MatVir

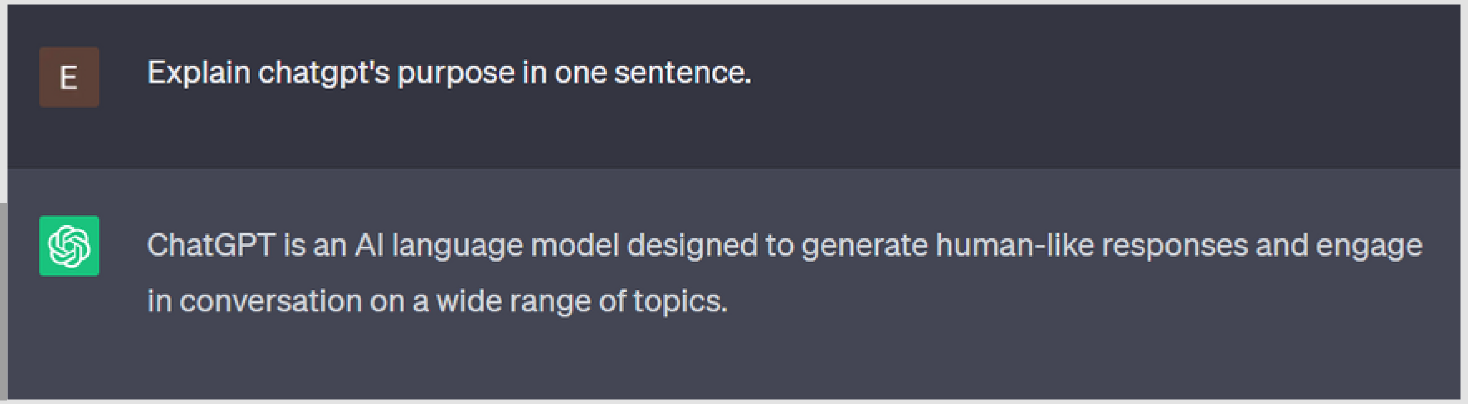
Virtual Material Image Generation Methods using Deep Learning

Group 7

E. Canty - T. Dupuis - T. Nadal - O. Mouwad - N. Jacques - M. Legris

Generative methods

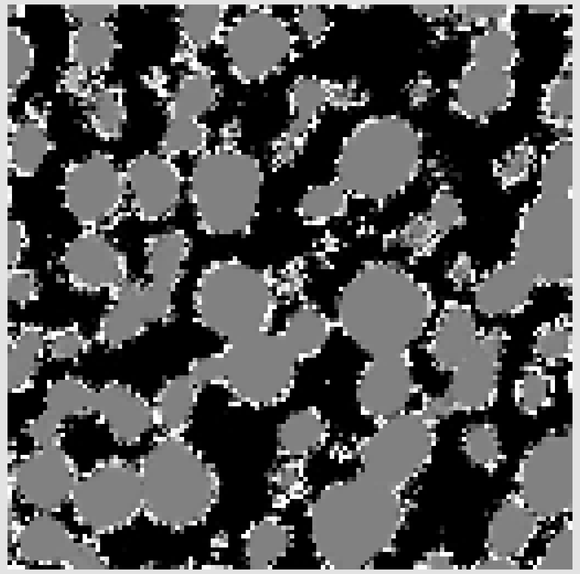
Chatgpt text generation :

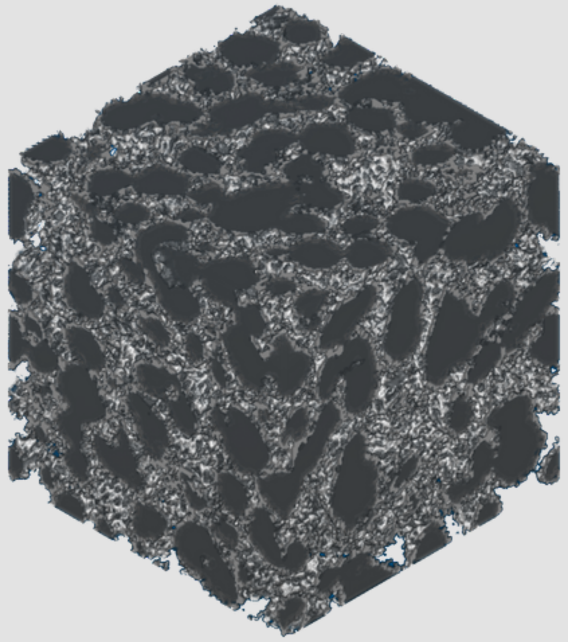


Midjourney image generation :

Material image generations in this project :

- NMC (Nickel Manganese Cobalt) Battery
- 3 phases

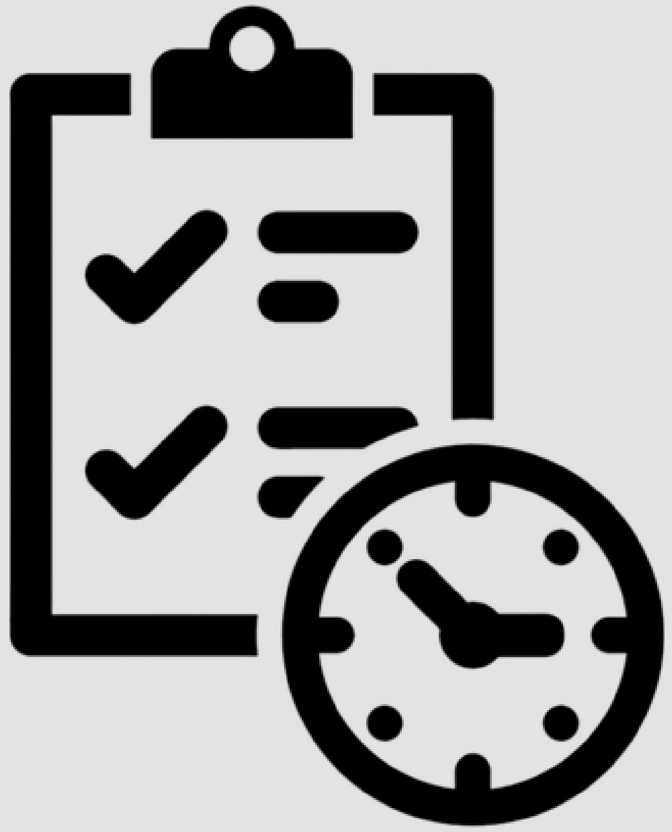




Project Management

Means of communication :

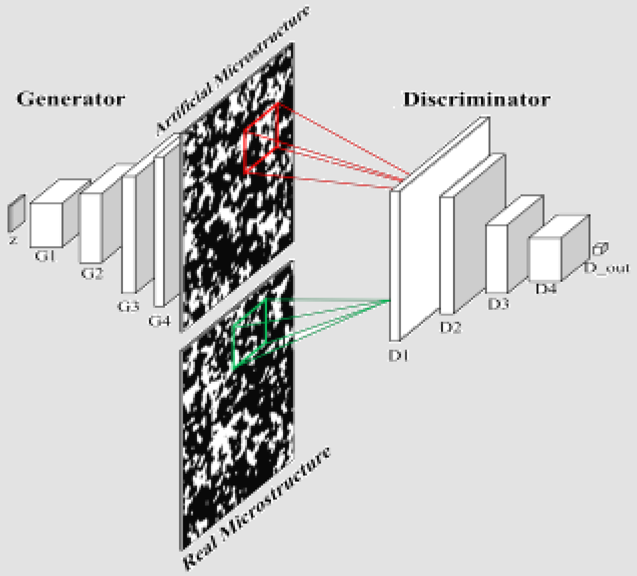
- Telegram group
- Mails
- Drive repertory



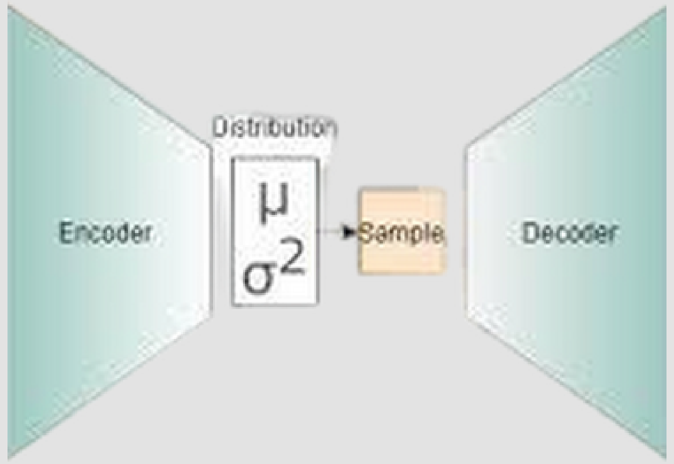
Project progress :

- Project Manager : E. Canty
- Weekly meetings with our head teacher : M. Yannick Berthoumieu and a PhD student : M. Pedro Coutinho
- A meeting in IMS lab (Laboratoire d'Intégration du Matériau au Système)

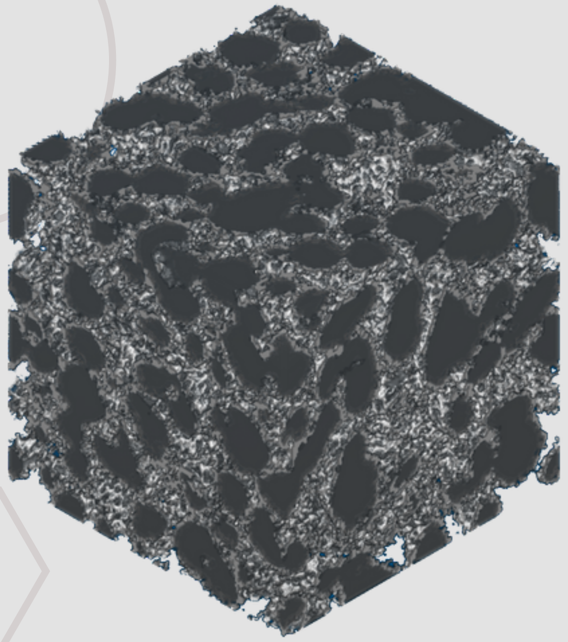
Project Management



GAN



VAE



SliceGan

E. Canty - T. Dupuis

- Presentation of GANs
- Limits of GANs and normalizations
- Selected parameters and obtained results

T. Nadal - O. Mouwad

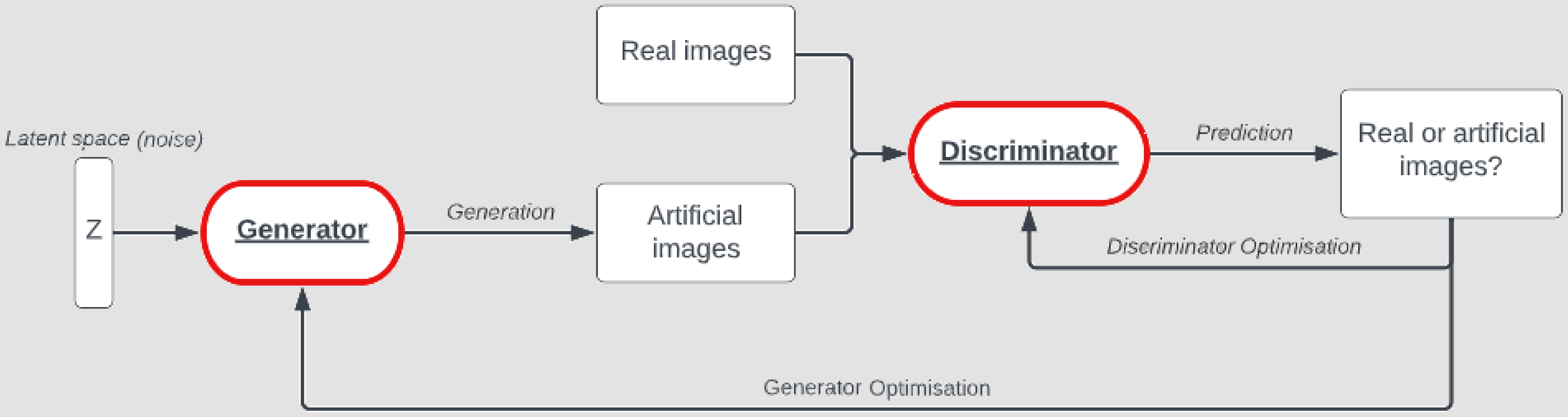
- Presentation of VAEs
- Implementation of VAEs
- VAE performance and limitations

N. Jacques - M. Legris

- Presentation of SliceGan
- Properties of the micro-structure
- Control over the properties
- Amelioration perspectives

GANs presentation

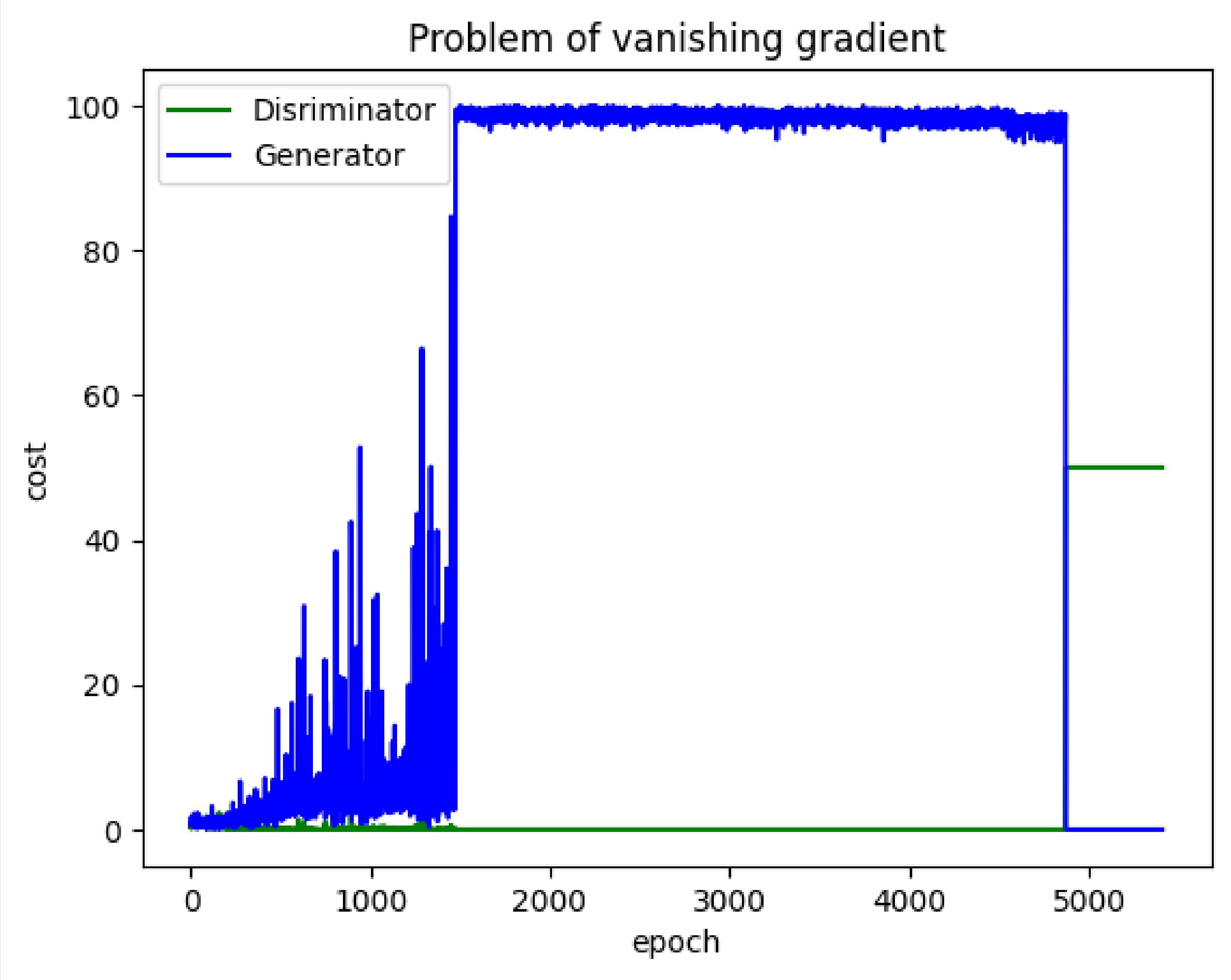
- 2 adversarial components
- Generator -> generate new images
- Discriminator -> predict if an image is real or generate



Limits of GANs and normalizations

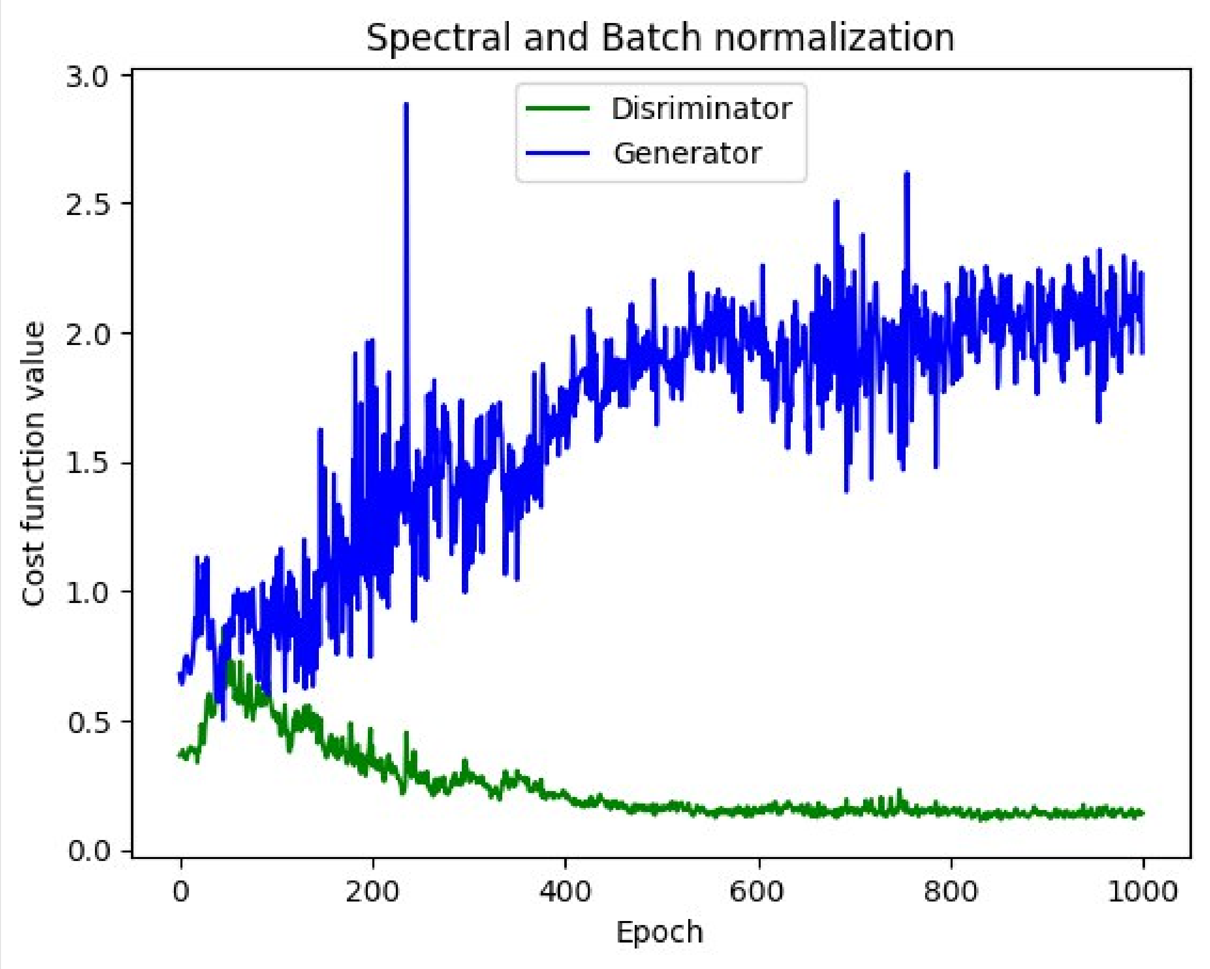
Limits of GANs

- Convergence Issue (speed and Local Optima)
- Require a large dataset to perform well
- Vanishing and Exploding Gradients

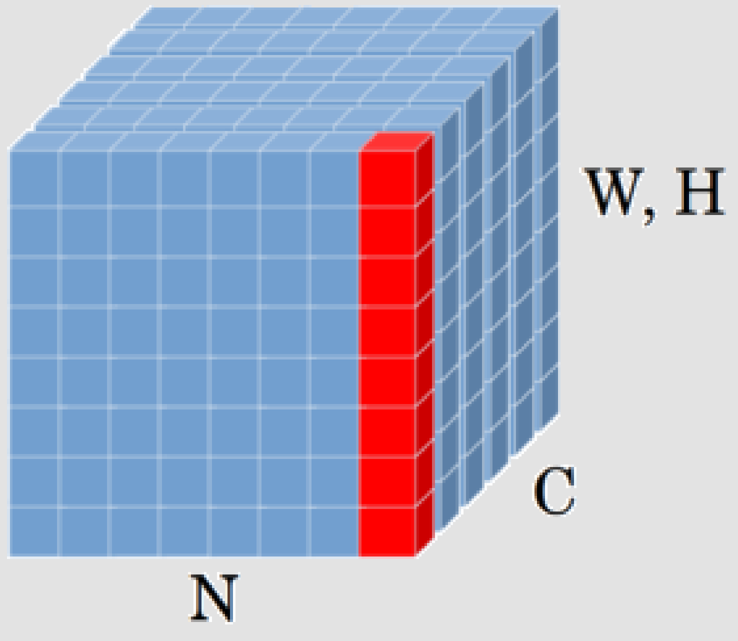


Spectral normalisation

- Ensuring swift convergence of the Discriminator
- Mitigate cases of degeneracy



Instance normalisation VS Batch normalisation

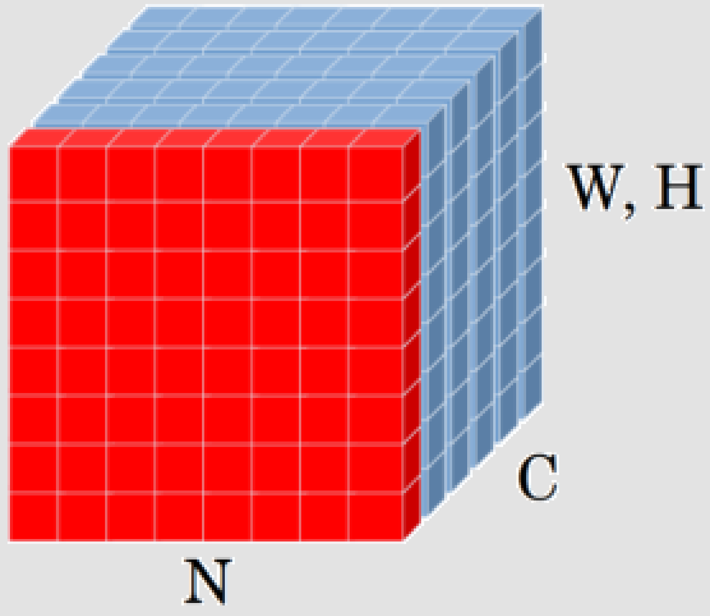


$$\mu_{ni} = \frac{1}{HW}\sum_{l=1}^{W}\sum_{m=1}^{H} x_{nilm}$$

$$\sigma_{ni}^2 = \frac{1}{HW}\sum_{l=1}^{W}\sum_{m=1}^{H} (x_{nilm} - \mu_{ni})^2$$

$$\mu_i = \frac{1}{NHW}\sum_{n=1}^{N}\sum_{l=1}^{W}\sum_{m=1}^{H} x_{nilm}$$

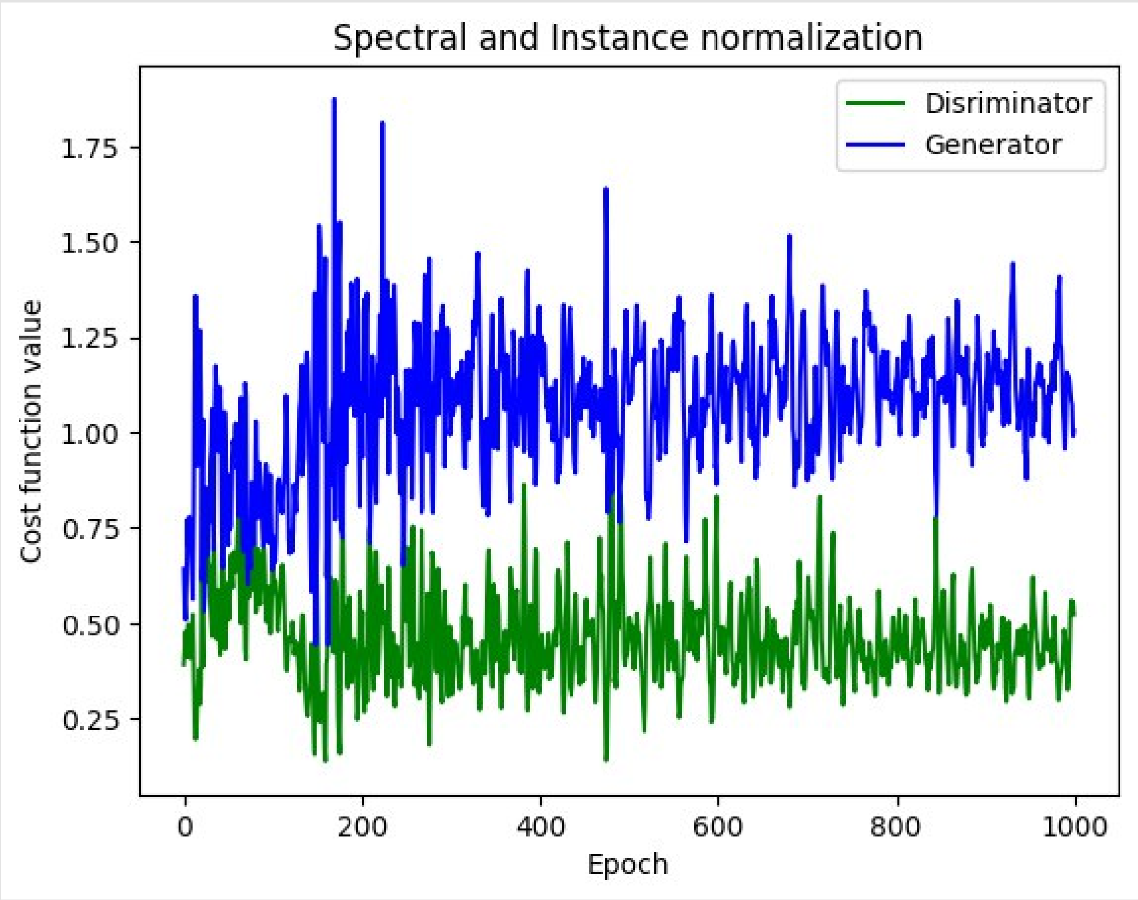
$$\sigma_i^2 = \frac{1}{NHW}\sum_{n=1}^{N}\sum_{l=1}^{W}\sum_{m=1}^{H} (x_{nilm} - \mu_i)^2$$



$$y_{nilm} = \frac{x_{nilm} - \mu_{ni}}{\sqrt{\sigma_{ni}^2 + \epsilon}} * \gamma + \beta$$

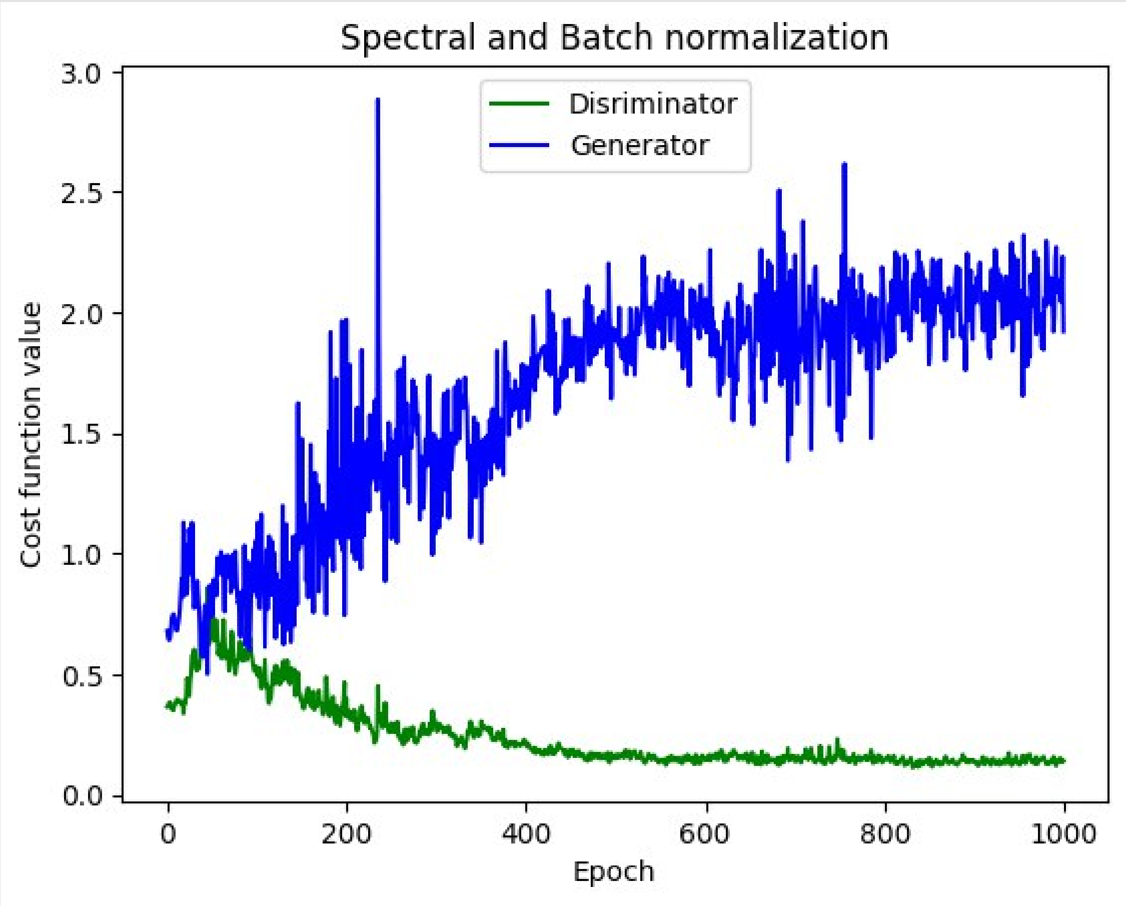
- Not dependant on the batch size

- Higher learning rates
- Improve generalization



Here, batch_size=64

Batch normalization leads to the optimal convergence of the discriminator



Selected parameters and obtained results

Parameters:

- batch-size=64
- Latent-space dimension=64
- 10000 epochs

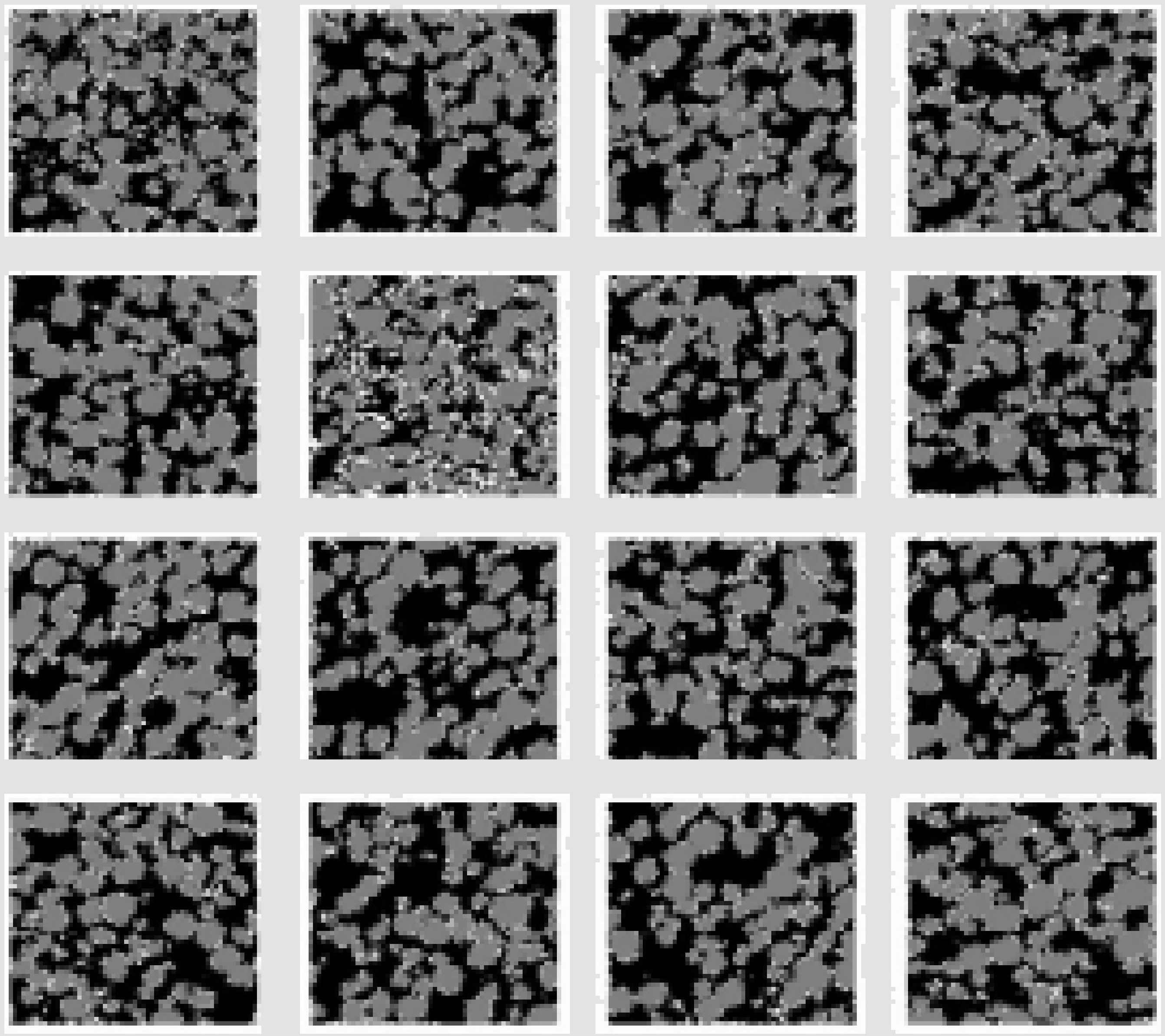


Figure 4: Real data

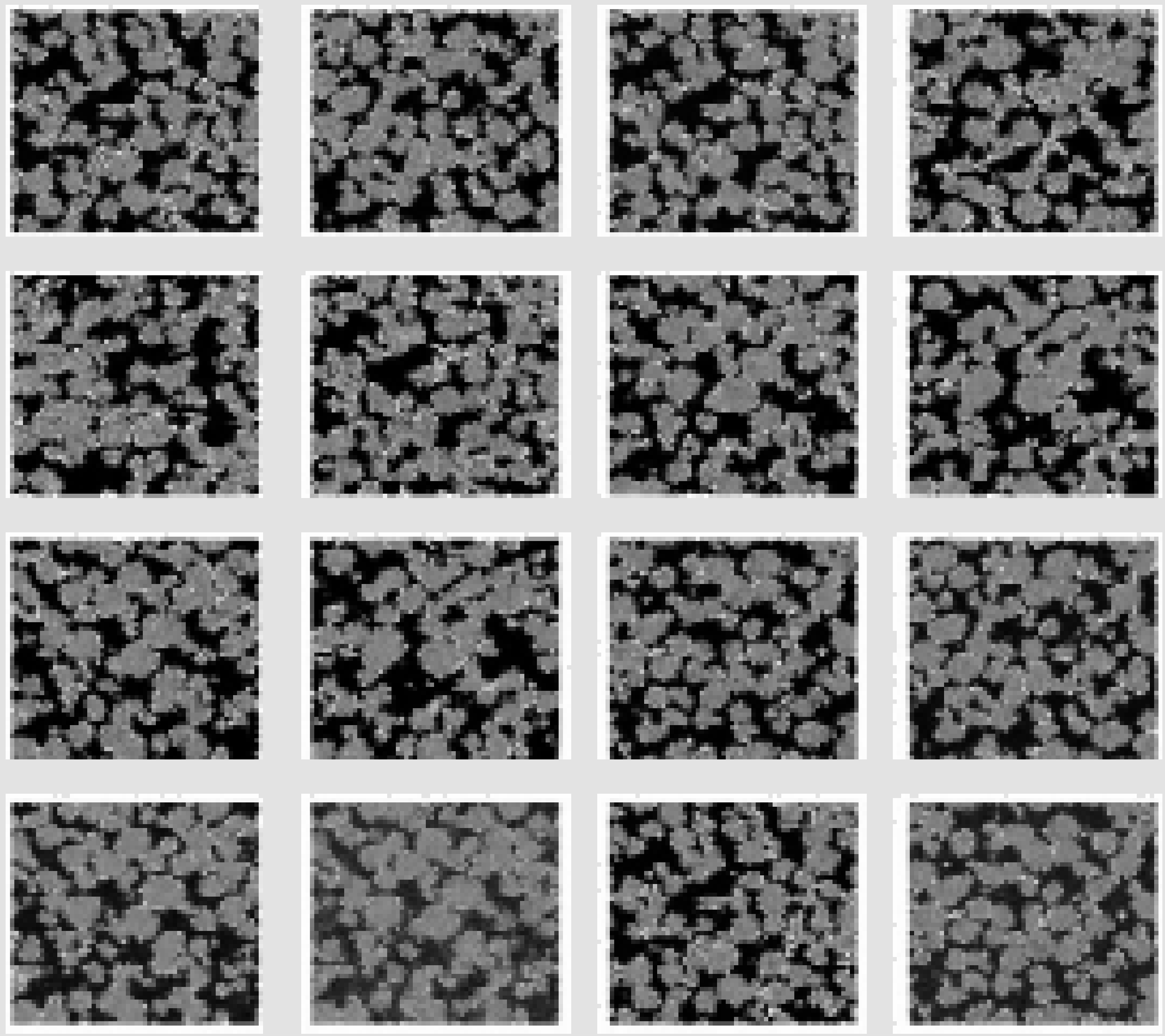
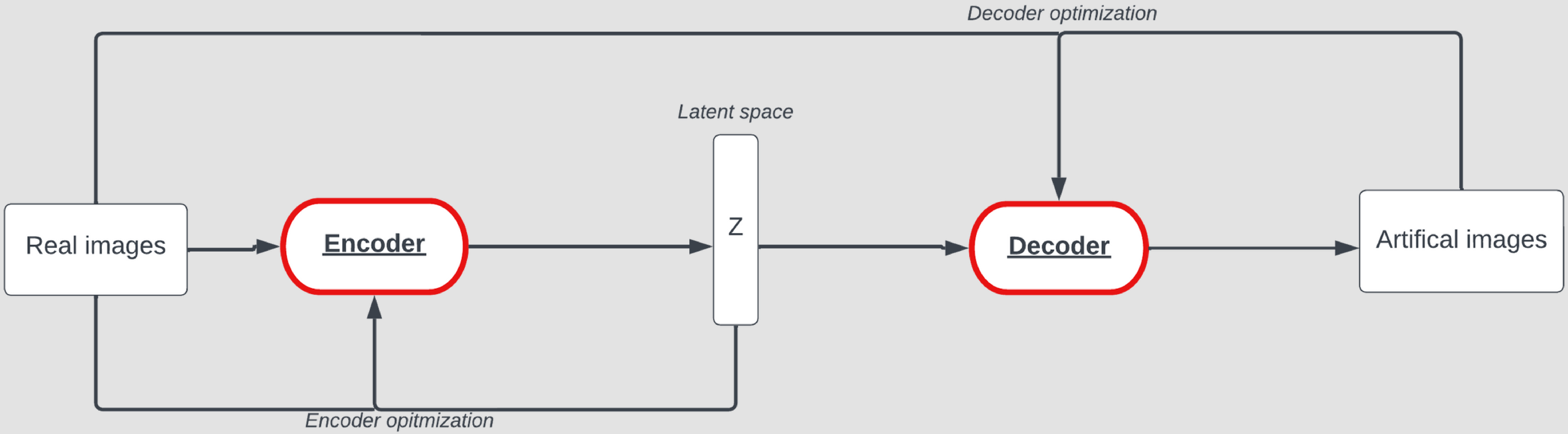


Figure 5: Generated images

VAE presentation

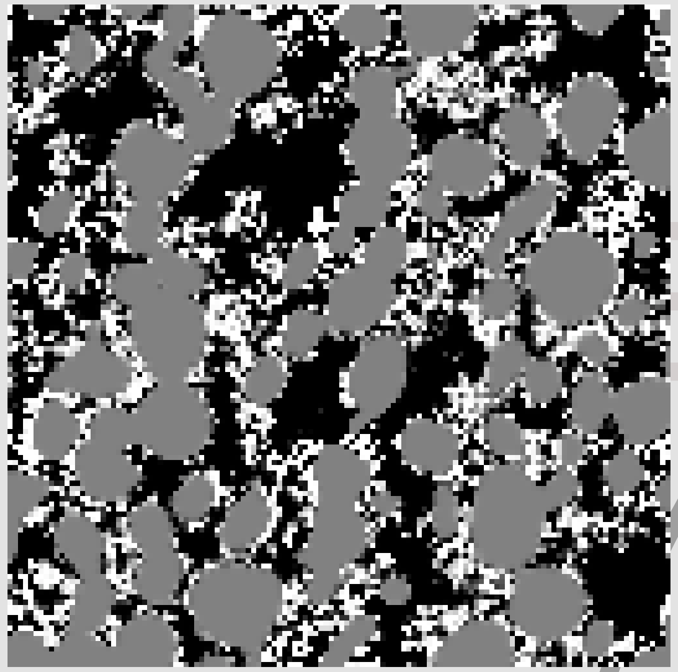
- 2 complementary neural networks
- Encoder -> Convert images into a latent space
- Decoder -> Generate images from the latent space

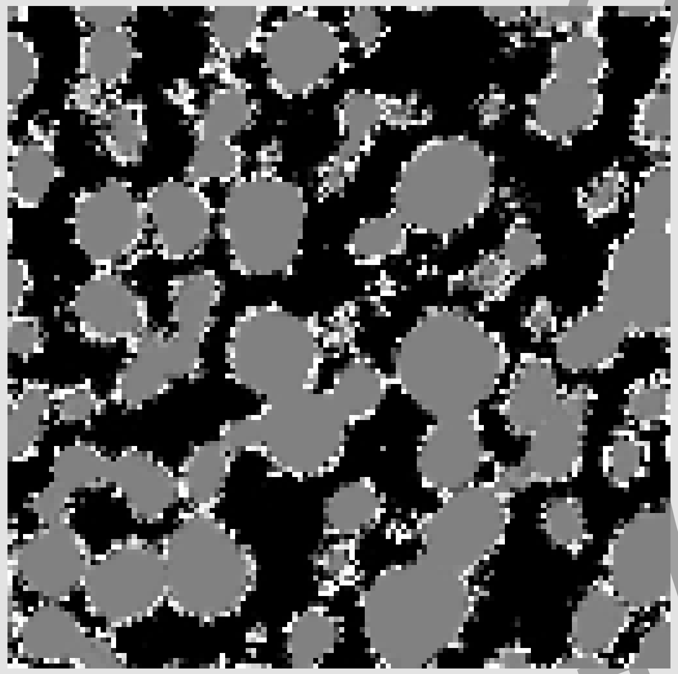


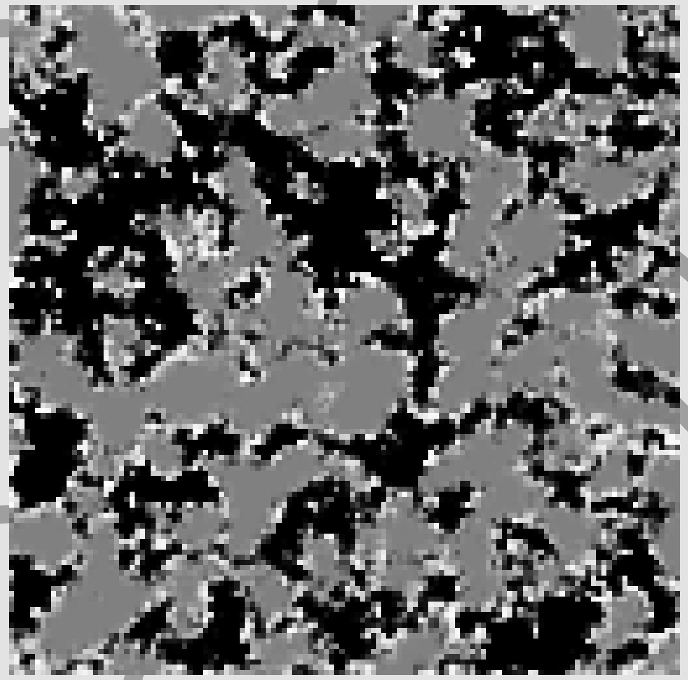
VAE results

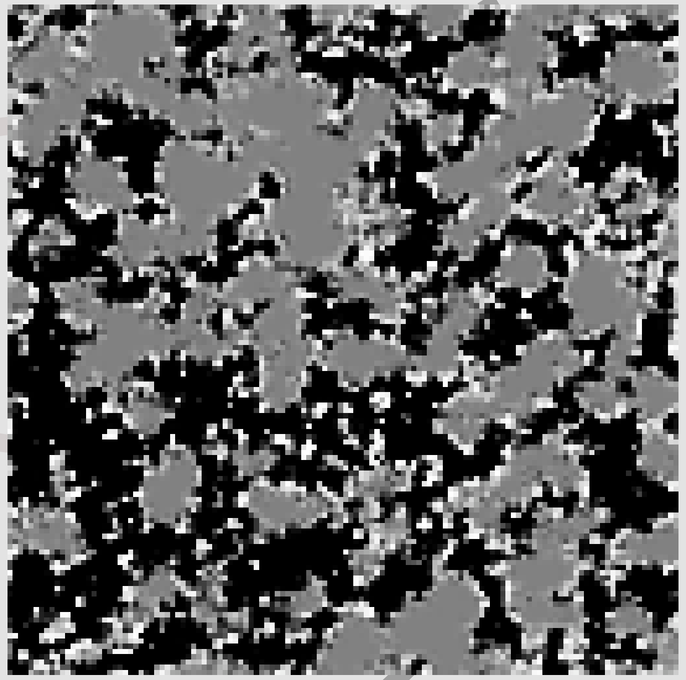
- 5-layer neural network on 128x128px images
- Presence of artefacts and the image are blurry

Training images





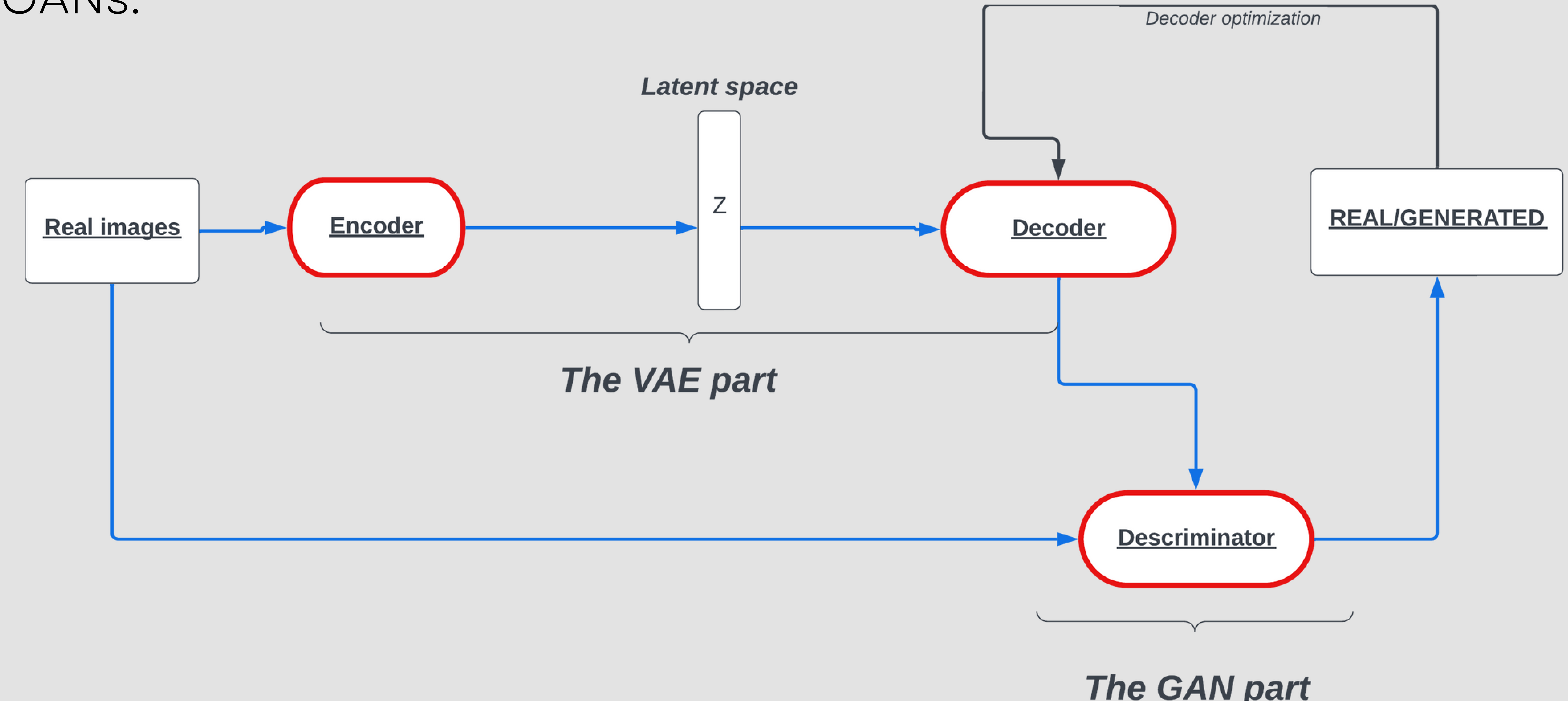




Generated images

VAE/GAN Presentation

- A VAE is combined with a GAN by collapsing the decoder and the generator into one.
- The goal is to use the strength of both VAEs and GANs.

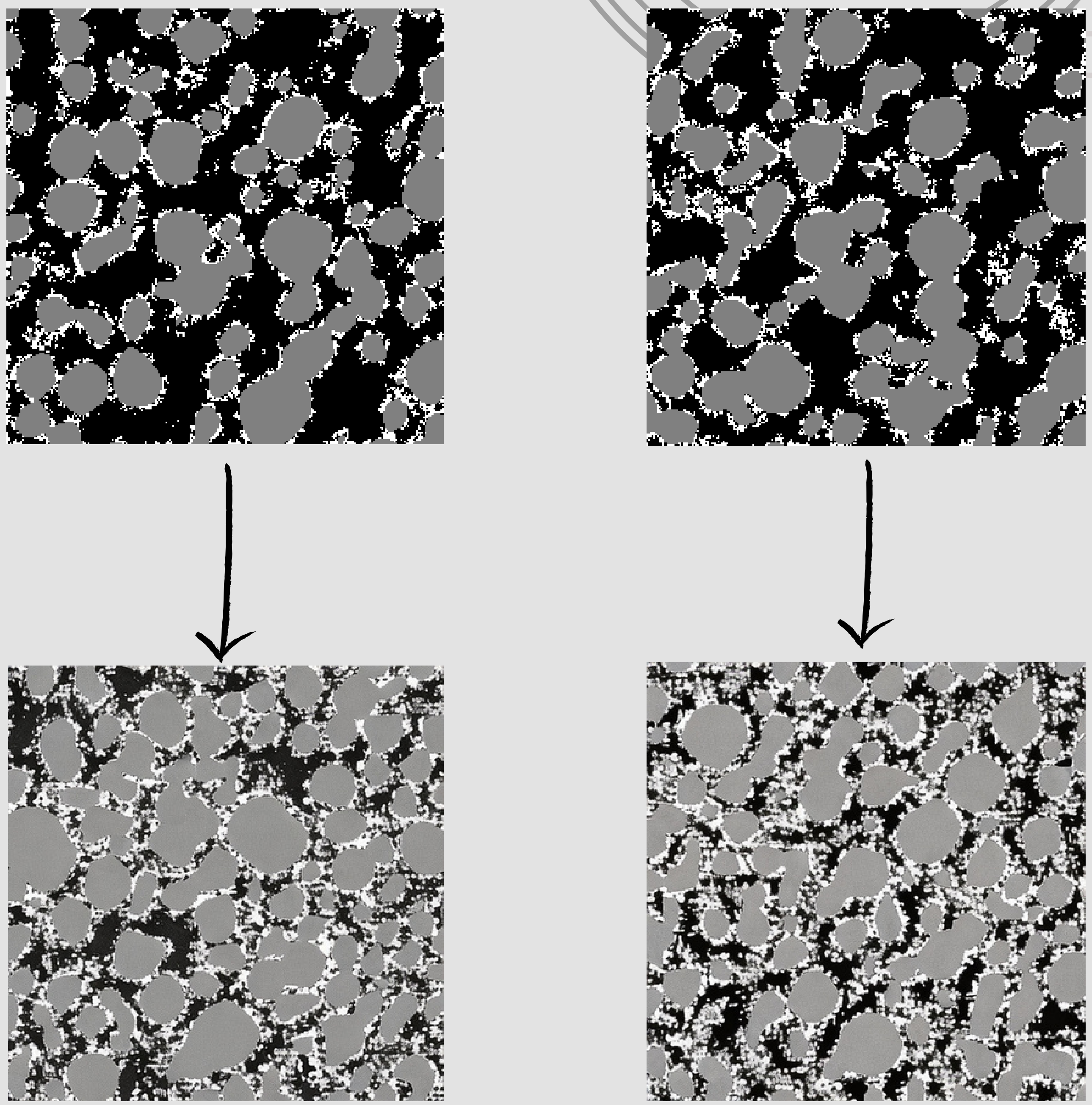


Results of the implementation of the model

- The combination of VAE and GAN techniques leads to improved sample quality compared to using either method individually.

- VAE/GAN Produce sharper images with more natural textures and face parts.

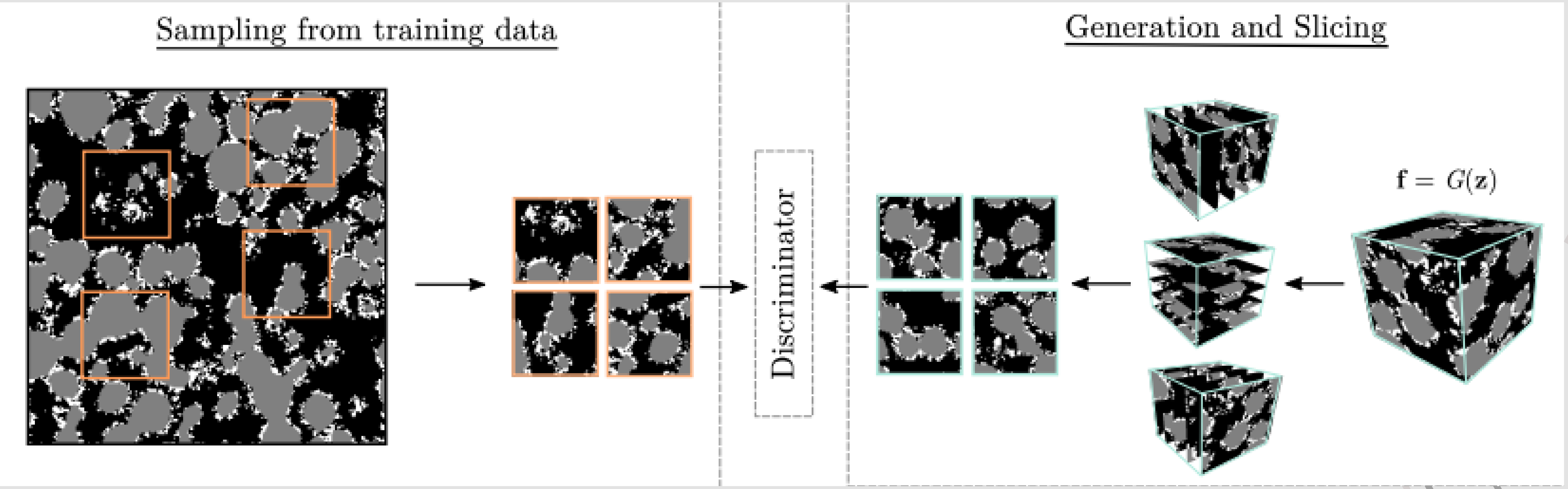
Training Images



Generated Images

SliceGan Presentation

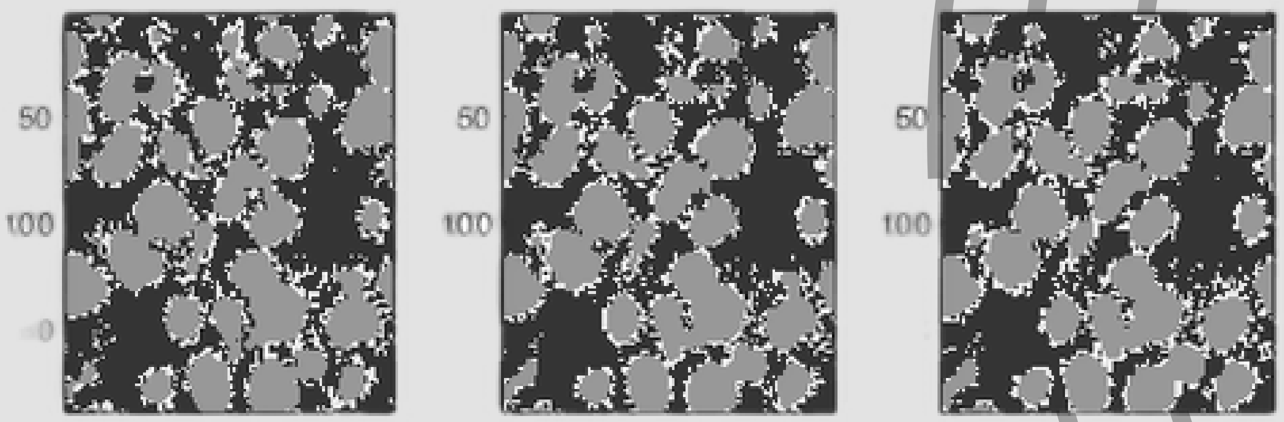
- 2D image to 3D datasets
- Like a GAN, comparison of synthetic and real datasets of a material, with a discriminator and a generator.

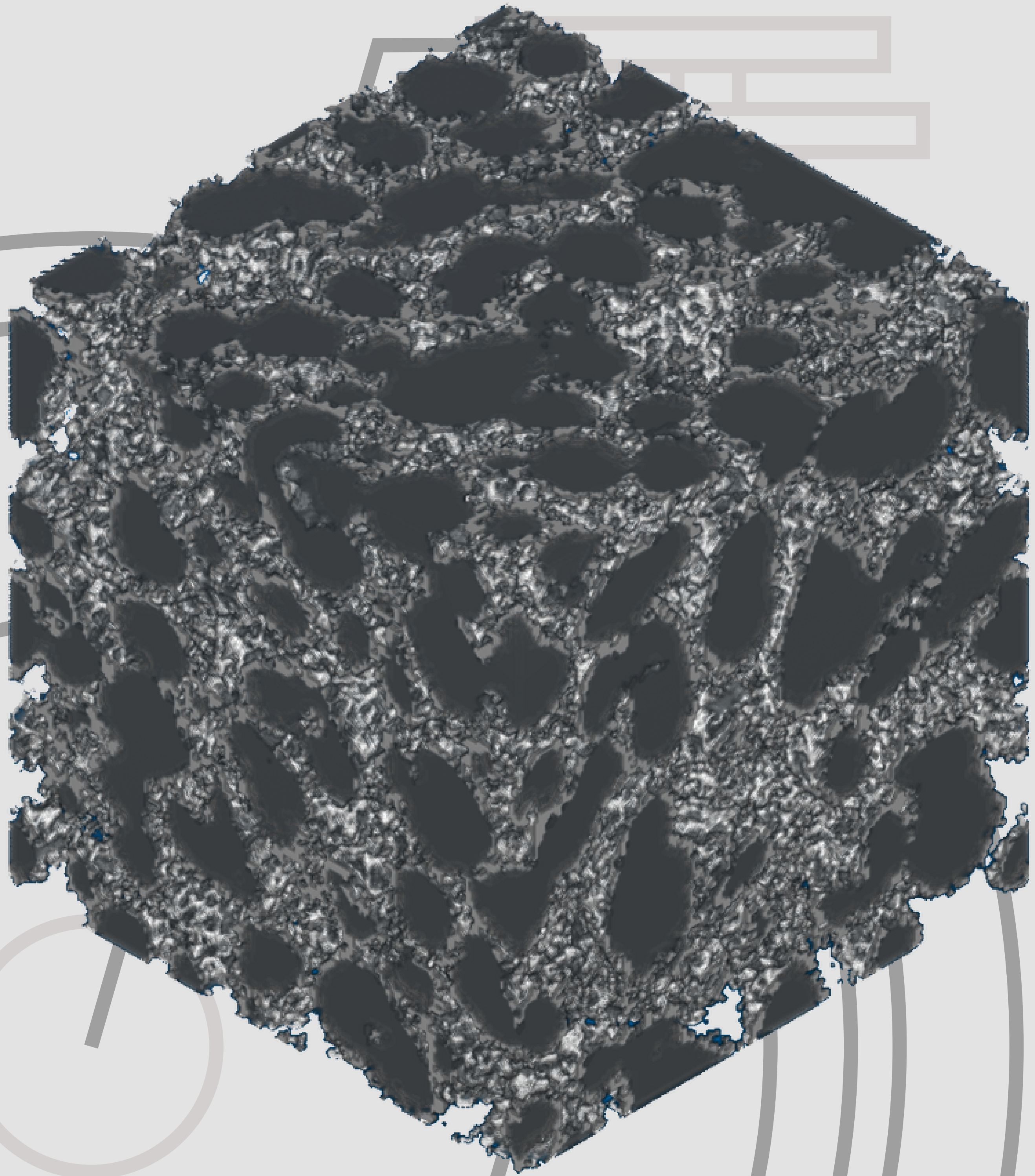


SliceGan Results

After the training of SliceGan :

- 252 layers of the micro-structure
- 3D volume of the generated micro-structure





Properties of the generated microstructure

1 Isotropy

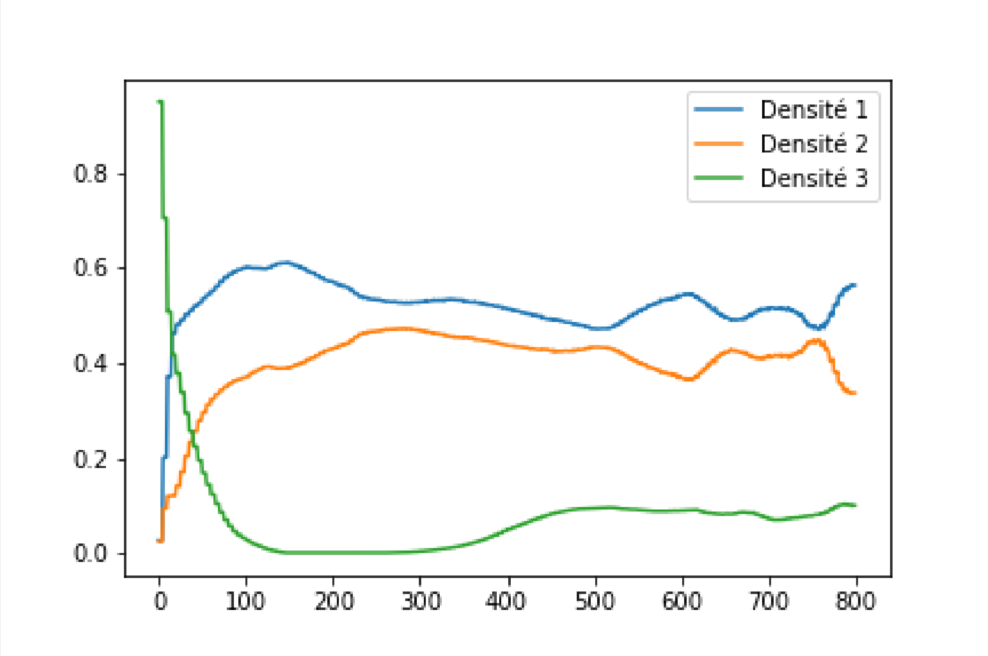
Uniformity of the material's properties in all orientations.

2 Composition

An NMC battery (Nickel Manganese Cobalt), with three distinct phases.

3 Density

Quantity of a substance per unit volume or unit area.



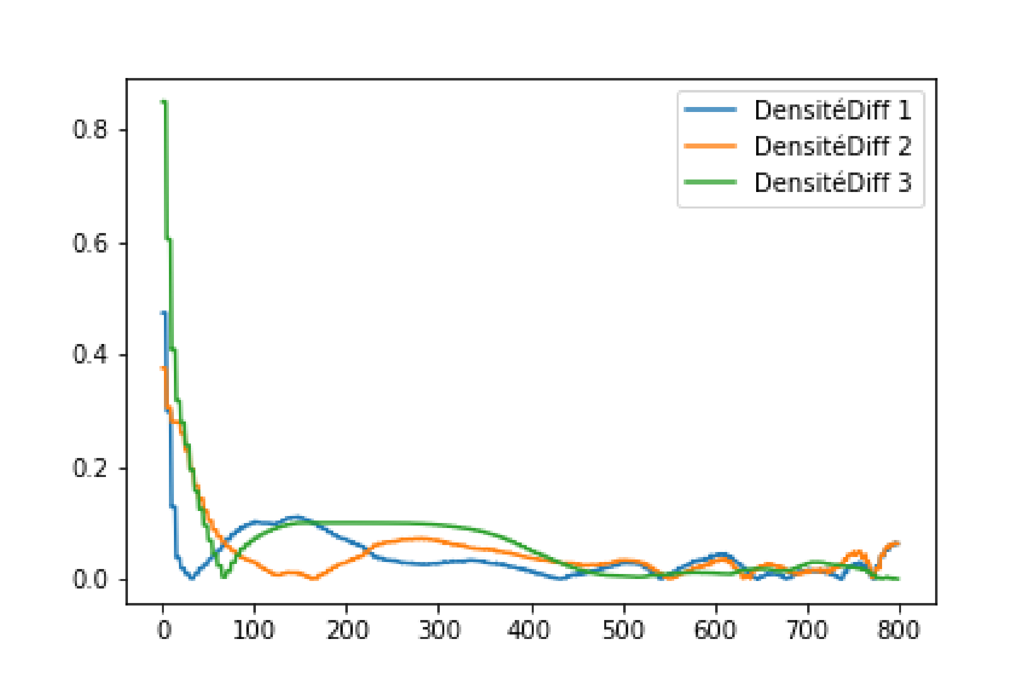
4 Elasticity

Ability of an object or material to resume its normal shape after being stretched or compressed.

Control over the microstructure's properties

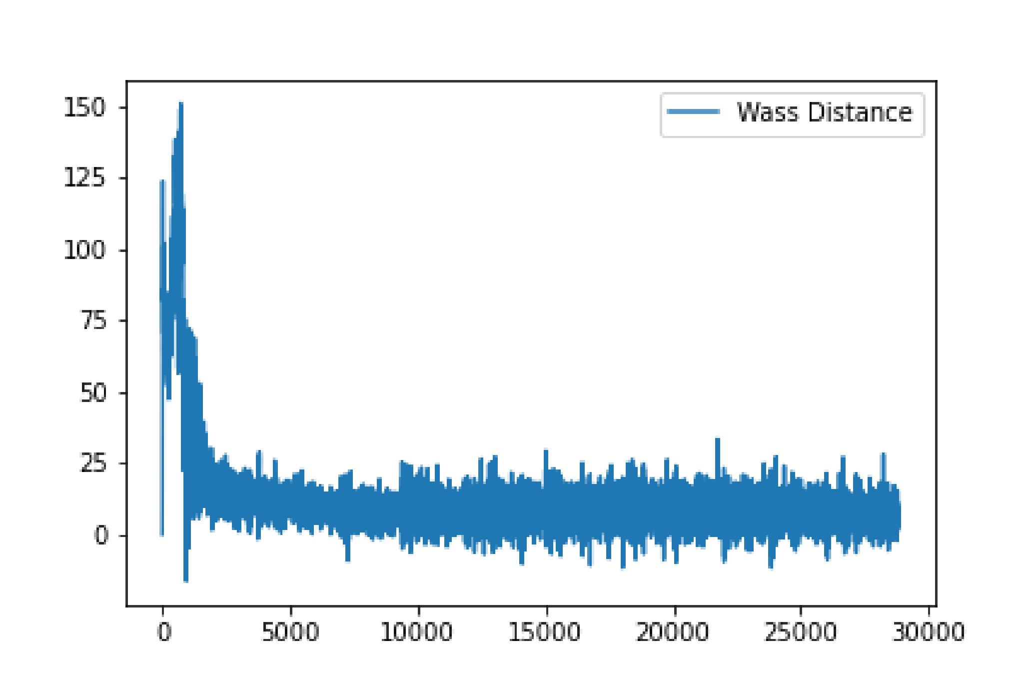
Density

The count of the number of pixels in a 2D image that are on the same phase divided by the total number of pixels.



New Loss Function

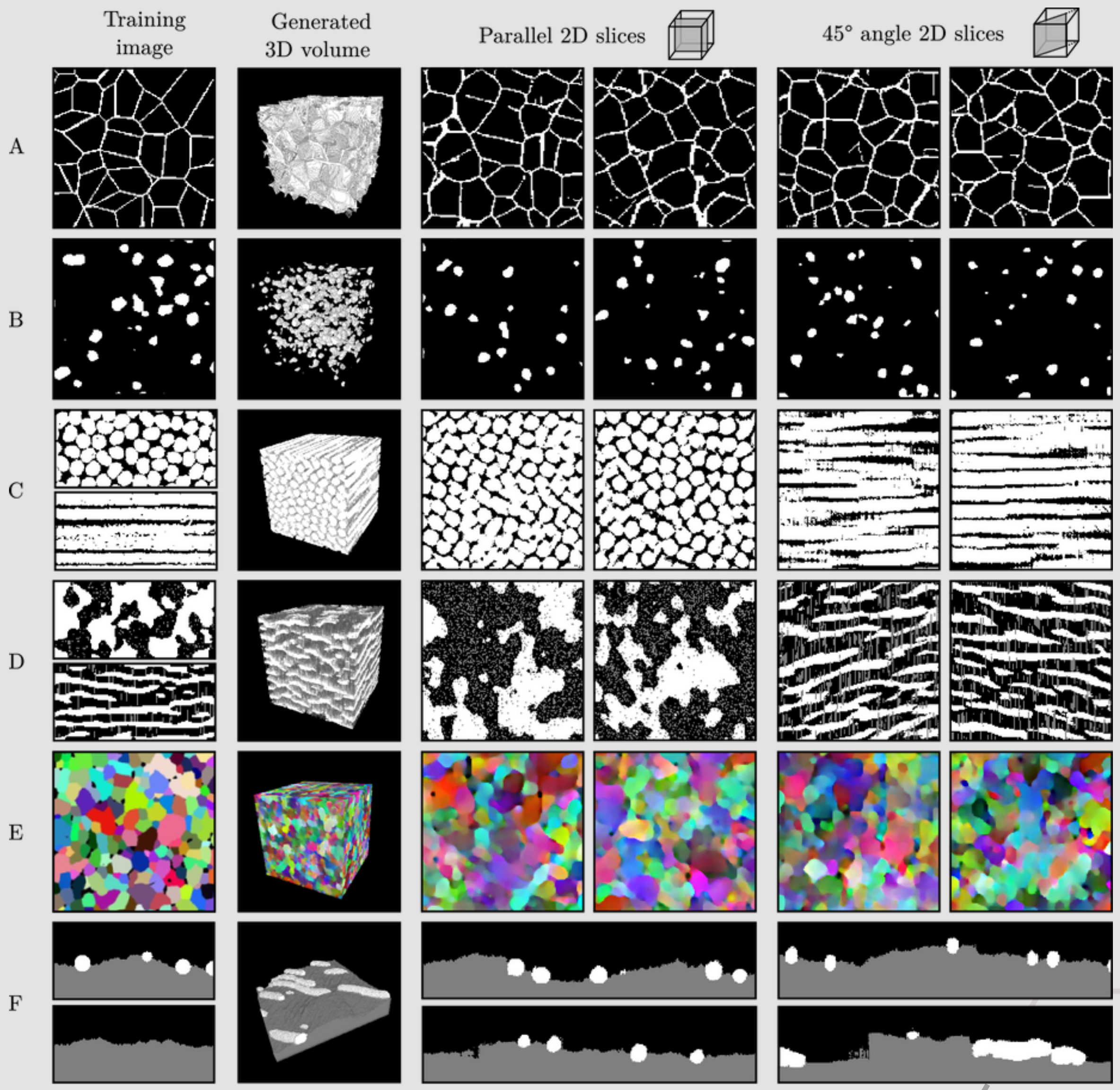
To control the properties, the loss function of SliceGAN has to be altered by introducing a density control mechanism.



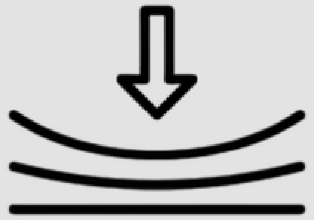
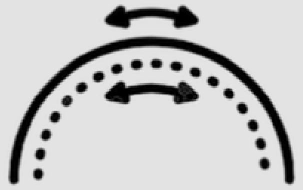
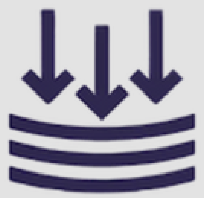
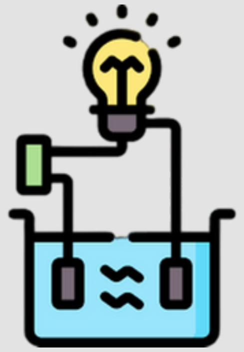
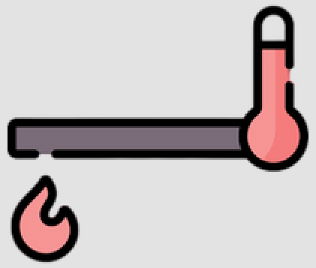
New Loss Function = Former Loss Function + α × Density Differences

Improvement perspectives

- To adapt SliceGan for anisotropic materials



- To control other properties, such as ductility, elasticity or rigidity

May 2023

Telecom 2 - Group 7

THANK YOU !