Generative Models part III

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Topics:
- Application of generative modelling in medical image analysis
- How to generated cardiac MR images with variations
- Evaluation of synthetic data
- Usability of synthetic data
- Use cases of synthetic data

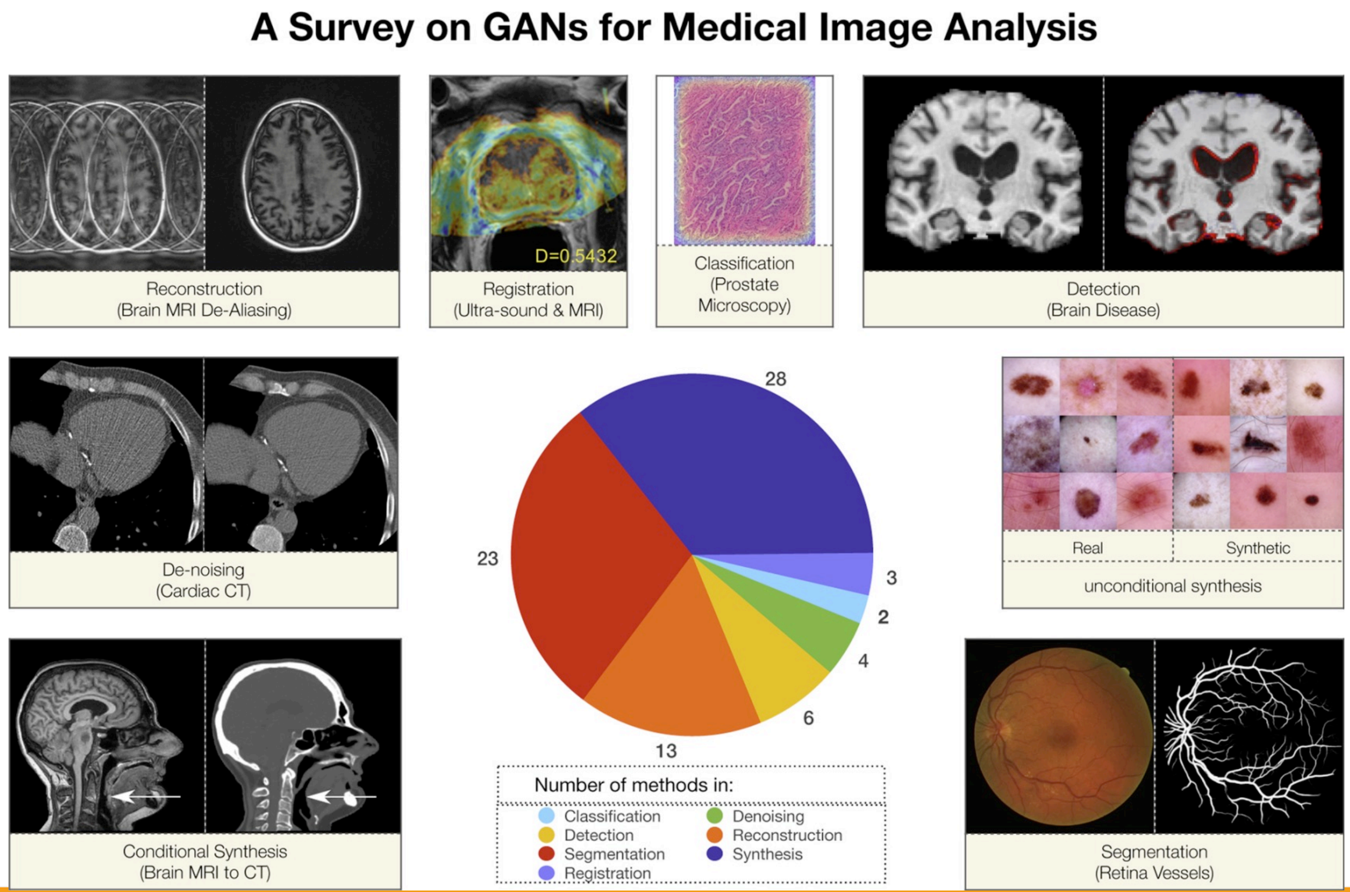
Learning objectives

The student can:

- Understand some of the applications of the synthetic data
- Learn about types of generative models
- Use generative models to enrich data
- Evaluate the quality of the synthetic data
- Investigate the usability of the synthetic data for DL training

Recap VAEs and GANs

- VAE
  - A generative model that learns to represent high-dimensional data, such as images, in a low-dimensional space.
- Conditional VAE
  - A conditional VAE learns to generate samples that are conditioned on some input, such as a class label or some other feature of the data.
- GAN
  - Another type of generative model that learns to generate new data samples that are indistinguishable from real data.
- Conditional GAN
  - A conditional GAN learns to generate samples that are conditioned on some input, such as a class label or some other feature of the data.



Application of generative modelling in medical image analysis

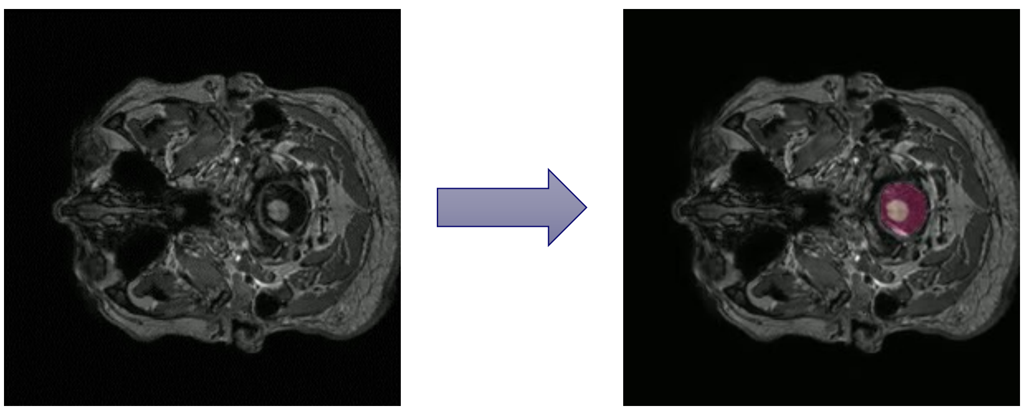
Motivation

- **Tackle the data related issue such as:**
  - Scarcity of annotated clinical data
  - Expensive data acquisition
  - Restrictive sharing policy
  - Subjective annotations
- **Synthesize cardiac images to:**
  - Augment the data
  - Develop new algorithms
  - Improve domain generalization and adaptation
  - Validate and benchmark

Medical image segmentation

- Partitioning of images into multiple segments:
  - Identifying pixels (voxels) of organs, tissues, or other biologically relevant structures
  - Gold standard: manual segmentation
  - Goal: automated methods for more accurate, efficient and reliable segmentation

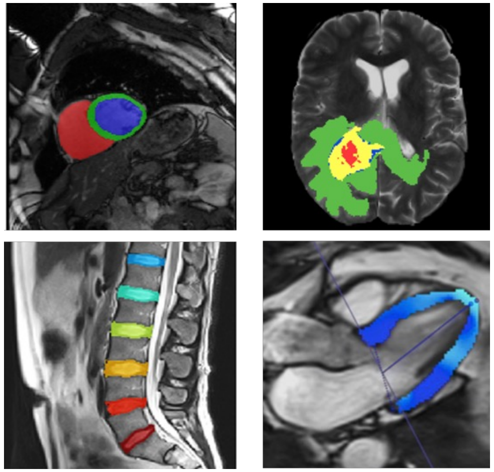
Deep learning (DL) - based



Courtesy of Yasmina Al Khalil

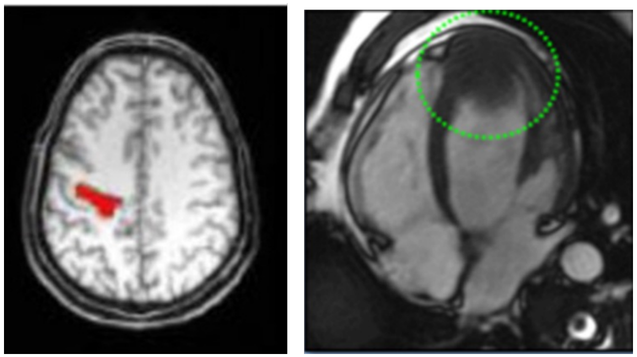
Many use cases for deep-learning based medical image segmentation

Quantitative analysis of medical images



Benefits: reduction in analysis time, reduction in inter- and intra-observer variation, enable better standardization in image analyis

Provide localization information

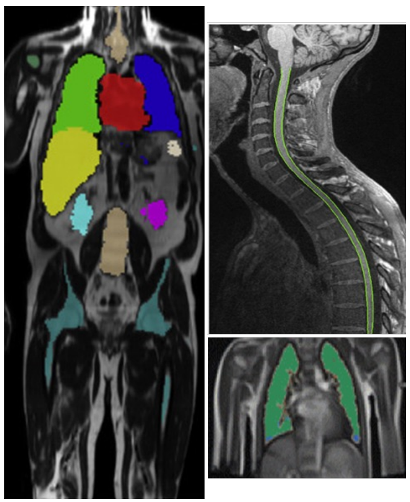


Benefits: provide interpretable pathology information

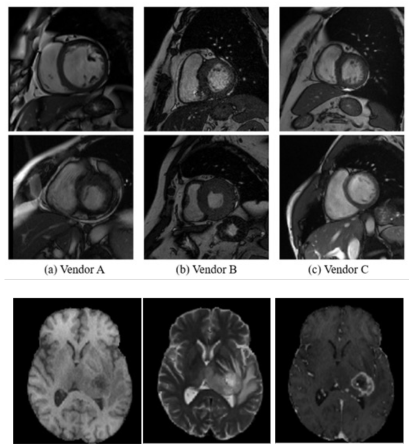
Courtesy of Yasmina Al Khalil

Many targets of interest … leading to many challenges!

Different structures...



Different modalities, image sequences and imaging protocols...



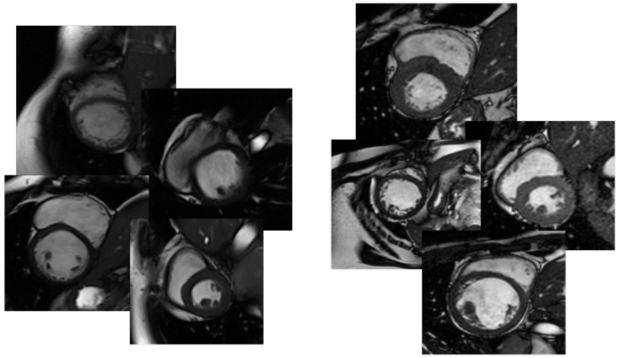
Different populations and hardware...

Huge problem space – challenging to develop a model generalizable and adaptable to all targets, while labeling training data for each structure, on each modality, for each patient population is not feasible.
How do we scale the training of segmentation networks and make them less sequence – dependent?

Model generalization

- Ability of segmentation models to retain their performance on data from various sources
  - Changes in acquisition sites, MRI scanners, MRI protocols → differences in appearance and quality
- Problem: **small** datasets for training cause models to **fail on unseen** data due to **domain shift**
- How to achieve model generalization and robustness?
  - Handling limited quantities of data
  - Reducing outliers – anomalies or extreme cases
  - Handling differences in appearance and tissue shape and/or pathological cases
  - Addressing missing sequences

Domain shift example

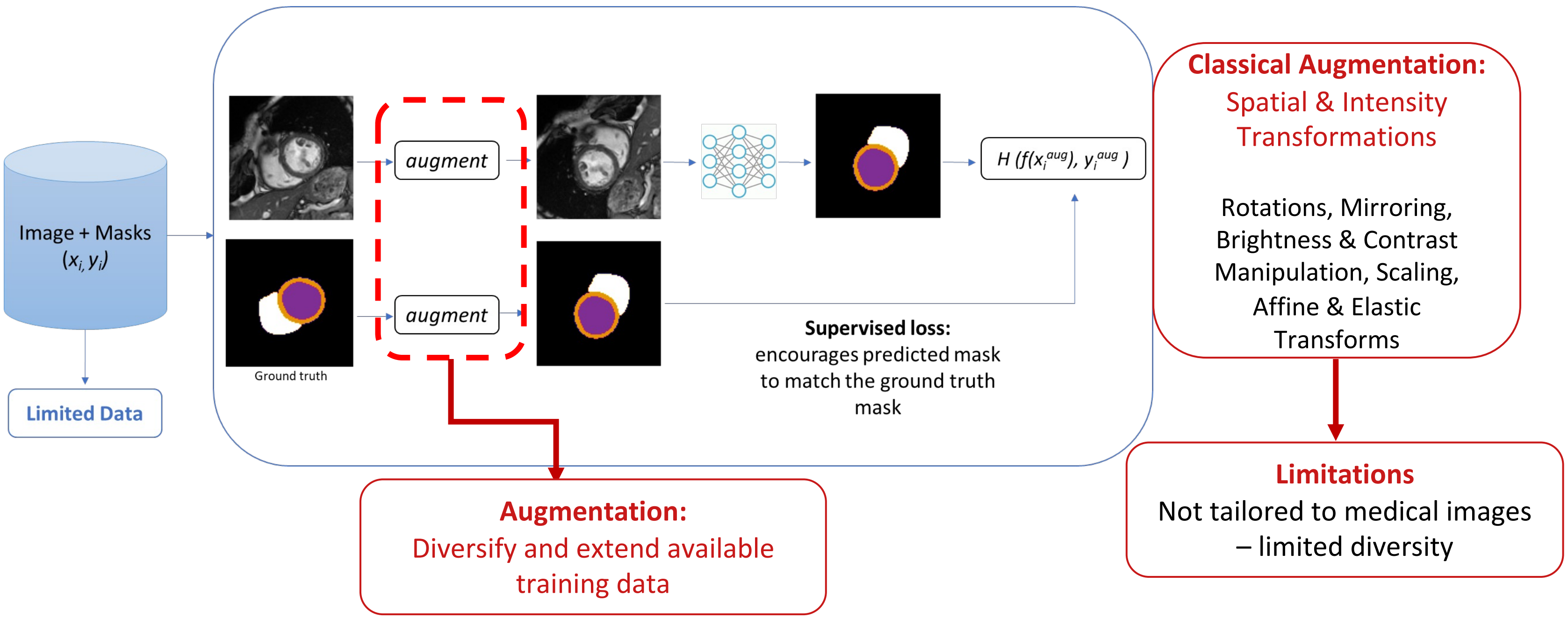


Source A Source B

Courtesy of Yasmina Al Khalil

Improving model performance in the presence of limited data

Using generated images as a data augmentation strategy to increase data diversity

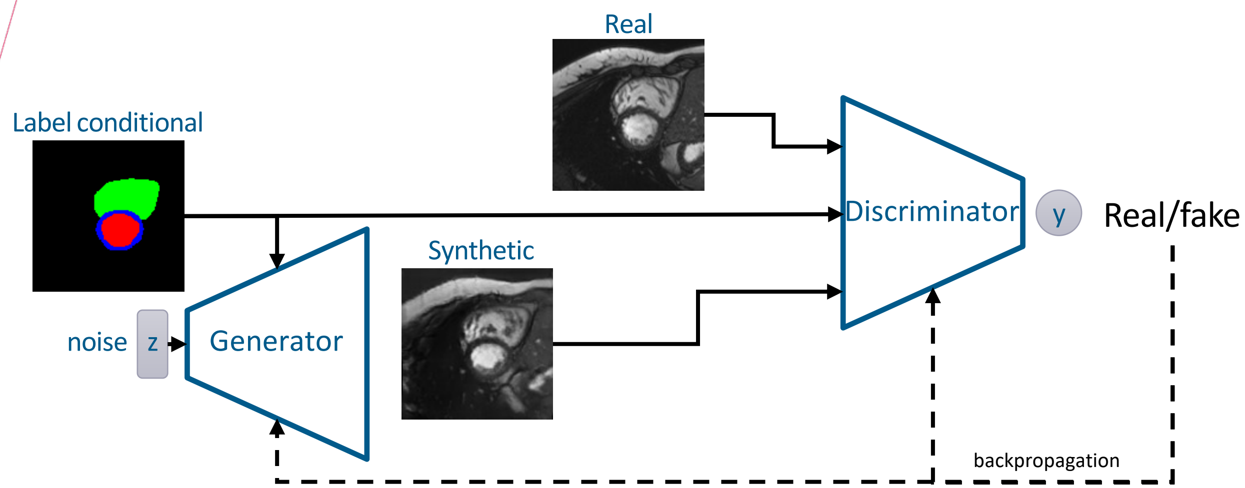


Can we use synthetic images to improve the performance of segmentation models?

Let's first understand how to synthesize images with variations…

The conditional **generator** translates input labels into synthesized images to trick the discriminator

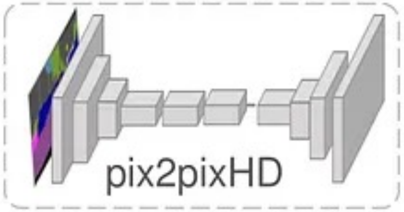
The conditional **discriminator** tries to identify real images from synthesized ones created by the generator



Why condition on labels?

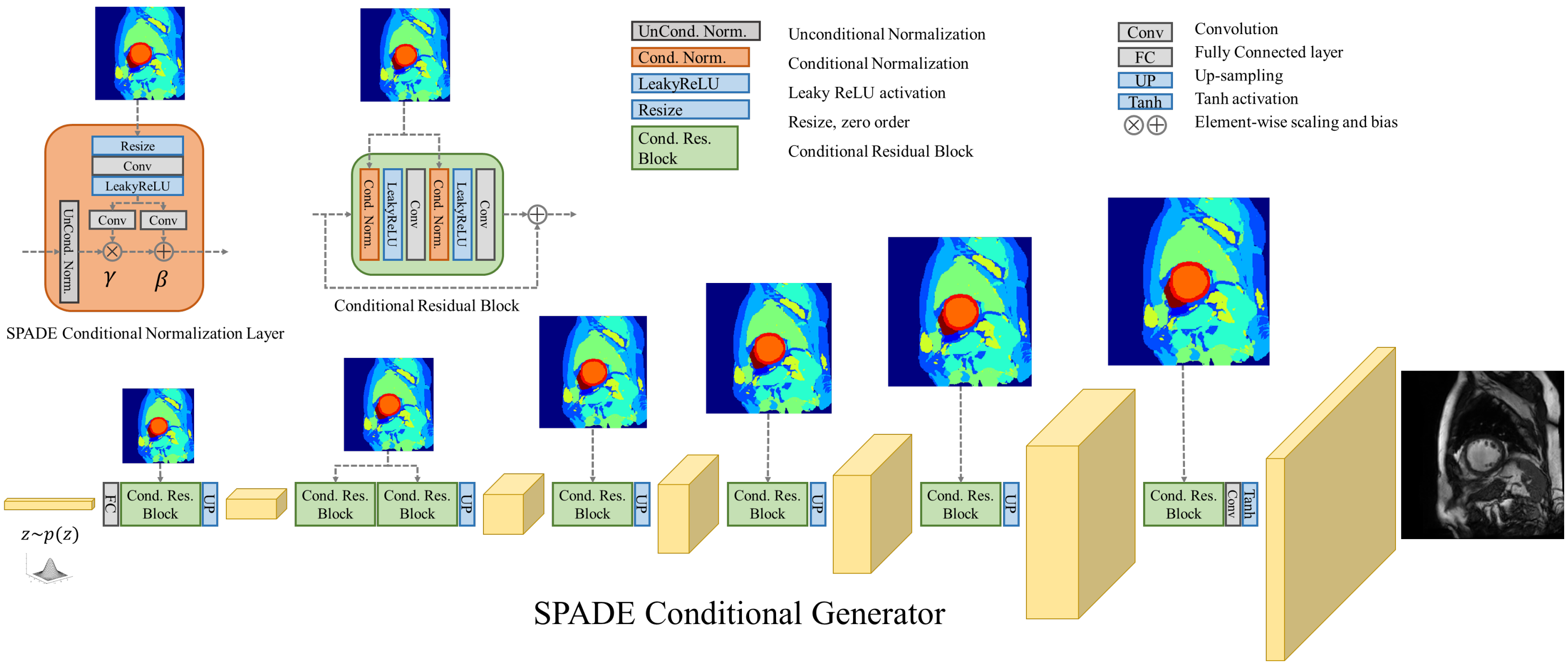
How to generated cardiac MR images using conditional GANs

Previous work



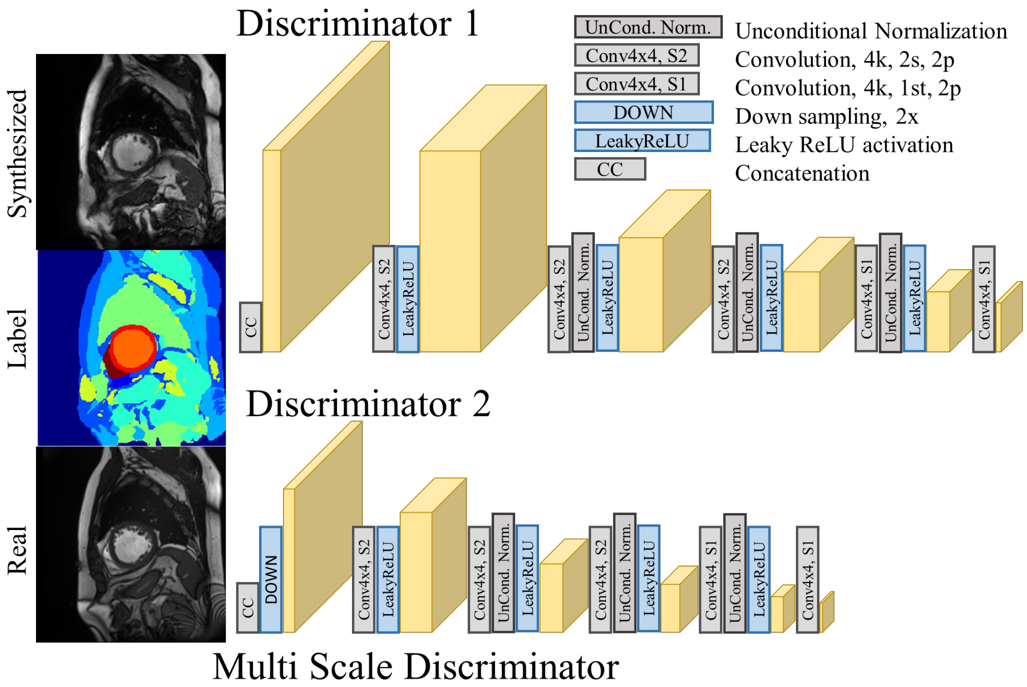
Generator architecture

SPADE normalization layers to preserve the anatomical information of the labels



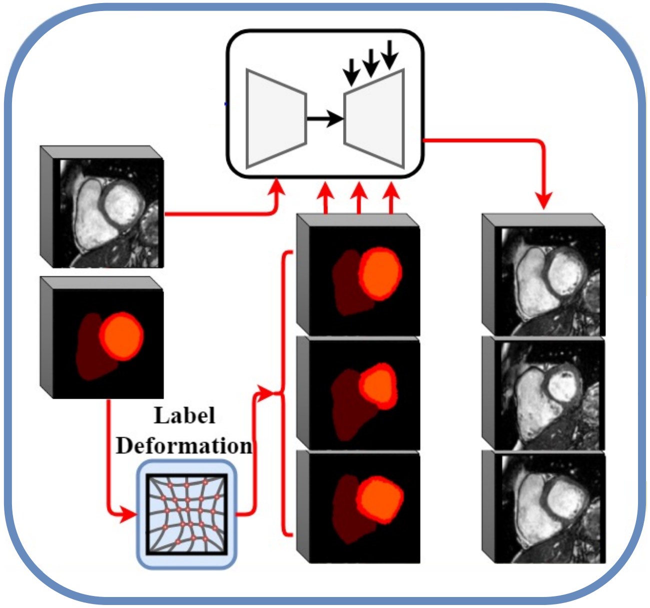
Discriminator architecture

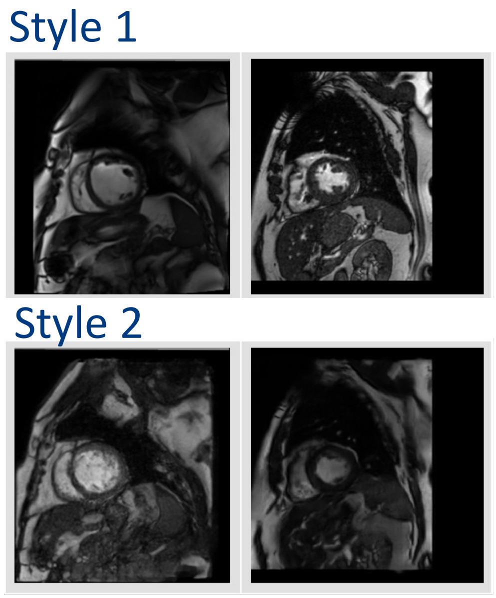
Multi-scale conditional discriminator



Important notes on generating diverse examples

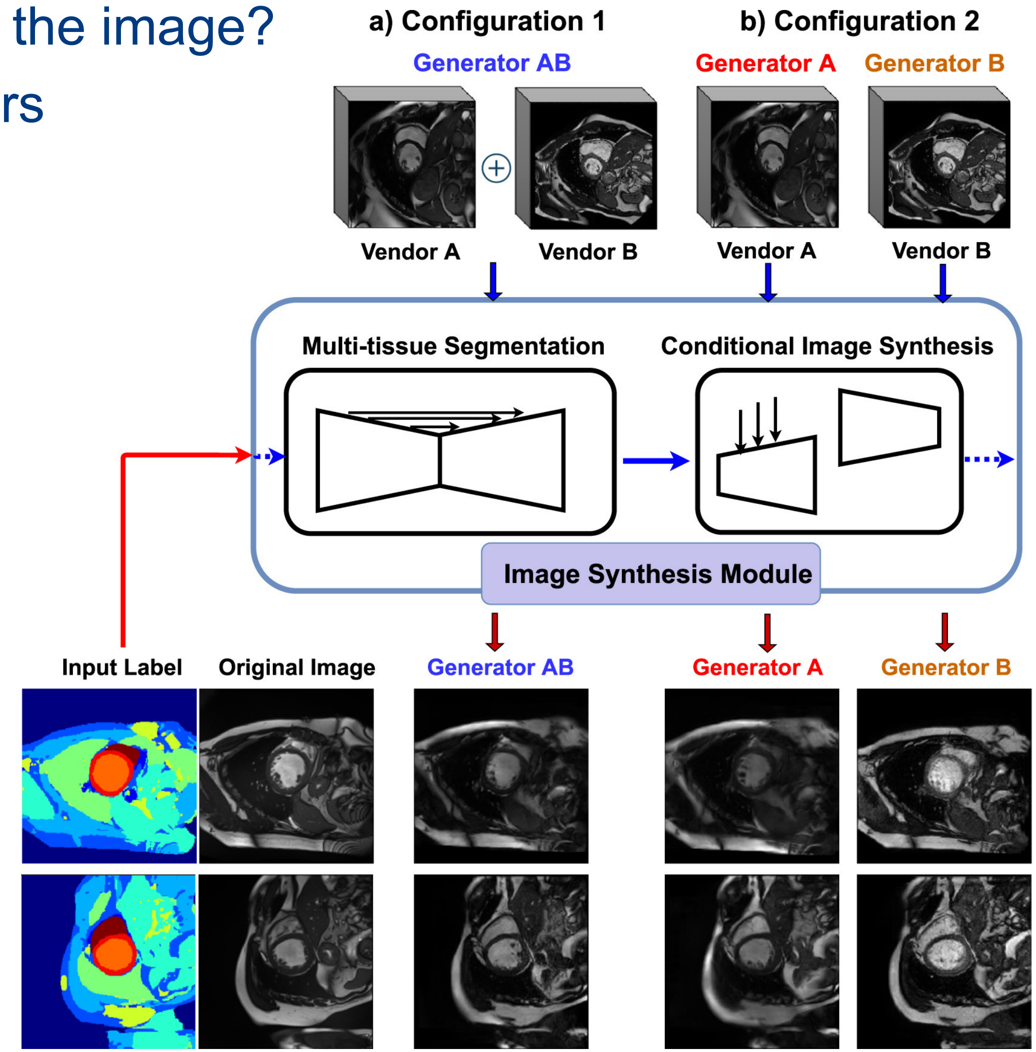
- Include contrast/style variation
- Include label deformation to provide anatomical variation in the generated data





How to control the style of the image?

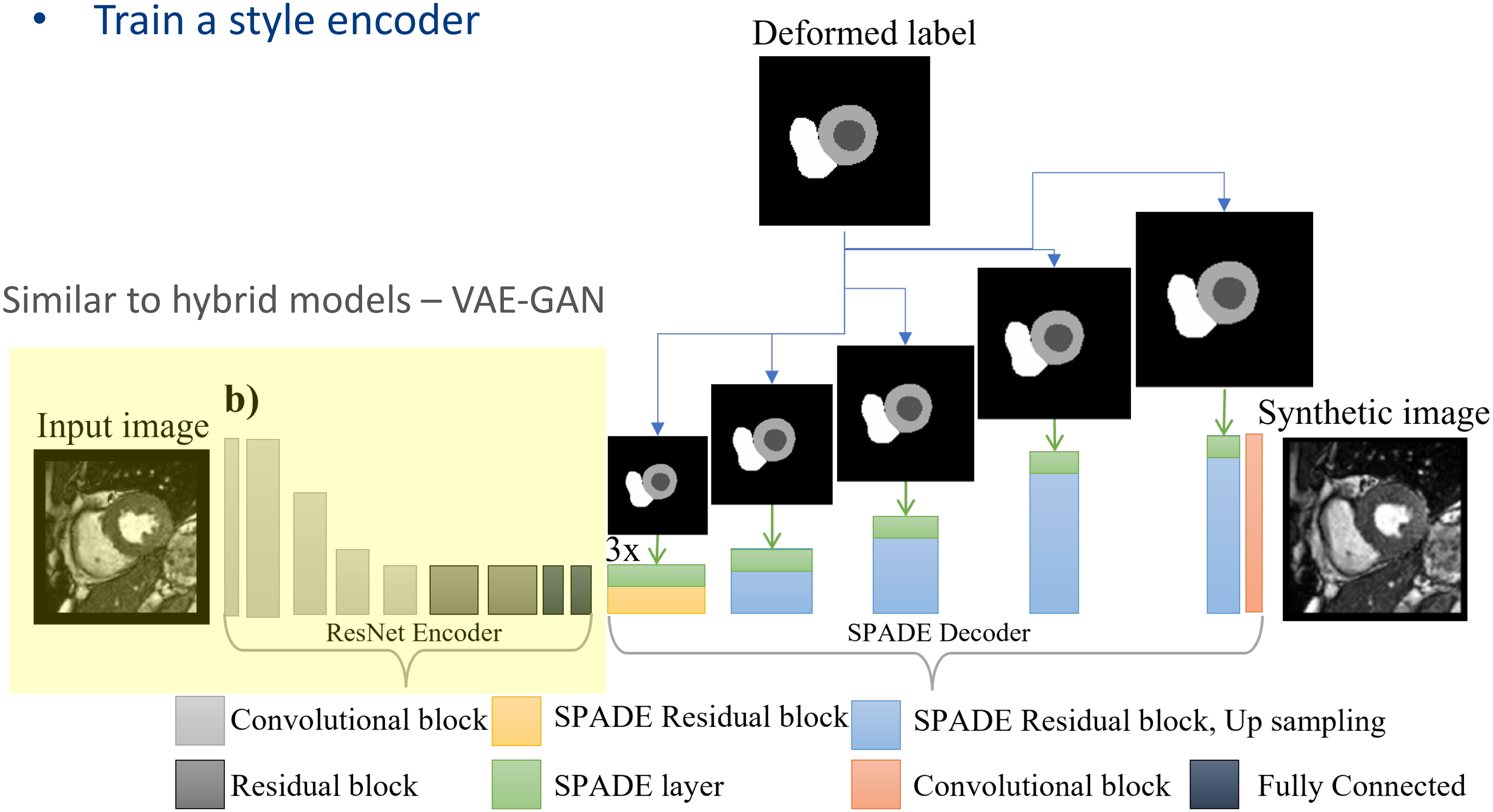
- Train multiple generators



How to control the style of the image?

- Train a style encoder

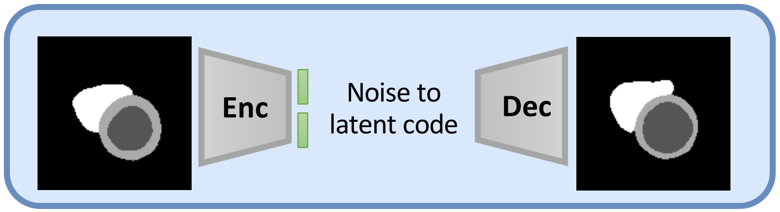
Similar to hybrid models – VAE-GAN



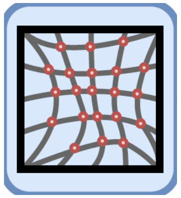
How to deform labels

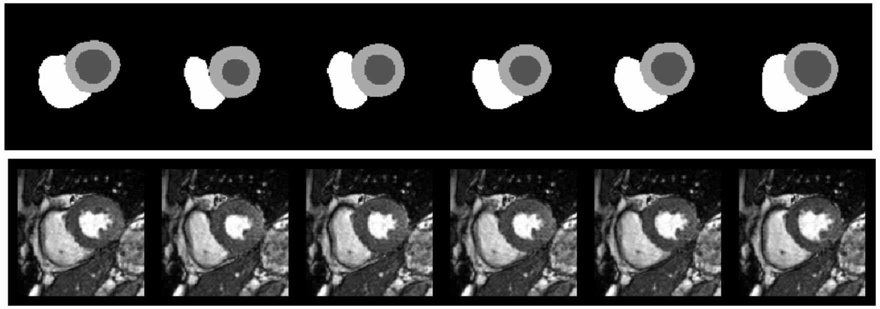
- Elastic deformation and morphological operations
- VAE to learn anatomical deformation

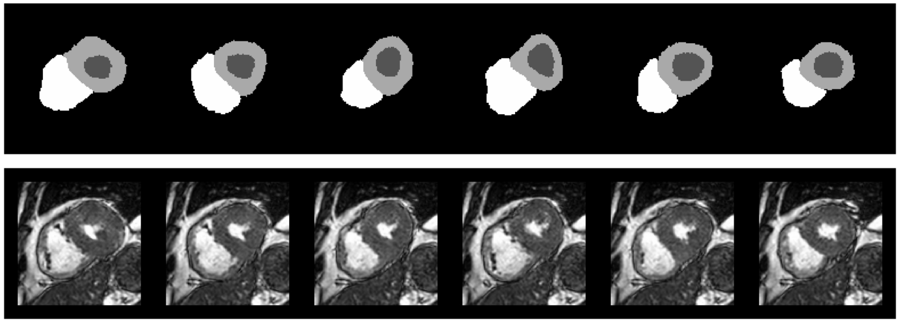
VAE based deformation



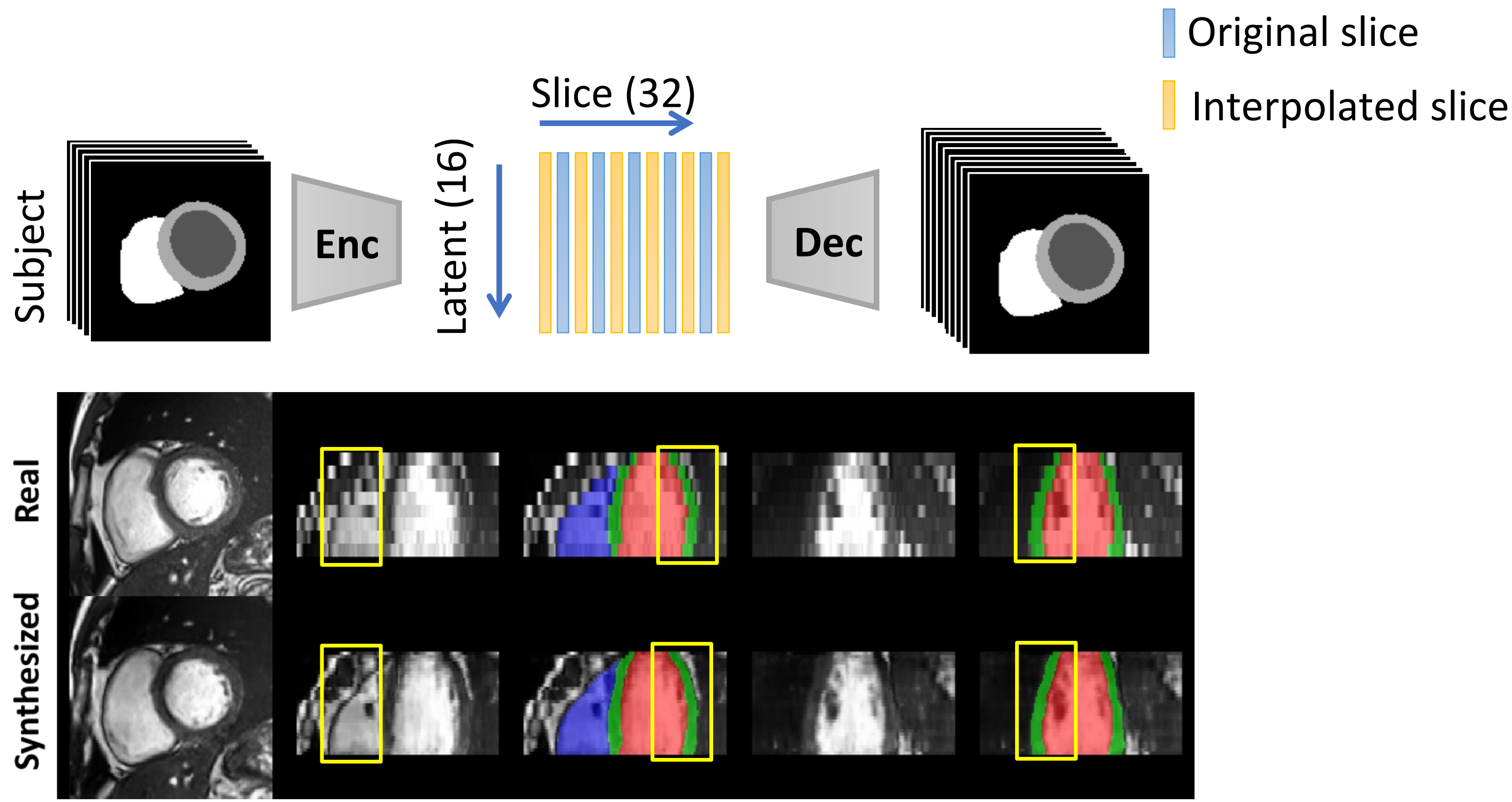
Random elastic deformation



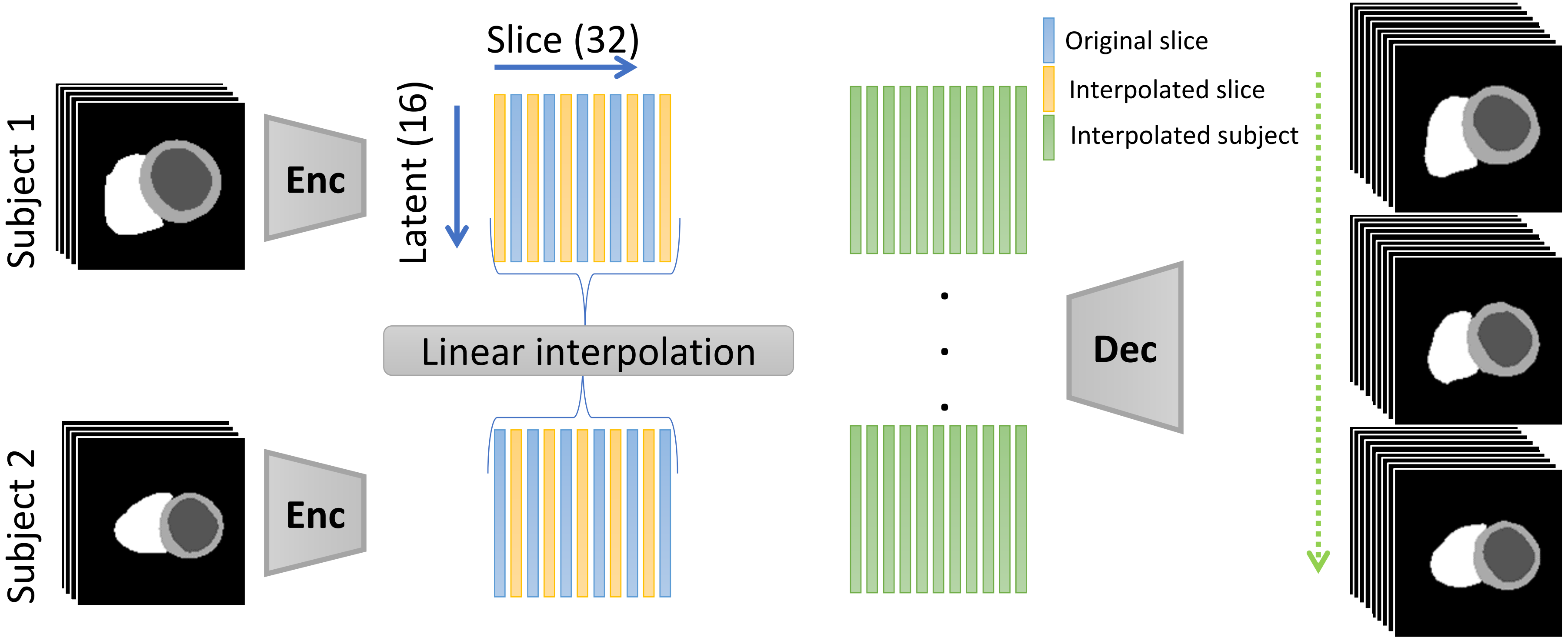




VAE to equalize the number of slices per subject



VAE to generate images with heart geometry in-between two subjects



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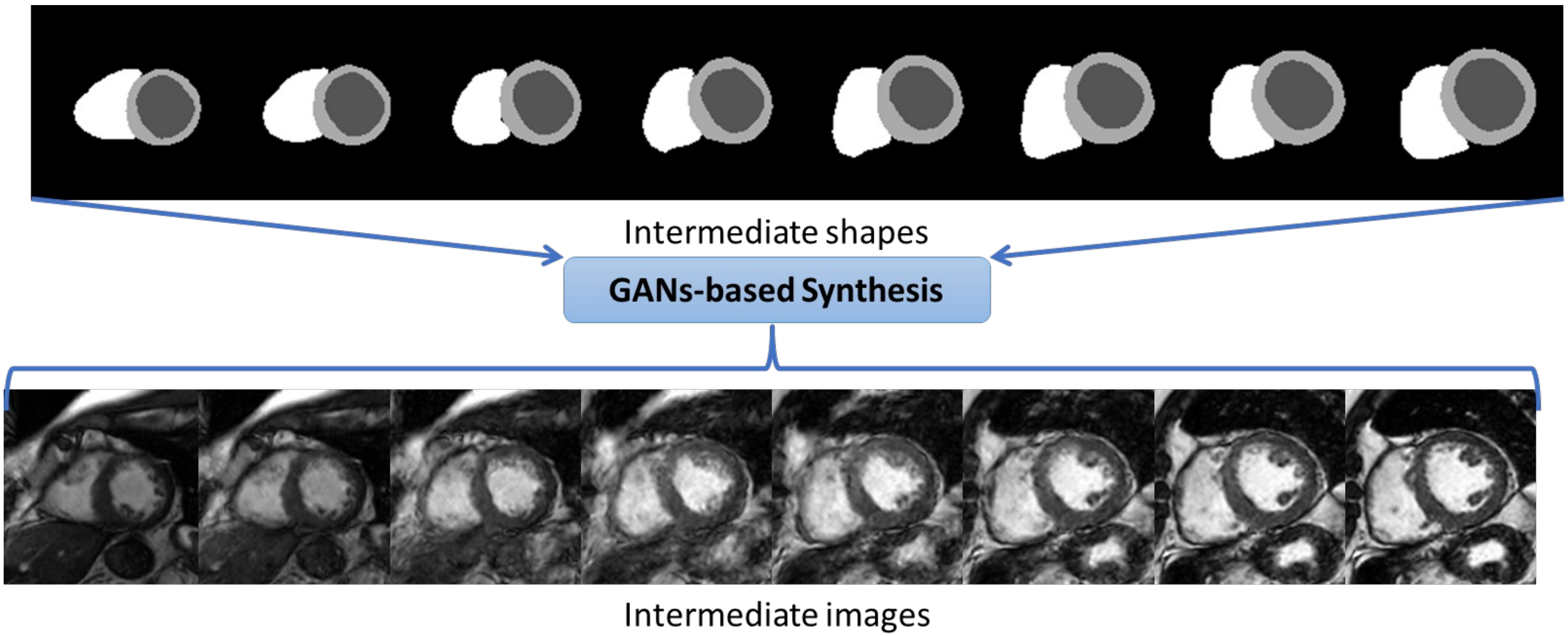
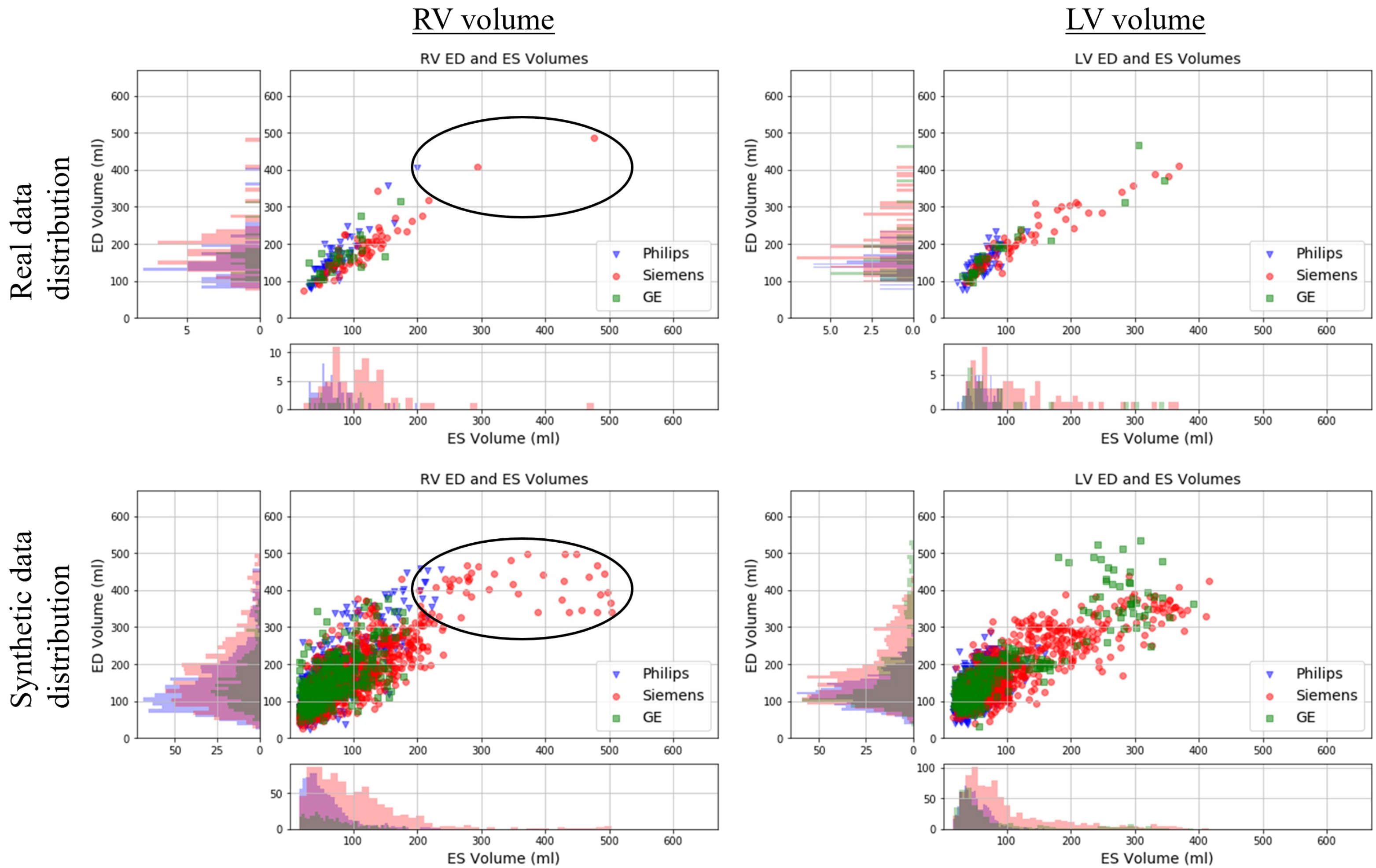
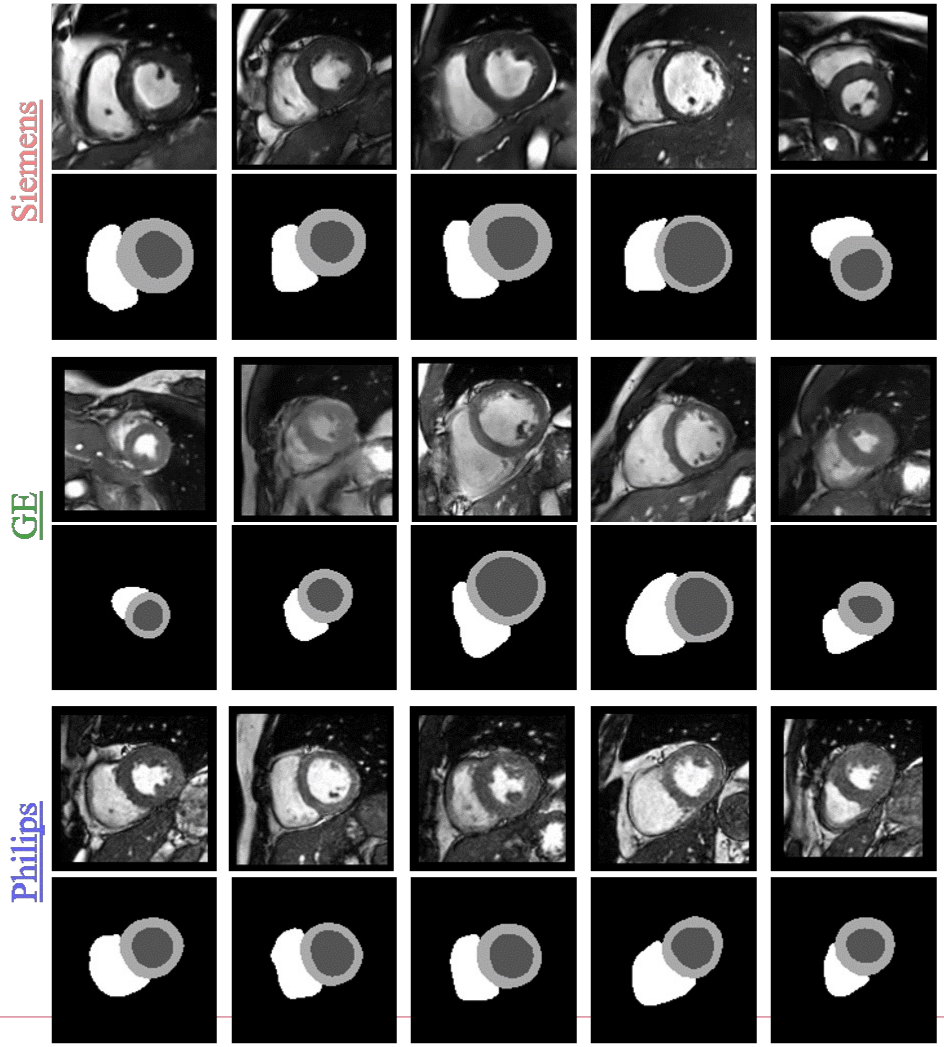


Targeted synthesis to increase the outlier cases



- Synthesizing data for each scanner vendor

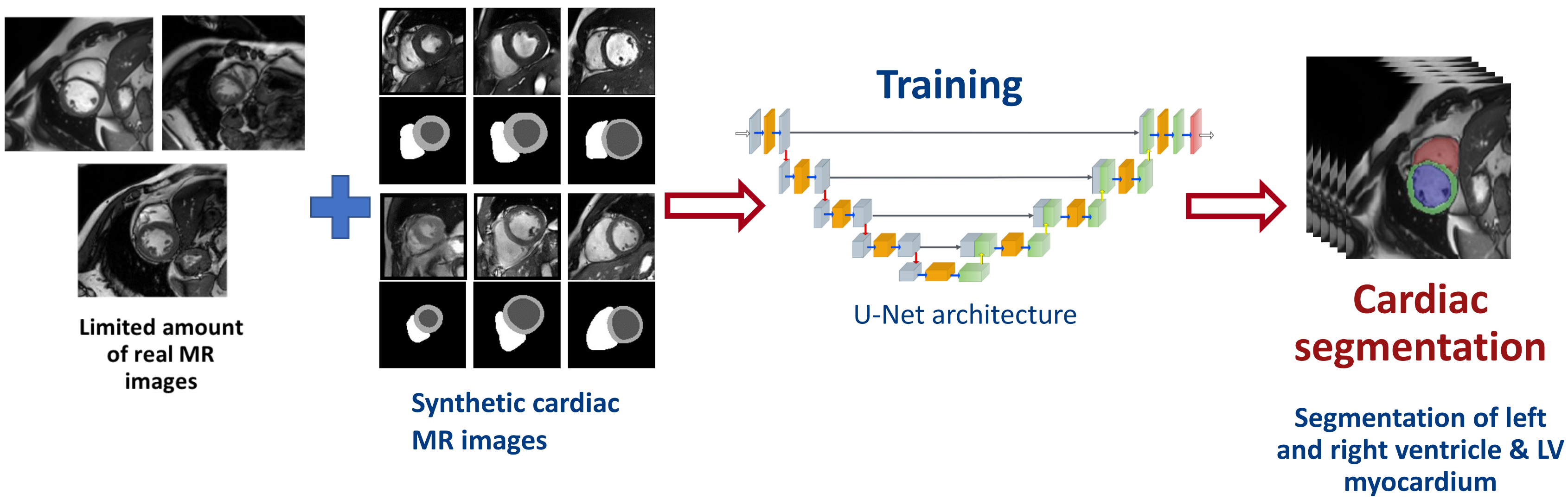


How to evaluate the realism of synthetic data

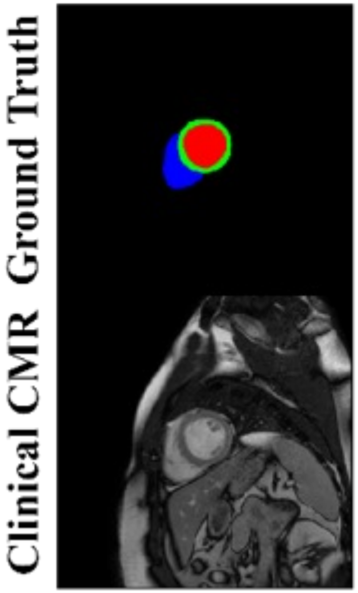
- Visual evaluation by clinician and expert in the fields
- Quantitative evaluation of individual examples using image quality metrics (comparing real image with the generated one)
- Evaluation of the synthesized database (FID, IS)

Improving model performance in the presence of limited data

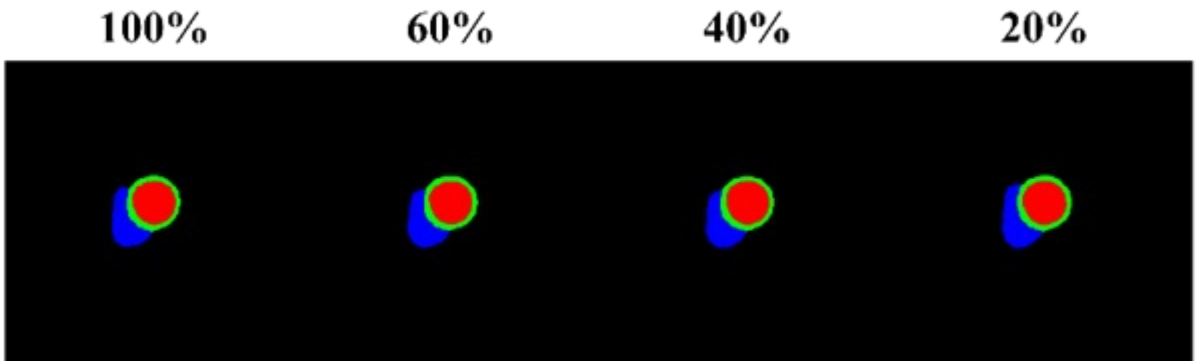
- ***Data augmentation*** experiment to assess the usefulness of synthetic data for improving the generalization and to increase data diversity
- ***Real data reduction*** experiment to evaluate the realism of synthetic data for replacing the real data



- ***Data augmentation*** with synthetic data can improve the generalizability of the segmentation network
- ***Real data reduction*** experiment suggests that we can reduce the real data and replace them with synthetic while retaining the performance

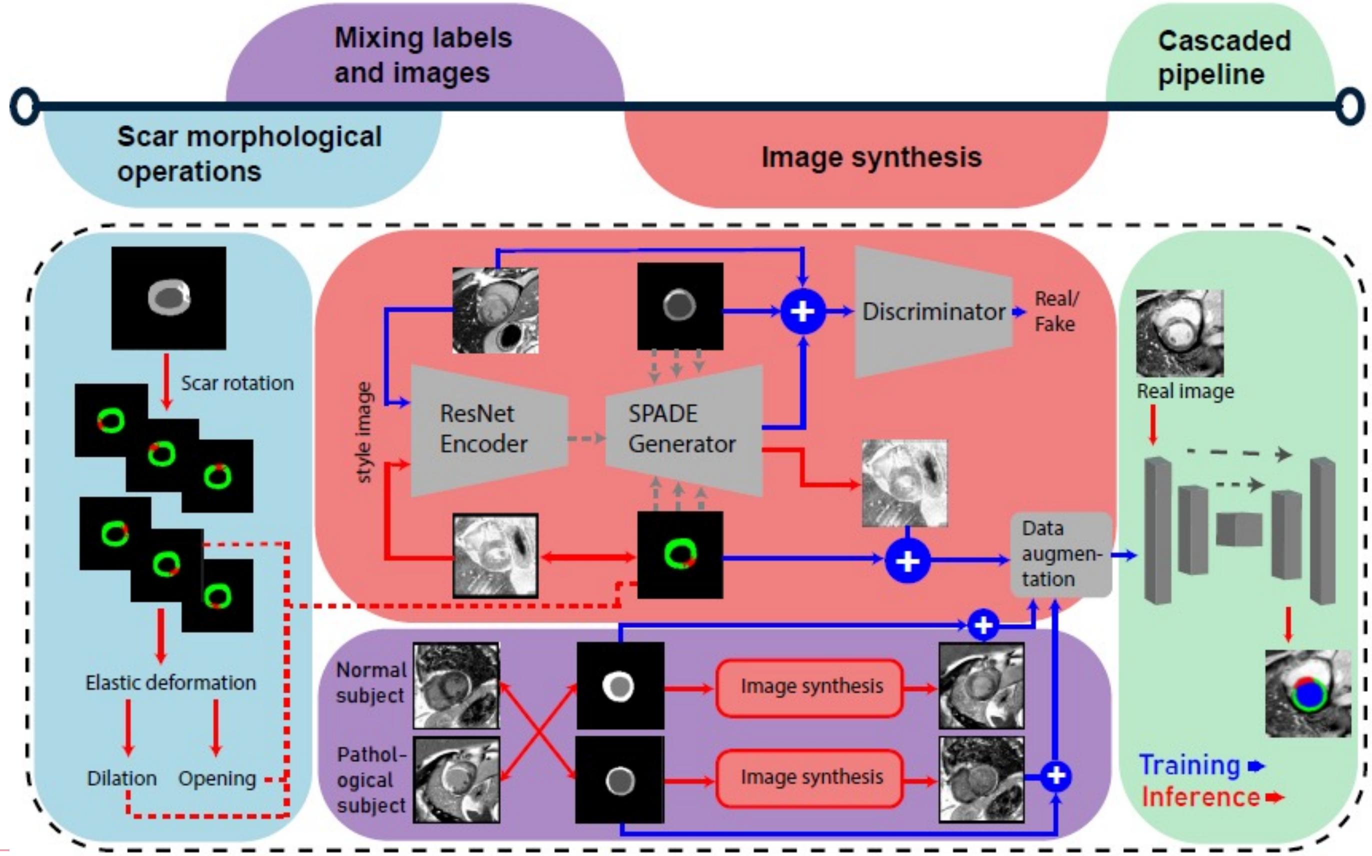


Of real data (=40 volumes)



Myocardial scar synthesis

- *Augmentation with synthetic data* ***improves myocardial scar quantification*** *in late-gadolinium enhancement (LGE)*



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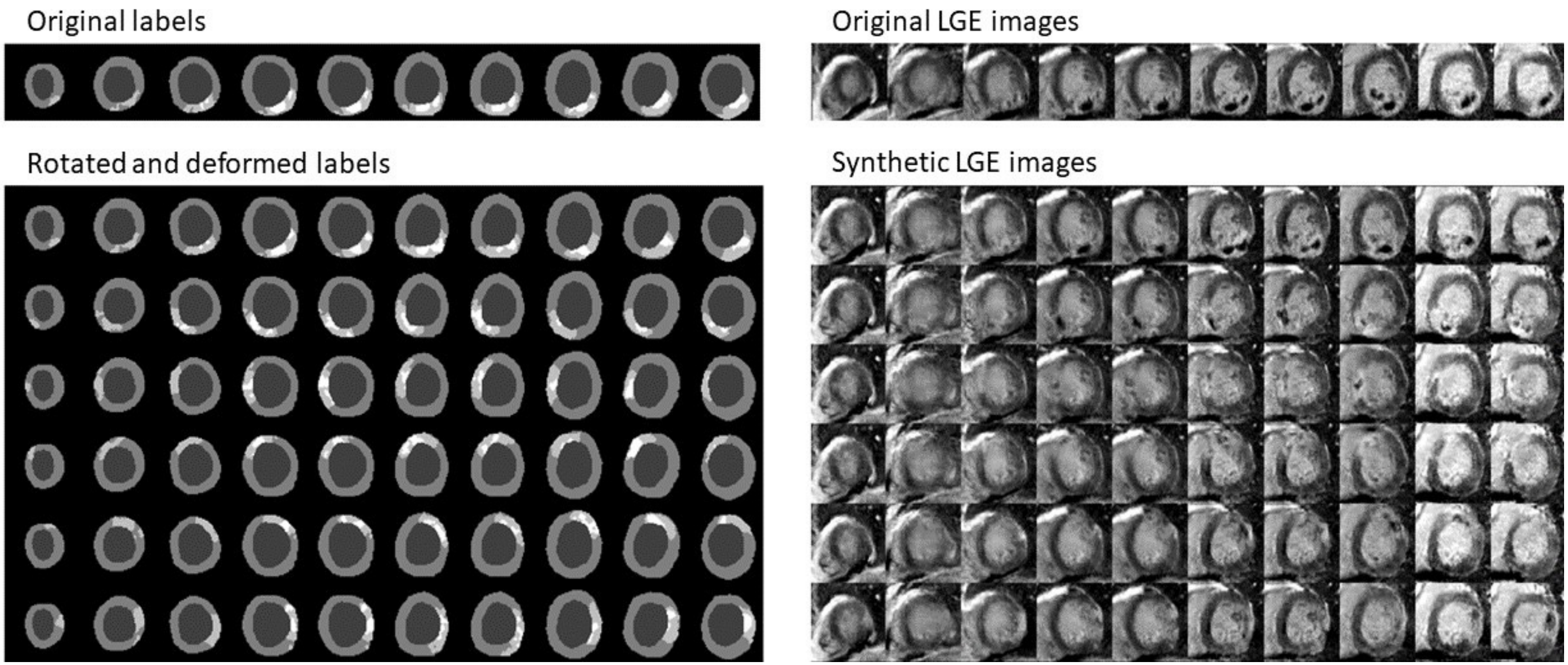
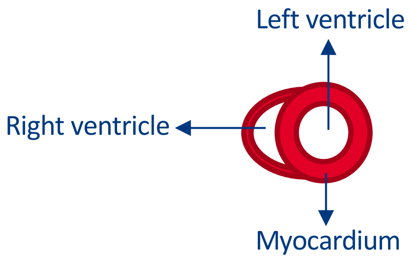
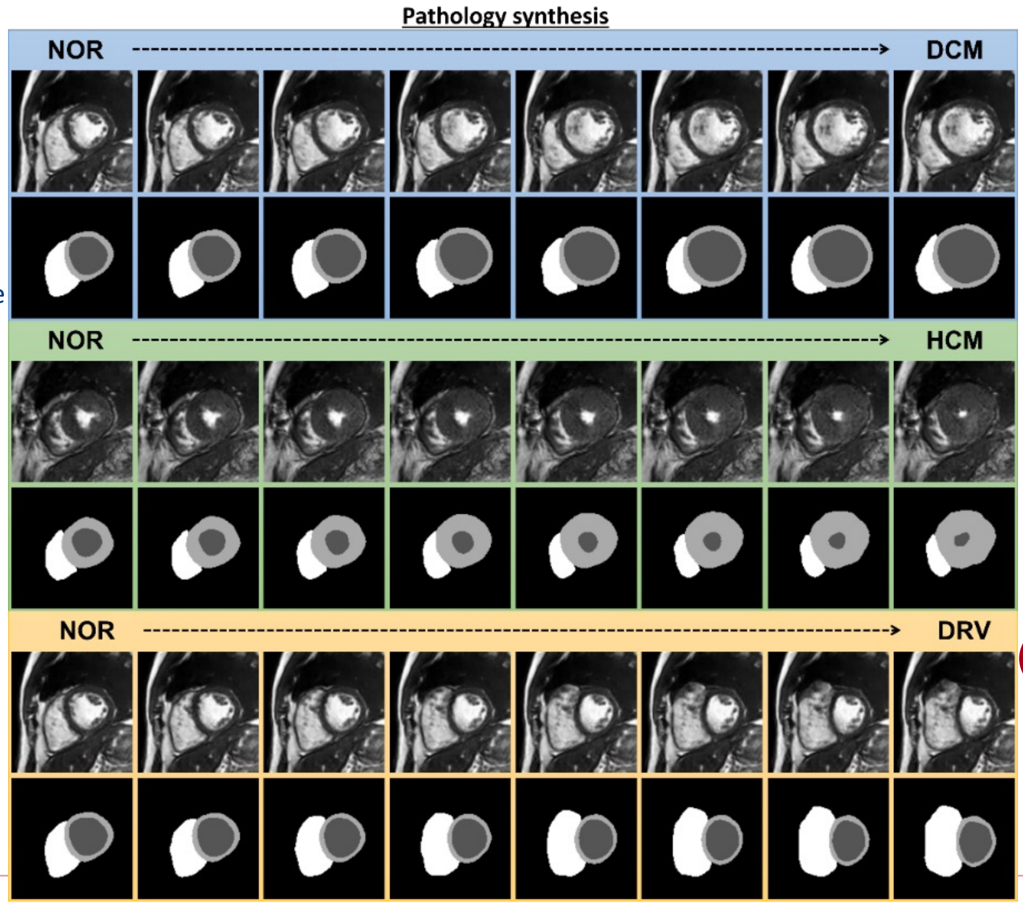


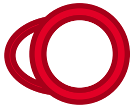
Targeted synthesis to increase pathological cases

- *Subjects with plausible anatomy and heart disease characteristics are synthesized in pathology synthesis*

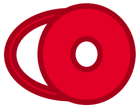


Normal heart (NOR)

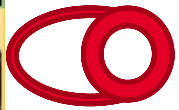




Diseased heart 1
Dilated Cardiomyopathy (DCM)



Diseased heart 2
Hypertrophic Cardiomyopathy (HCM)



Diseased heart 3
Dilated Right Ventricle (DRV)

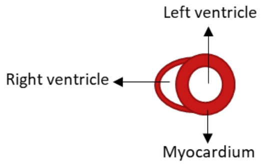
- *Augmentation with pathology synthetic data **improves the model generalization to different heart diseases***

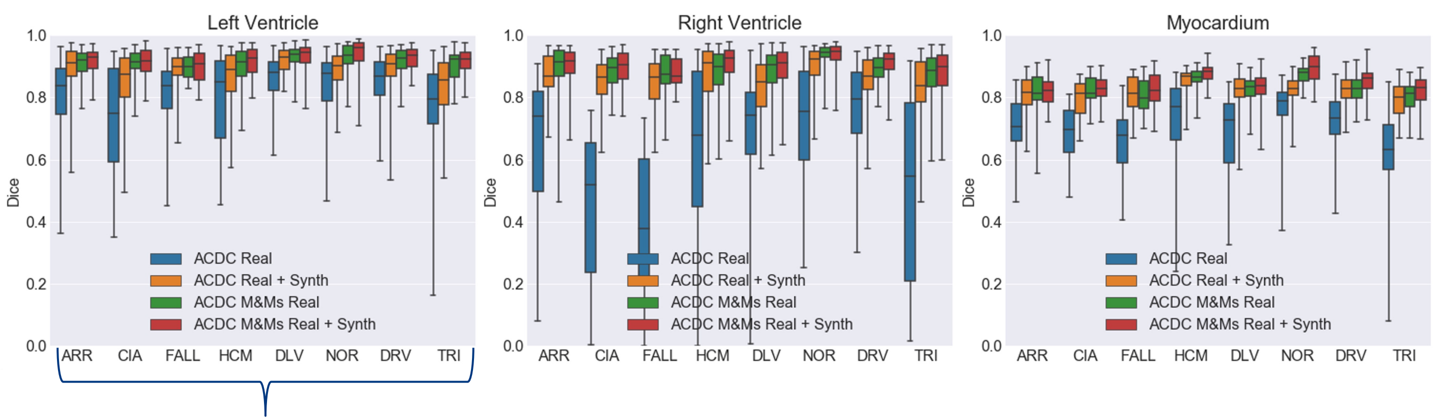
ACDC Real: Trained with real ACDC data

ACDC Real + Synth: Trained with addition of pathology synthesis data

ACDC M&Ms Real: Trained with real ACDC and M&Ms data

ACDC M&Ms Real + Synth: Trained with all real and synthesized data





Different heart pathologies

Conclusions

- Cardiac MR image synthesis can provide solutions to
  - Generate substantial number of images with variations in anatomy and contrast
  - Tackle medical data scarcity for deep-learning applications
  - Boost the performance of segmentation models
  - Improve the robustness of models to handle subjects with heart pathology

Learning objectives

The student can:

- Understand some of the applications of the synthetic data
- Learn about types of generative models
- Use generative models to enrich data
- Evaluate the quality of the synthetic data
- Investigate the usability of the synthetic data for DL training

IMAG/e

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Questions?