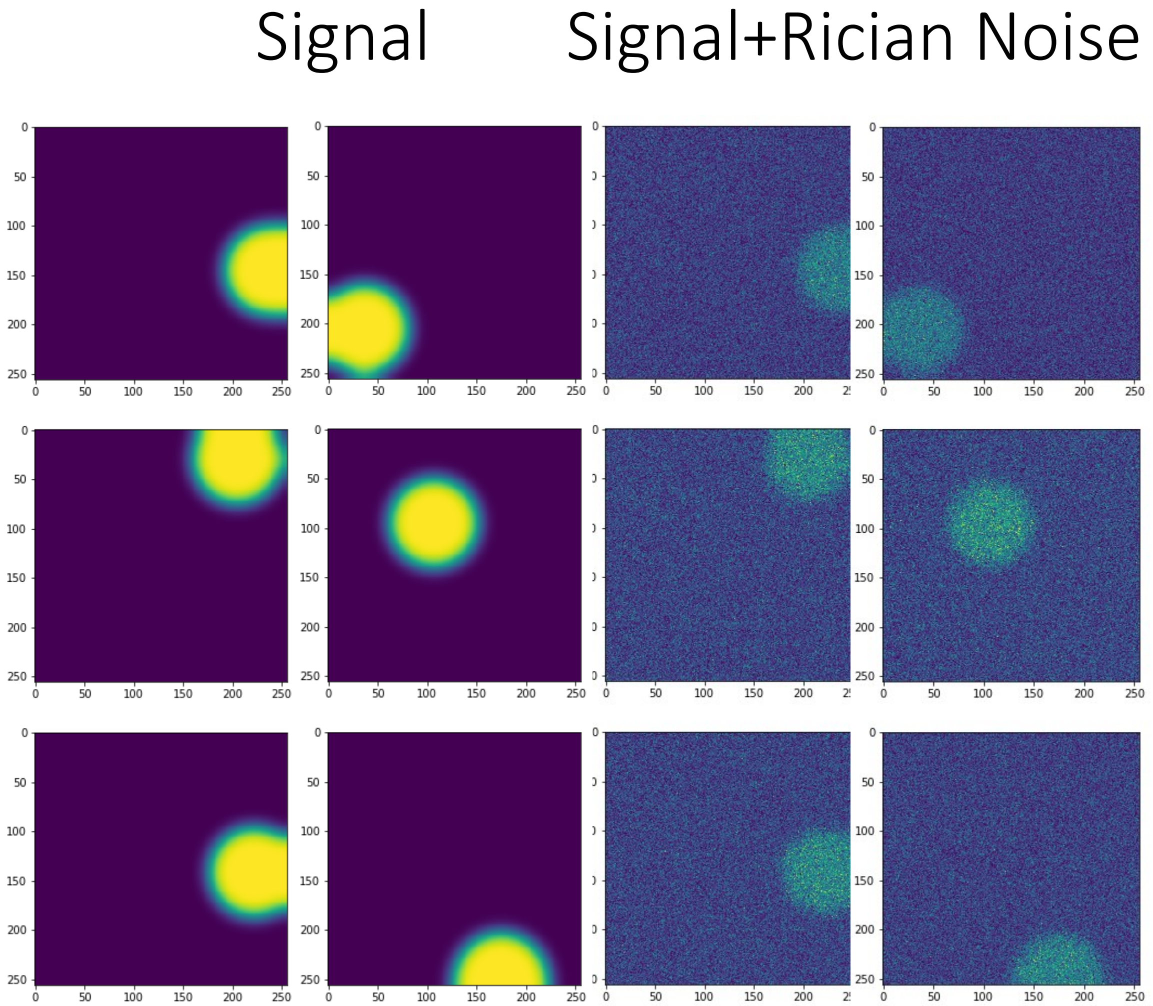
Generation parameters:

- Signal = 1000
- Sigma = 700
- Image Size = 256x256
- Blobsize = 1
- Nseeds = 1
- Gaussian Filter

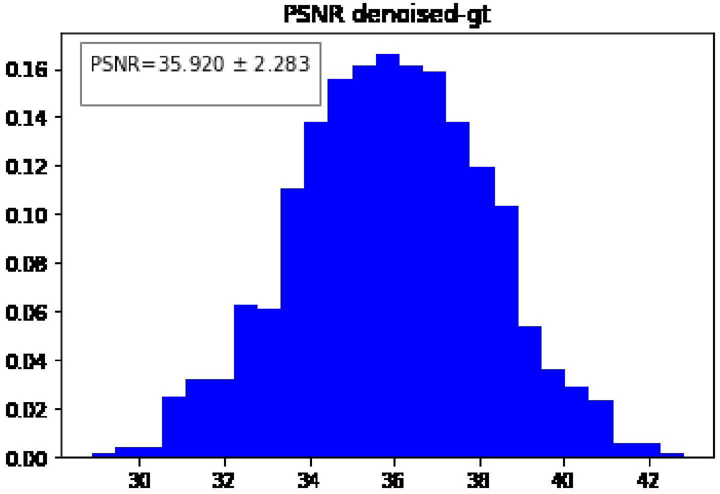
10000 images:

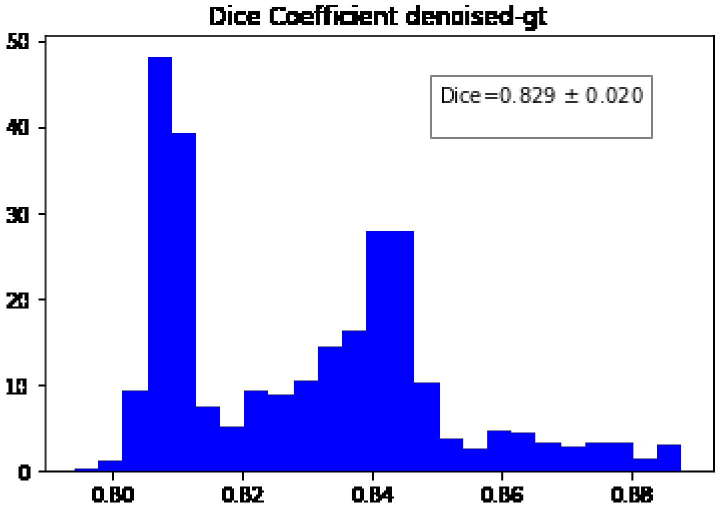
- 7200 train set
- 1800 validation set
- 1000 test set

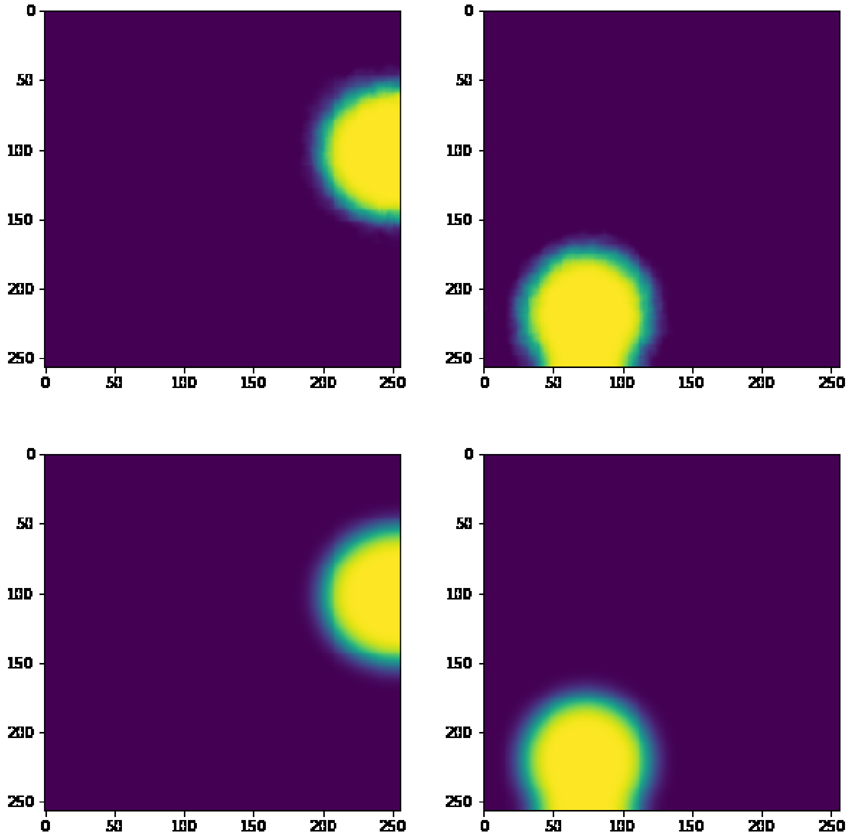
Using the <u>same architectures</u> used for dataset 1

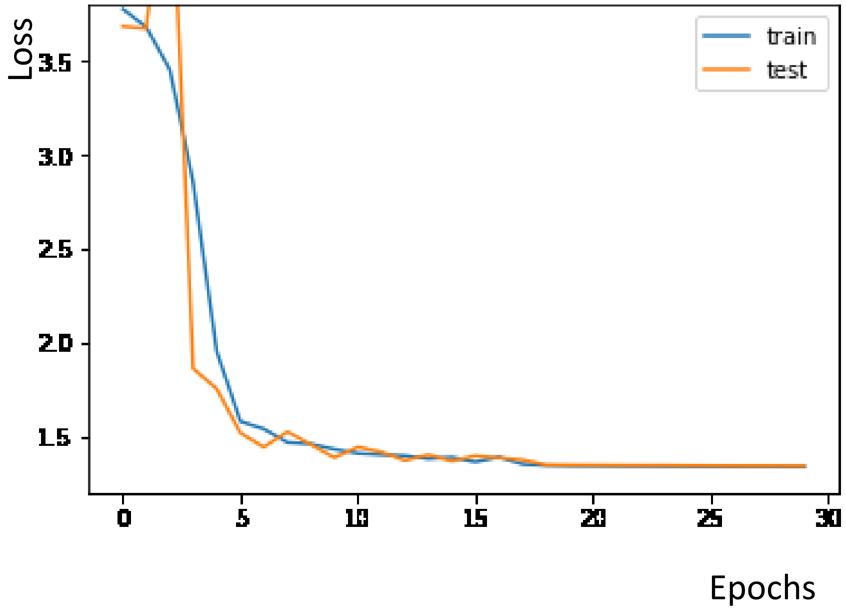


Denoising autoencoder results



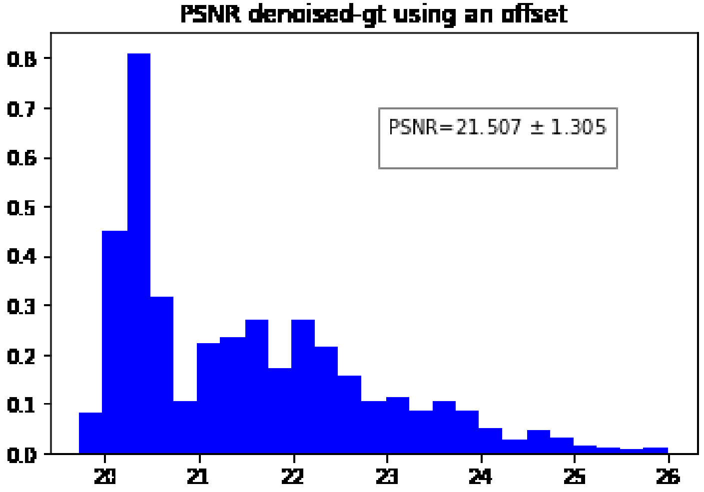


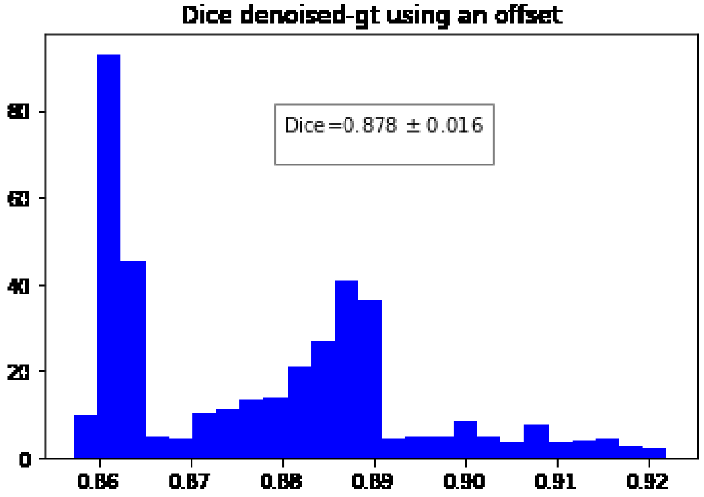




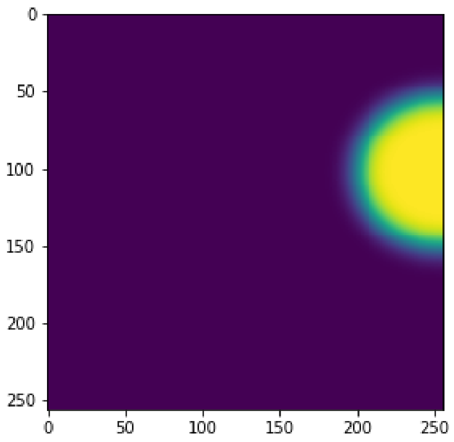
	PSNR (dB)	Dice Coeff.
DAE	35.920 ± 2.283	0.829 ± 0.020

Denoising autoencoder results with an offset

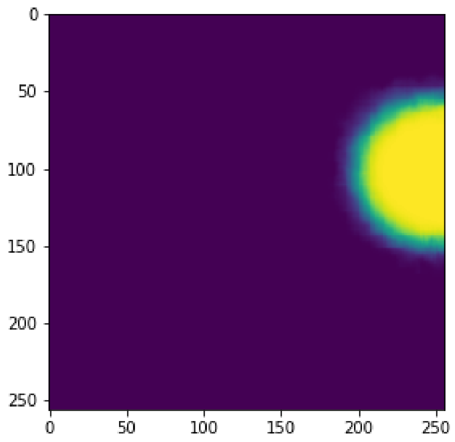




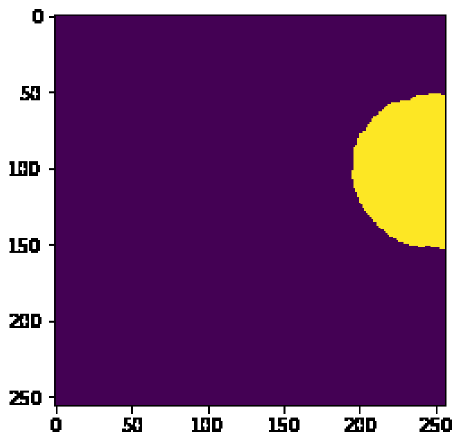
	PSNR (dB)	Dice Coeff.
DAE	35.920 ± 2.283	0.829 ± 0.020
DAE with offset	21.507 ± 1.305	0.878 ± 0.016



GT

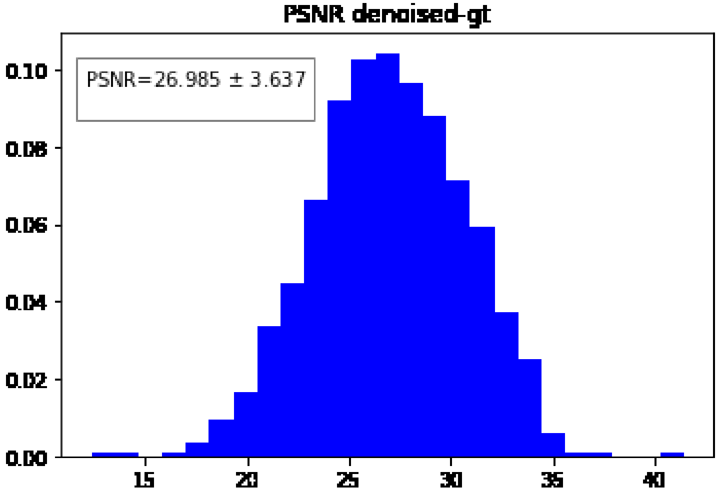


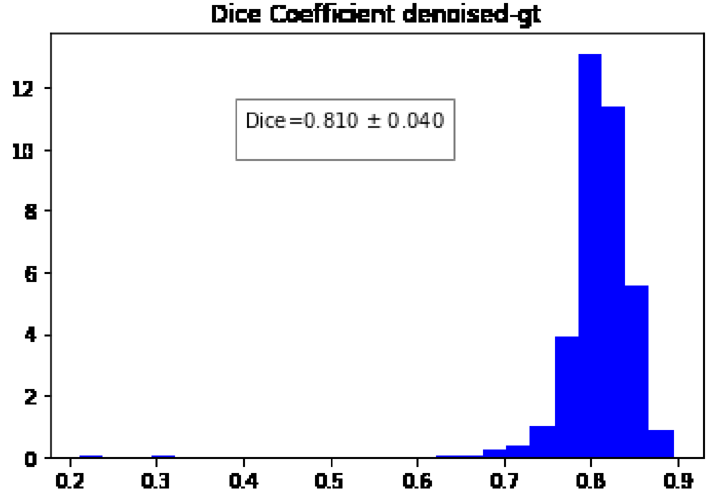
PREDICT

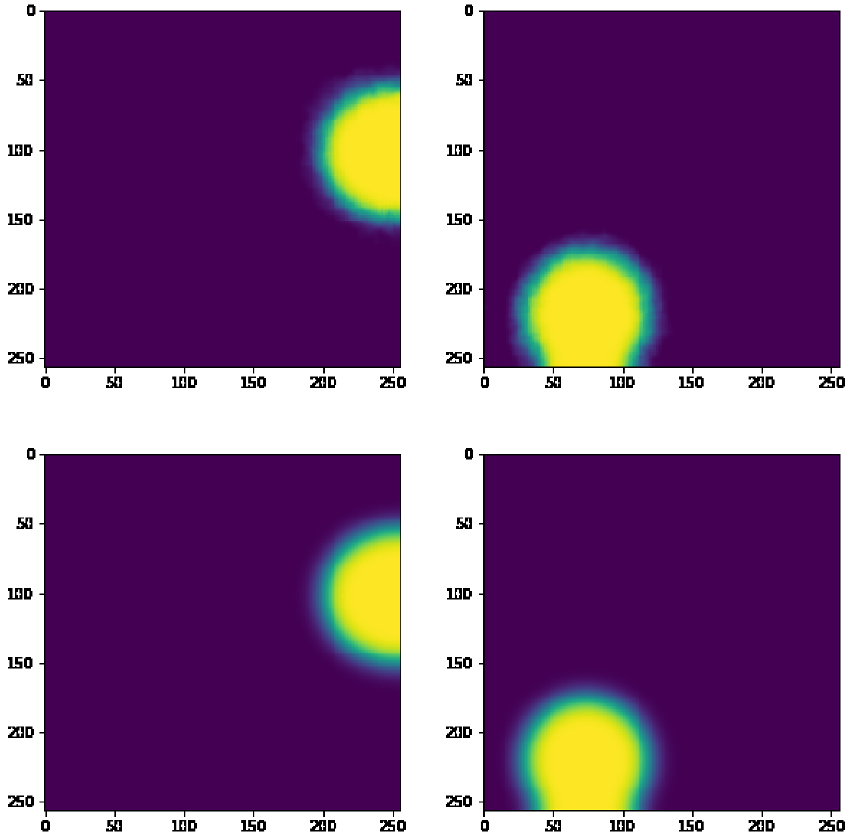


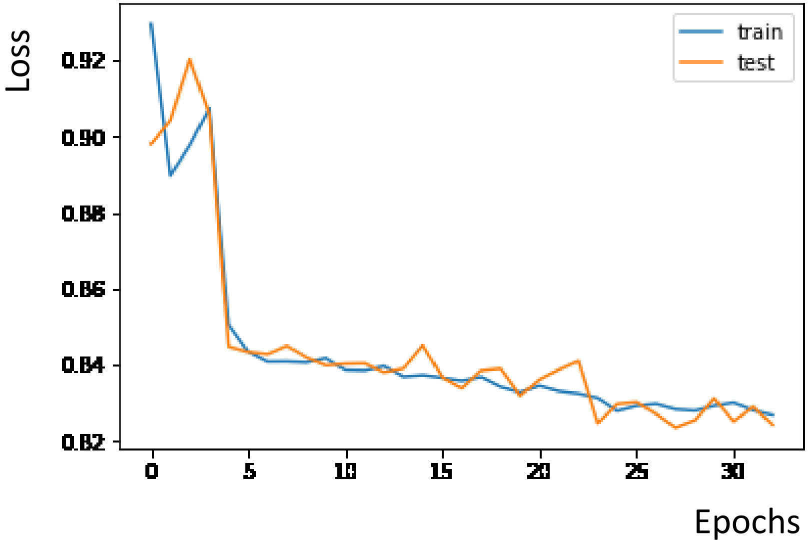
PREDICT+OFFSET

Variational autoencoder results



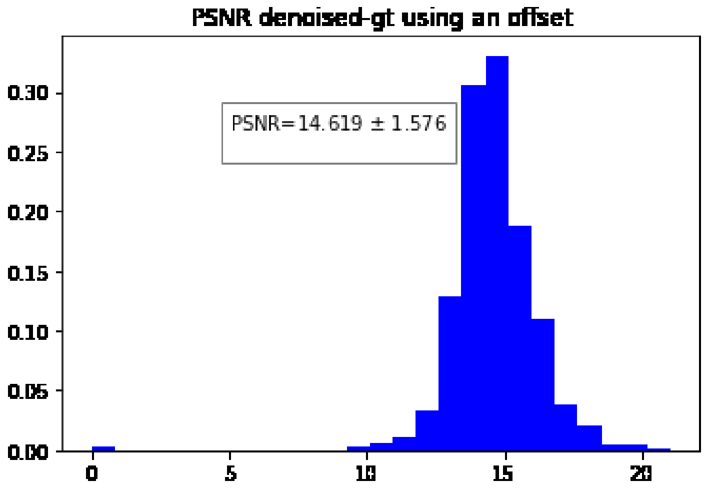


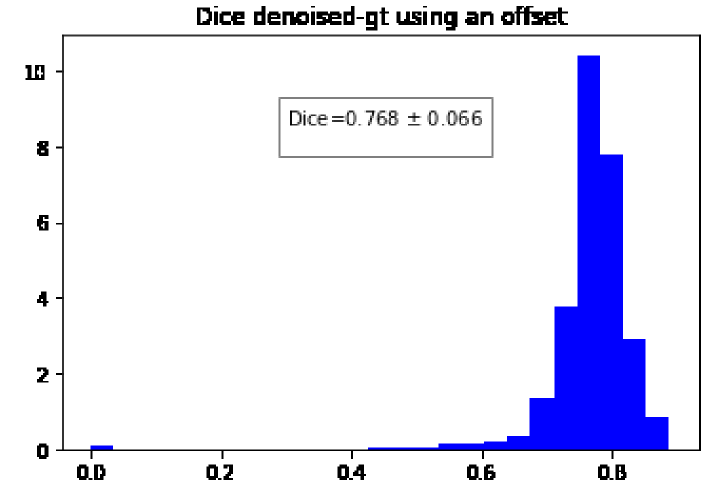




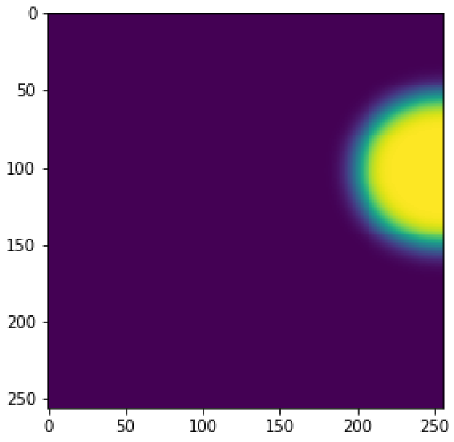
	PSNR (dB)	Dice Coeff.
VAE	26.985 ± 3.637	0.810 ± 0.040

Variational autoencoder results with an offset

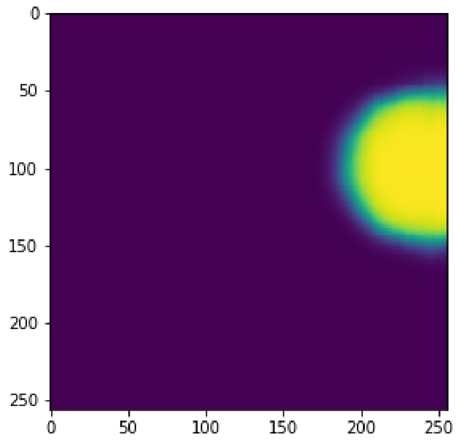




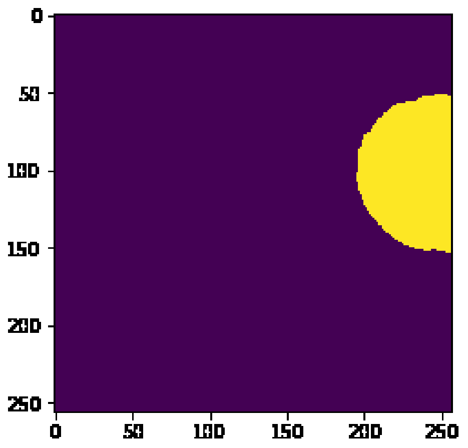
	PSNR (dB)	Dice Coeff.
VAE	26.985 ± 3.637	0.810 ± 0.040
VAE with offset	14.619 ± 1.576	0.768 ± 0.066



GT

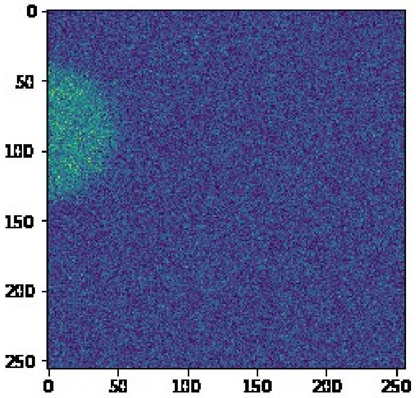


PREDICT

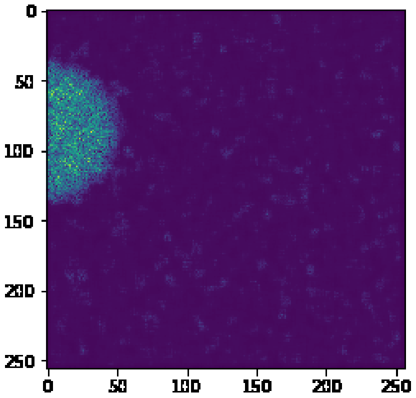


PREDICT+OFFSET

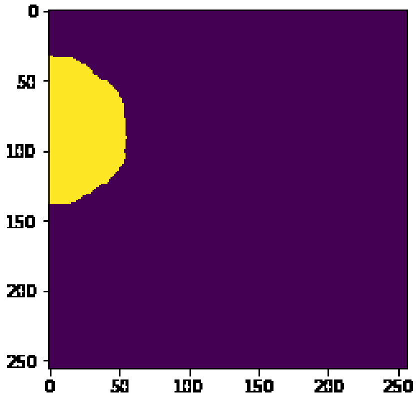
Using Wiener filter+offset+median filter



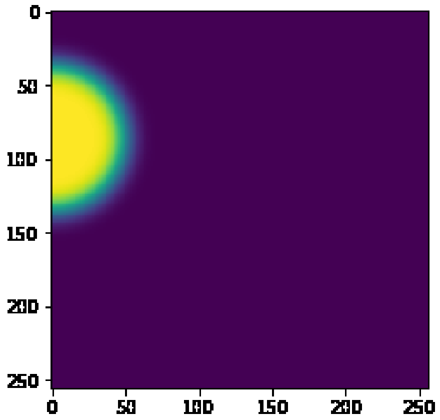
TEST



WIENER FILTER

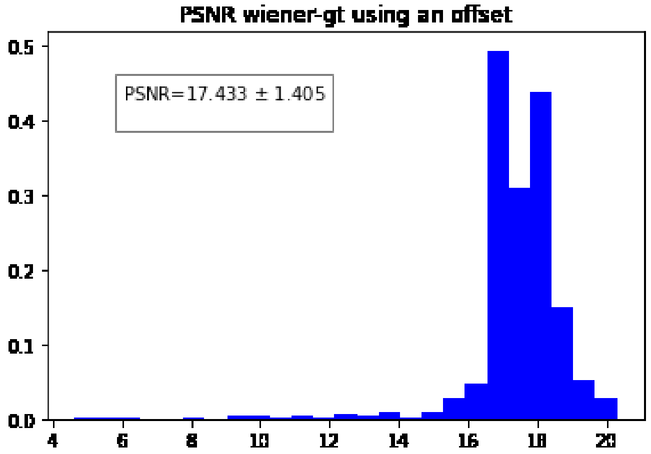


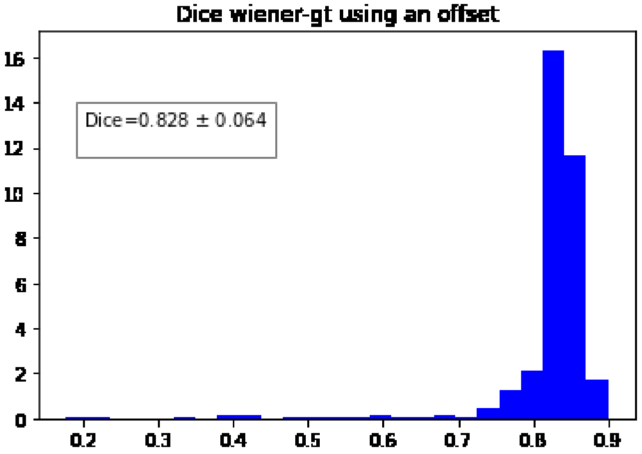
MEDIAN FILTER



GT

	PSNR (dB)	Dice Coeff.
Wiener filter	17.433 ± 1.405	0.828 ± 0.064

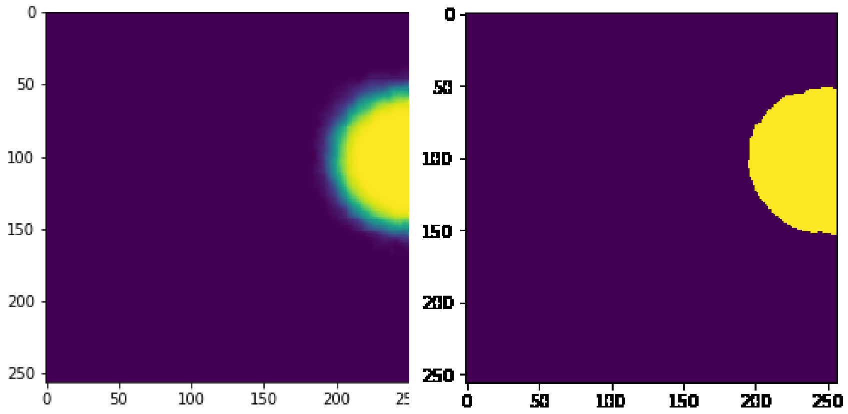




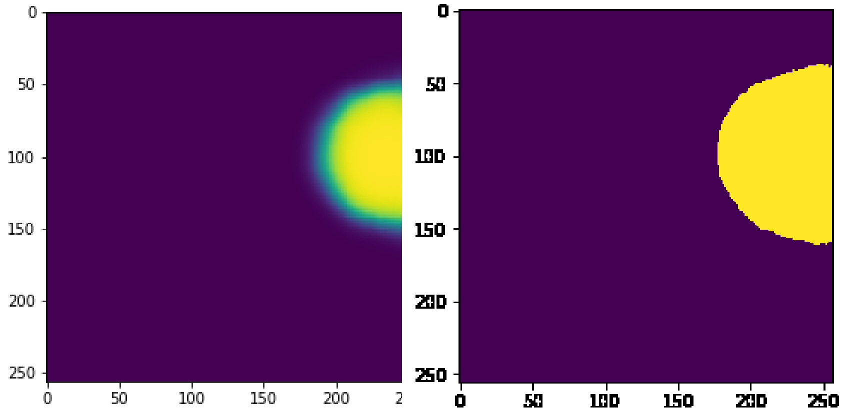
Results dataset 2

	PSNR (dB)	Dice coefficient
Noised Images	5.863 ± 0.332	0.334 ± 0.008
DAE	35.920 ± 2.283	0.829 ± 0.020
DAE with offset	21.507 ± 1.305	0.878 ± 0.016
VAE	26.985 ± 3.637	0.810 ± 0.040
VAE with offset	14.619 ± 1.576	0.768 ± 0.066
Wiener filter with offset	17.433 ± 1.405	0.828 ± 0.064

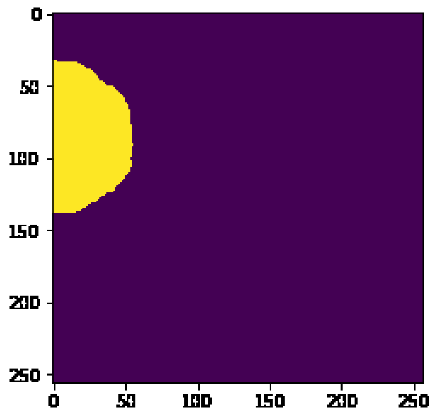
- The denoise is good as a Wiener filter ✓
- For a generative model performance are lower as expected ✓



DAE



VAE



WIENER+OFFSET

Dataset 3

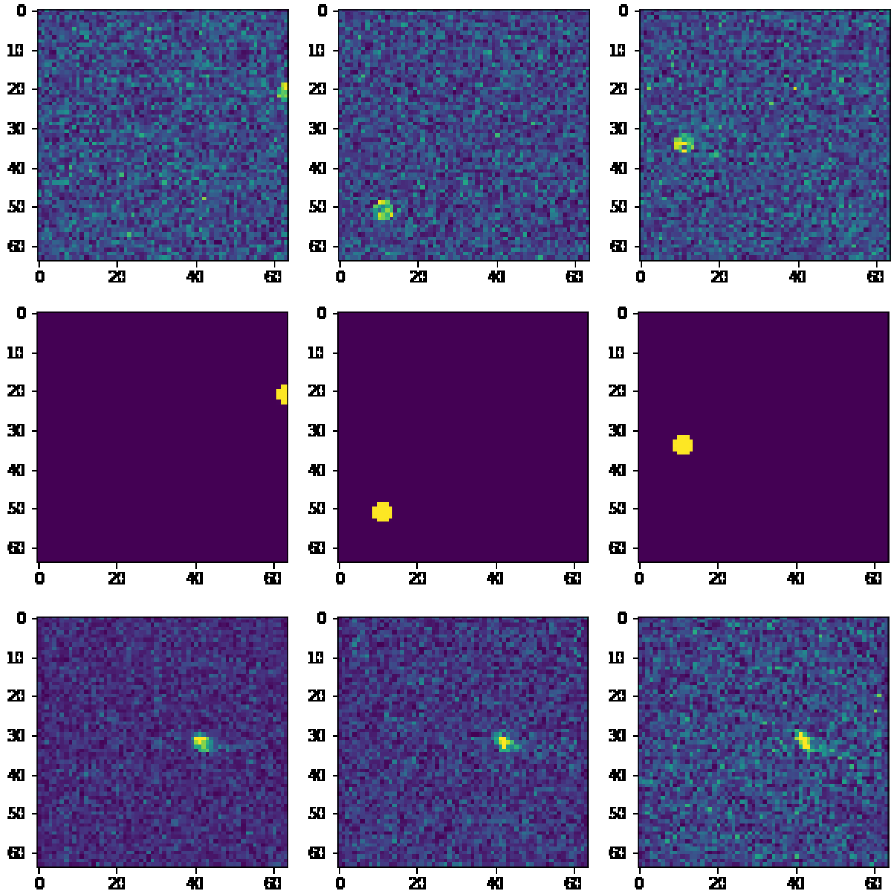
- Test the reconstruction: do DAE and VAE generalize the reconstruction of signals with different shapes?

Generation parameters:

- Signal = 1500
- Sigma = 900
- Image Size = 64x64
- Blobsize = 0.3
- Nseeds = 1

10003 images:

- 7000 train set
- 3000 validation set
- 3 test set

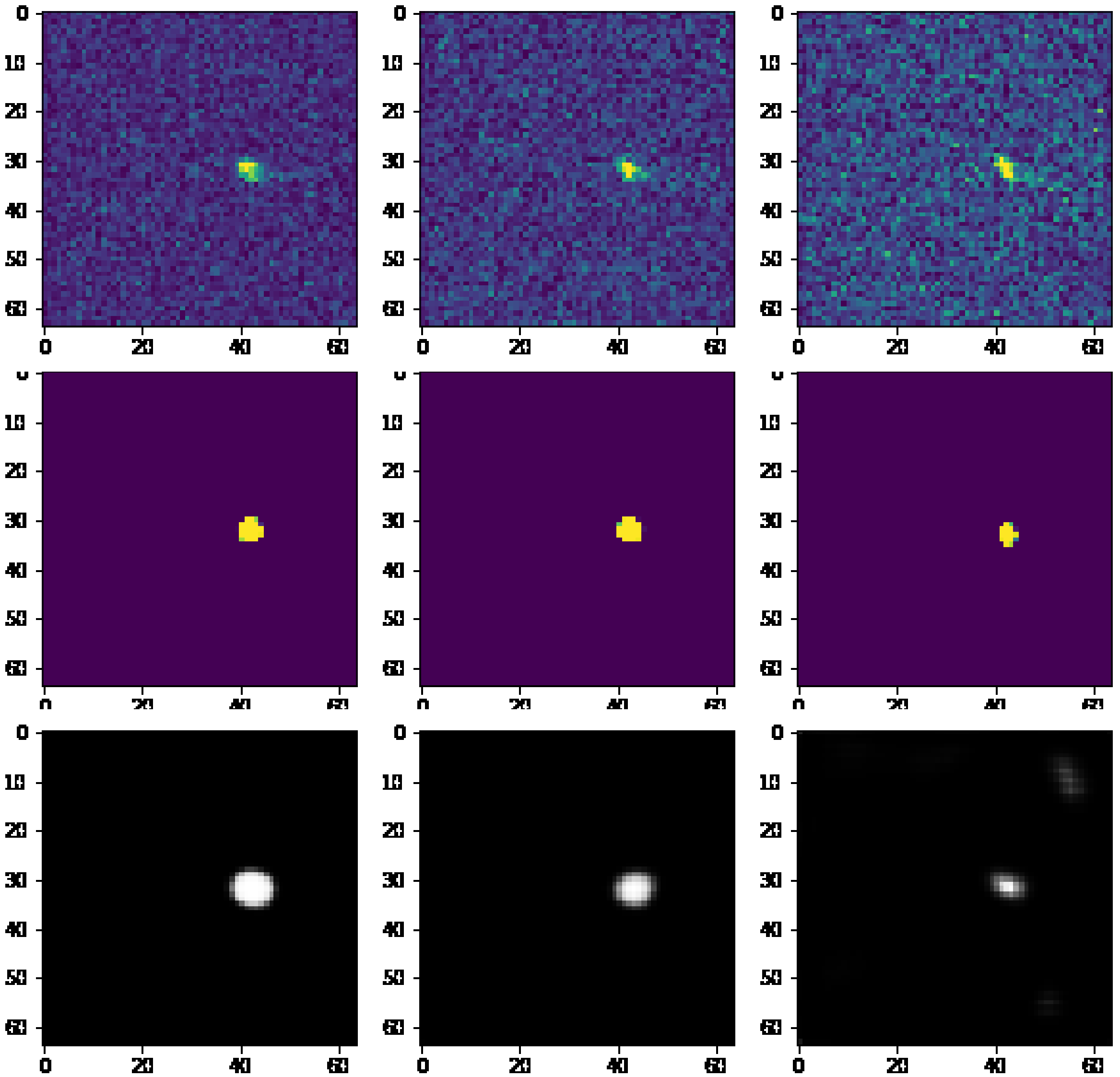


Results dataset 3

- DAE/VAE don't generalize in reconstruction ✗
- Two possible strategies:

  a) DAE/VAE trained with deformed signals shapes.

  b) try with a different network DnCNN.



Dataset 4

Generation parameters:

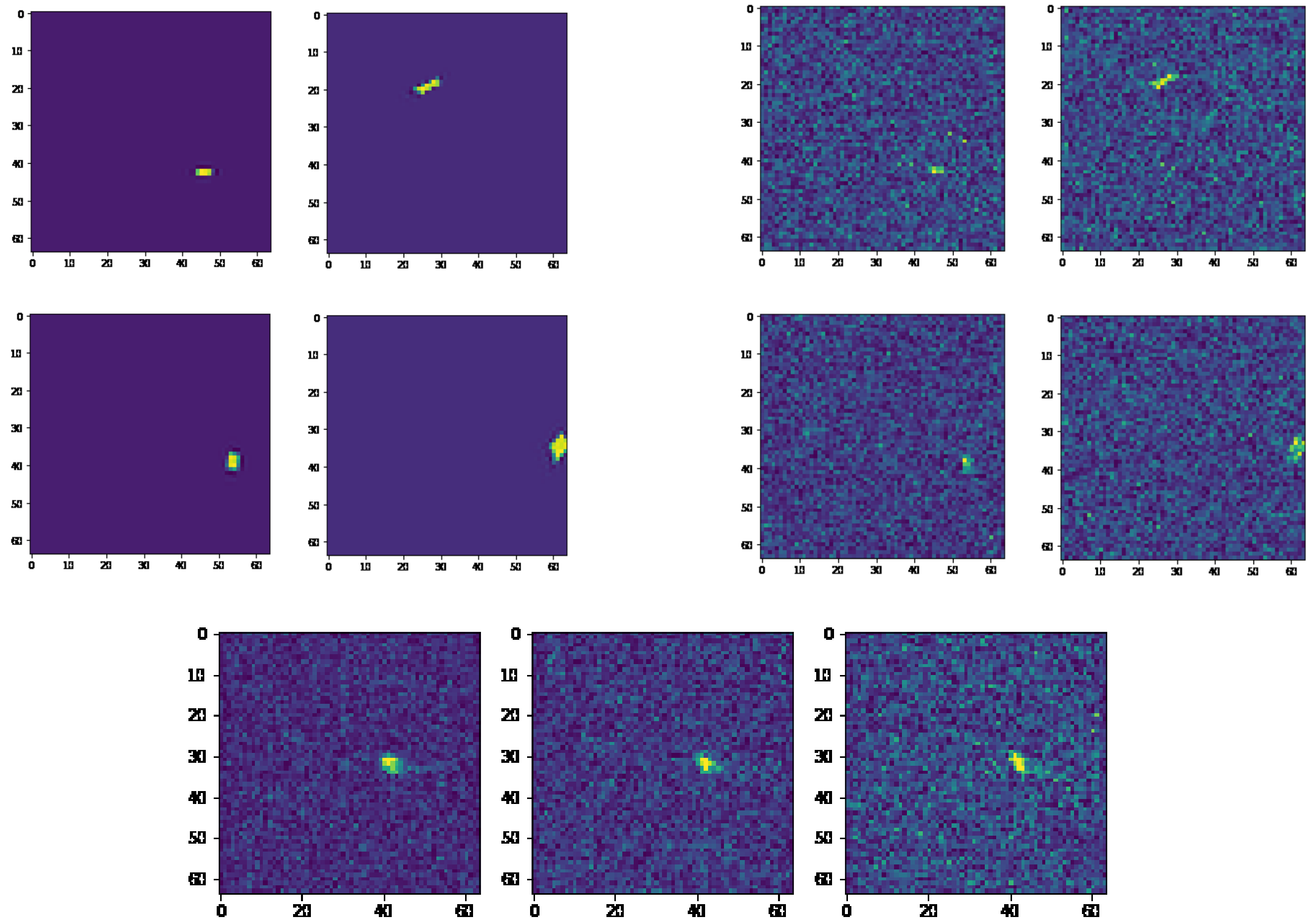
- Signal = 1500
- Sigma = 900
- Image Size = 64x64
- Blobsize = 0.2/0.5
- Nseeds = 1
- Gaussian filter
- Elastic deformation

10003 images:

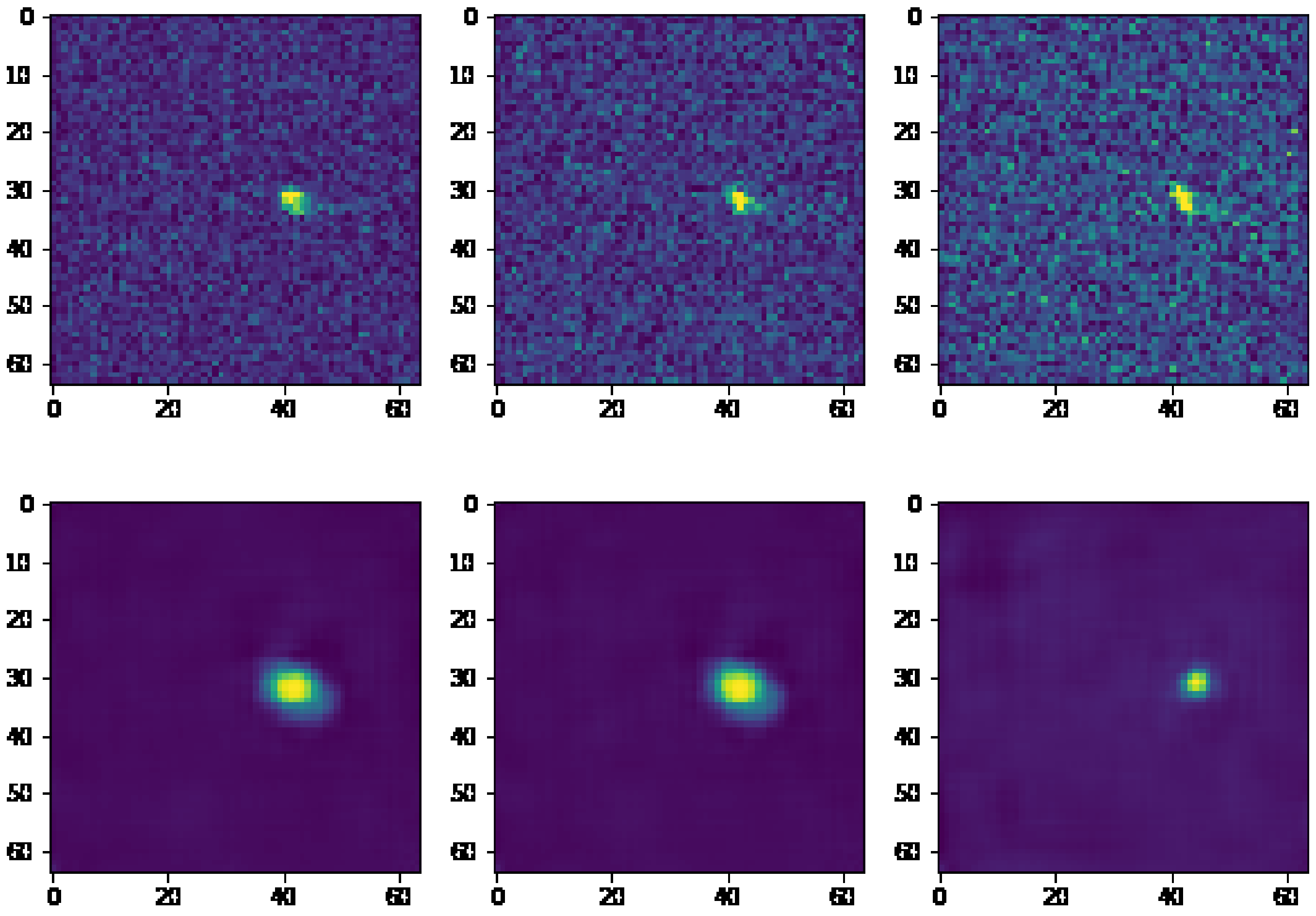
- 7000 train set
- 3000 validation set
- 3 test set

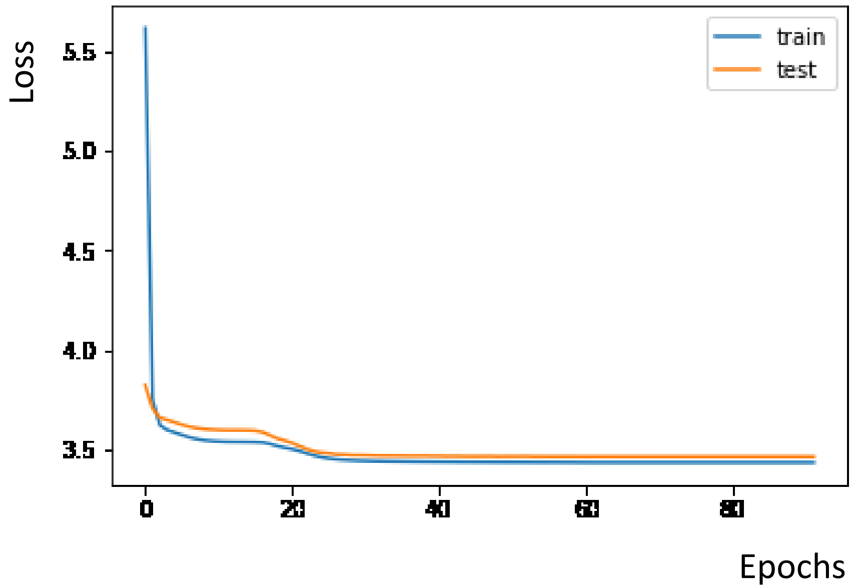
Signal

Signal+Rician Noise



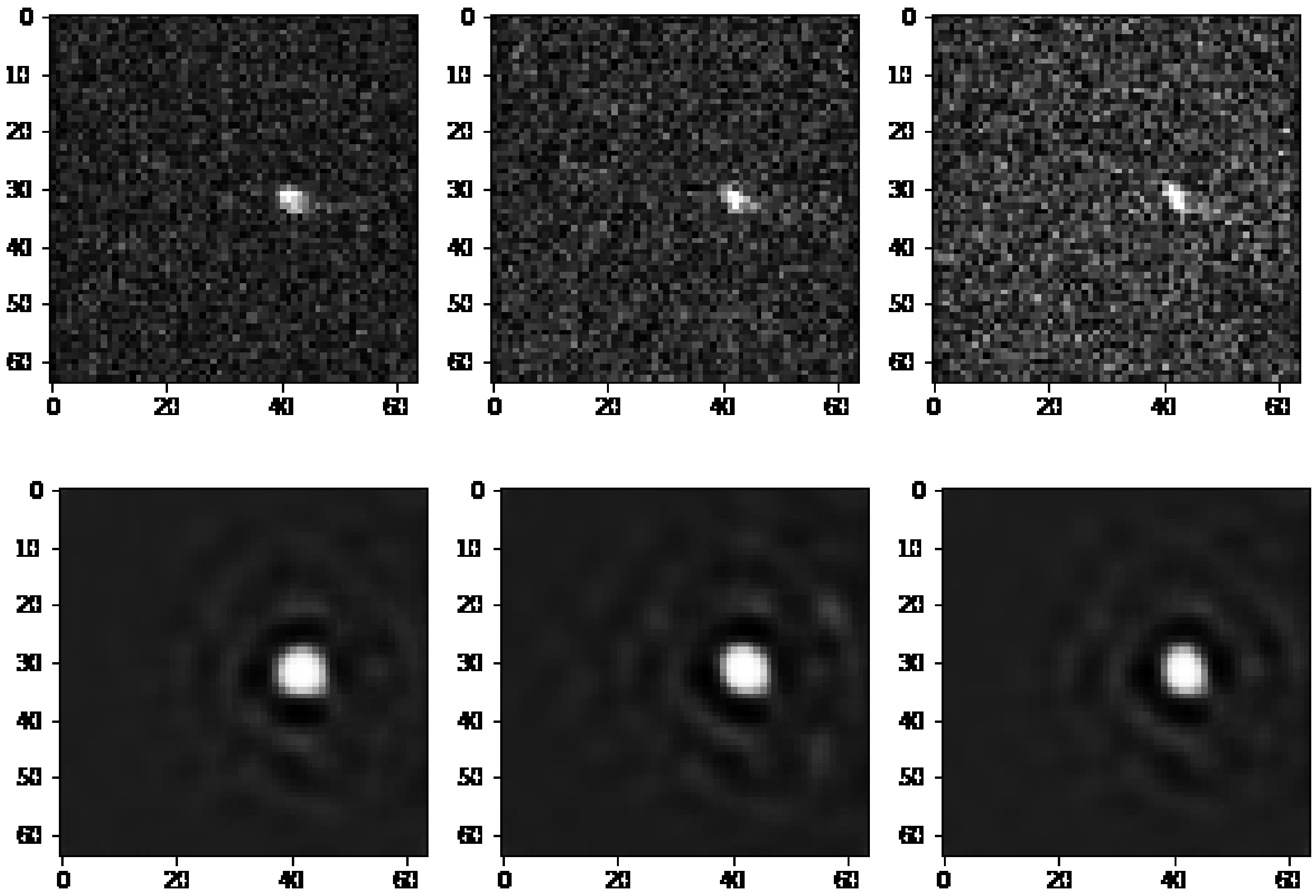
Denoising autoencoder results

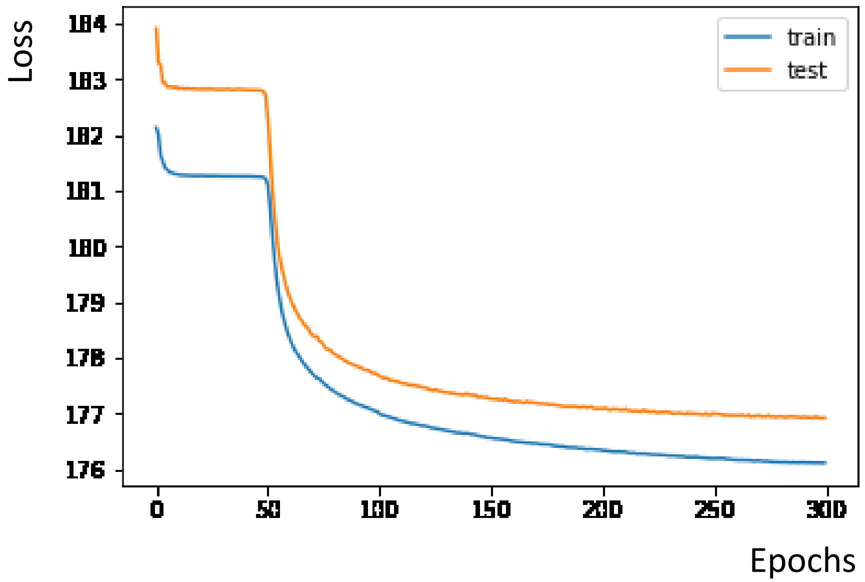




	Shannon Entropy
MRI 1	11.996
MRI 2	11.995
MRI 3	11.997

Variational autoencoder results

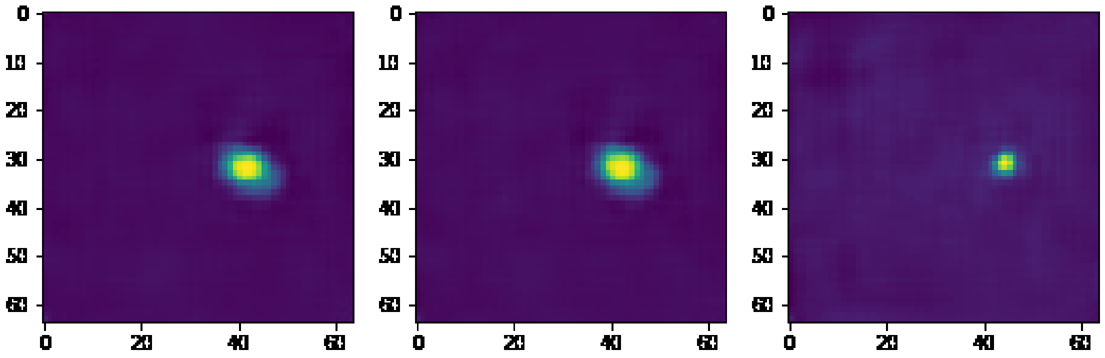


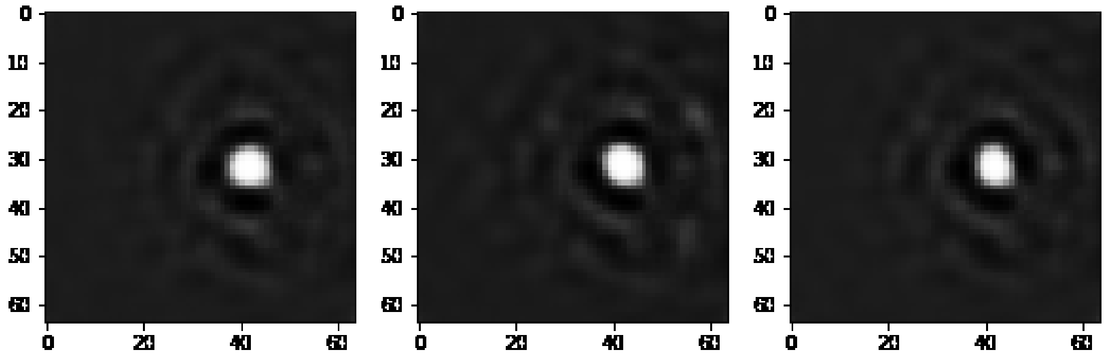


	Shannon Entropy
MRI 1	11.982
MRI 2	11.981
MRI 3	11. 988

Results dataset 4: A plan

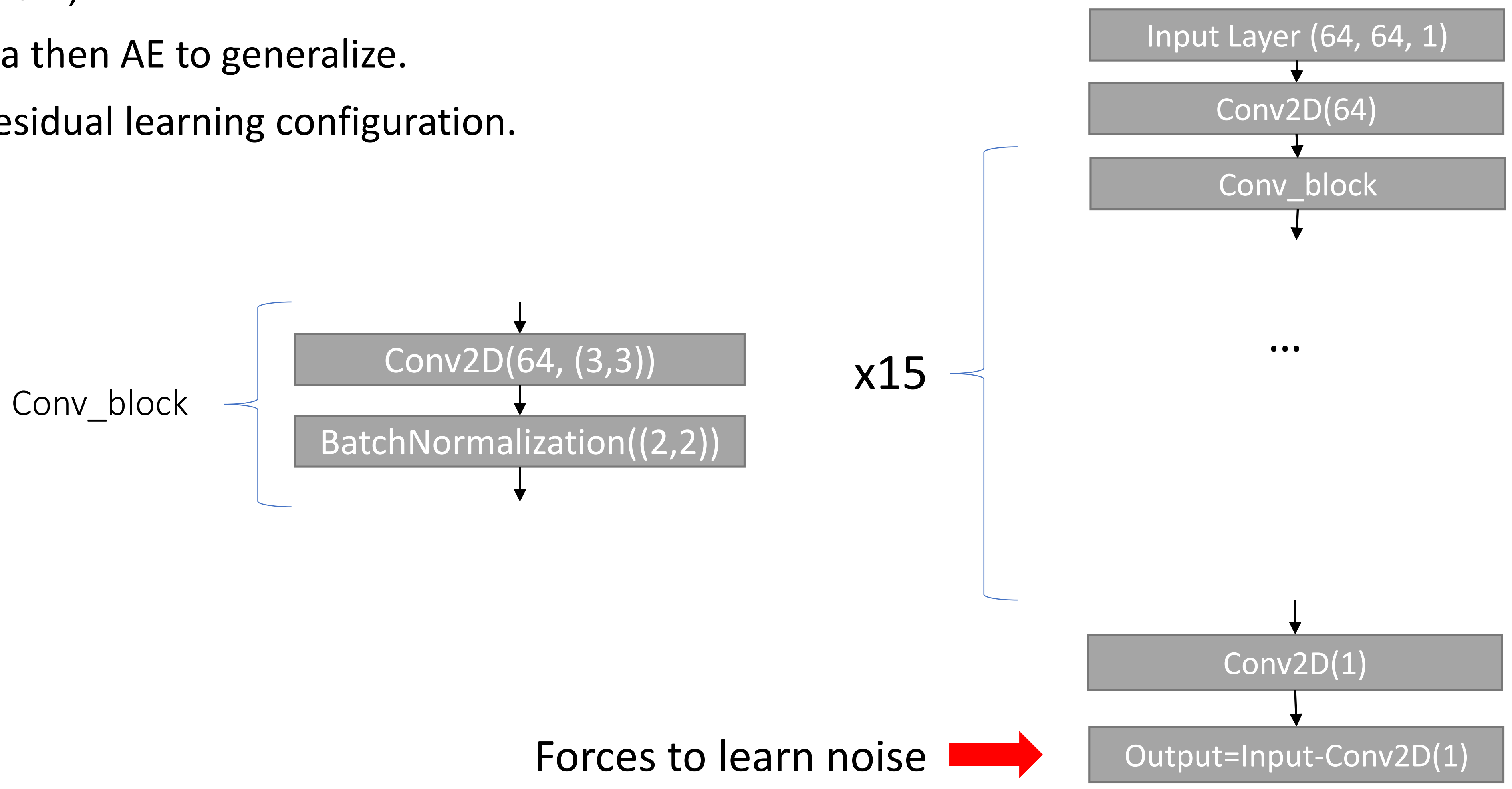
- Reconstructions are a little bit better then before ✓
- But not so good, I need greater dataset for an appropriate generalization ✗



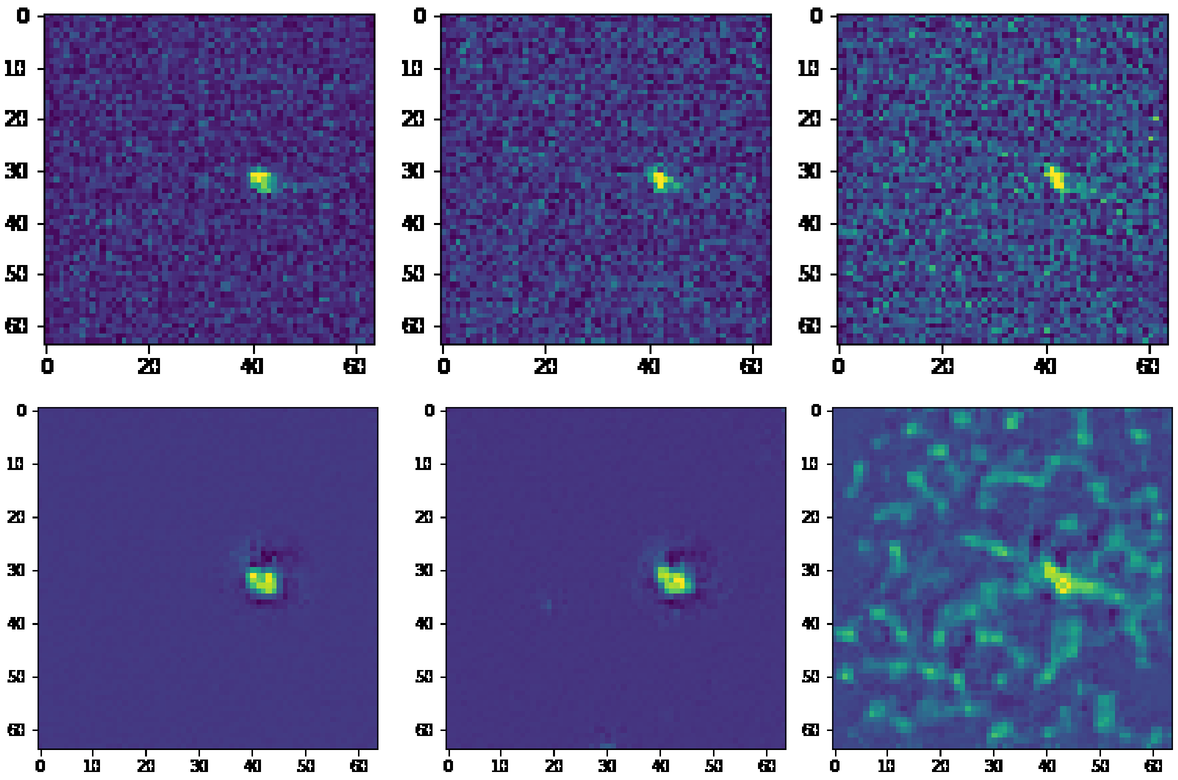


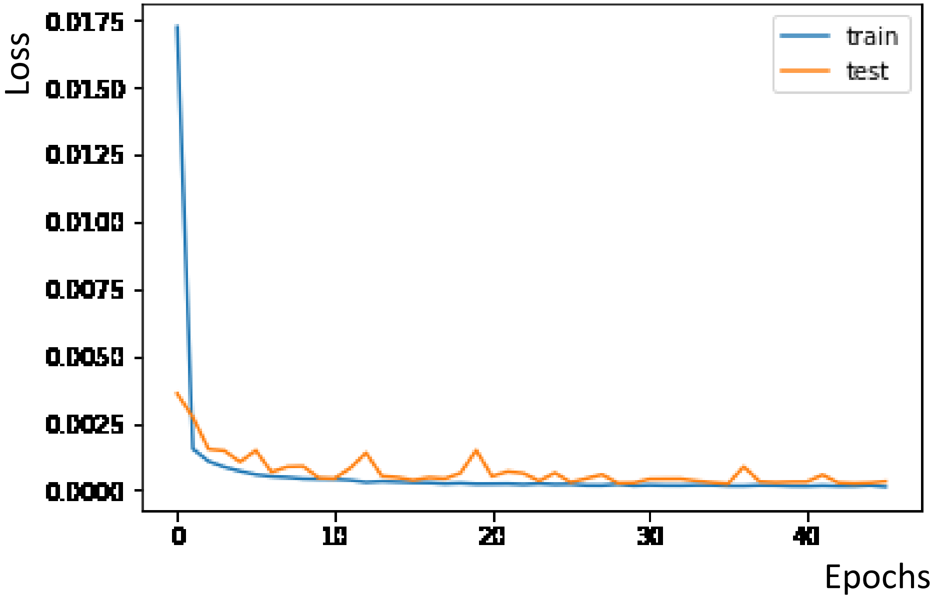
Dataset 4: B plan

- Try with a different network, DnCNN.
- DnCNN needs fewer data then AE to generalize.
- Used as denoiser with residual learning configuration.



Results of DnCNN





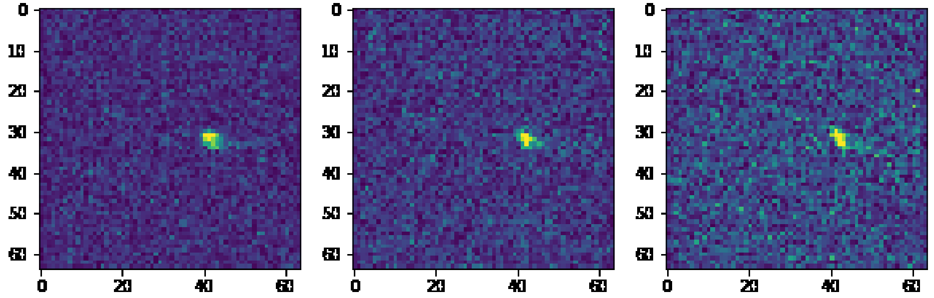
	Shannon Entropy
MRI 1	11.996
MRI 2	11.995
MRI 3	11.999

- DnCNN results are good as the best DAE (the one with infinite power generalization) and of the Wiener filter ✓
- DnCNN generalizes better with different shapes ✓

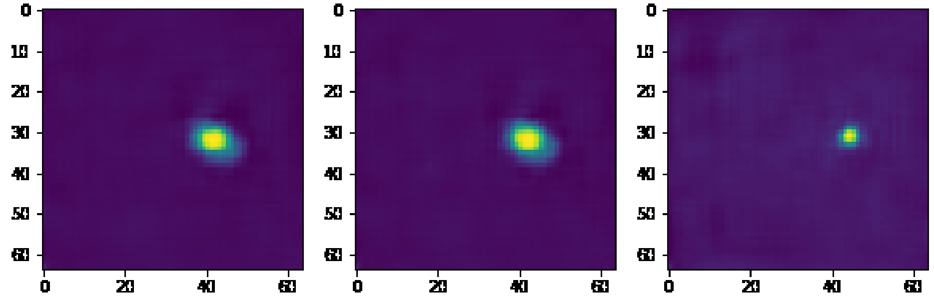
Results dataset 4

Shannon Entropy	MRI 1	MRI 2	MRI 3
DAE	11.996	11.995	11.997
VAE	11.982	11.981	11. 988
DnCNN	11.996	11.995	11.999
Wiener	11.999	11.999	11.999

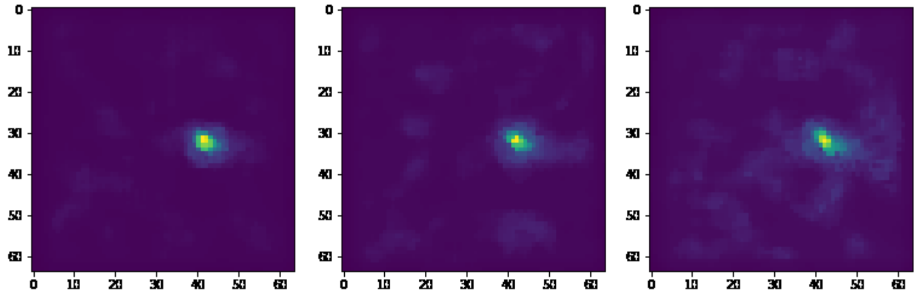
MRI



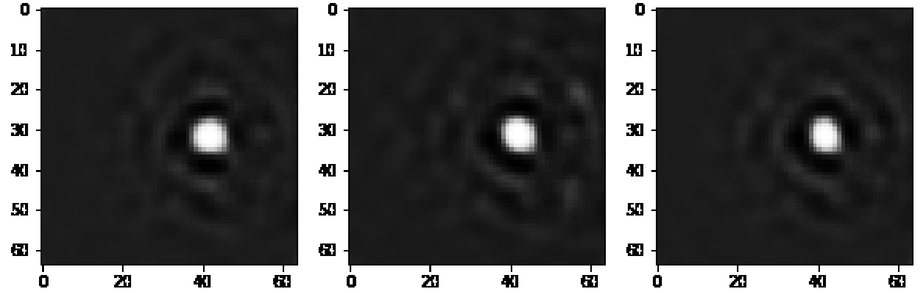
DAE



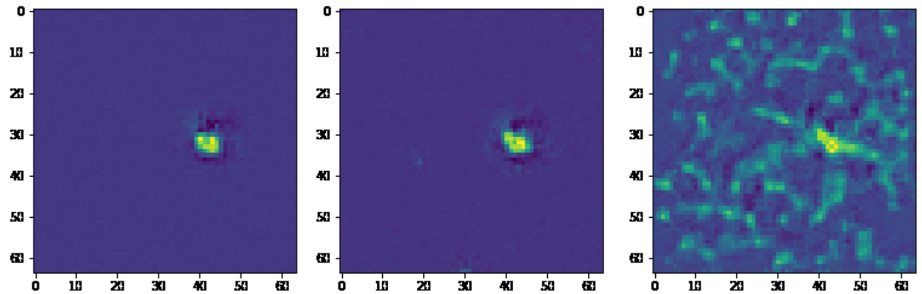
Wiener



VAE



DnCNN



Conclusions…

- Denoising is good, but DnCNN and Wiener work better then DAE/VAE.
- Wiener eliminates the noise, but produces artifacts. Maybe others non-Rician noise sources.
- DnCNN produces really good results in 2/3 MRI. Statistic is too low, but could be different acquisition conditions or problematics.
- Tested three different deep neural network architectures for denoising:

  - DAE: works well in recognizing and removing the noise, needs large data-augmented samples in order to not learn shapes in the training set.

  - VAE: as expected underperform with the DAE but can be used to produce large samples for training of the DAE/DnCNN.

  - DnCNN: best results, same level as Wiener filter, in terms of noise removal and good generalization to different shape (need to be quantitatively assessed).