

# Cardiac cine-MRI sequences synthesis using deep learning generative models

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# Content

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## ① Introduction

## ② Results

# Introduction

# Motivation

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World Health Organization

- CVDs are the number 1 cause of death globally: more people die annually from CVDs than from any other cause.
- State of the art is full of machine learning techniques such as a neural network that are pretty dependant on the amount of data.

# Dataset

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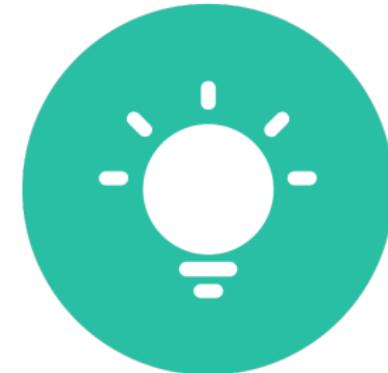
## Sunnybrook Cardiac Data

- Dims: 256x256x3 to 128x128x3
- 45 cine-MRI images from a mixed of patients
- Each slice has 20 frames (Cardiac cycle).

# Purpose

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- Cope with data scarcity in the medical area to improve machine learning methods.
- Create data close enough to a training distribution while constraining valuable aspects of the image.



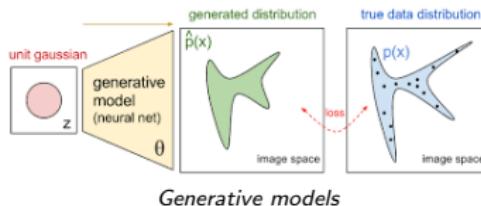
# Data augmentation

Some techniques:



*Transformations*

*Traditional*



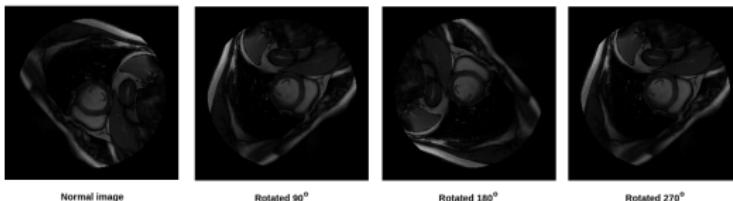
	Original	Sub-policy 1	Sub-policy 2	Sub-policy 3	Sub-policy 4	Sub-policy 5
Batch 1						
Batch 2						
Batch 3						

*Learning the Augmentation*

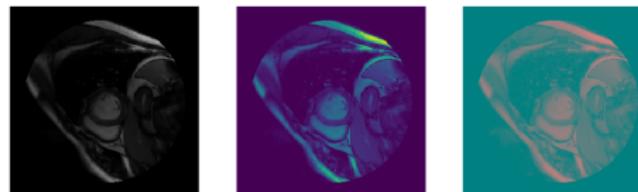
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# Common techniques

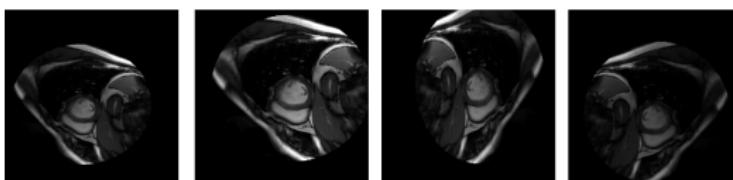
Affine transformations



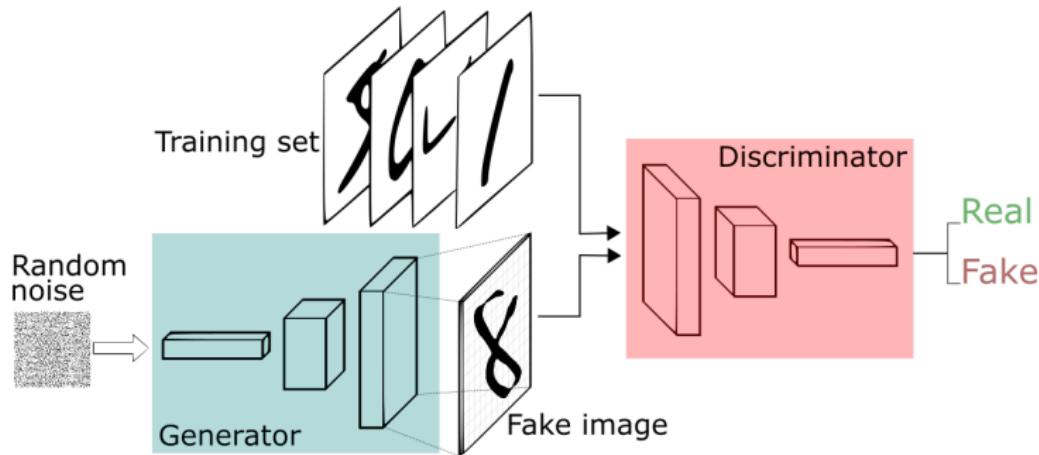
Photometric transformations



Other transformations



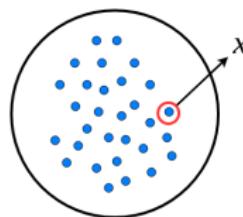
# Generative adversarial nets



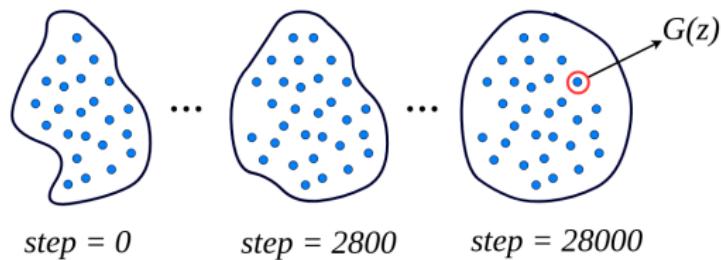
# How GANs work?

Real distribution

$$pr(x)$$



Generated distribution  $p_g(x)$

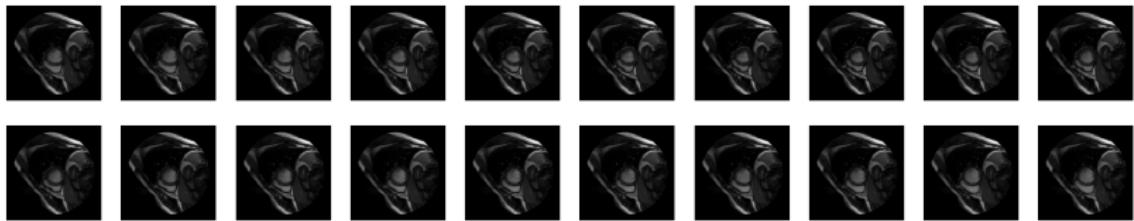


$$\min_G \max_D V(D, G) = E_{x \sim p_{data}(x)}[\log D(x)] + E_{z \sim p_z(z)}[\log(1 - D(G(z)))] \quad (1)$$

# First approach 128x128 DCGAN

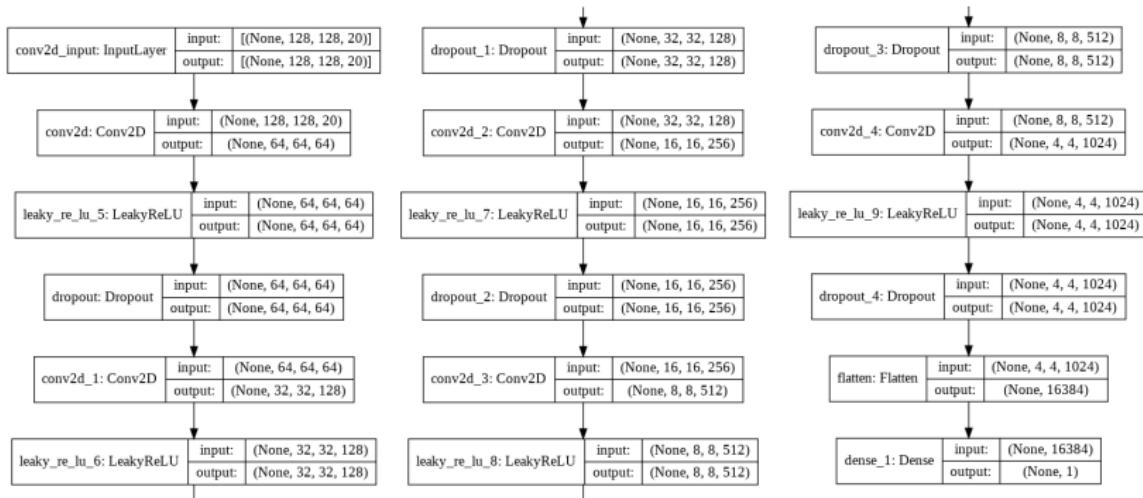
# Training data

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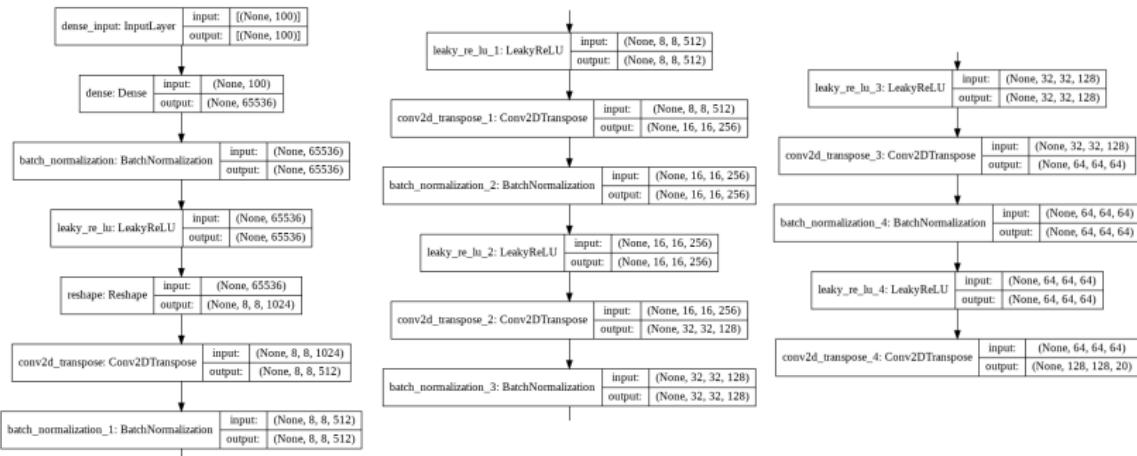


Read every image in the dataset in grayscale and downsample them to 128x128 pixels to stack them in the channels dimension.

# Generator architecture

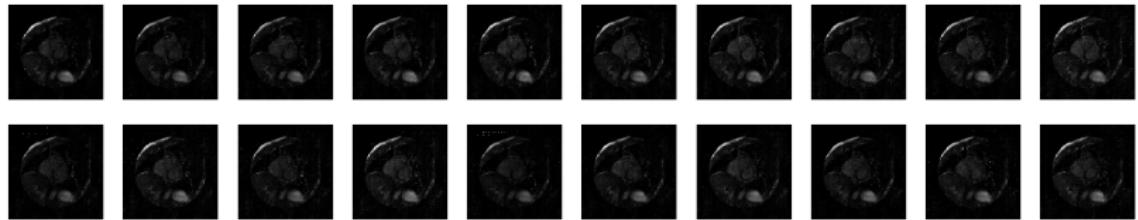


# Discriminator architecture



## Generated images

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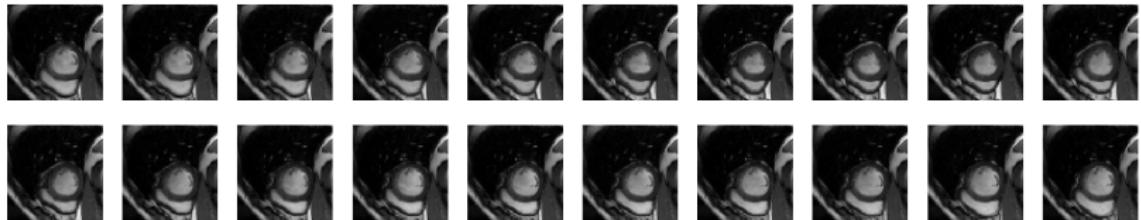


Our first approach generated very noisy samples but succeeded to learn the more general features of cine-MRI like the black contour and basic structure of the heart.

# Second approach 64x64 DCGAN

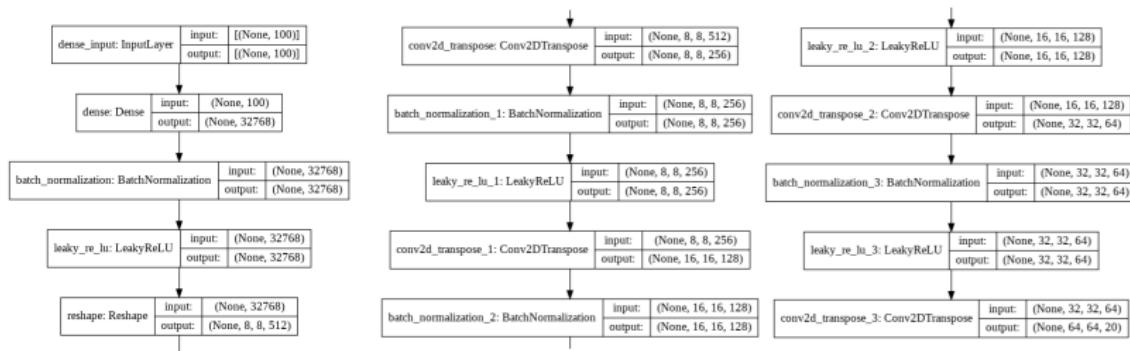
# Training data

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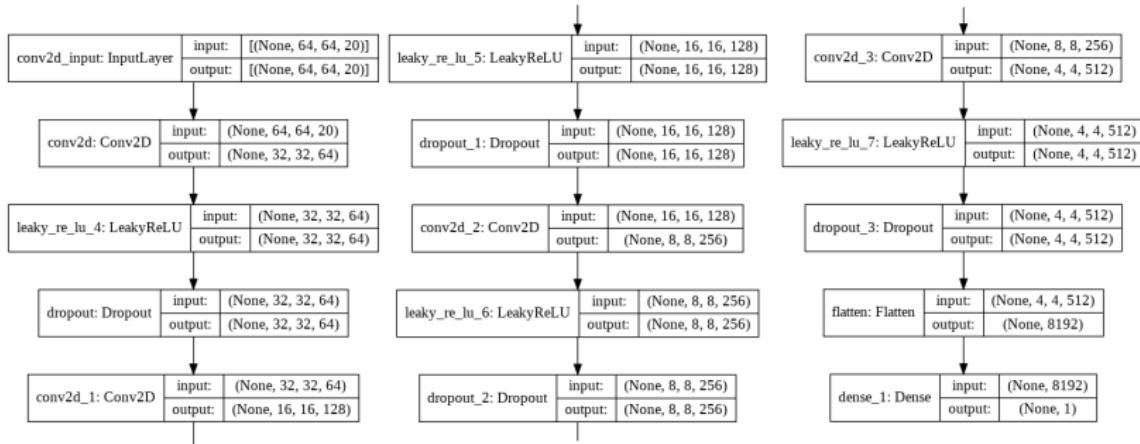


Read every image in the dataset in grayscale, crop the image until there's only the left and right ventricle remaining and downsample them to 64x64 pixels to stack them in the channels dimension.

# Generator architecture

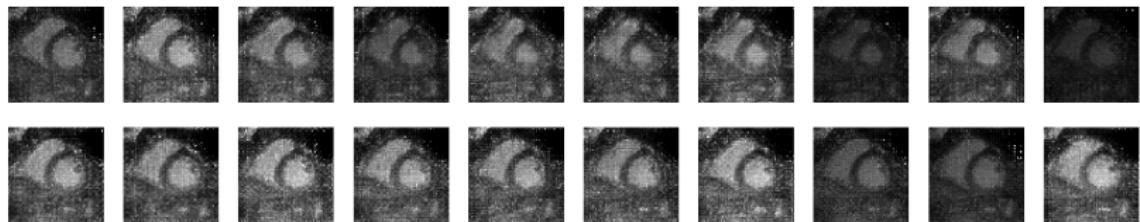


# Discriminator architecture



## Generated images

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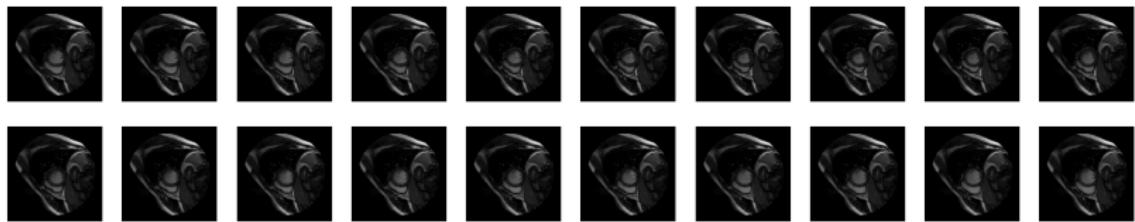


Our second approach also generated noise samples. Nevertheless, it keeps some relationship between each frame which is key in cardiac cycles and generated a somehow correct shape for the left and right ventricle.

# Third approach Progressive Growing DCGAN

# Training data

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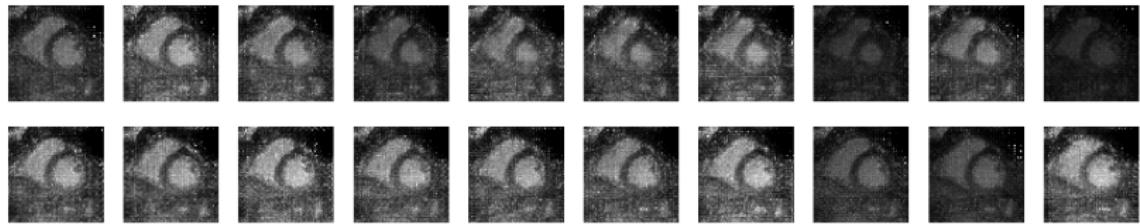
This time we will leave the images in their original size, read them in grayscale and stack them in the channels dimension.

# Progressive Growing architecture

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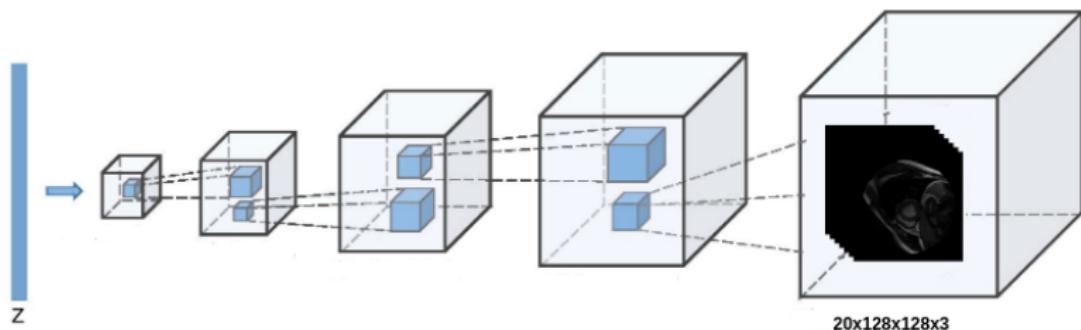
## Generated images

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Our first approach generated very noise samples but succeeded to learn the more general features of cine-MRI like the black contour and basic structure of the heart.

# Why not using 3D DCGAN?



For more information go to:

[https://github.com/Sangohe/CV-Cardiac\\_Cycle\\_Generation](https://github.com/Sangohe/CV-Cardiac_Cycle_Generation)