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# Muographic Image Up-Sampling with Machine Learning for Built Infrastructure Applications

**Mode 2024 – Valencia**

**William O’Donnell**, David Mahon, Guangliang Yang, Simon Gardner

WORLD CHANGING GLASGOW

THE TIMES THE SUNDAY TIMES GOOD UNIVERSITY GUIDE 2024 SCOTTISH UNIVERSITY OF THE YEAR

# 1. MOTIVATION

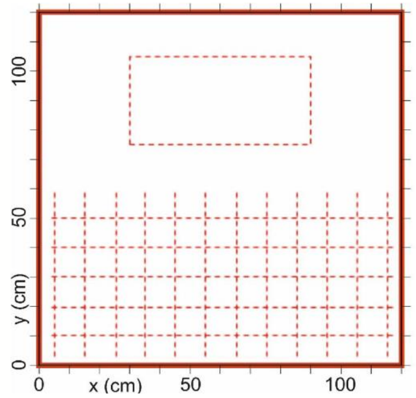
# PROBLEM: Non-Destructive Testing of Built Infrastructure

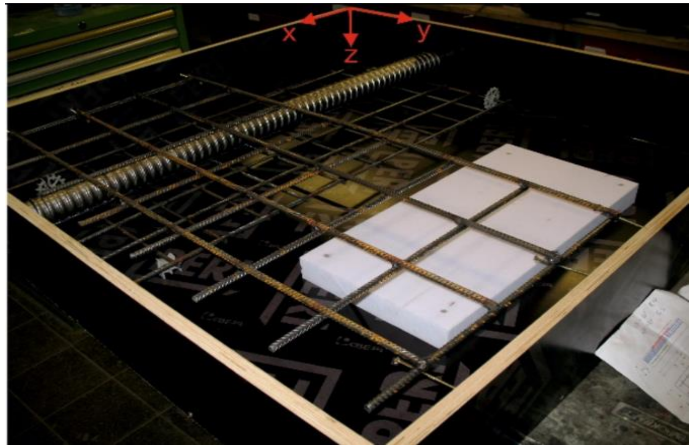
- It has been widely established that there is a growing amount of aged, concrete infrastructure coming to end of life.
- However, current NDT techniques are limited in establishing high quality reconstructions of concrete interiors.
- A 2019 [1] study tested and compared NDT techniques:
  - X-Ray laminography
  - Ground penetrating radar (GPR)
  - Ultrasound
  - **Muography**

[1] Journal of Nondestructive Evaluation (2021) 40:65 https://doi.org/10.1007/s10921-021-00797-3

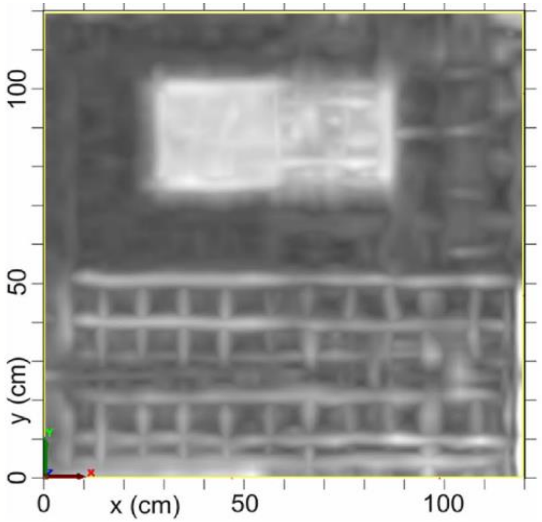
# PROBLEM: Non-Destructive Testing of Built Infrastructure

Reference, z = 17cm

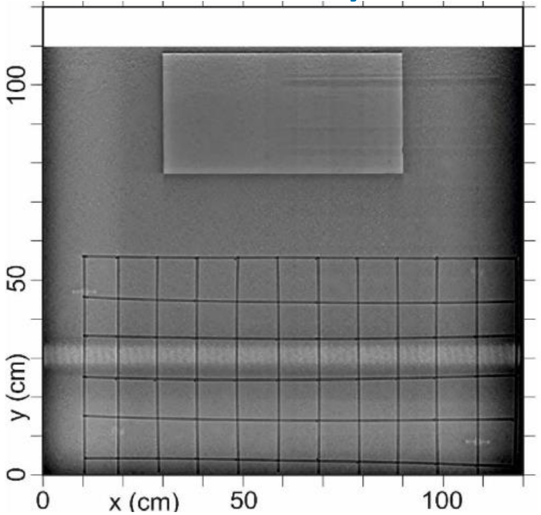


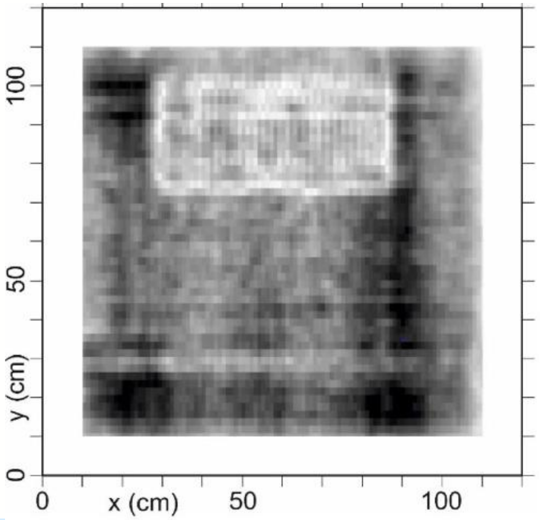

GPR



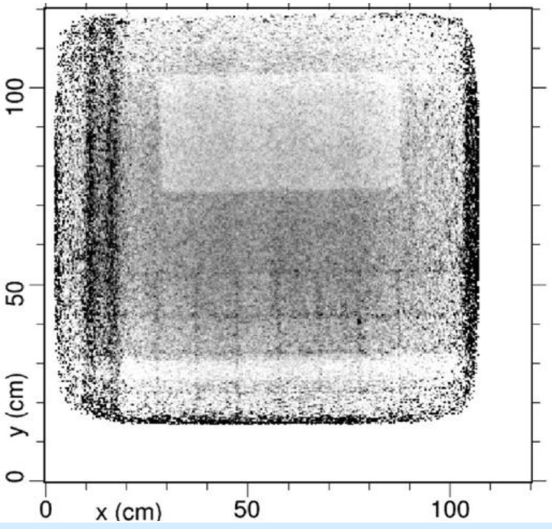

X-Ray




Ultrasound




Muography

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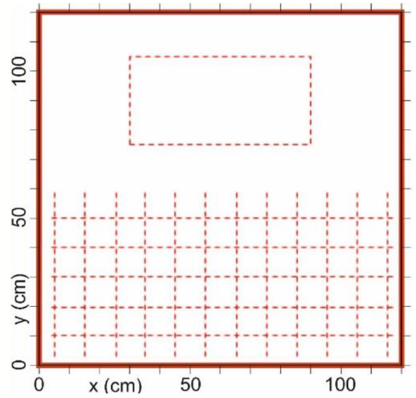
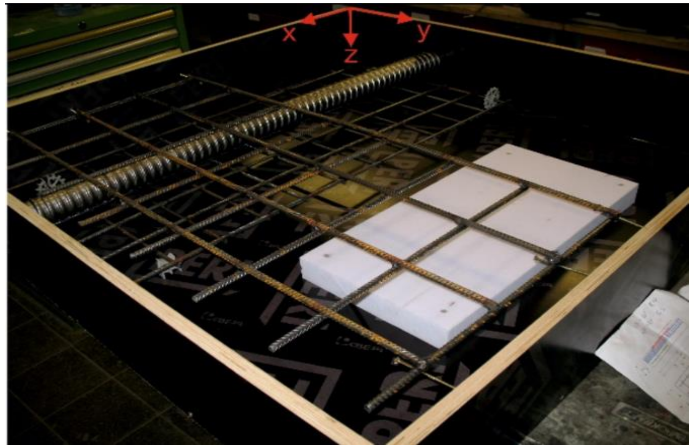
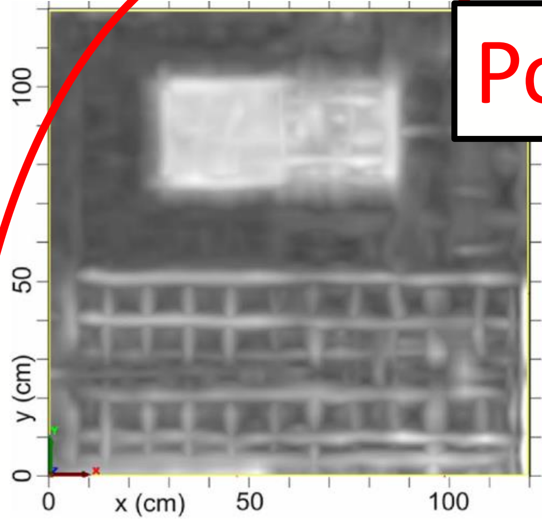
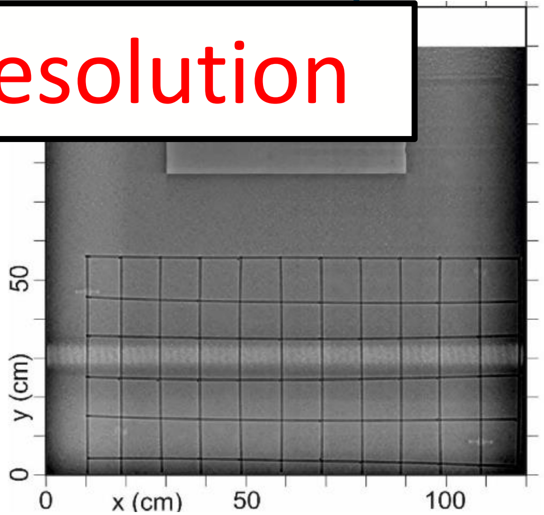



GPR

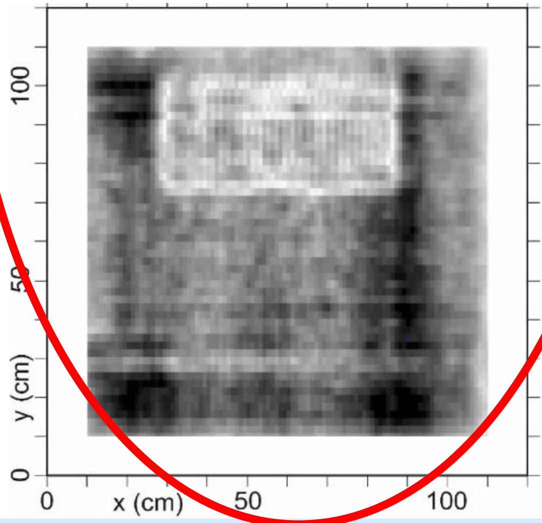



X-Ray

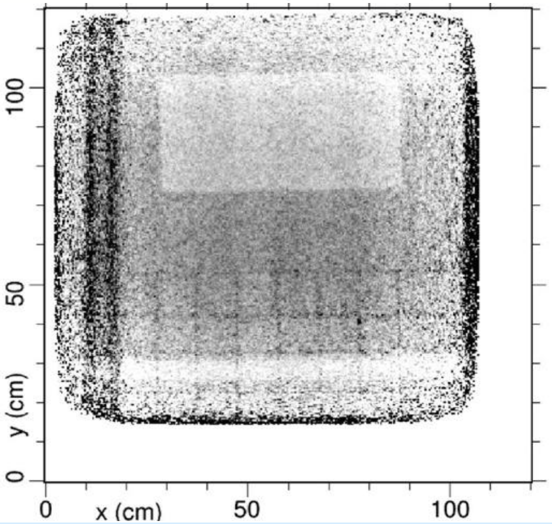



Poor Resolution

Ultrasound




Muography

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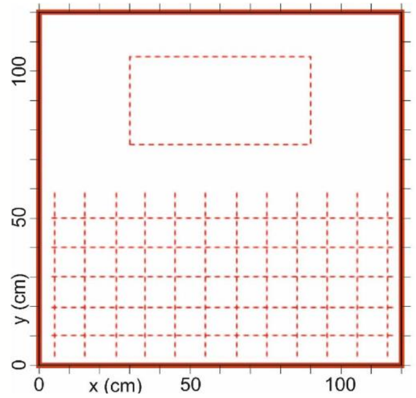
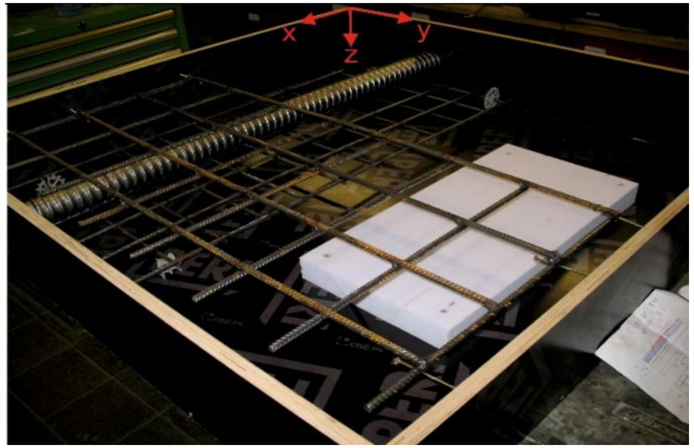
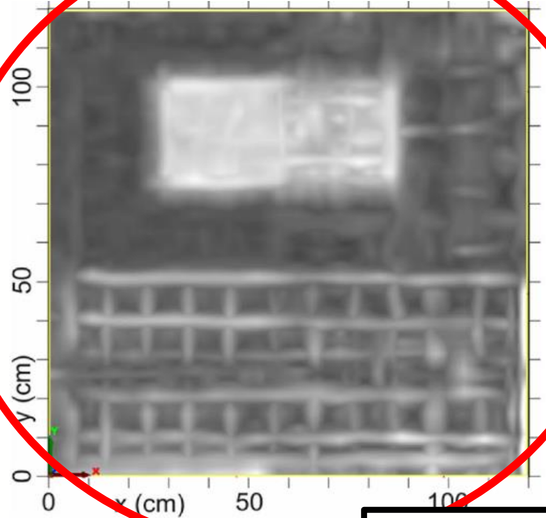
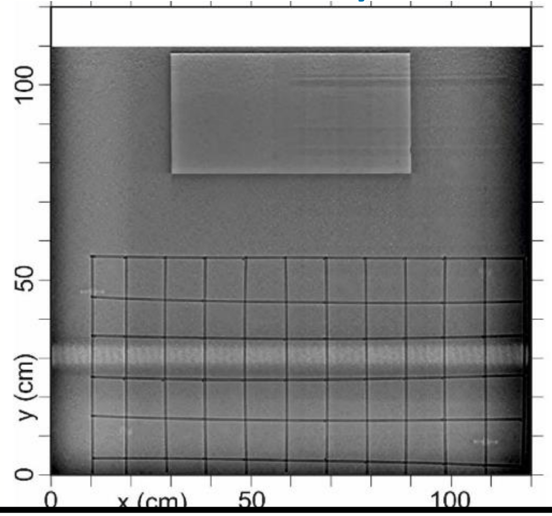


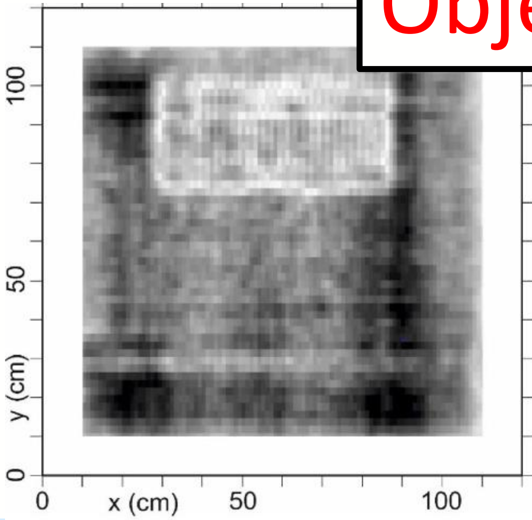

GPR

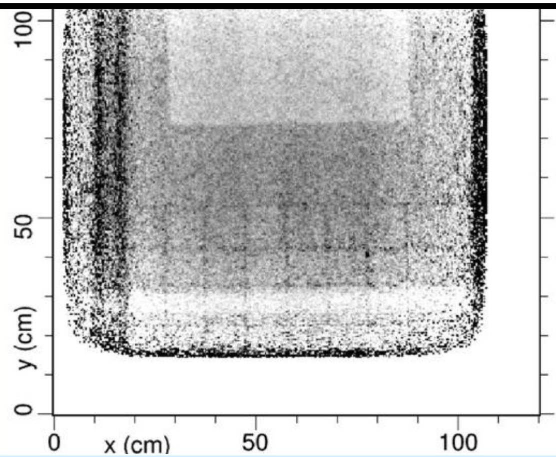



X-Ray




Ultrasou




Object sizes misrepresented

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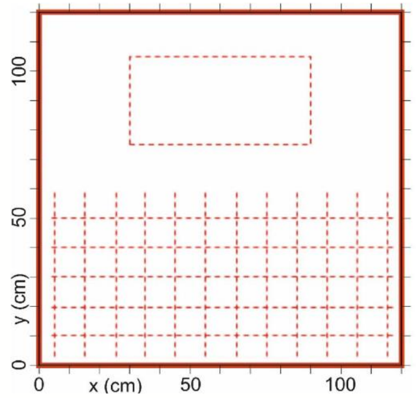
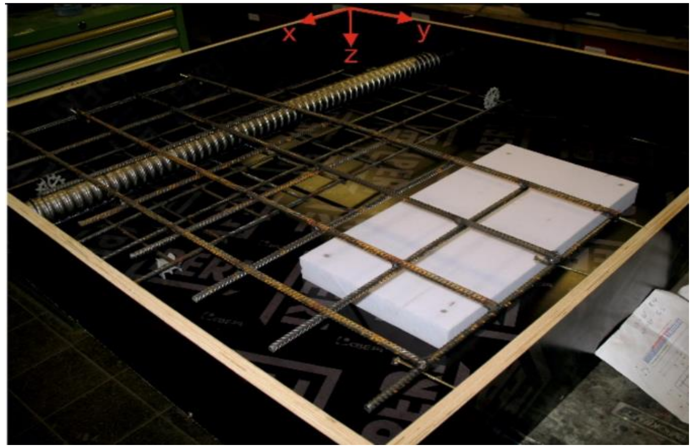
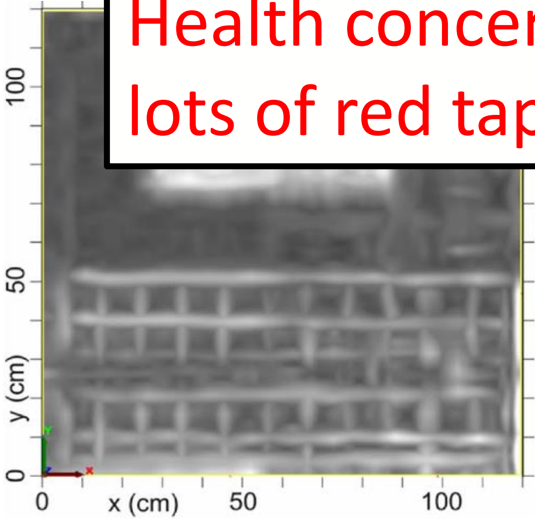
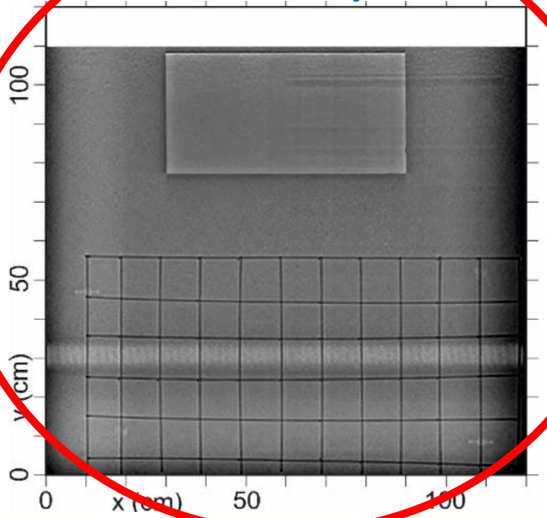


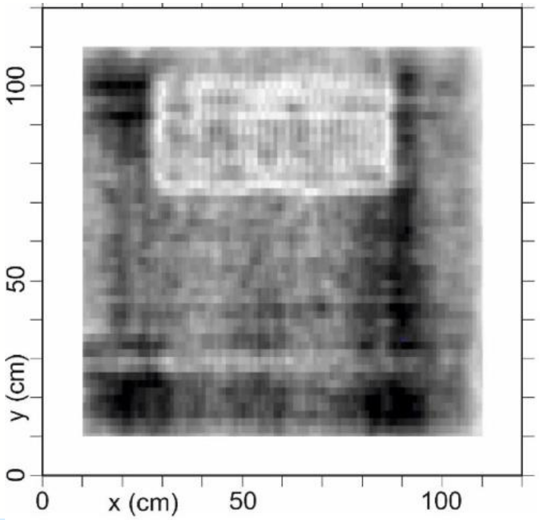

Health concerns: lots of red tape



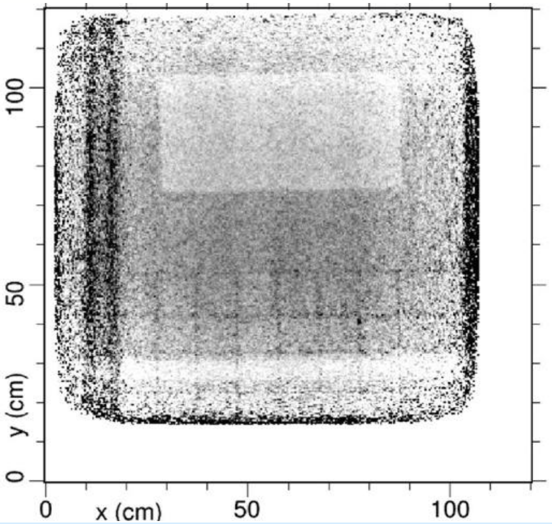

X-Ray




Ultrasound




Muography

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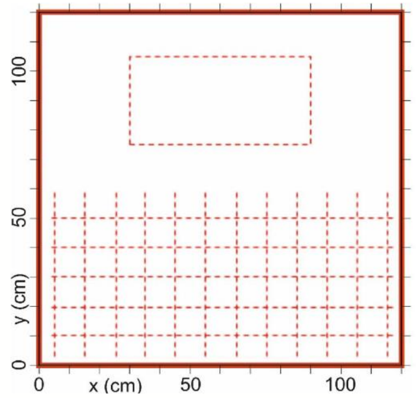
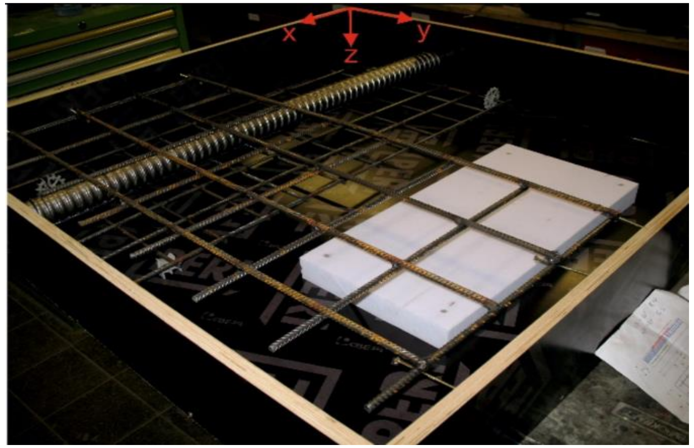
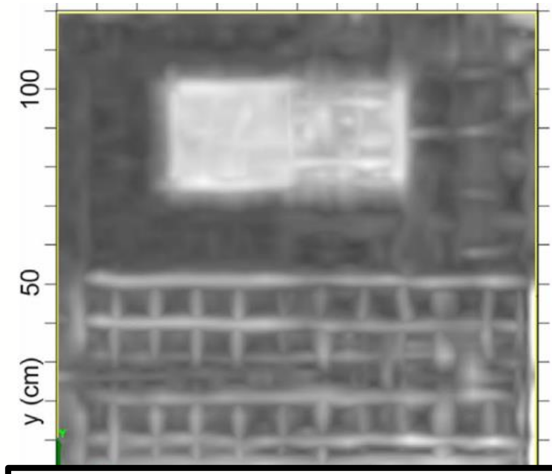
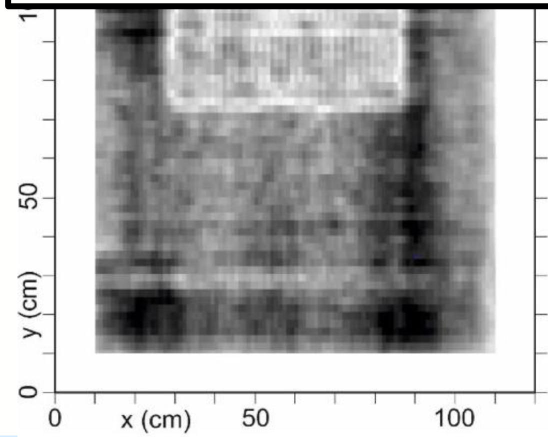


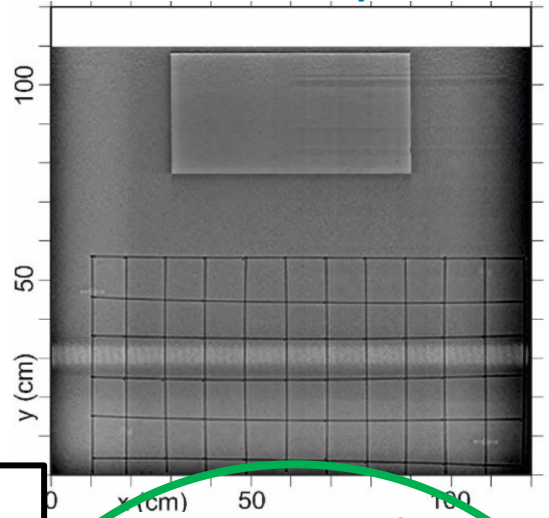

GPR



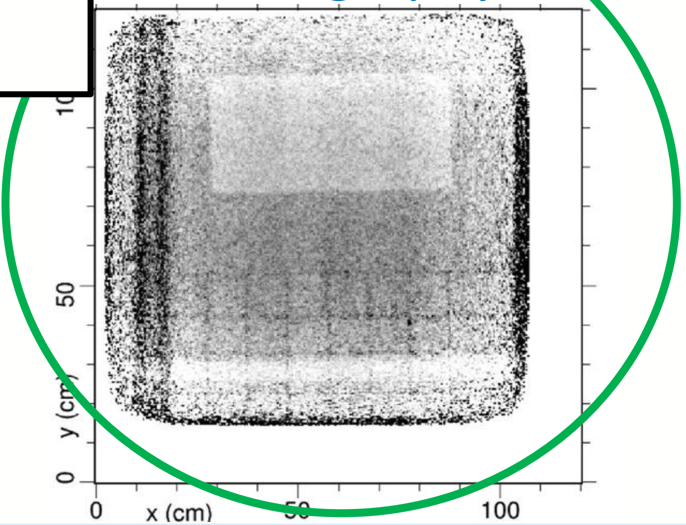

- Good Resolution
- High Depth




X-Ray




Muography

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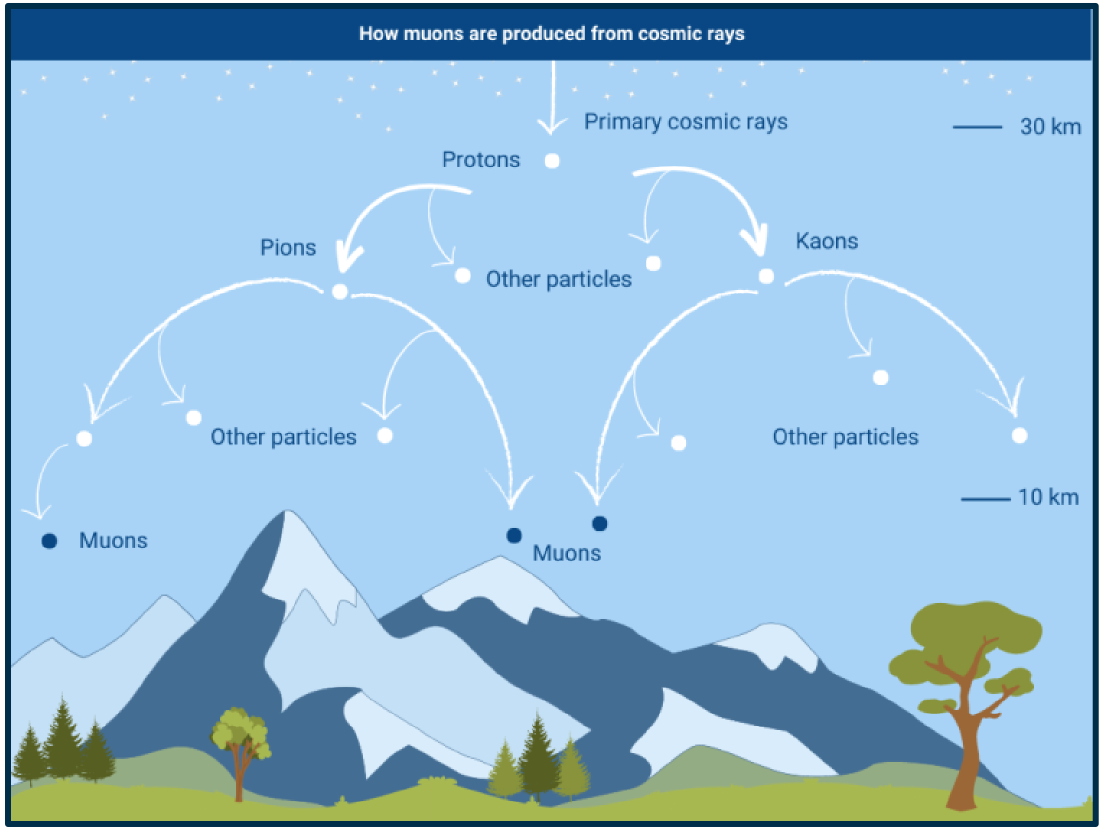
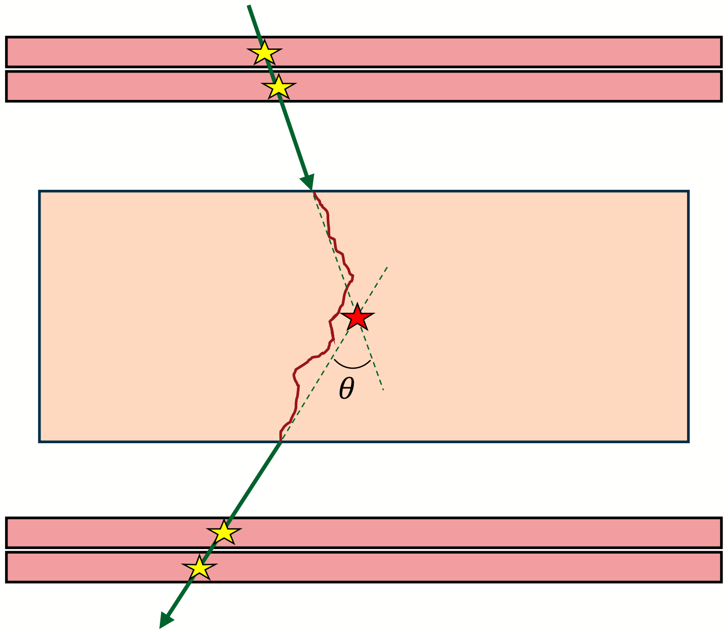
# What is Muography?

- Muons are produced from the interaction of high energy **cosmic rays** and atomic nuclei in the upper atmosphere.
- They are **highly penetrating** **(~4GeV/c)**.
- However, a relatively **low flux** $(\mathbf{1cm^{-2}min^{-1}})$.
- Primary interaction is Coulomb scattering – common detectors are Emulsion Plates, gas detectors or **scintillators**.



# Limitations of Muography

We will be utilising muon scattering tomography, as opposed to absorption radiography.

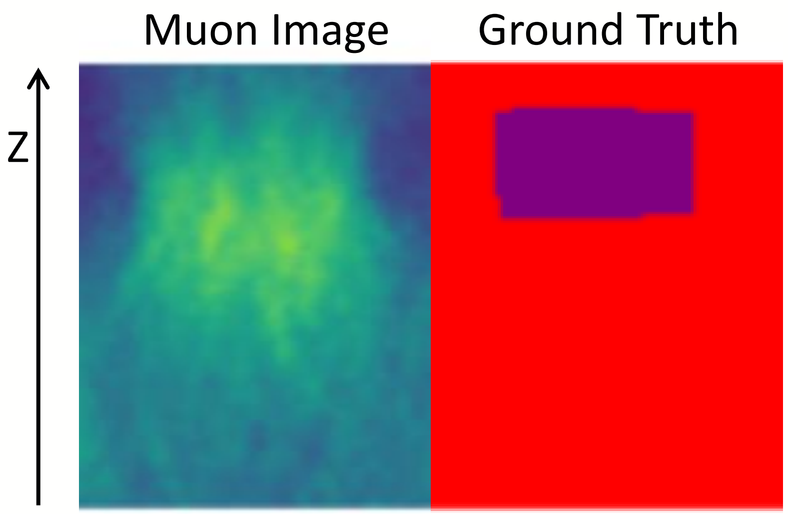



## 1. Muon imaging time

- Relies on a low **natural** muon flux.
- **Multiple scattering** makes it hard to model the muon path.
- Thus, requires high statistics - so images can take **days to months** to give reliable results.

## 2. Z-plane smearing

- Objects **'smear'** in the direction perpendicular to the detector plane, creating **shadows or artefacts**.
- Limited **angular acceptance** ($\pm 30°$) and **inverse imaging problem** greatly reduce z resolution.



# 2. WHY USE MACHINE LEARNING?

# Why Use Machine Learning?

- **Interpretability:** Humans are limited visually and cognitively for pattern interpretation, when compared to an ML model.

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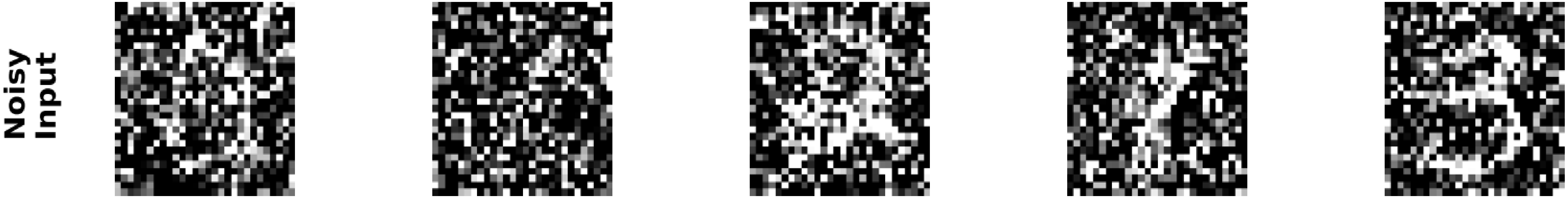
- **To what confidence can you correctly label these five noisy MNIST images (digits 0-9)?**



# Why Use Machine Learning?

- **Interpretability:** Humans are limited visually and cognitively for pattern interpretation, when compared to an ML model.

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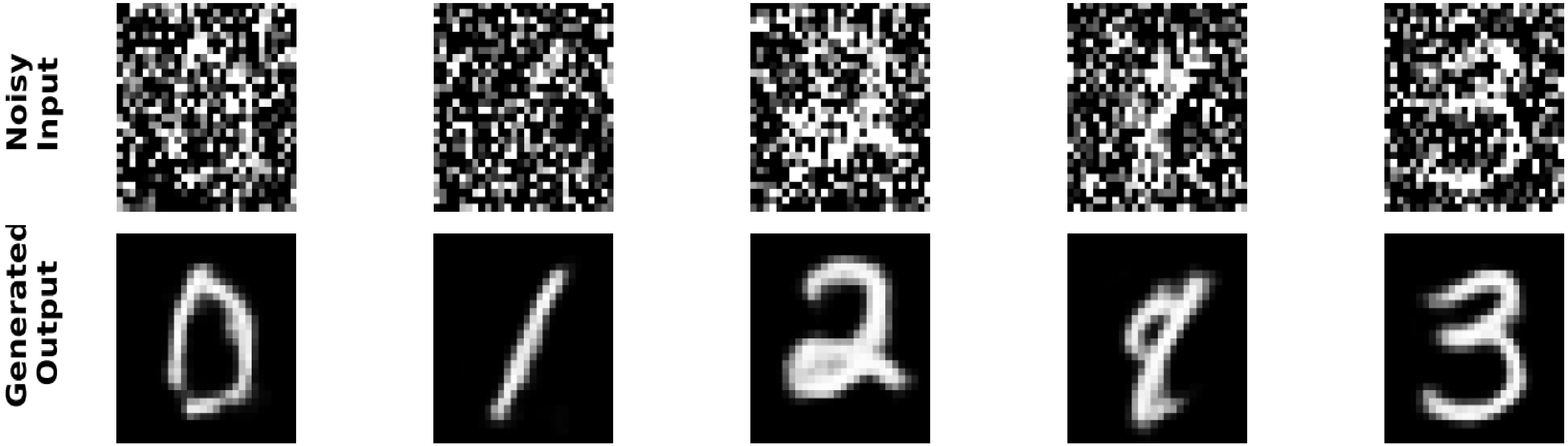
- **This is how a simple model (U-Net) performed at a denoising task:**



# Why Use Machine Learning?

- **Interpretability:** Humans are limited visually and cognitively for pattern interpretation, when compared to an ML model.

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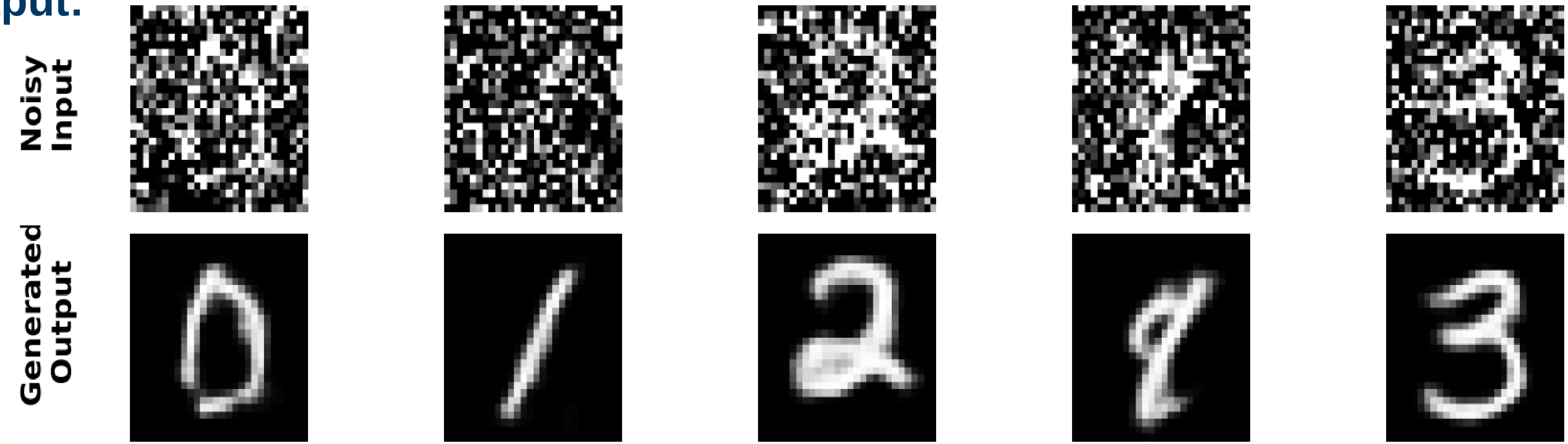
- **This is how a Bayesian classifier (ensemble of models) interpreted the denoised output:**




| | | | | | |
|---|---|---|---|---|---|
| **Label** | 0 | 1 | 2 | 8 | 3 |
| **Confidence** | 97.6 % | 99.9 % | 99.8 % | 52.3 % | 98.7 % |

# Why Use Machine Learning?

- **Interpretability:** Humans are limited visually and cognitively for pattern interpretation, when compared to an ML model.

---

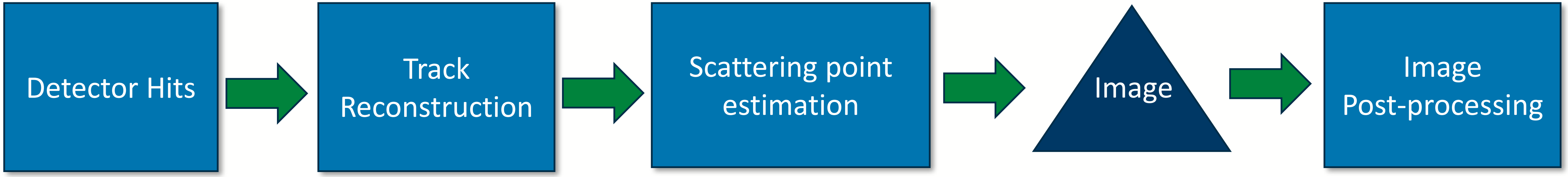
- **And the Ground truth:**

**Ground Truth**

**Generated Output**

| **Label** | 0 | 1 | 2 | 8 | 3 |
|---|---|---|---|---|---|
| **Confidence** | 97.6 % | 99.9 % | 99.8 % | 52.3 % | 98.7 % |

# Why Use Machine Learning?




- We are choosing to focus on ML for image post-processing.
- This allows for **abstract feature learning**, improving the perception and visualisation of images (as with MNIST example).
- We can use ML to perform:
  - **Up-sampling: reducing long imaging times.**
  - **Segmentation: reducing smearing effects.**

# 3. CURRENT WORK

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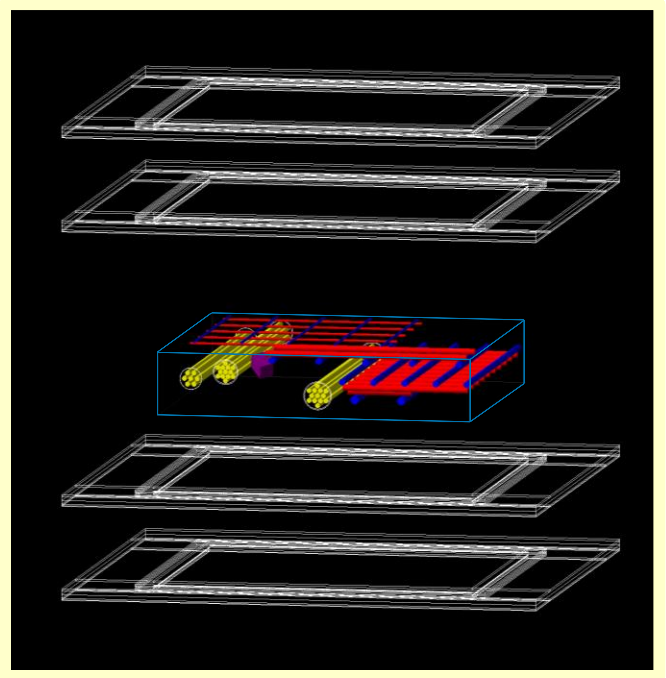
# Creating a Dataset

- For a **supervised** task, we need inputs matched with ground truth labels.
- Due to the long sampling times, and volume of data required, we cannot rely on real data.
- We instead use muography data from physics simulations for ML model training.

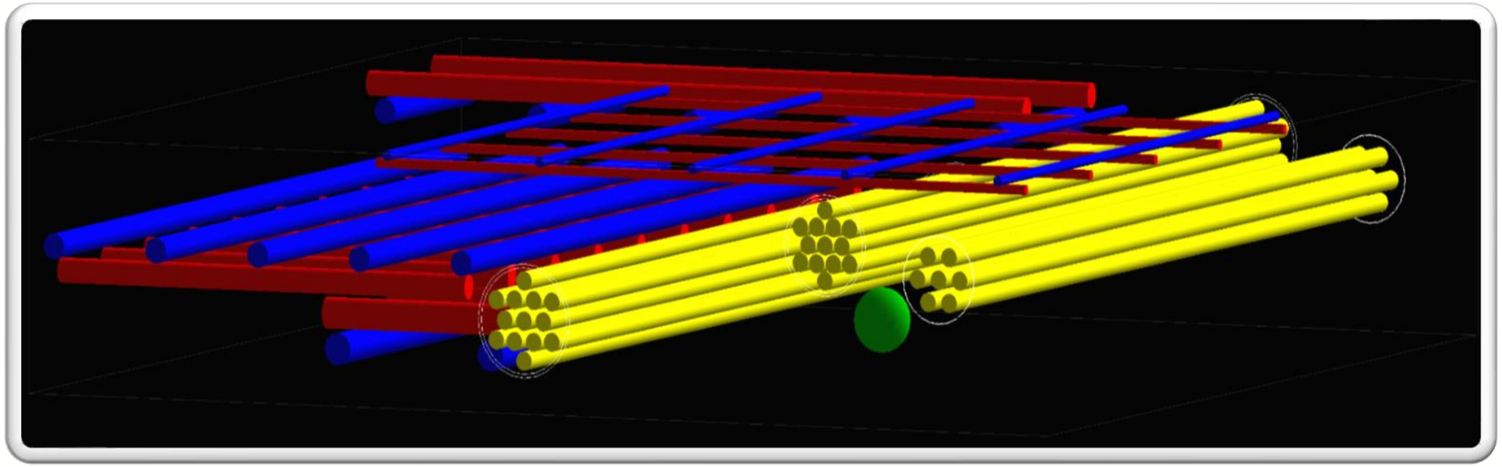



**Simulation Specs:**
- **Framework:** Geant4 with Ecomug.
- **Detector:** Lynkeos Muon Imaging System (MIS).
- **Block Dimensions:** 1m x 1m x 0.2m.
- **Sampling time:** 100 days ($14.4 \times 10^6$ muons/day).
- Image reconstruction using point of closest approach (PoCA).

# Creating a Dataset

<u>**Geometry Contents:**</u>

- 500 unique geometry configurations.
- **Rebar Grids**: 1-4 per volume, placed in XY plane.
- **Tendon Ducts:** 0-3 per volume, spanning along XZ or YZ planes.
- **Air voids:** 0-3 per volume, spherical.
- **'Unknowns':** 0-2 per volume, random shape and density.



- Dataset Diversity:
  - Randomise number of objects
  - Randomise placement.
  - Randomise geometric characteristics of objects.
- **Muon hits are gathered, scattering angles calculated, then volume is voxelised.**

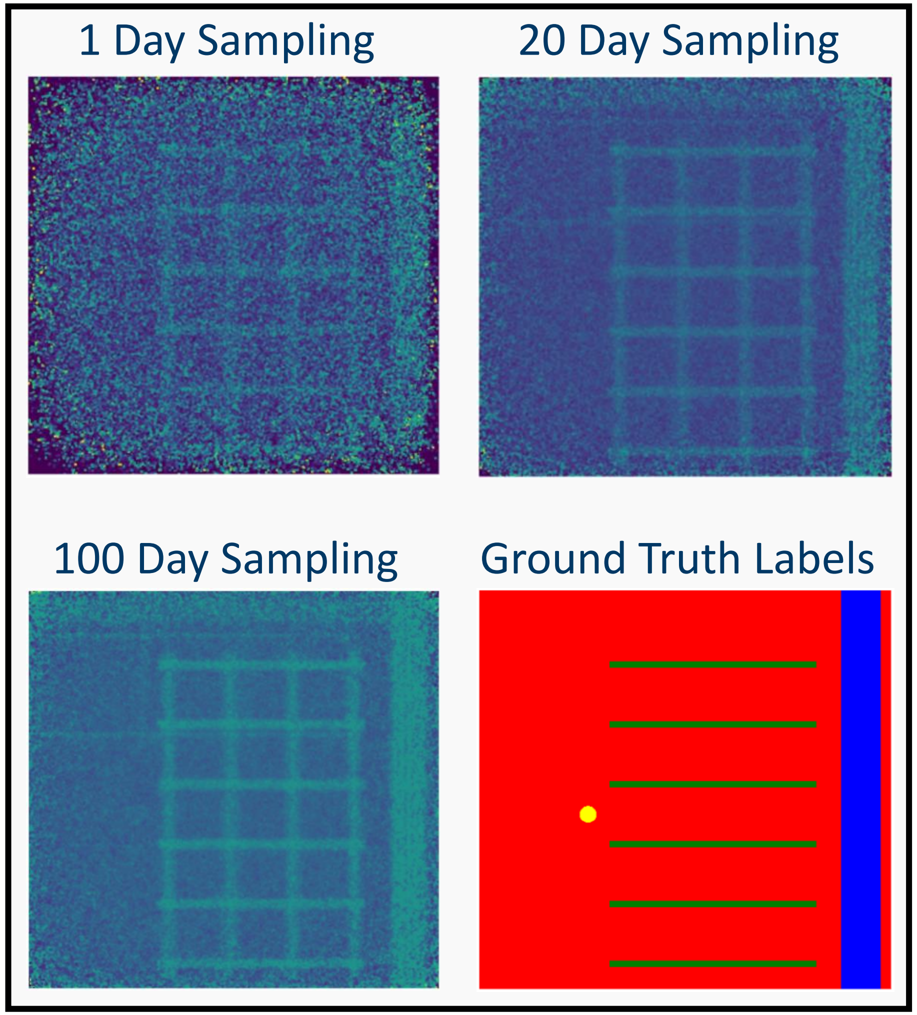
# Creating a Dataset

- 2D Image resolution (XY plane): 500x500 pixels, 2mm

- **Model Inputs:**
  - 100 image slices from each geometry.
  - Each slice has 100 different versions with a different sampling rate (increments of 1 day).
  - Input sampling rates are randomly sampled at each epoch for model generalisation.

- **Image Up-Sampling Ground Truths**:
  - Use the highest available sampling rate: 100 days

- **Segmentation Ground Truths:**
  - Produced directly from the Geant4 geometries, sliced up to produce a ground truth for each geometry slice.
  - One-hot encoded for model training.



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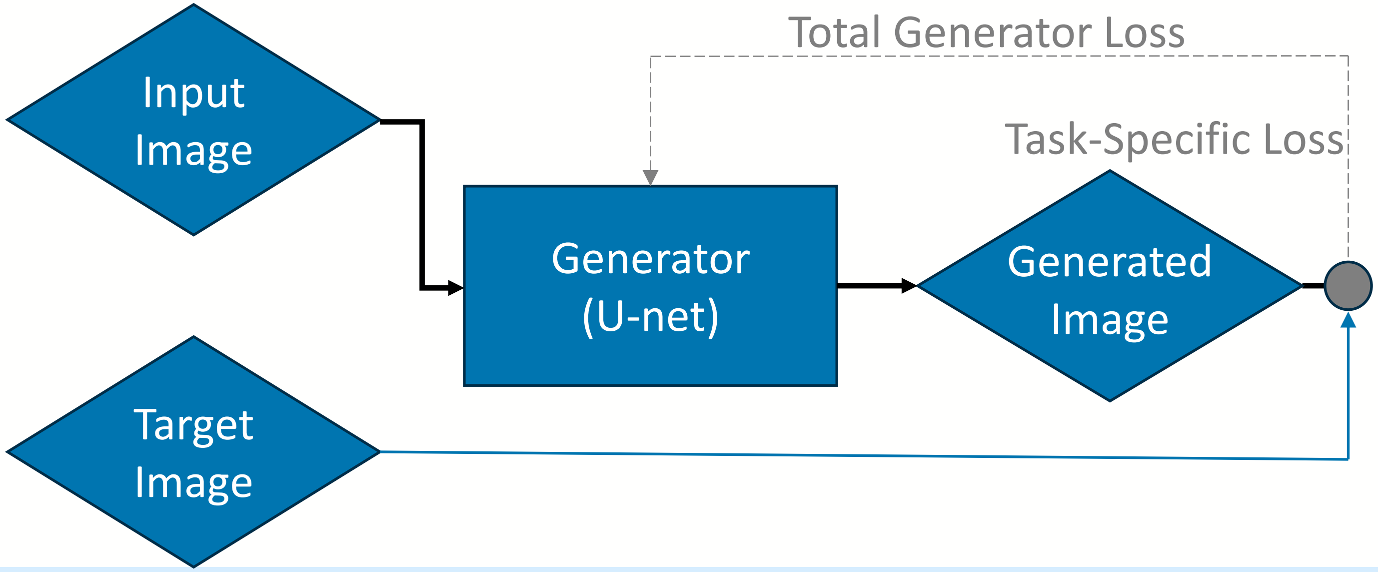
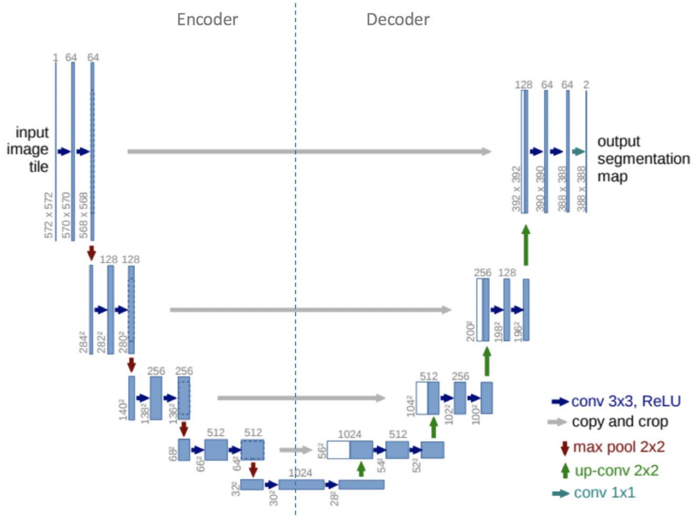
# The Conditional GAN (cGAN)

- cGANs are the supervised version of the GAN (conditioned on an input).
- Contain two parts: **generator** and **discriminator**.
- **Adversarial process**: compete until Nash equilibrium is reached.
- The model used is heavily based on the pix2pix architecture [2].

[2] https://phillipi.github.io/pix2pix/



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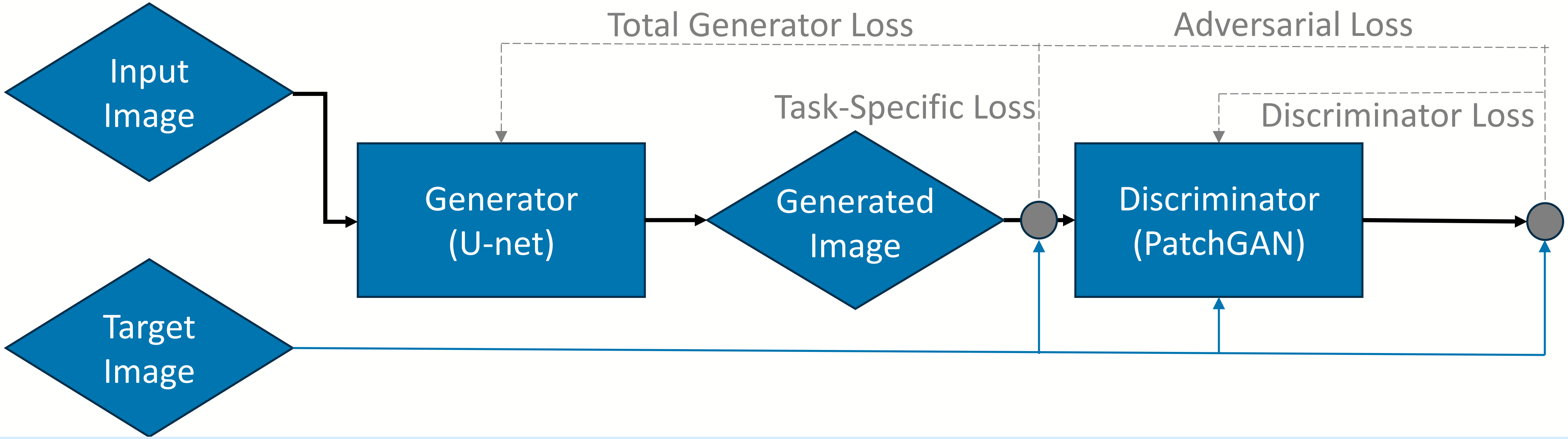
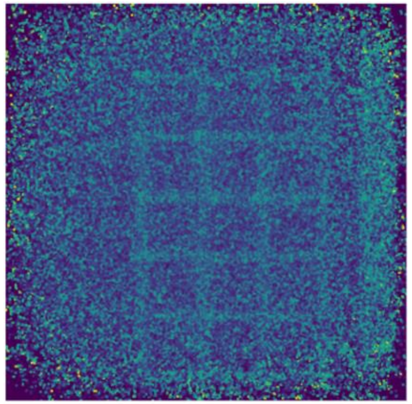


# Task 1: Image to Image Up-Sampling

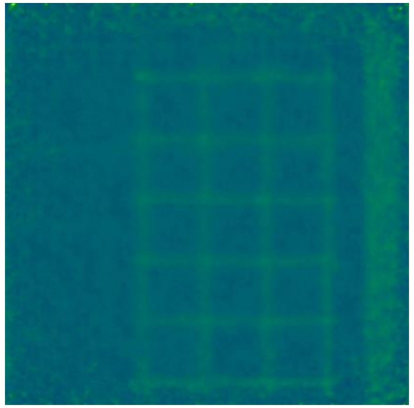
**Model:**
- pix2pix cGAN architecture: **U-Net** generator, **PatchGAN** discriminator.
- Based on the open-source **pix2pix** [2] architecture.
- **Optimiser**: ADAM
- **Loss functions**: MAE (generator), MSE (discriminator).

[2] https://phillipi.github.io/pix2pix/

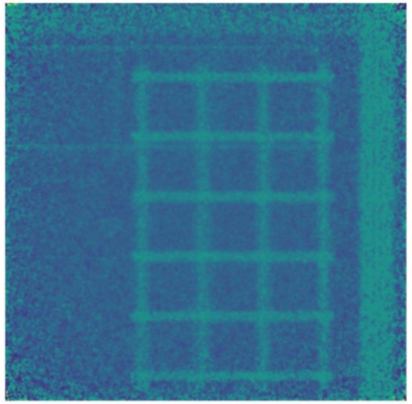
Input:
1 Day Sampling



Output:
Up-Sampled Image



Reference Truth:
100 Day Sampling

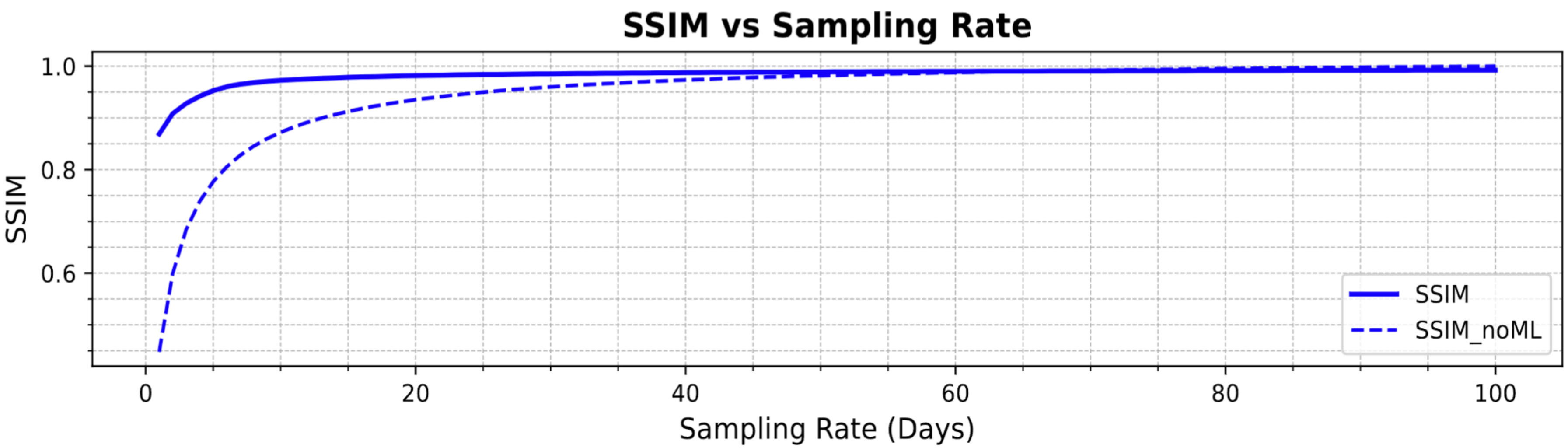


# Preliminary Results: Up-Sampling

- Up-sampling **works well up to a ~60-day** sampling rate, after which the input images perform better.
- Up-sampled images should ideally perform no worse than input images.
- However, these metrics don't capture the full picture.
- Image segmentation can help better understand feature representation.

Structural Similarity Index Measure (SSIM) assesses:

- Luminance
- Contrast
- Structure



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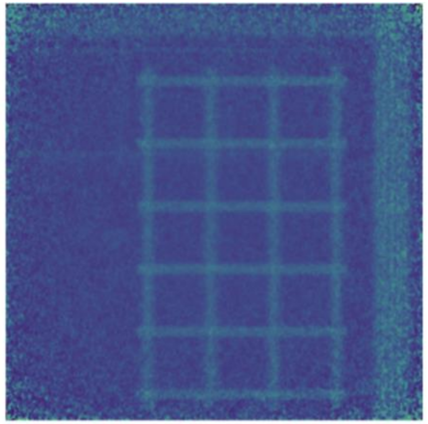
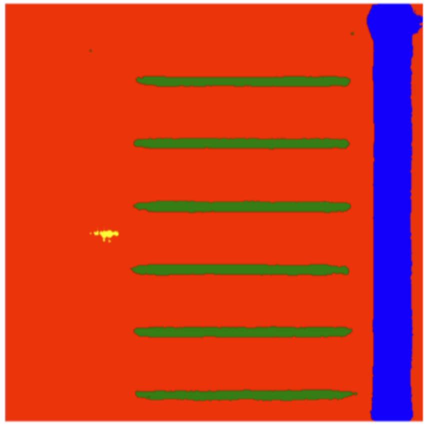
# Task 2: Image Segmentation

- Performed on the **highest sampling** (100-day data), for development.
- Utilises the ground truth geometries from our simulation setup.
- **X-Y plane segmentation** – no z-information.
- Labels: concrete, rebar, ducts, voids, unknowns.
- Model: Same as up-sampling model, using DICE and cross-entropy losses.

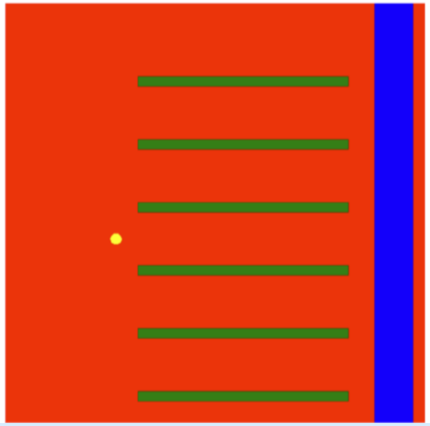
Input: 100 Day Muon Image



Output: Segmentation Map



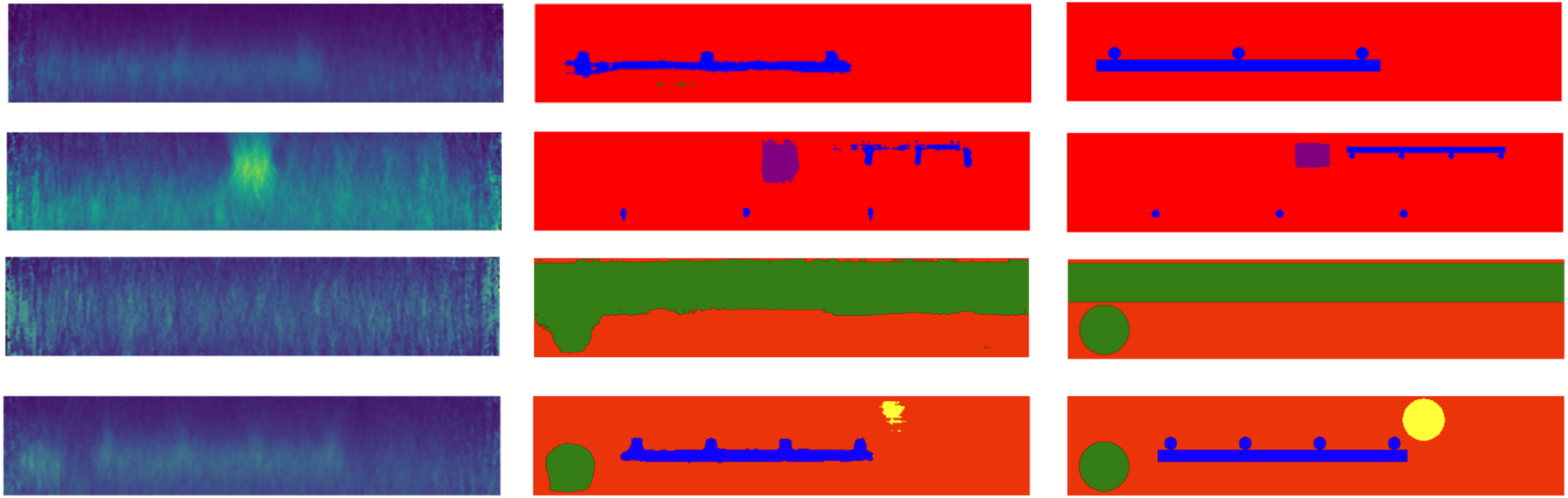
Reference: Ground Truth



# Preliminary Results: Segmentation

- Let's look at z-plane discrimination by stacking our XY slices to create a volume, then looking side-on (500x100 pixels).

**XZ Muon Slices** | **XZ Output Segmentation Maps** | **XZ Truth Segmentation Maps**



Segmentation Key: Blue = Rebar Grid, Green = Tendon Duct, Yellow = Air Void, Purple = Unknown (Lead Block)

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# Preliminary Results: Segmentation

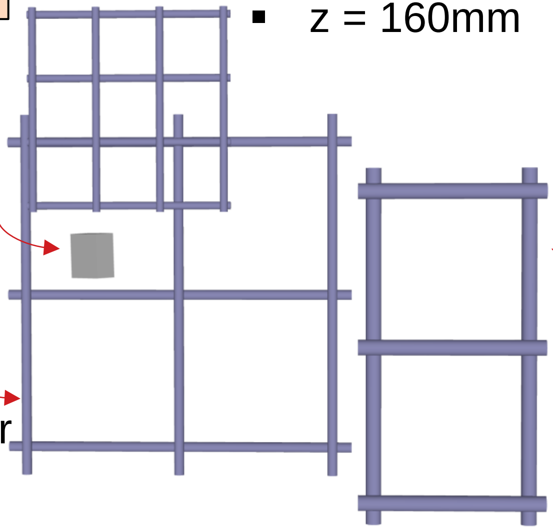
**Ground Truth**

Rebar Grid 1:
- 12 mm Diameter
- z = 160mm

Lead Block
- z = 145 mm

Rebar Grid 2:
- 25 mm Diameter
- z = 85 mm

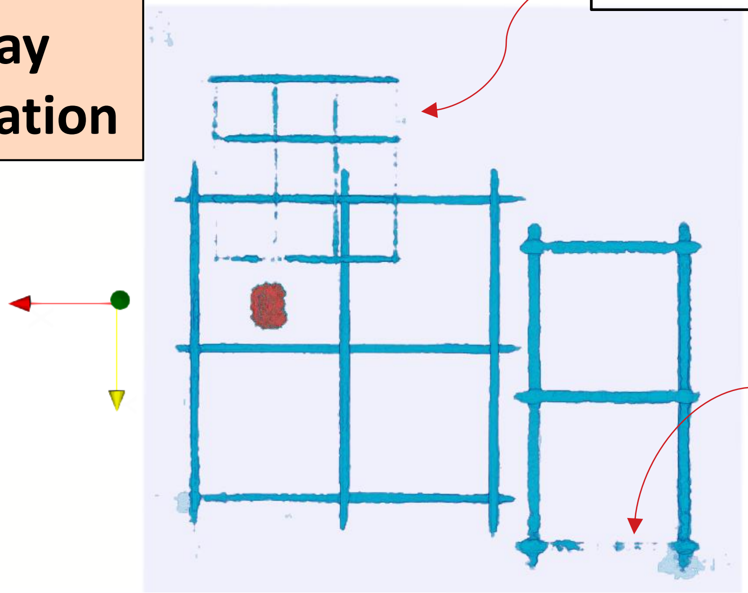
Rebar Grid 3:
- 16 mm Diameter
- z = 54 mm

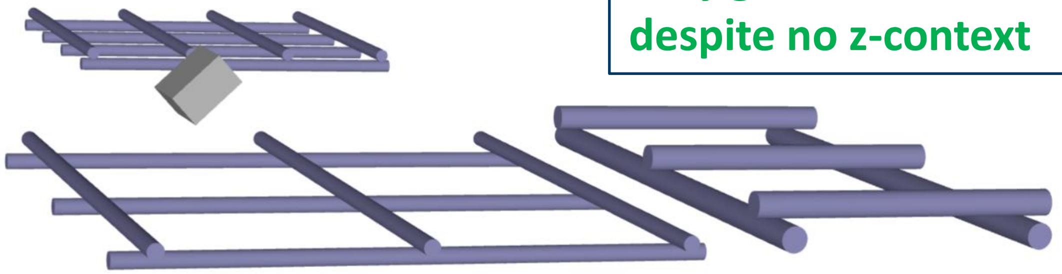


**100-Day Segmentation**

Thinner rebar is patchy

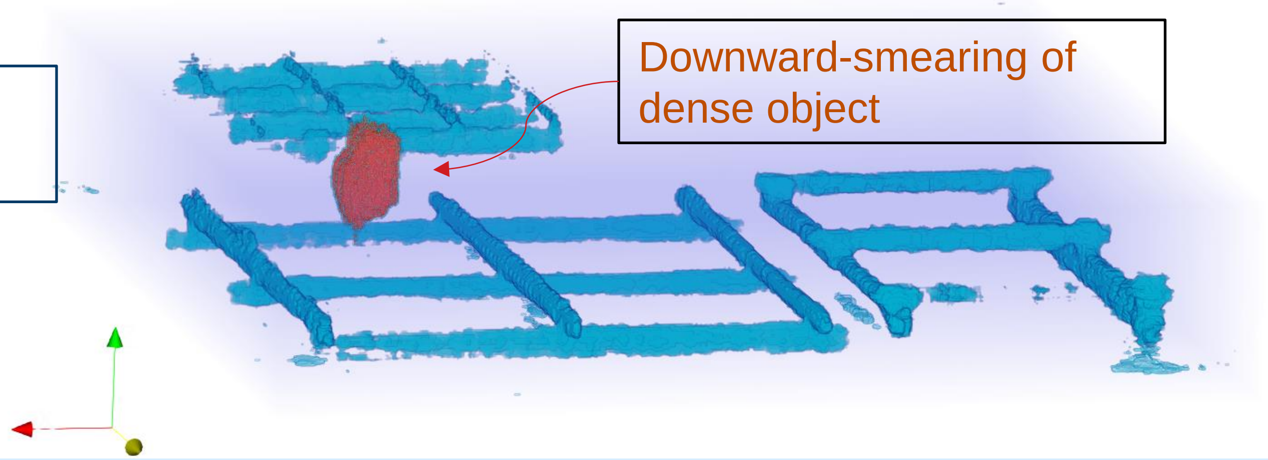
Rebar near edges is patchy





**Very good z-resolution, despite no z-context**

Downward-smearing of dense object



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# Preliminary Results: Segmentation

## Ground Truth

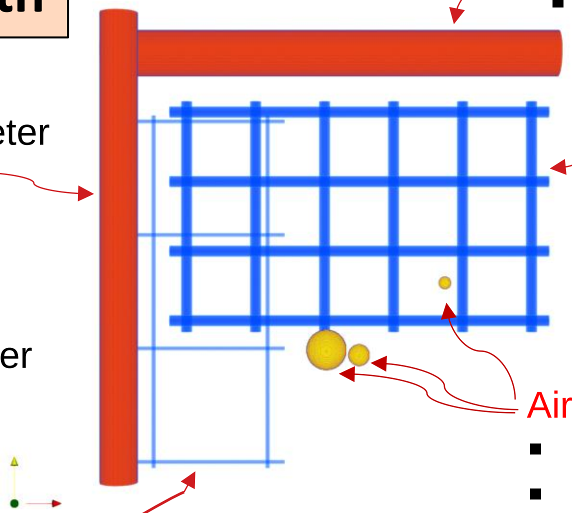
Duct 1:
- 80 mm Diameter
- z = 53 mm

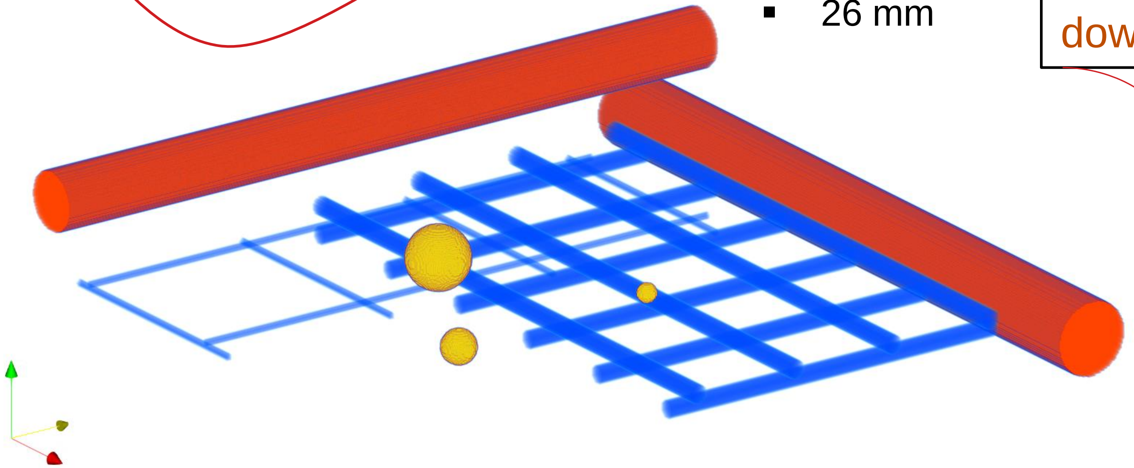
Duct 2:
- 100 mm Diameter
- z = 75mm

Rebar Grid 1:
- 25 mm Diameter
- z = 107 mm

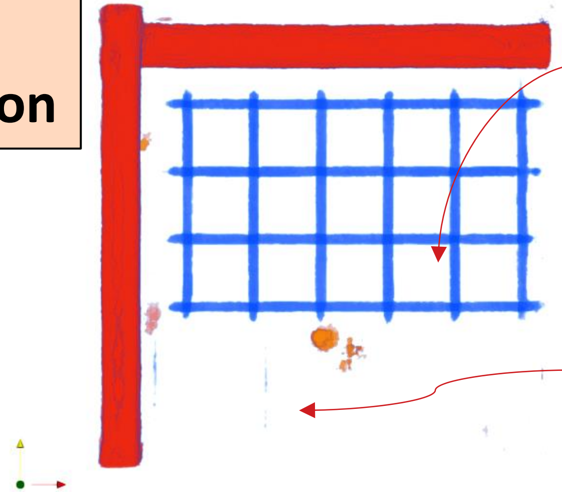
Rebar Grid 2:
- 10 mm Diameter
- z = 152 mm

Air Voids (diameter):
- 84 mm
- 47 mm
- 26 mm



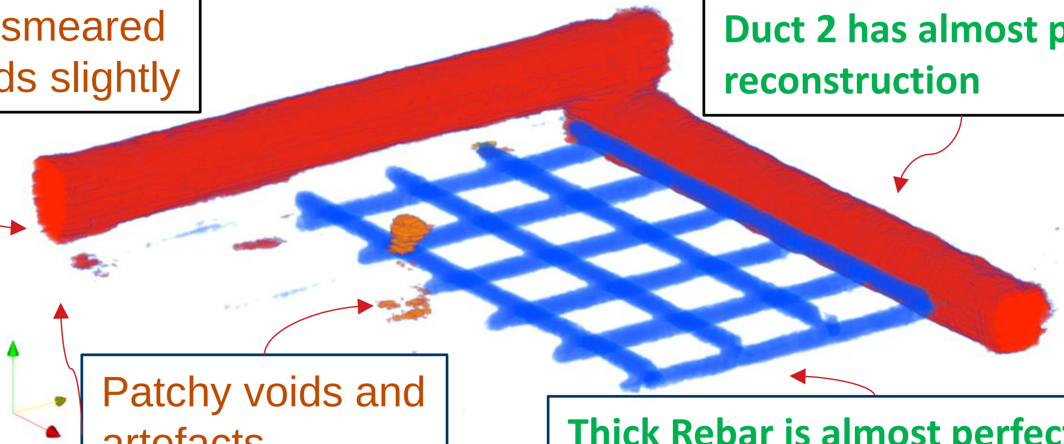


## 100-Day Segmentation



Smallest void non-existent

Thin bottom rebar is almost non-existent



Duct 1 is smeared downwards slightly

Duct 2 has almost perfect reconstruction

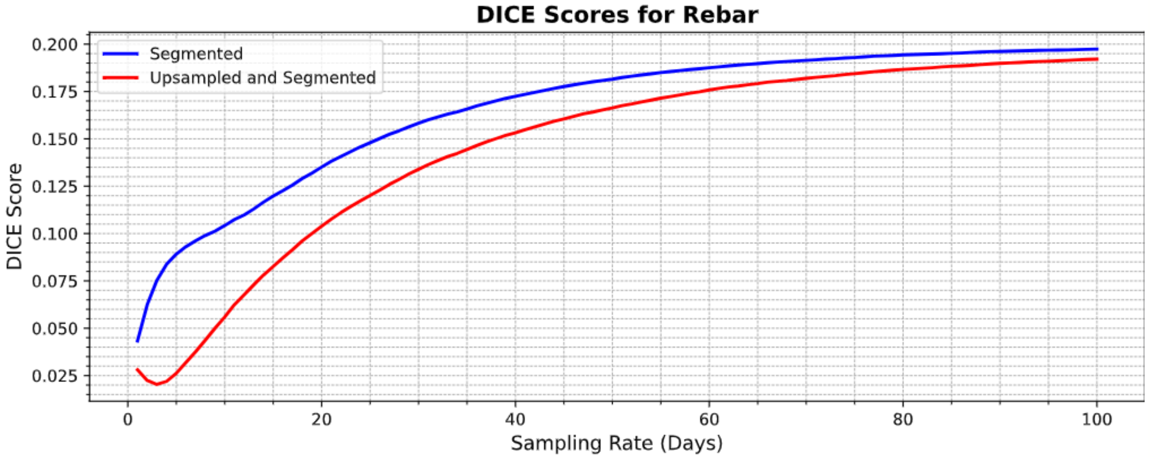
Patchy voids and artefacts

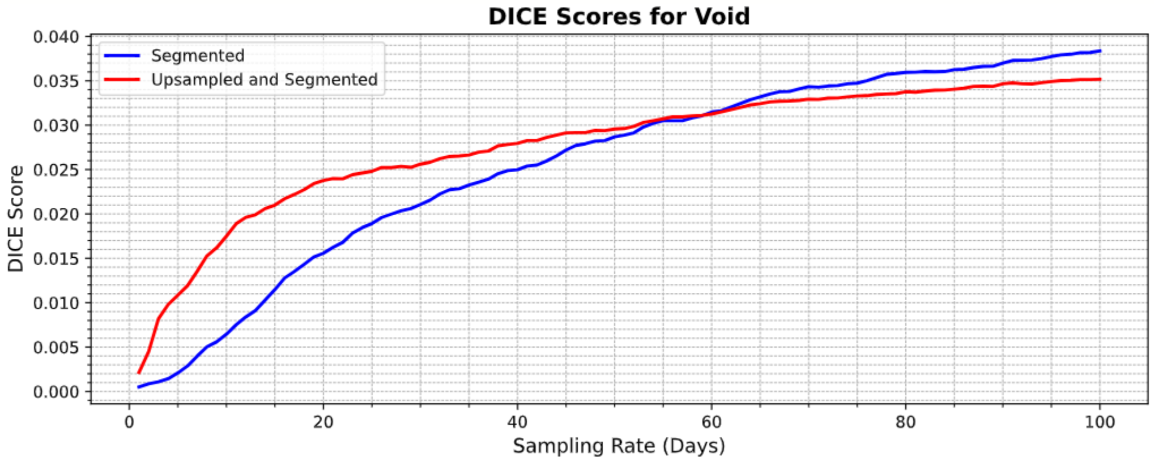
Thick Rebar is almost perfectly reconstructed

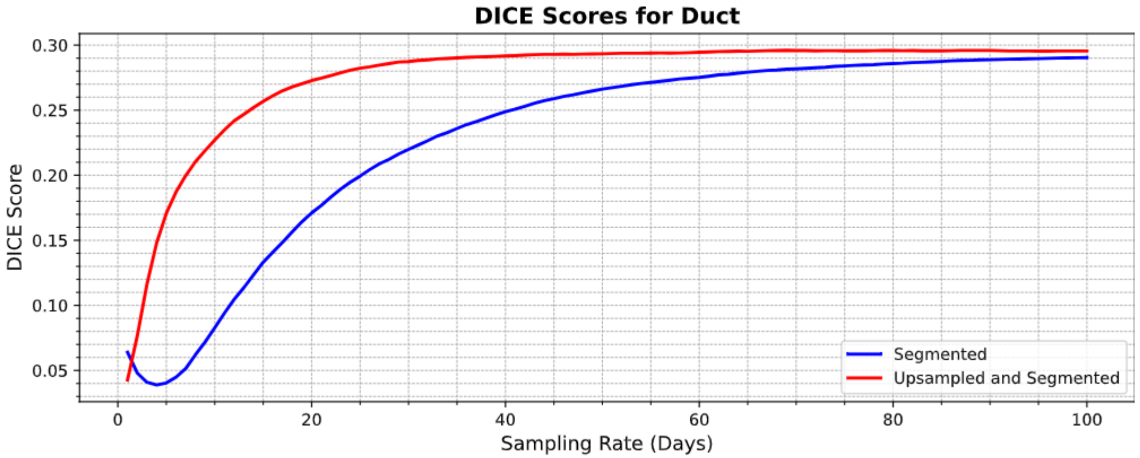
# Preliminary Results: Up-sampling and Segmentation

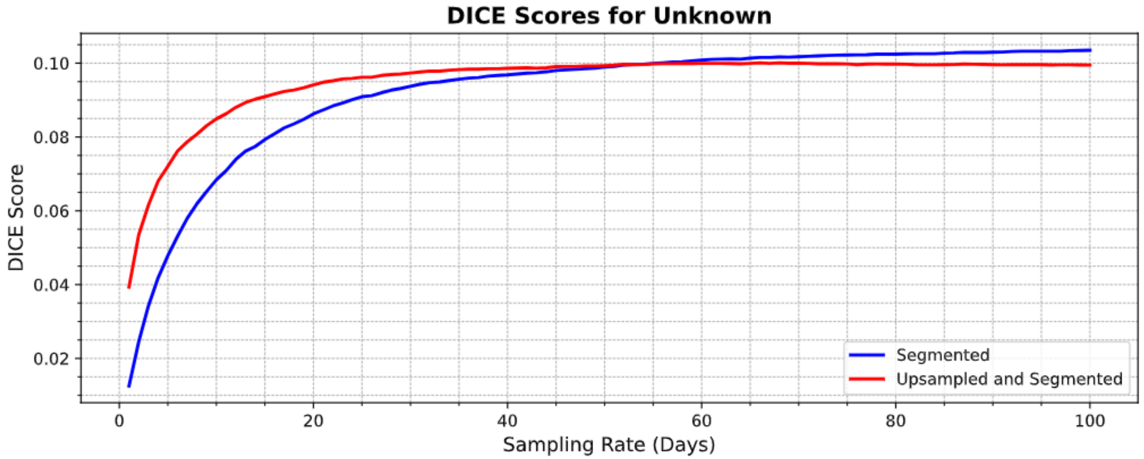
$$\text{Dice}_i = \frac{2 \times \text{TP}_i}{2 \times \text{TP}_i + \text{FP}_i + \text{FN}_i}$$

- Performs well when classes are unbalanced.
- Dice coefficient ranges from 0 (bad) to 1 (good).



# 4. FUTURE WORK/CONCLUSIONS

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# Future Work

## 1. Model Optimisation

- Model is in early stages and requires development for reliable reconstruction of all materials.
- Move towards models that increase context size: **global** context, **3D** context.
- Optimisation of method (do we up-sample, then segment – or do we make one model for end-to-end).

## 2. Defect Segmentation Task

Primary goal is to perform defect segmentation. Defects include:

- ➢ Rebar corrosion.
- ➢ Voids, honeycombing and cracks in concrete.
- ➢ Tendon duct: strand placement/corrosion, air spaces.

## 3. Model Generalisation

- Assessing models on real datasets.
- Non-ideal object placement.
- Handling of different detector orientations.
- Handling of a variety of detector spacings.

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# Conclusion

**Problem:**

- A new technique is **urgently** required for high resolution NDT of built infrastructure.
- **Muography** can be used to do this but suffers from **long imaging times** and z-plane **smearing.**

**Solution:**

- We can use ML techniques to **limit imaging times** through up-sampling and **reducing smearing effects** with segmentation.
- *Preliminary results* show that these techniques can be successfully applied to muon scans.

**Moving Forward:**

- Further **model optimisation** and experimentation will aim to **improve the reliability** of current ML outputs.
- We ultimately aim to be able to identify the **minimum time required** to scan a given volume, whilst maintaining accuracy in **defect classification**.

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# Thanks for Listening

**Additional thanks to my supervisors D. Mahon, G. Yang and S. Gardner, as well as E. Niederleithinger from BAM for their guidance and support.**

# Backups

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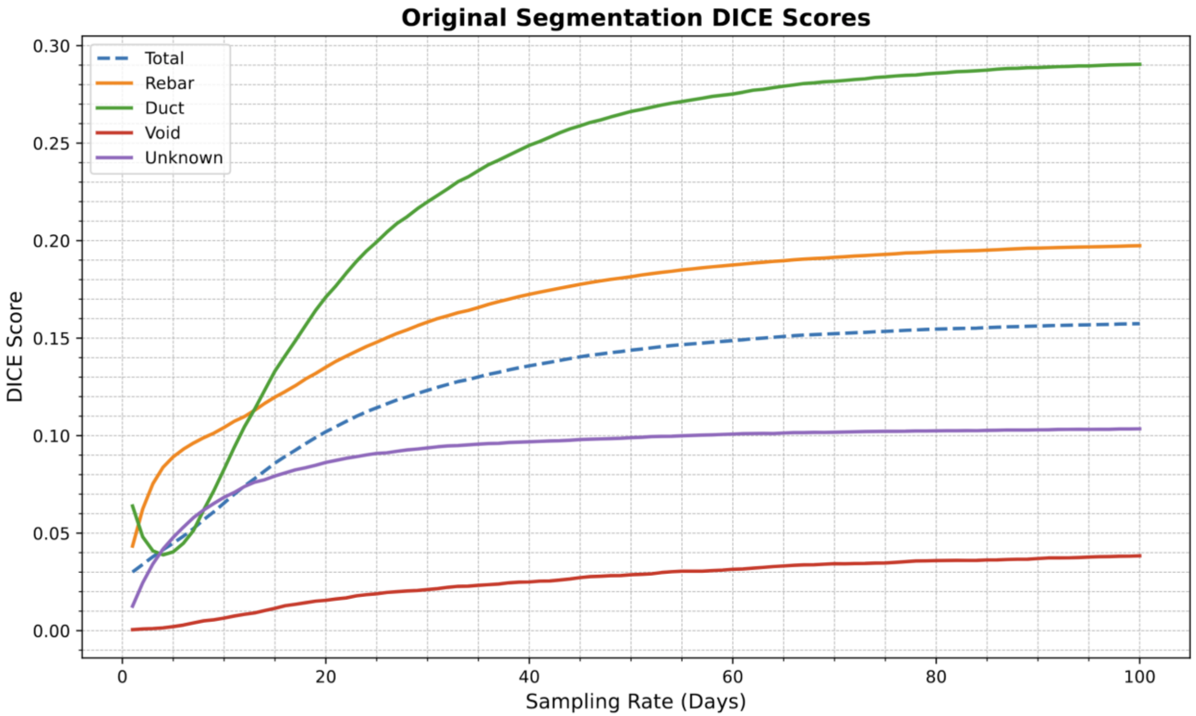
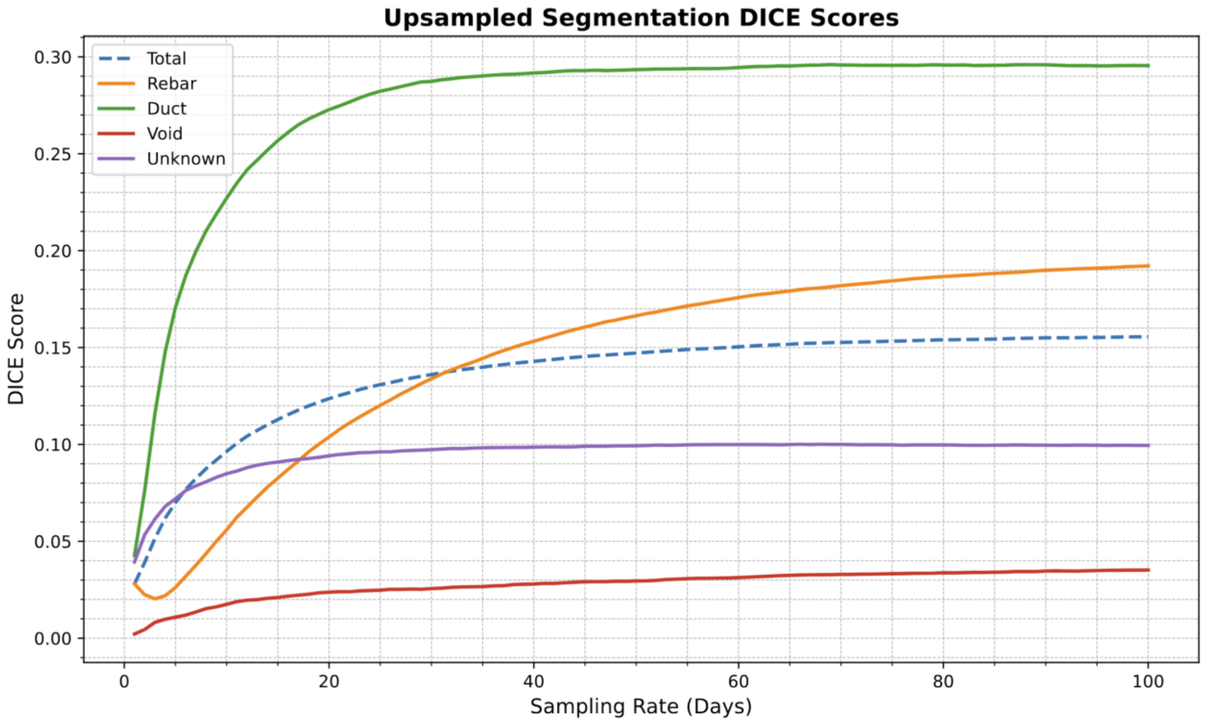
# Preliminary Results – Up-sampling and Segmentation



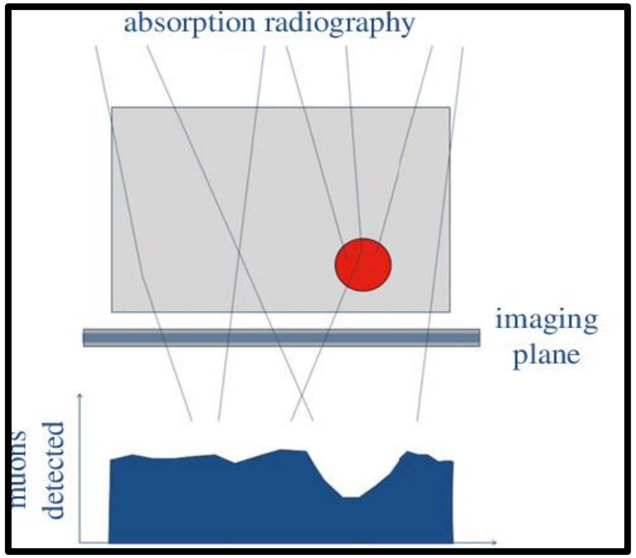



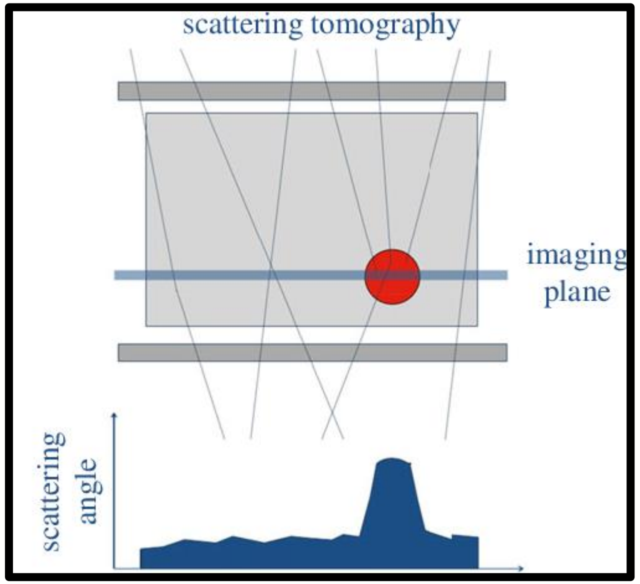
# What is Muography?

- **Absorption Radiography:**
  - Uses muon **attenuation** (stopping).
  - Two detector planes **behind** the object are required.

- **Scattering Tomography:**
  - Uses reconstructed **scattering angles** of muons.
  - Two detector planes **in front and behind** the object are required.

- This has been successfully applied to:
  - Nuclear waste characterization,
  - Border control,
  - Mining,
  - (and others).



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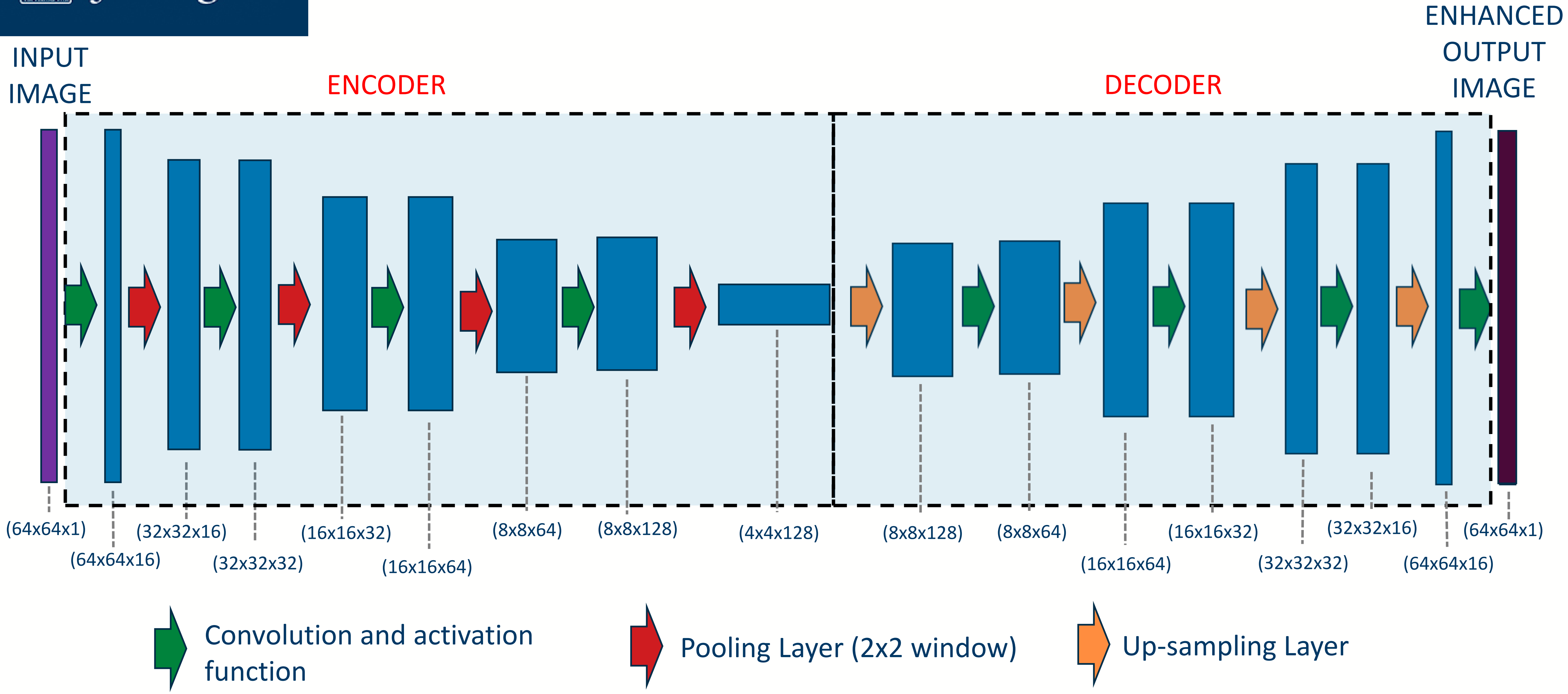
# CNN: Encoder-Decoder Architecture



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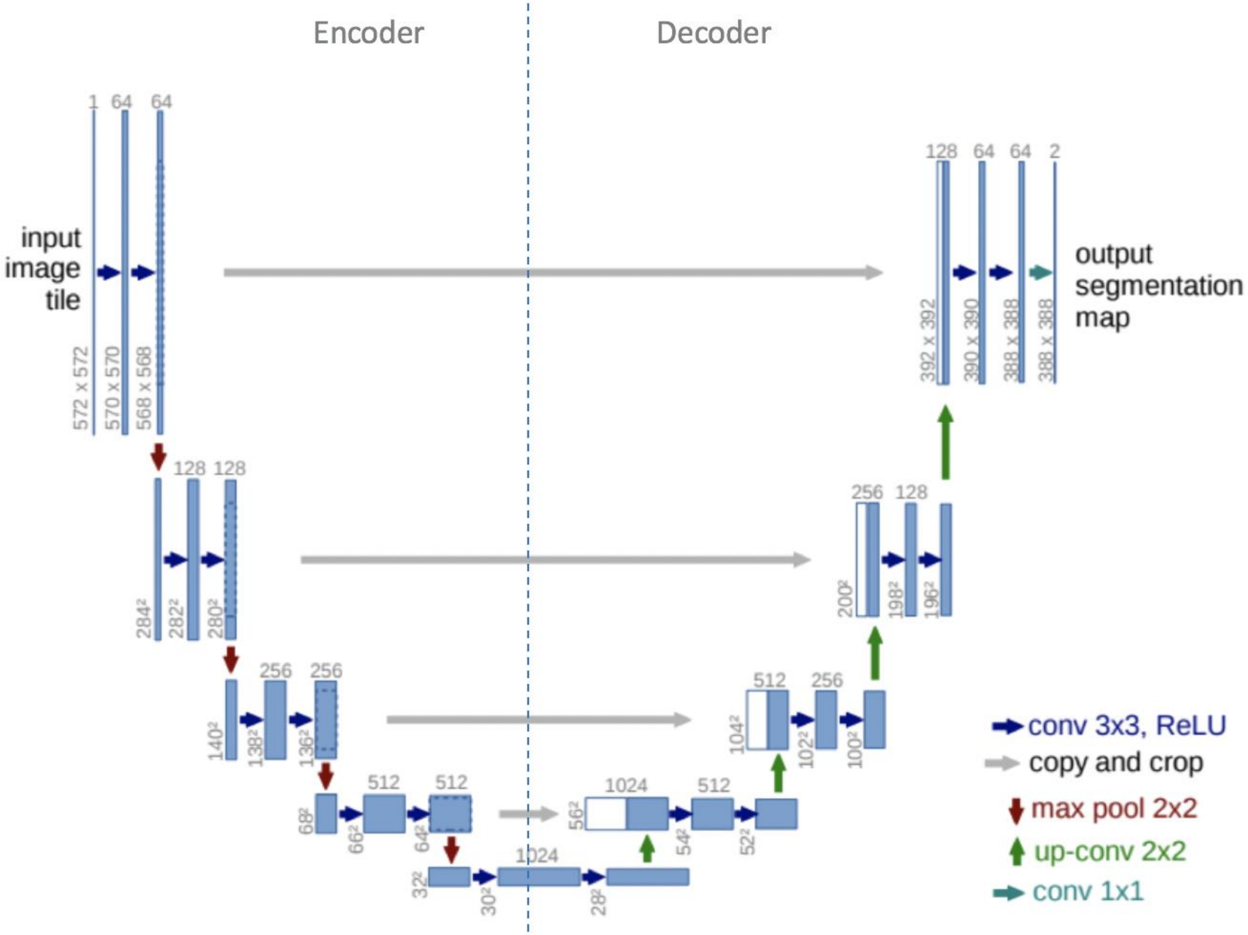
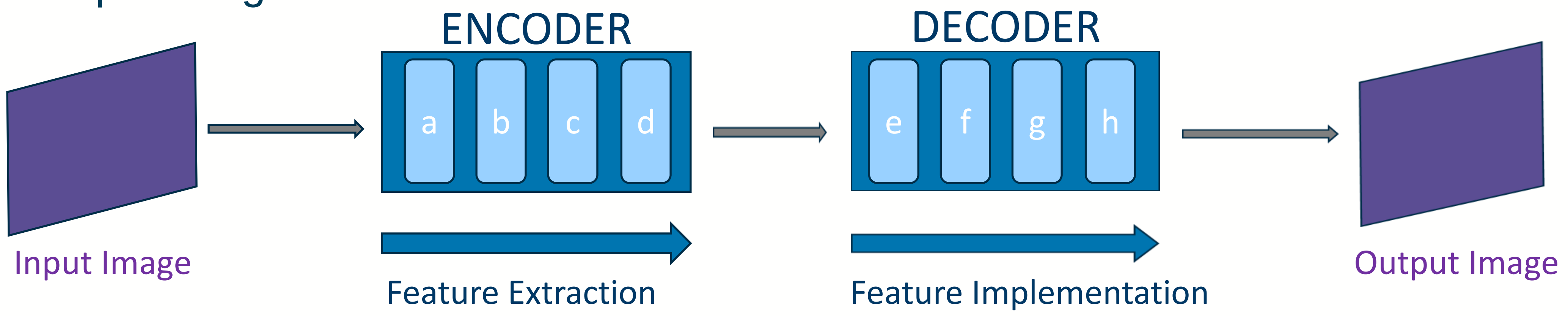
# U-Nets

- Standard encoder-decoder CNNs are lossy – lose information.
- Introduce 'skip connections' between layers in the encoder and decoder.
- Allows for uncaptured, minor details to be preserved while keeping model complexity low.
- U-Nets are widely used for I2I translation tasks, especially in medical imaging.



# Encoder-Decoder Architecture

- For image translation, we need to extract features from the input image and build them back into an output image.




- There are two main techniques for feature extraction in machine learning:
    - Convolutional layers – *Convolutional Neural Networks (CNNs)*
    - Attention blocks – *Vision Transformers (ViTs)*

- We will explore using the older, but well established CNNs.

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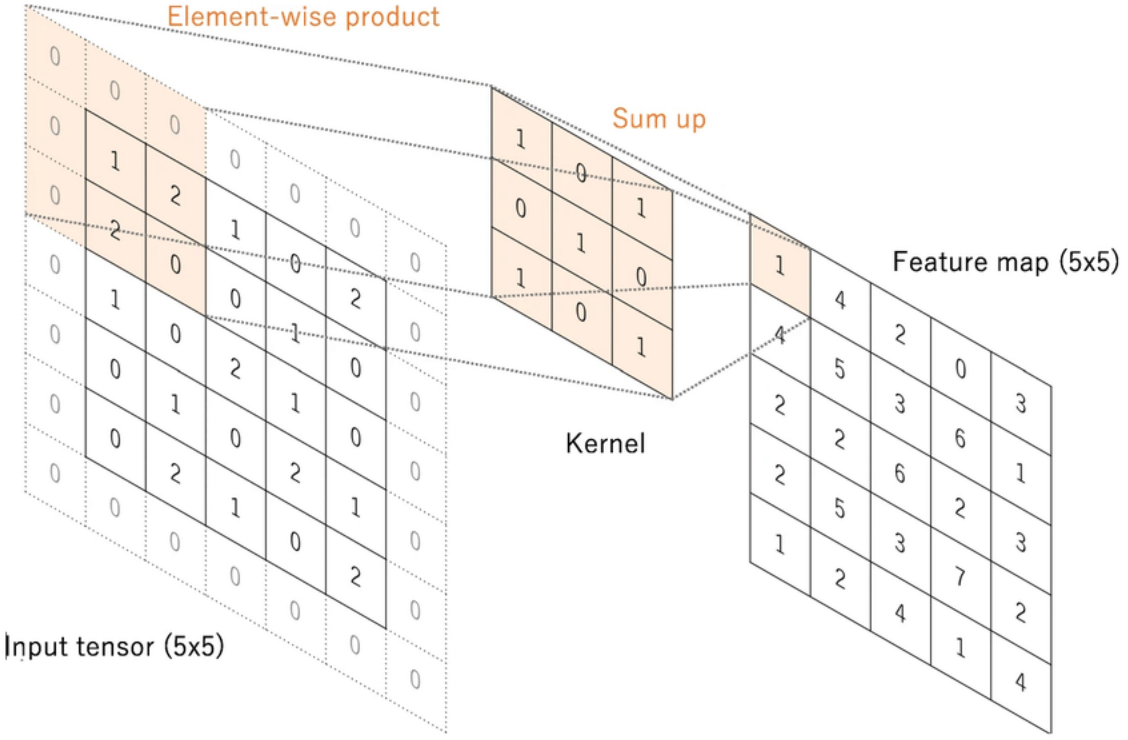
# Convolutional Feature Extraction

- Convolution operations have been used for image processing for a long time.
- The feature extracted from an input image depends on the kernel.
- Convolution of the input with a kernel produces a feature map.
- Many different kernels can be performed, each looking for different features and each producing a feature map.




$$= \sum_{i=1}^{3} \sum_{j=1}^{3} \begin{bmatrix} 0*1 & 0*0 & 0*1 \\ 0*0 & 1*1 & 2*0 \\ 0*1 & 2*0 & 0*1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} = 1$$

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# Convolution in CNNs

- CNNs however learn the kernels they use – allowing for complex task-specific learning.
- The learnable parameters in a CNN are the components of these kernels – each containing a set of weights ($w_{i,j}$) and a single bias term ($b$):

$$O_{i,j} = w_{i,j} \times I_{i,j} + b$$

- $I_{i,j}$ is the input (3x3 window of input)
- $w_{i,j}$ are the weights of the 3x3 kernel
- $b$ is the bias term
- $O_{i,j}$ is the 3x3 output of the element-wise product with bias.

9 params for one 3x3 kernel

| | | |
|---|---|---|
| $w_{0,0}$ | $w_{1,0}$ | $w_{2,0}$ |
| $w_{0,1}$ | $w_{1,1}$ | $w_{2,1}$ |
| $w_{0,2}$ | $w_{1,2}$ | $w_{2,2}$ |

$+ b$

# Convolution in CNNs

- As well as task-specific learning, CNNs also allow for complex hierarchical feature extraction using multiple layers.
  - – Top layers extract simple features such as edges.
  - – Deeper layers can extract complex features, combining information of the feature maps from the previous layer (e.g. boxes).