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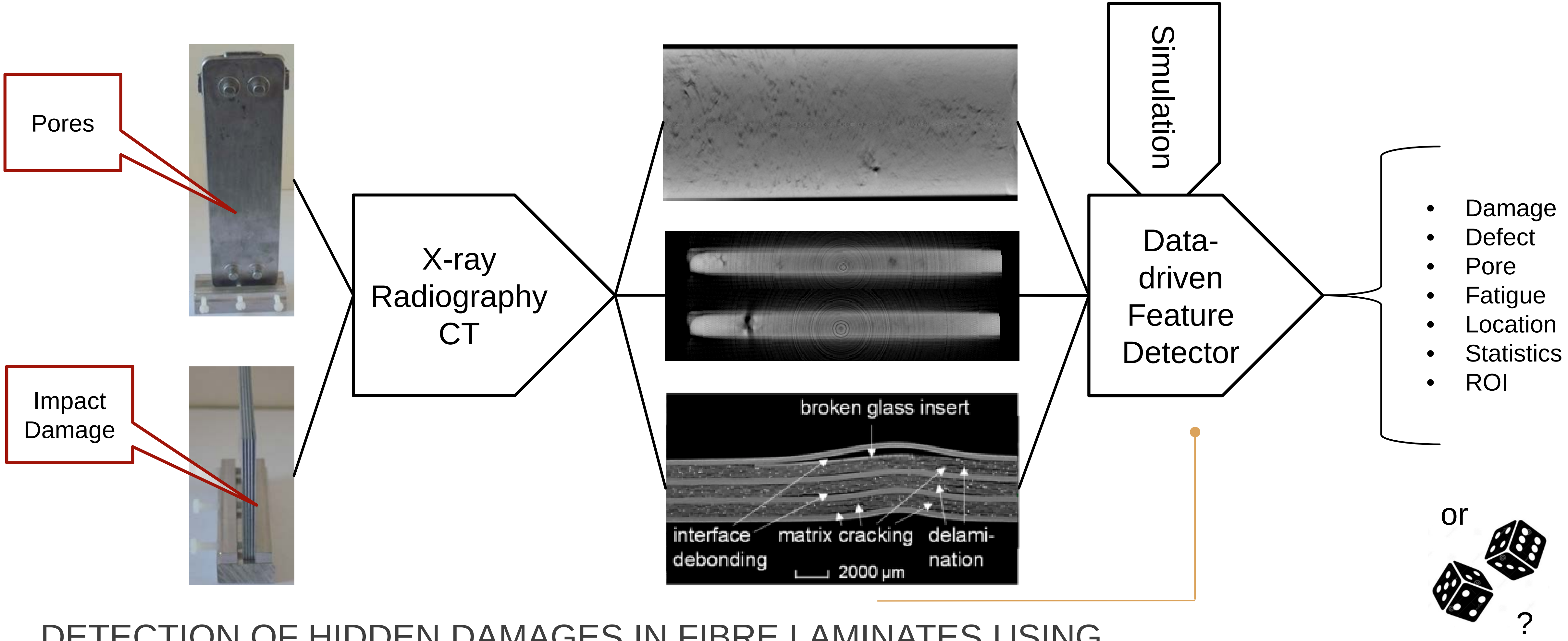


DETECTION OF HIDDEN DAMAGES IN FIBRE LAMINATES USING LOW-QUALITY TRANSMISSION X-RAY IMAGING, X-RAY DATA AUGMENTATION BY SIMULATION, AND MACHINE LEARNING

Stefan Bosse

FEMS Euromat 2023 - 07.09.2023

Universität Bremen

CONTENT

INTRODUCTION

- Spatially resolved Inspection and Testing of structures requires **image-based measuring methods**
- **Non-destructive testing** (NDT) of metal-based structures can exploit different imaging methods, mainly:
  - **X-ray** Radiography (single projection) and Computer Tomography (CT, multi-projection)
  - Guided **Ultrasonic Waves** (GUW) and Ultrasonic Sonography
- Homogeneous as well as Composite Materials can be tested, but reflection and diffraction can have a significant impact on image quality!
- **Detection of hidden damages, defects, and impurities (e.g., pores) is still a challenge**!

Primary Goal. Automated Damage, Defect, and Impurity Detection in materials and structures including composites using single X-ray projection images (from LowQ/MidQ devices) and data-driven feature marking models (Convolutional Neural Networks).

INTRODUCTION

Different specimens, structure geometries, materials, and defects are considered in this work! They pose different coincidence between material and image features.

1. **Homogeneous aluminum die casting plates (150x40 mm) with gas pore defects**
2. **Composite Fibre Metal Laminate plates (FML, aluminum and PREG layers, 50 x 50 mm) with impact damages posing layer delaminations, deformation, cracks, and kissing bond defects.**

Secondary Goal. Migration from laboratory (HighQ/MidQ) to in-field (LowQ) measuring techniques and devices.

INTRODUCTION

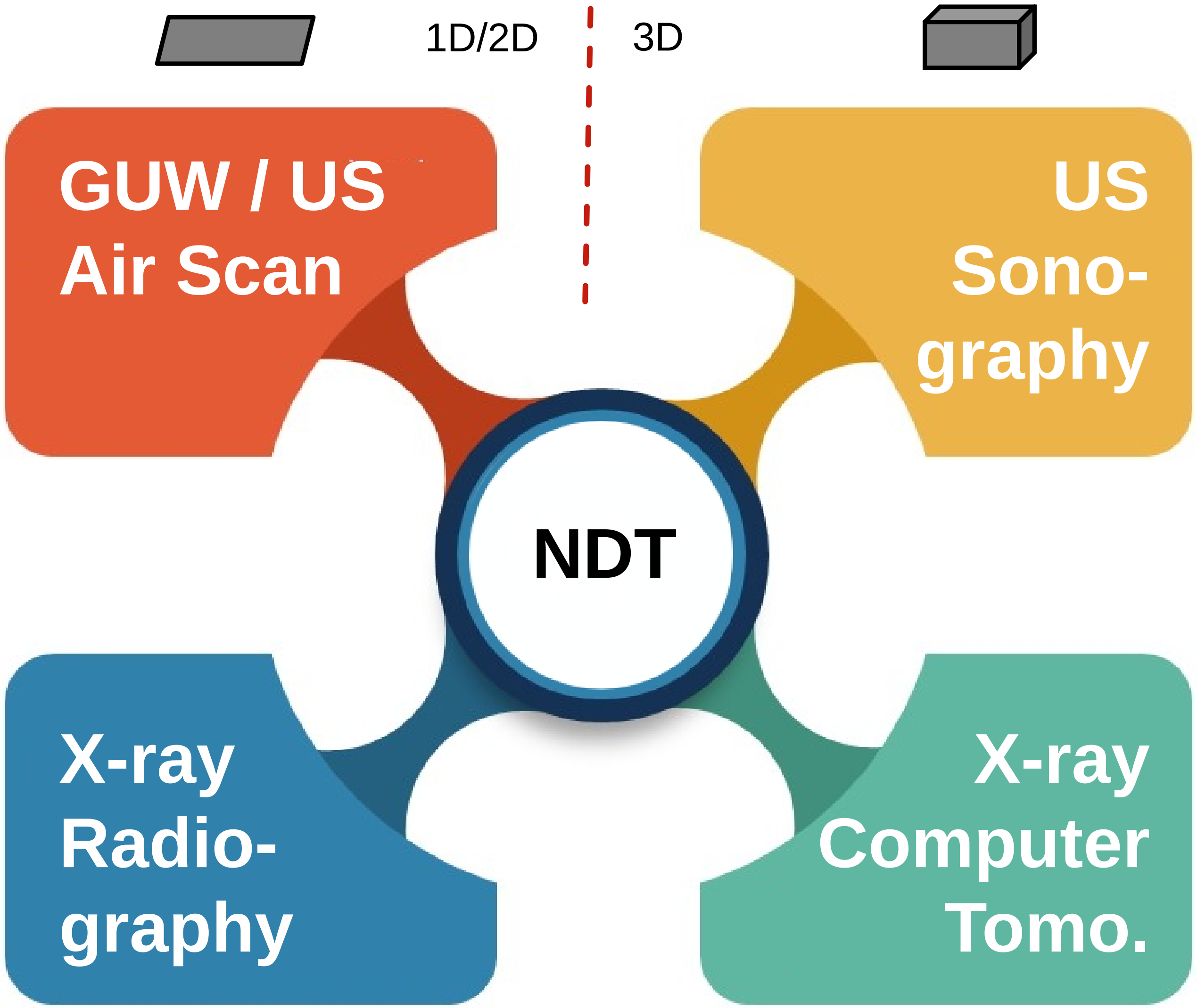
- Feature detection and marking in measuring images can occur on different levels:
  - **Region-of-Interest Search**
  - **Feature Maps**
  - **Damage and defect classification**
  - **Damage and defect localisation**
  - **Global statistical aggregates (e.g., pore density, distribution)**
- Either classical numerical and model-based algorithms (e.g., edge detection using a Soebel filter or Canny detectors) or data-driven models are used for feature marking („Machine Learning“)

Data-driven models require data! Data must contain a sufficient statistical variance and distribution of features to be detected. That‘s the first issue with most engineering data! Additionally, supervised data modelling requires accurately labelled strong feature examples, commonly not available, and being the second issue and downfall in data-driven modelling.

TAXONOMY OF NDT MEASURING TECHNIQUES

- Ultrasonic Wave Interaction: Material Density Variation
- Dispersion, Reflection, Mode Conversion

- X-ray Wave Interaction: Material Density Variation
- Transmission, Absorption



- Reflection
- Time-of-Flight
- Sonogram

- Transmission, Absorption
- Multiple Projections
- Reconstruction + Filtering

GUW/US VERSA X-RAY RADIOGRAPHY/CT

- X-ray images can be simulated with high accuracy with respect to real measured images[1]
- X-ray images enable direct interpretation and feature* detection (e.g., damages), but, not all features are directly visible and need to be intensified (contrast/SNR by algorithms)
- Ultrasonic signals cannot be simulated with high accuracy with respect to real measured images; there is a large reality gap!
- Features* are hard to be detected directly, advanced filtering and complex feature extraction models are required.

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* Feature Classes: Damages, Defects, Inhomogenities, Pores, Delamination, Cracks
[1] Simulation of X-ray projections on GPU: Benchmarking gVirtualXray with clinically realistic phantoms, Jamie Lea Pointon, Tianci Wen, Jenna Tugwell-Allsup, Aaron Sújar, Jean Michel Létang, and Franck Patrick Vidal Computer Methods and Programs in Biomedicine, 2023.….

DATA-DRIVEN NDT FRAMEWORK

Radiography

One Projection

Transmission

MidQ and LowQ Devices

Input data for inference with data-driven predictor models

CT

Multiple Projections

MidQ and HighQ Devices

Used for detailed material and defect characterisation

Input for CAD models and simulatio

ML

Data-driven Modelling

Feature/ROI Marking

Pore Analysis

Damage Detection

Anomaly Detection

Supervised / Unsupervised

Semi CT

Some Projections

LowQ Devices

Reconstruction or Feature Extraction by data-driven CNN ML models

Simulation

2D/3D

Raytracing

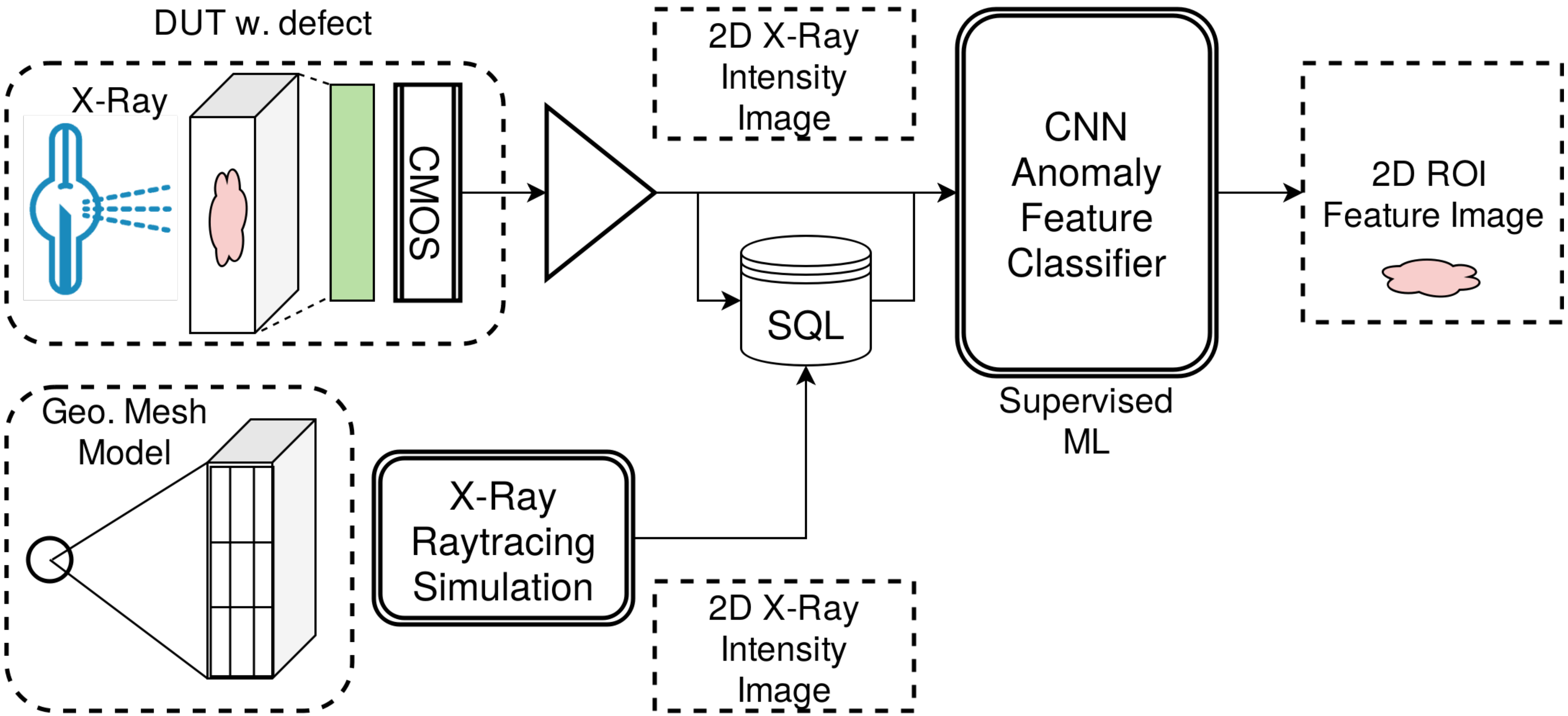
Transmission

(Reflection and Diffraction neglected)

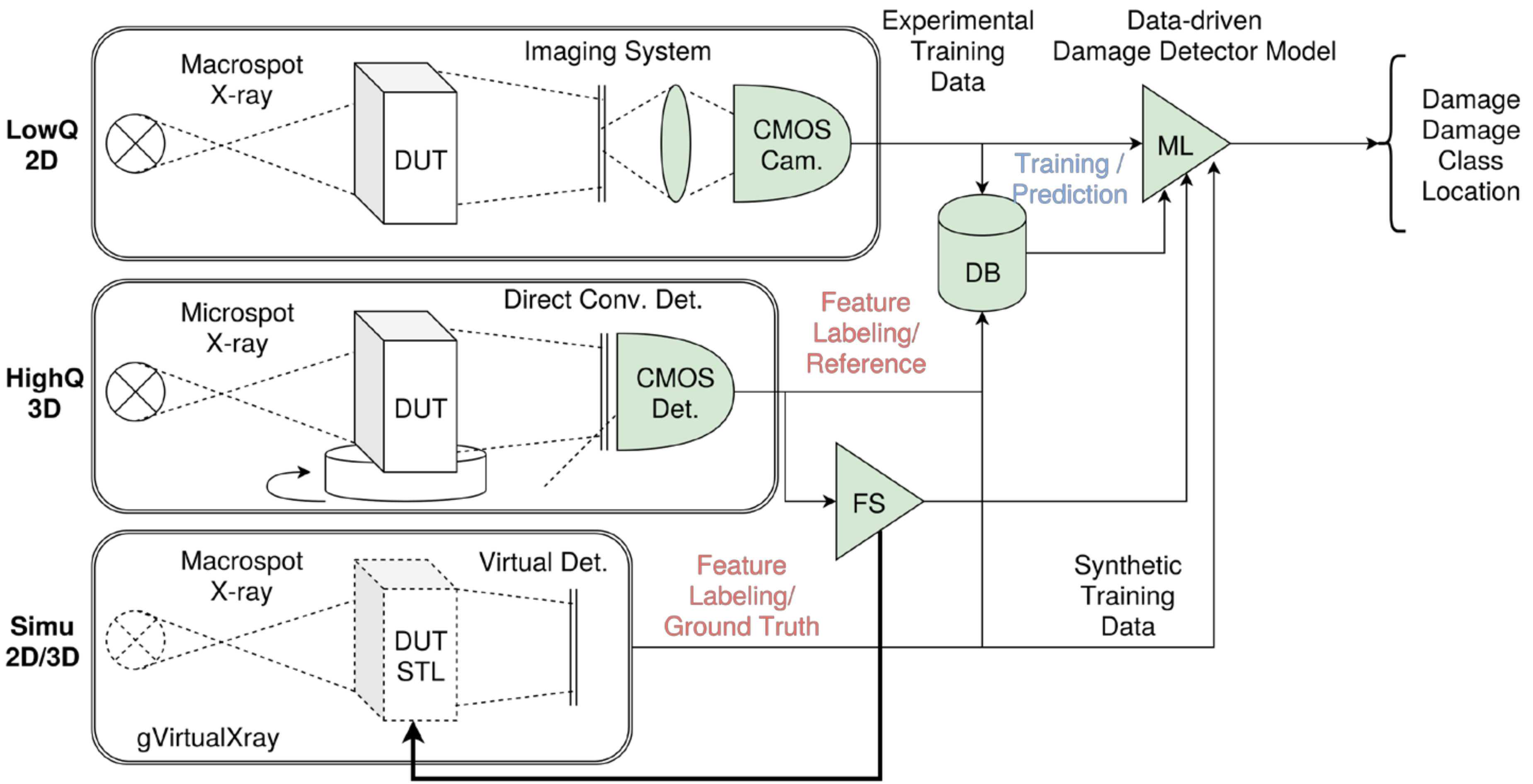
Input data for training of data-driven predictor models

Data and Meth. Fusion

PRINCIPLE CONCEPT



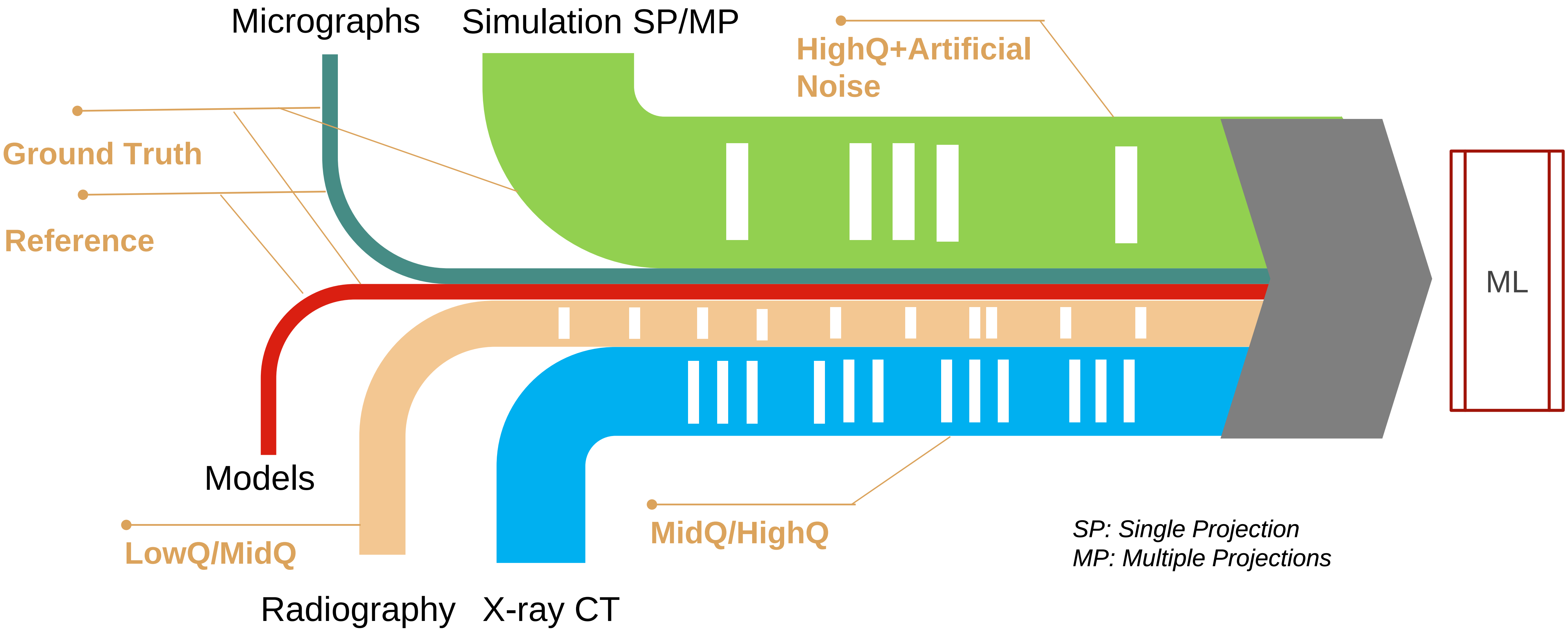
ADVANCED CONCEPT



DEVICE CLASSES

	HighQ	MidQ	LowQ
Single Projection	✓	✓	✓
Mult-Projection (Rotation)	✓	✓	✓
X-ray Tube Focal Diameter	5µm	0.8mm	0.8mm
X-ray Voltage/Current	-120 kV/2 mA	-120 kV/10 mA	-70 kV/1 mA
Detector	2000x2000 20 µm Direct Sci./Imag.	1000x1000 200 µm Direct Sci.	2000x1000 3/40 µm Screen/Imaging
Digital Resolution [Bits]	16	16	12
Sampling Time	100 ms-5 s	10 ms-1 s	5 s
Distance Object/Source	5-10 cm	10-50 cm	20 cm
Costs	500 k€ (Zeiss)	100 k€ (IFAM)	1 k€ (Bosse)

DATA AND DATA SETS



SP: Single Projection
MP: Multiple Projections

KEY RESULTS AND CHALLENGES

Specimens:

1. Aluminum die casted plates with pores, Fraunhofer IFAM Bremen (Dirk Lehmhus)
2. GLARE Fibre Metal Laminate plates (5 layers) with impact damages , DFG research group 3022 (Bremen, Hamburg, Braunschweig, Siegen)

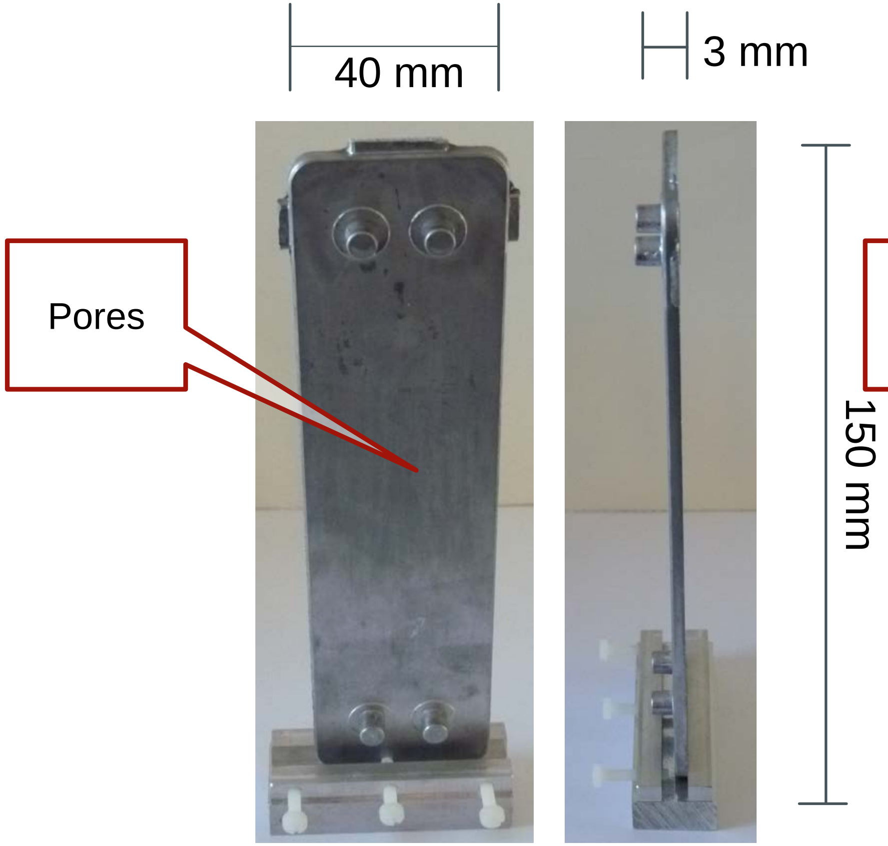
Objectives (Hypothesis: Can the goal be reached with the proposed method and data?)

1. Pore detection (feature marking) from single frontal LowQ X-ray projections using a Convolutional Neural Network
2. Damage or anomaly feature marking in 3D CT reconstructed HighQ image volumes using a Convolutional Neural Network

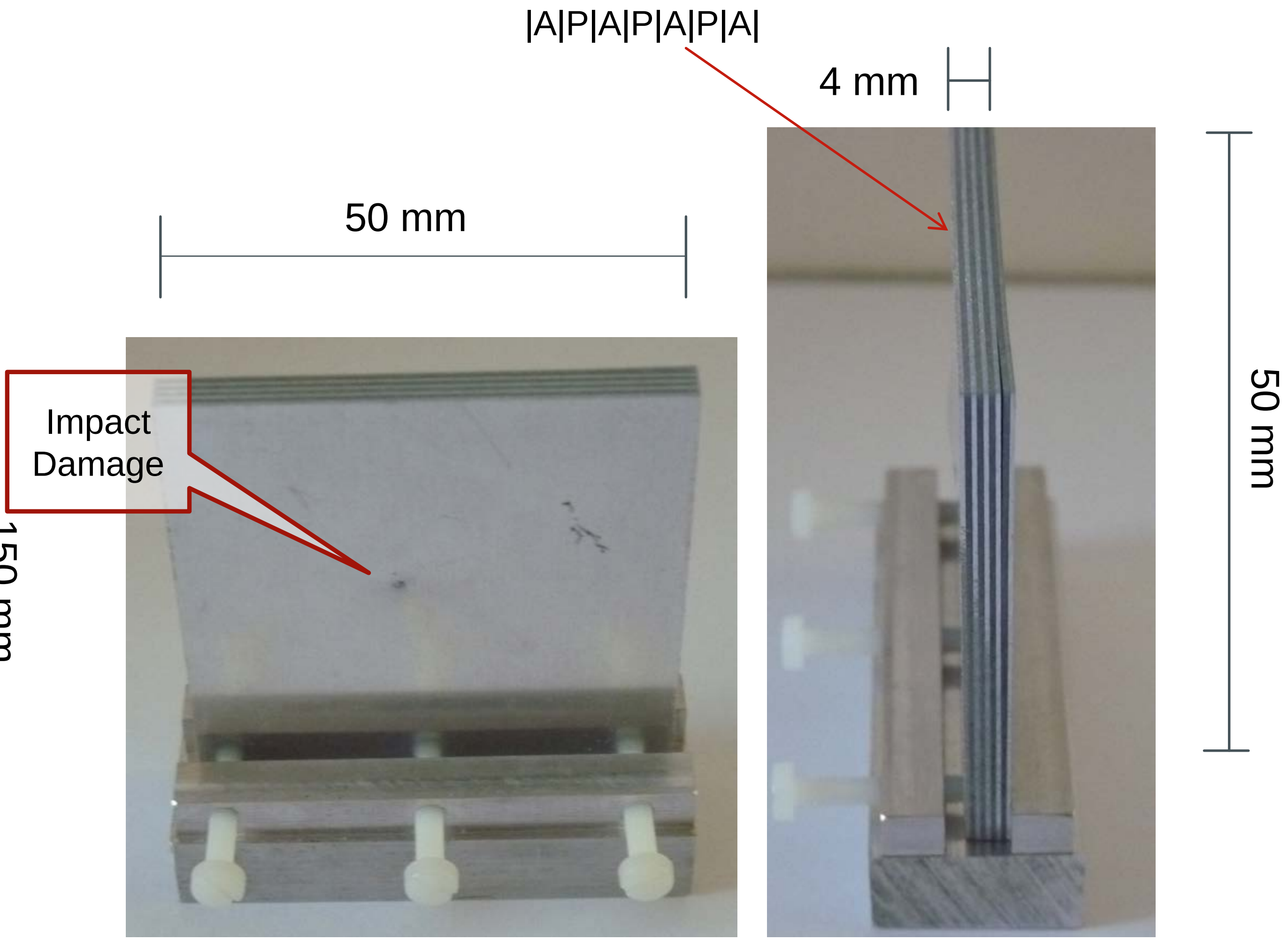
Measurements

1. MidQ X-ray (IFAM), single and multi-projection images (CT, 400/800 projections) 60 kV, 2 mA, 1000 x 1000 pix. SSD, 200μm LowQ X-ray (Bosse), single projection images, 55 kV, 1mA, 1920 x 1080 pix, Imaging detector with CMOS sensor, 40 μm
2. HighQ X-ray (Zeiss Xradia μCT) multi-projection images (CT, 800 projections), 110 kV, 1 mA, 2000 x 2000 pix. SSD, 20 μm

SPECIMENS

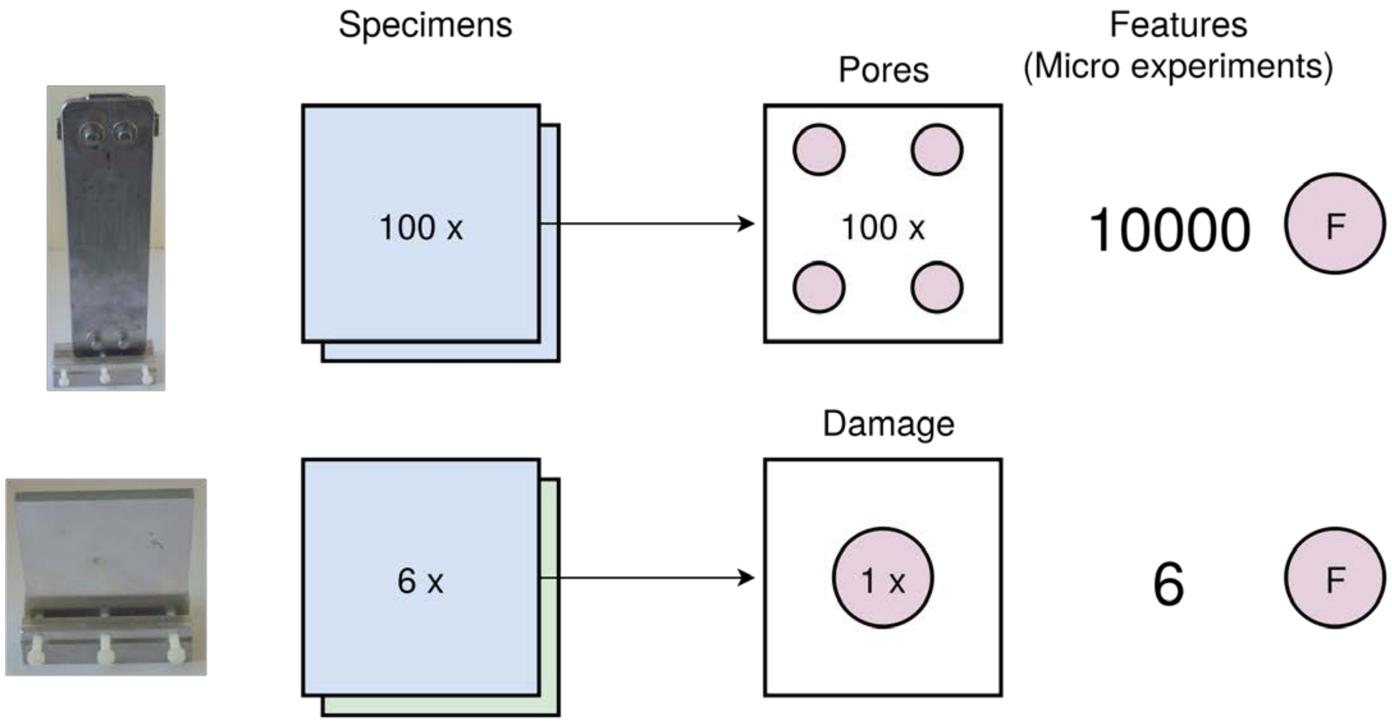


1. Aluminum Die Casting Plate (IFAM)



2. GLARE FML Plate (DFG FOR 3022)

DATA VARIANCE: THE FIRST CHALLENGE

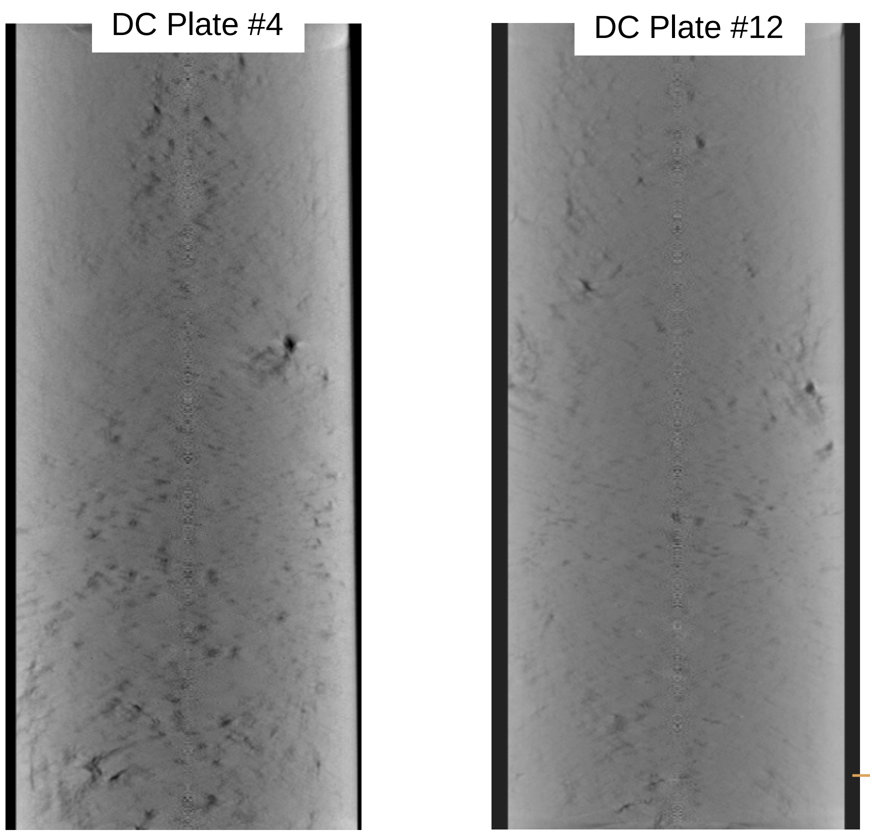


In this work a semantic pixel classifier is used for feature marking. From the model point of view, each pixel (and neighbour pixels) of an X-ray image is a sample instance!

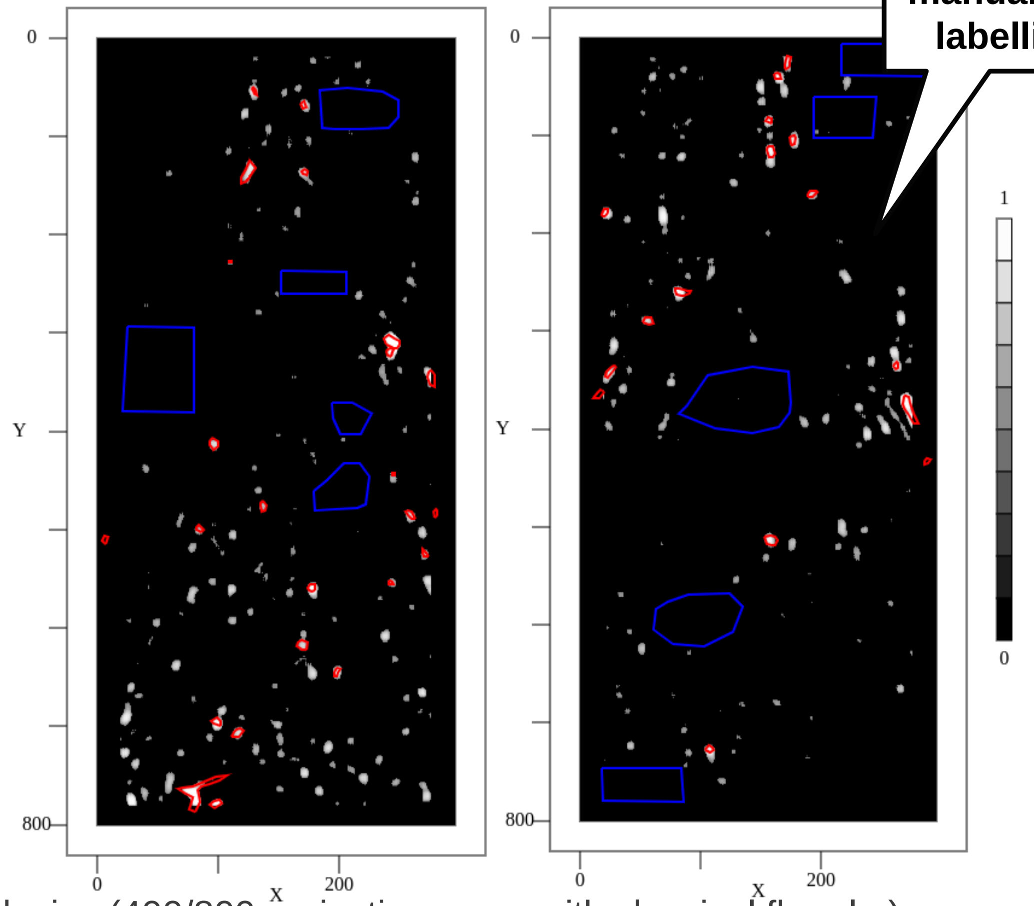
COMPARISON RECONSTRUCTED MIDQ 3D CT AND 2D CNN PORE FEATURE MARKING

Feature Labelling: Second Challenge

Trained w **Real** Images and **hand-made manual ROI labelling**

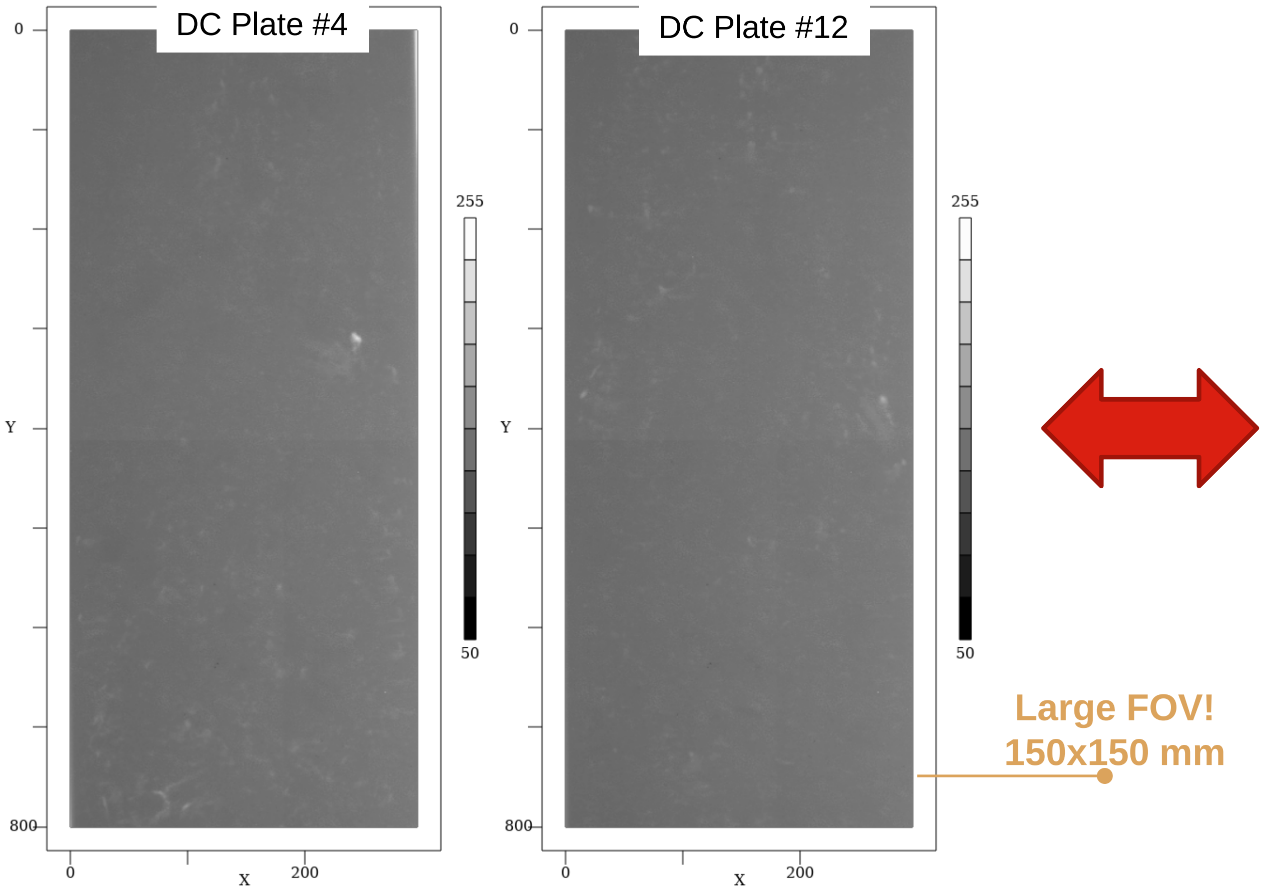


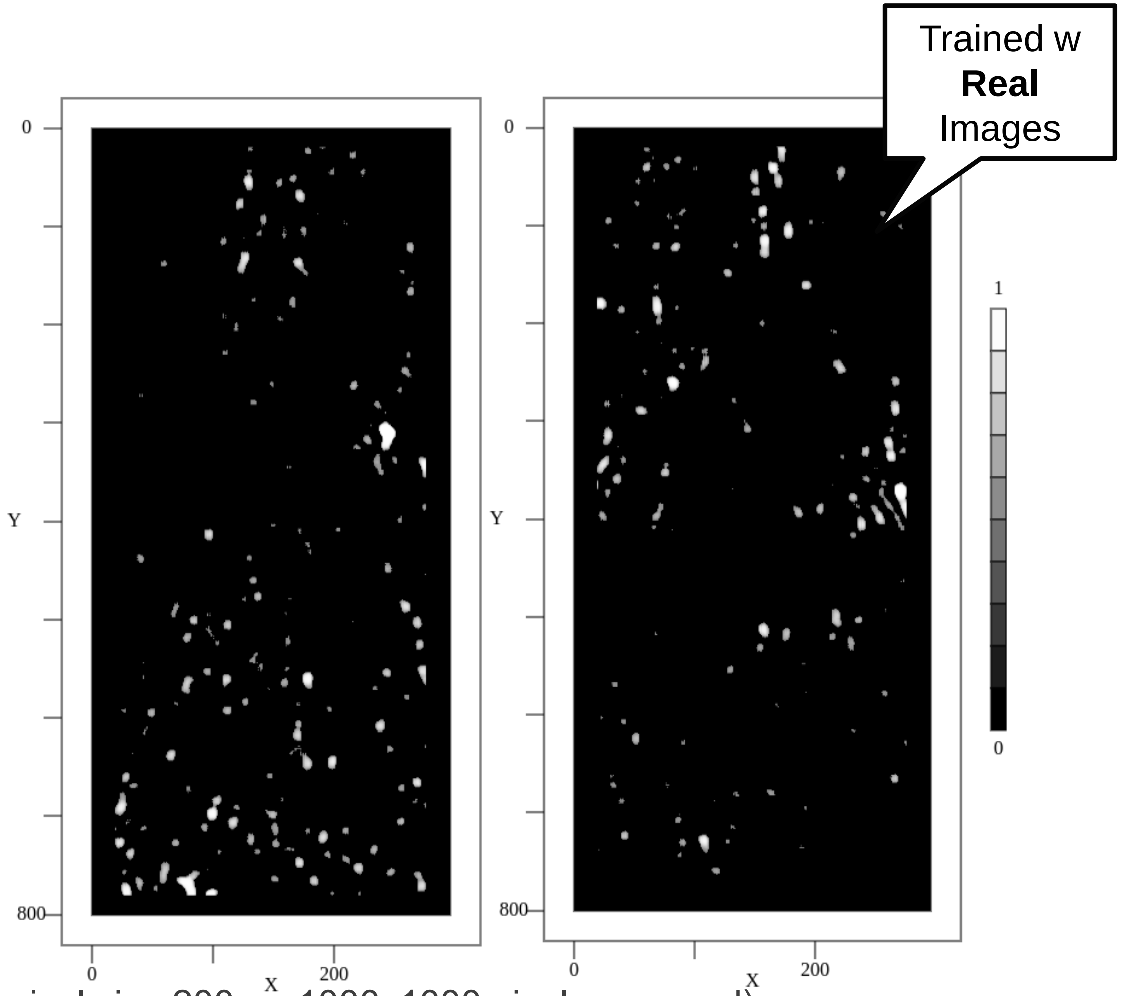
Large FOV! 150x150 mm



- Left: Volume projection of reconstructed CT images with data from a MidQ device (400/800 projections, rec. with classical fbp alg.)
- Right: CNN Pixel Classifier Feature Marking image predicted from single projection image (MidQ), trained with real images [8-8]

COMPARISON MIDQ RADIOGRAPHY AND CNN PORE FEATURE MARKING (R)

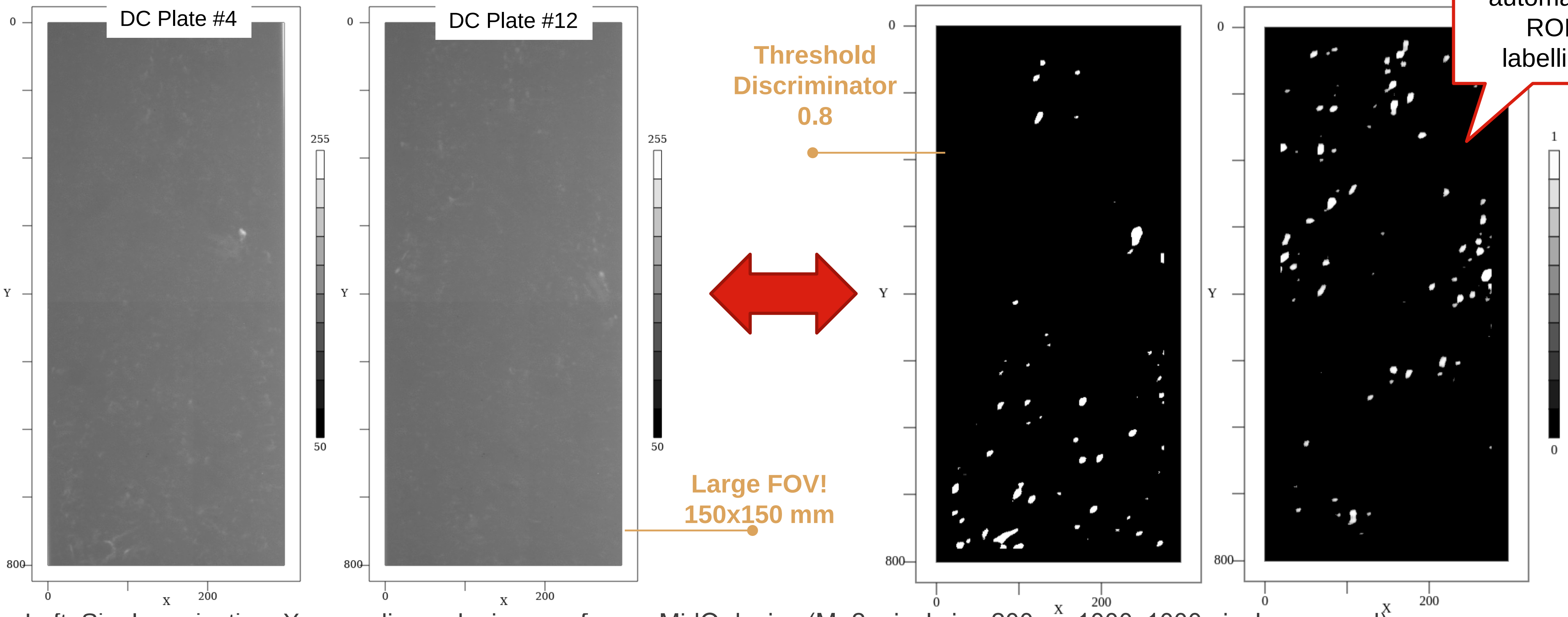




- Left: Single projection X-ray radiography images from a MidQ device (M=2, pixel size 200µm 1000x1000 pixels, cropped)
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image (MidQ), trained with real images [8-4]

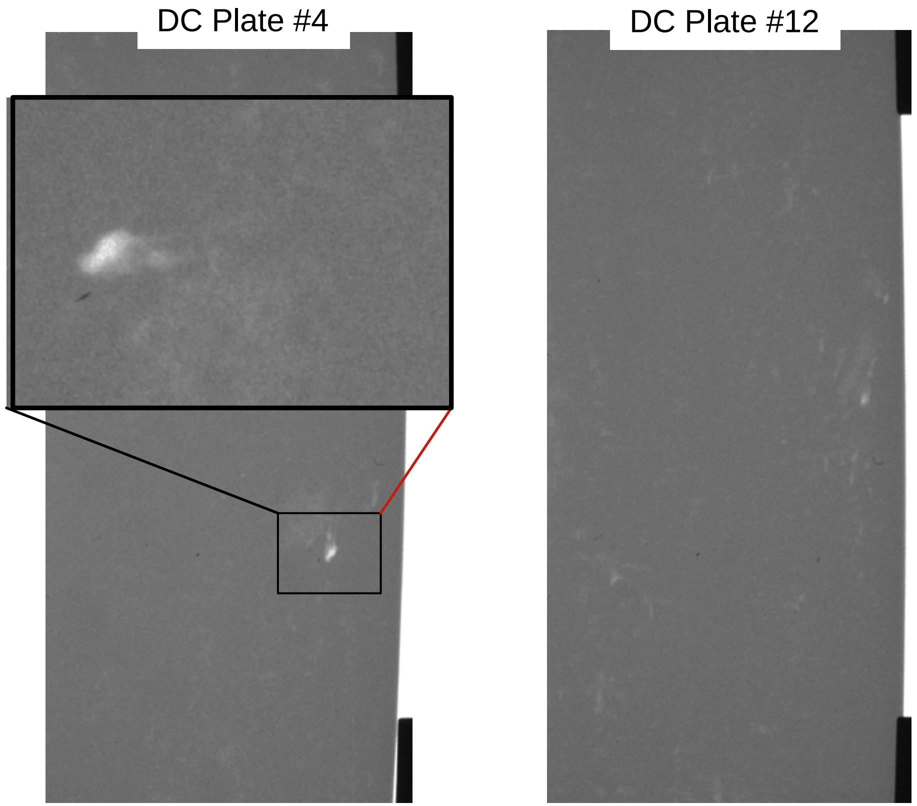
COMPARISON MIDQ RADIOGRAPHY AND CNN PORE FEATURE MARKING (S)

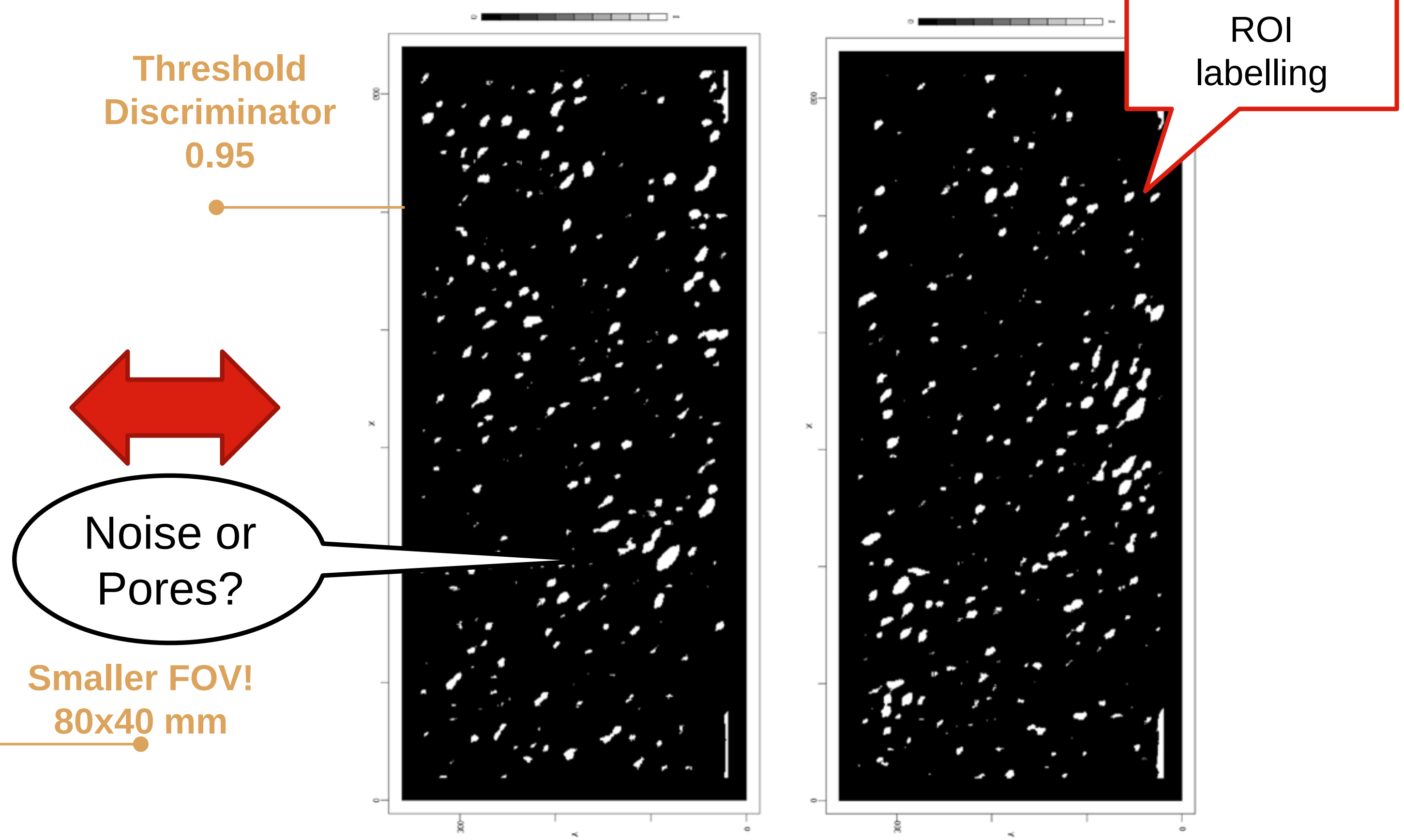
Trained w **Synthetic** Images and CAD model-based automated ROI labelling



- Left: Single projection X-ray radiography images from a MidQ device (M=2, pixel size 200μm 1000x1000 pixels, cropped)
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image (MidQ), trained with synthetic images [8-8-4]

COMPARISON LOWQ RADIOGRAPHY AND CNN PORE FEATURE MARKING (S)



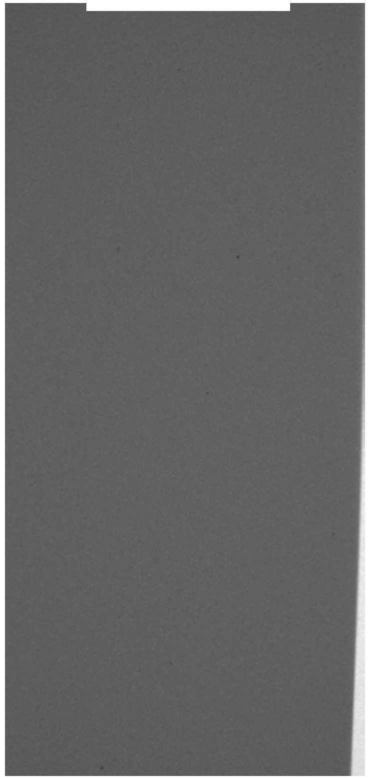


- Left: Single projection X-ray radiography images from an Imaging LowQ device (M=1, eff. pixel size 40µm 1920x1080 pixels)
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image (LowQ), trained with synthetic images [8-8-4]

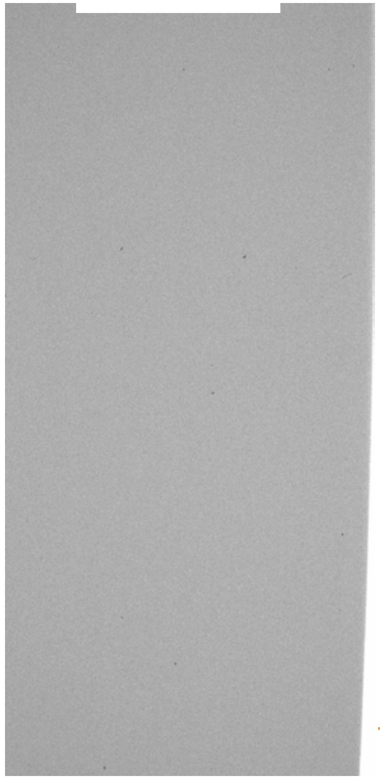
COMPARISON LOWQ RADIOGRAPHY AND CNN PORE FEATURE MARKING (S)

Trained w **Synthetic** Images and CAD model-based automated ROI labelling

Ex Plate #1



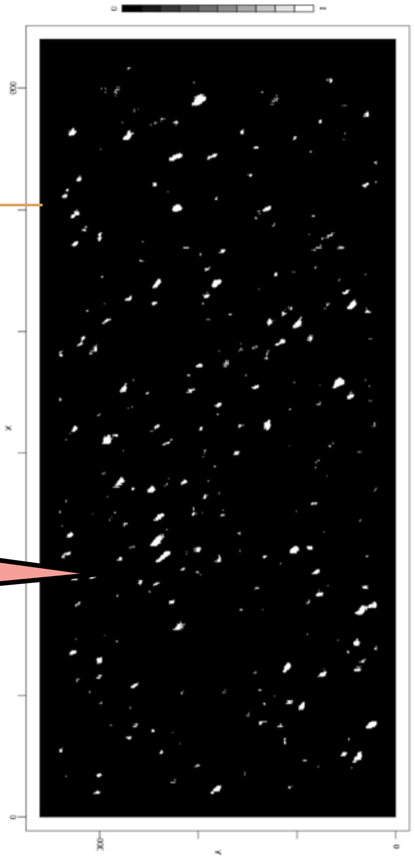
Ex Plate #1



Threshold Discriminator 0.95

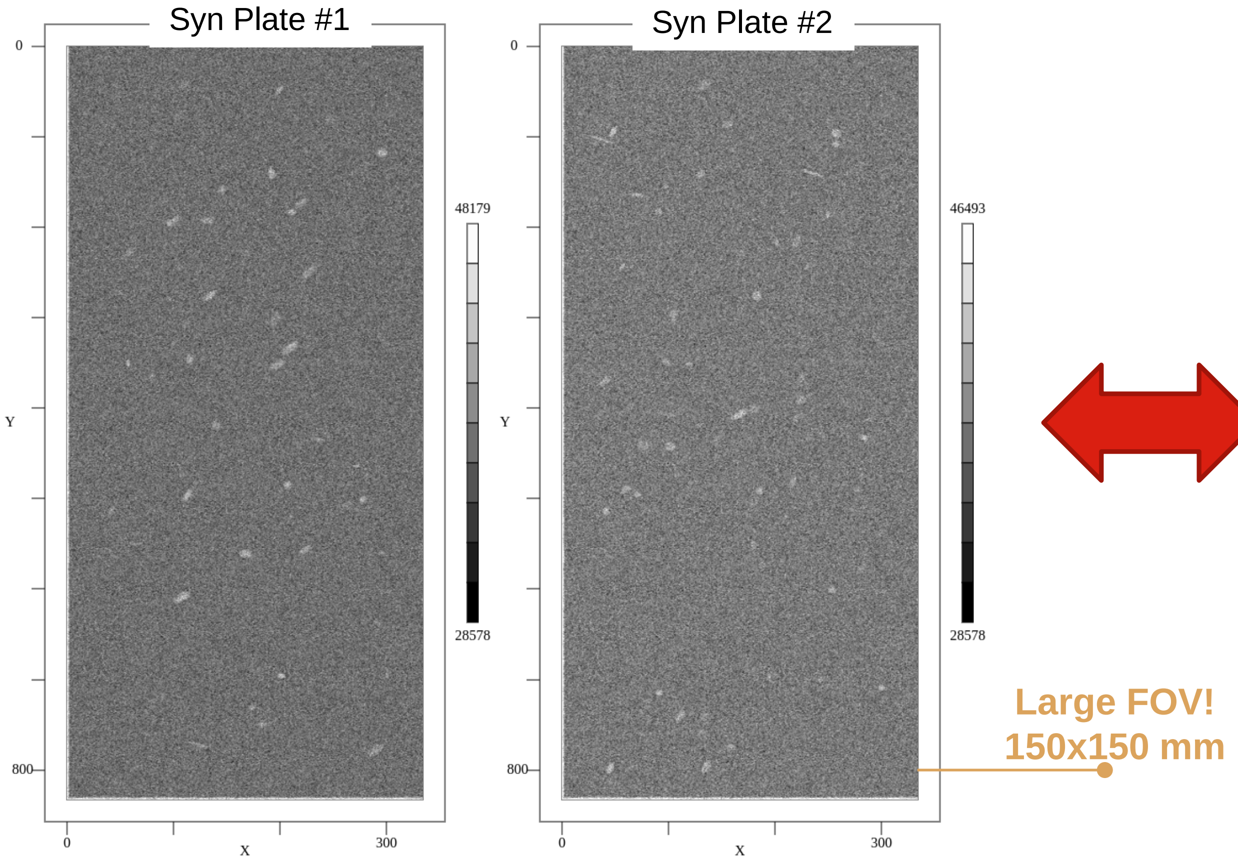
Noise!

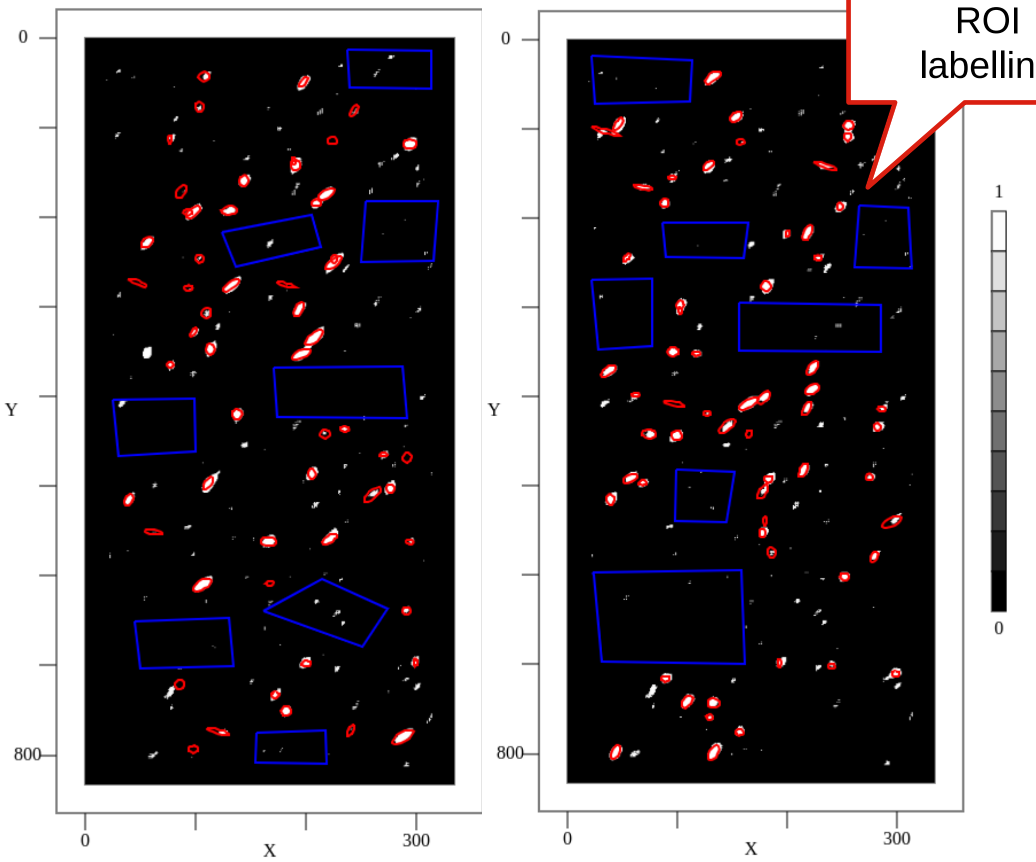
Smaller FOV! 80x40 mm



- Left: Single projection X-ray radiography images from an Imaging LowQ device // **Extruded aluminum plates** (d = 2 mm)
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image (LowQ), trained with synthetic images [8-8-4]

COMPARISON SIMULATED RADIOGRAPHY AND CNN PORE FEATURE MARKING (GROUND TRUTH)

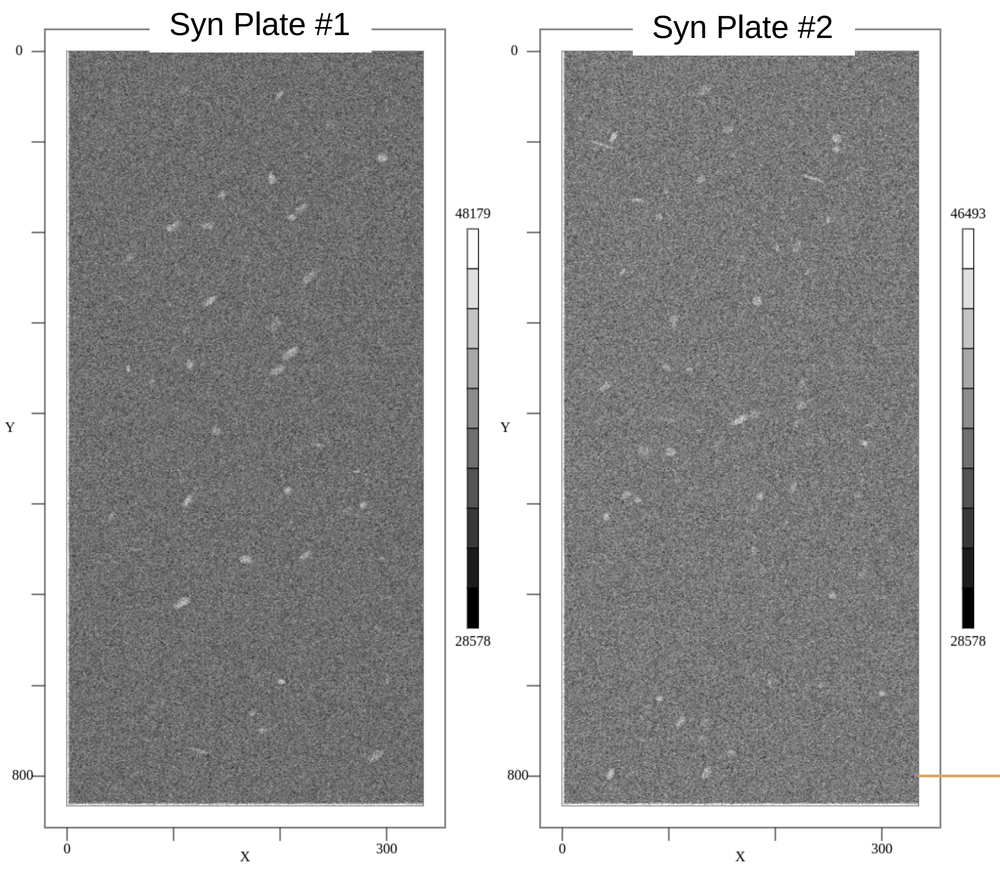




- Left: Single projection X-ray radiography images from XraySim (M=2, pixel size 150µm 1000x1000 pixels, cropped) // **Synthetic Plate**
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image [8-8-4]

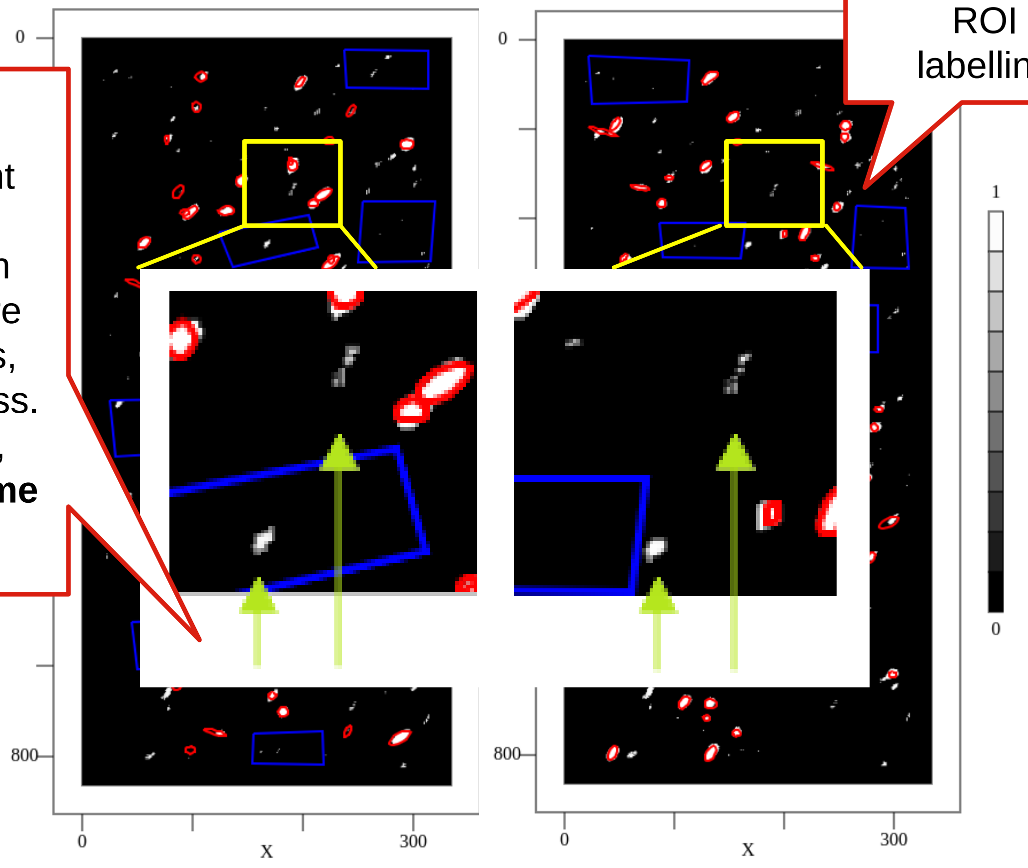
COMPARISON SIMULATED RADIOGRAPHY AND CNN PORE FEATURE MARKING (GROUND TRUTH)

Trained w **Synthetic** Images and CAD model-based automated ROI labelling



Large FOV! 150x150 mm

Two independent plates and images with different pore distributions, different gauss. pixel noise, **produce same artifacts**!

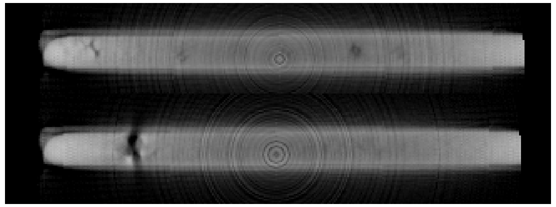


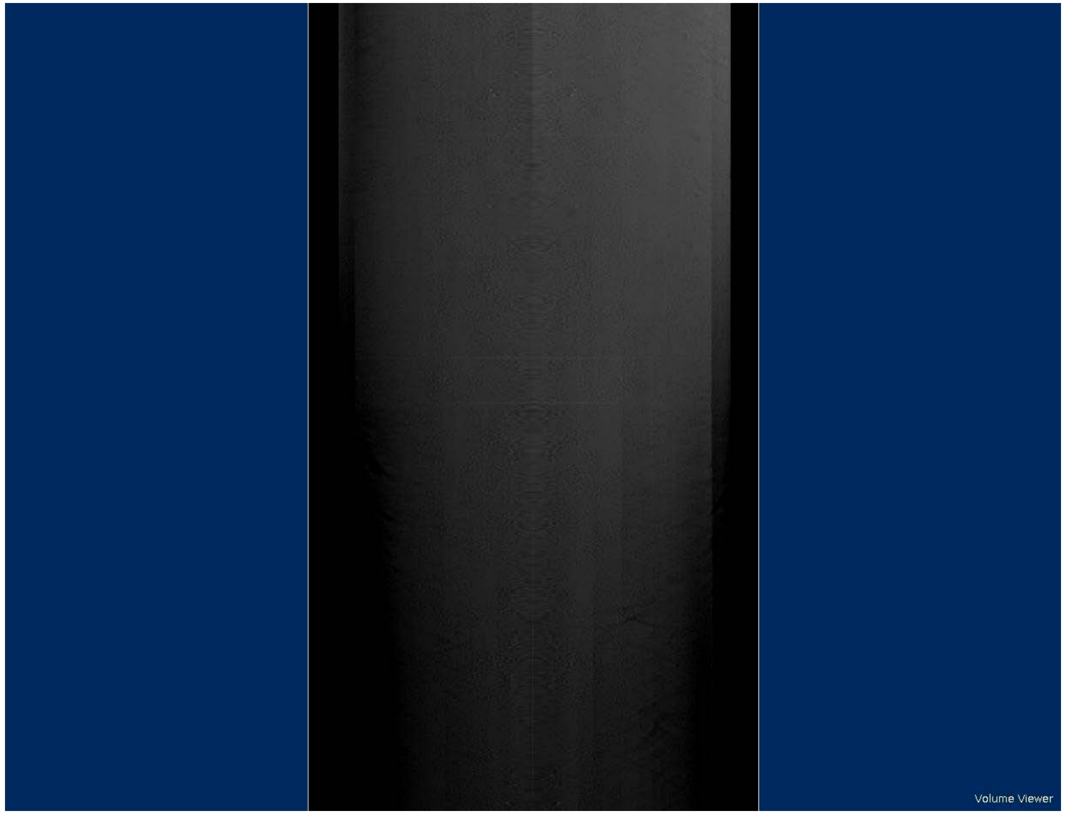
- Left: Single projection X-ray radiography images from XraySim (M=2, pixel size 150µm 1000x1000 pixels, cropped) // **Synthetic Plate**
- Right: CNN Pixel Classifier Feature Marking predicted from single projection image [8-8-4]

PORE INSPECTION AND CHARACTERISATION BY CT

It is a challenge to estimate pore shapes (geometry, size), density, spatial distribution, and to distinguish reconstructed pores from image artifcats and noise!

- Manual measuring of shape parameters of selected pores (e.g., using ImageJ analysis software) with ellipse approximation
- Automated pore analysis by point clustering methods and ellipsoid approximation





PORE INSPECTION AND CHARACTERISATION BY CT

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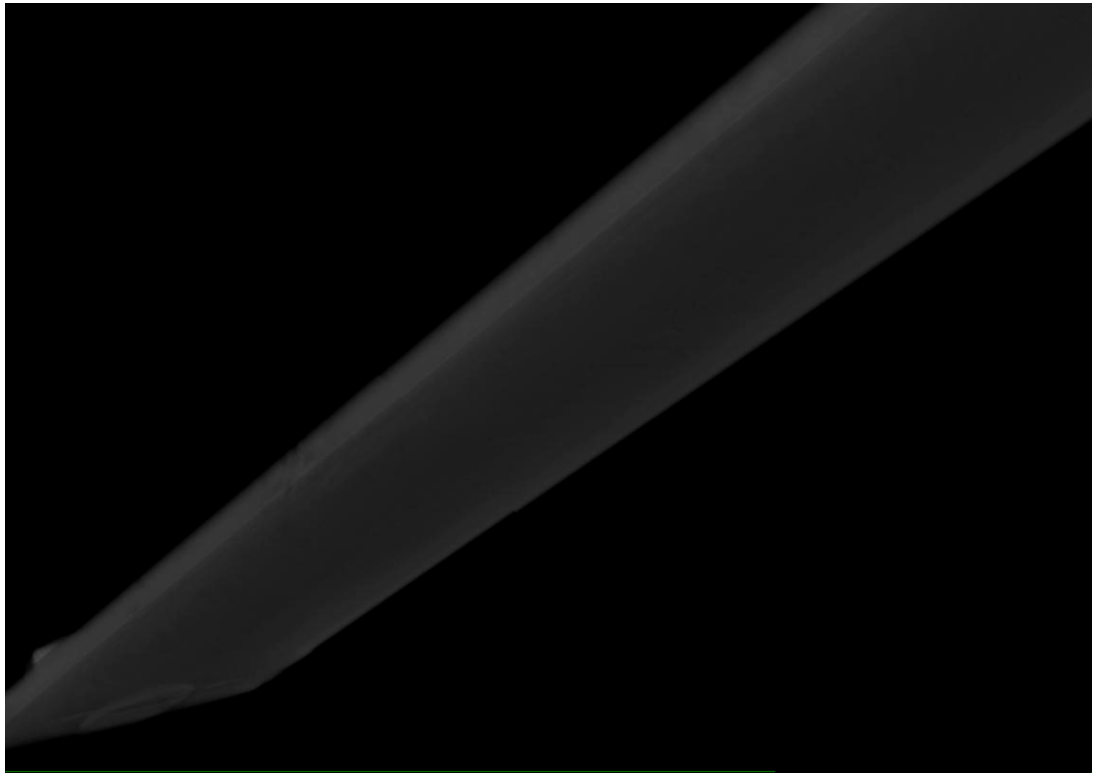

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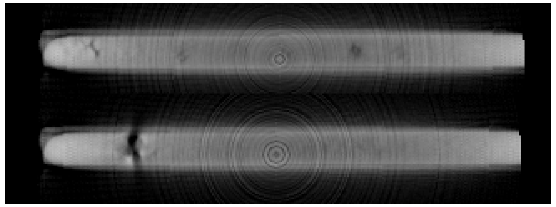
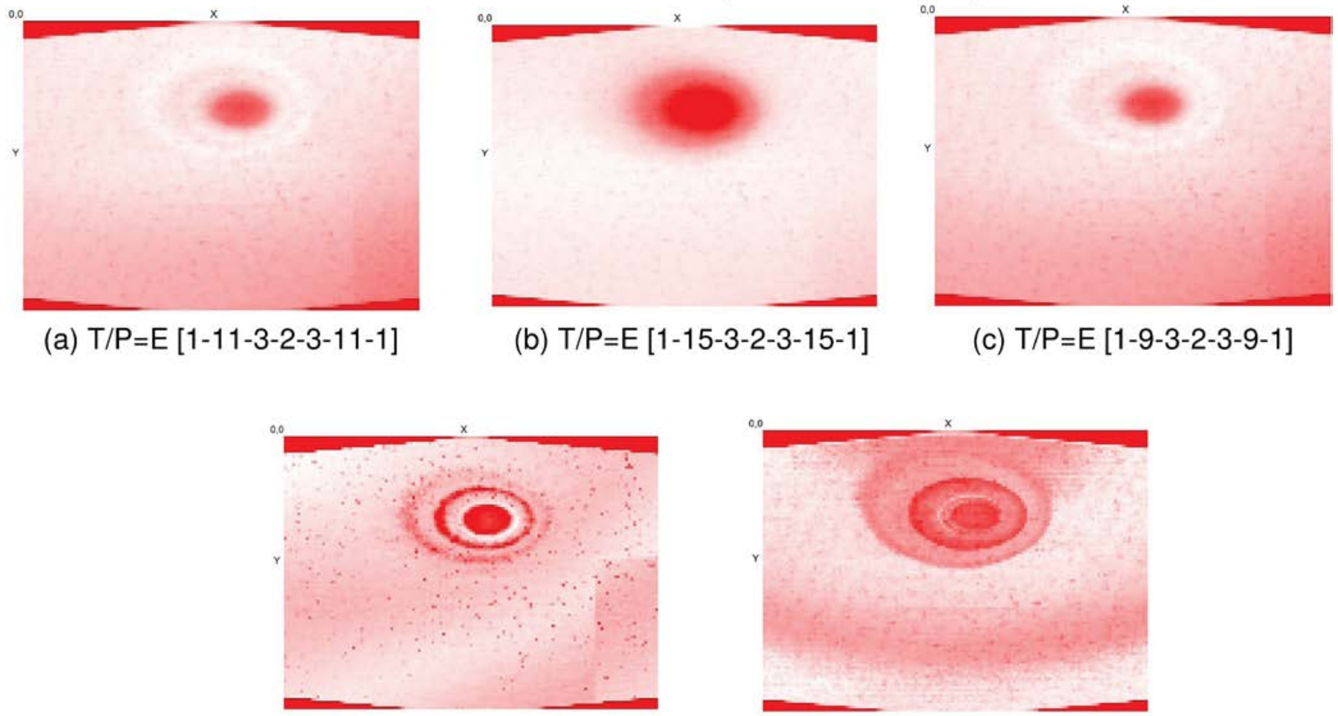


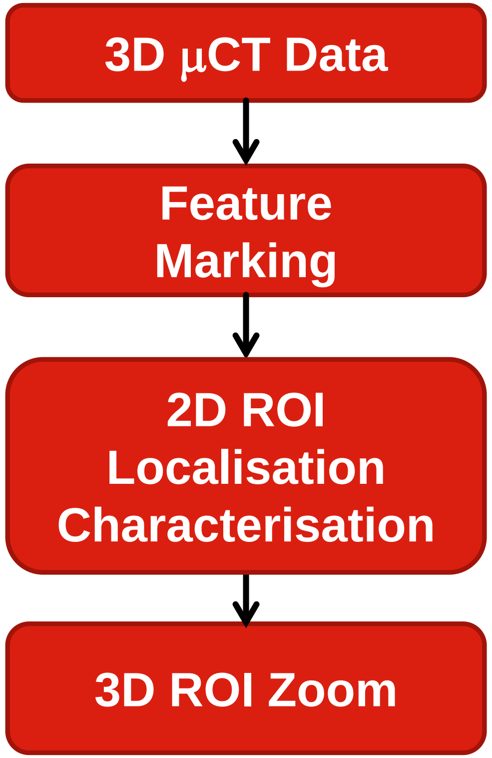
ANOMALY DETECTION IN FML CT DATA (NEGATIVE TRAIN.)

LSTM Autoencoder MAE Map GLARE 543-Impact-C1



(a) T/P=E [1-11-3-2-3-11-1] (b) T/P=E [1-15-3-2-3-15-1] (c) T/P=E [1-9-3-2-3-9-1]

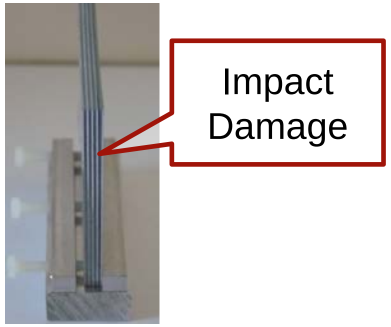
(d) T=F P=E [1-9-3-2-3-9-1] (e) T=F P=E [1-9-3-2-3-9-1]

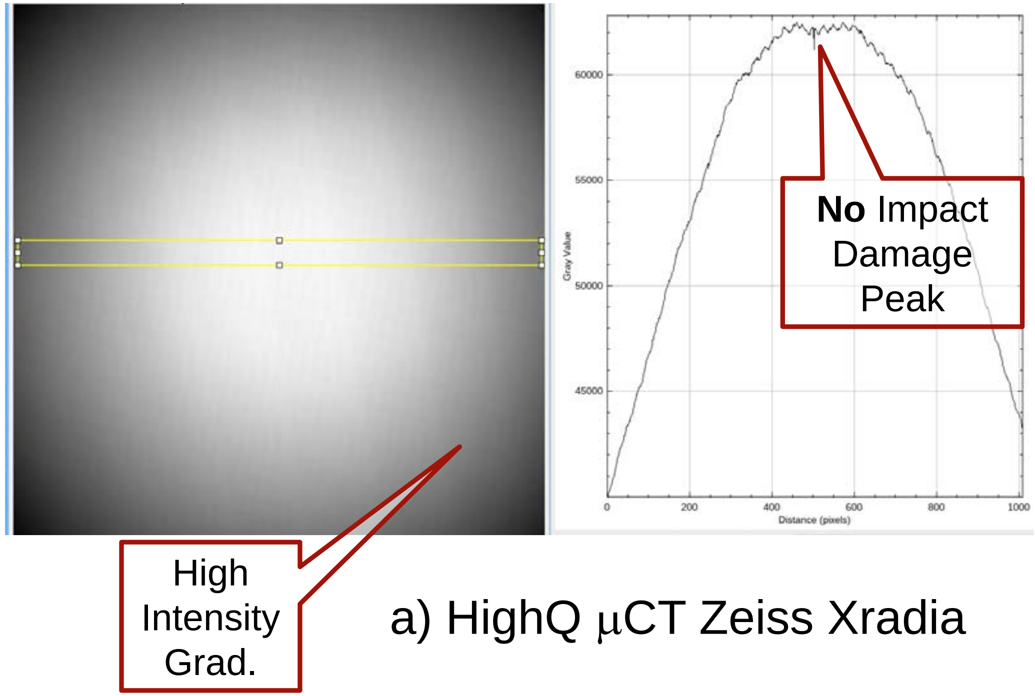


- A **LSTM Autoencoder** is used as an anomaly detector. Shown is the feature marking of the AE (top view of the X.ray CT volume)
- Specimen: FML plate with impact damage. A.E: Different AE model configurations and trainings // Data from **HighQ** device

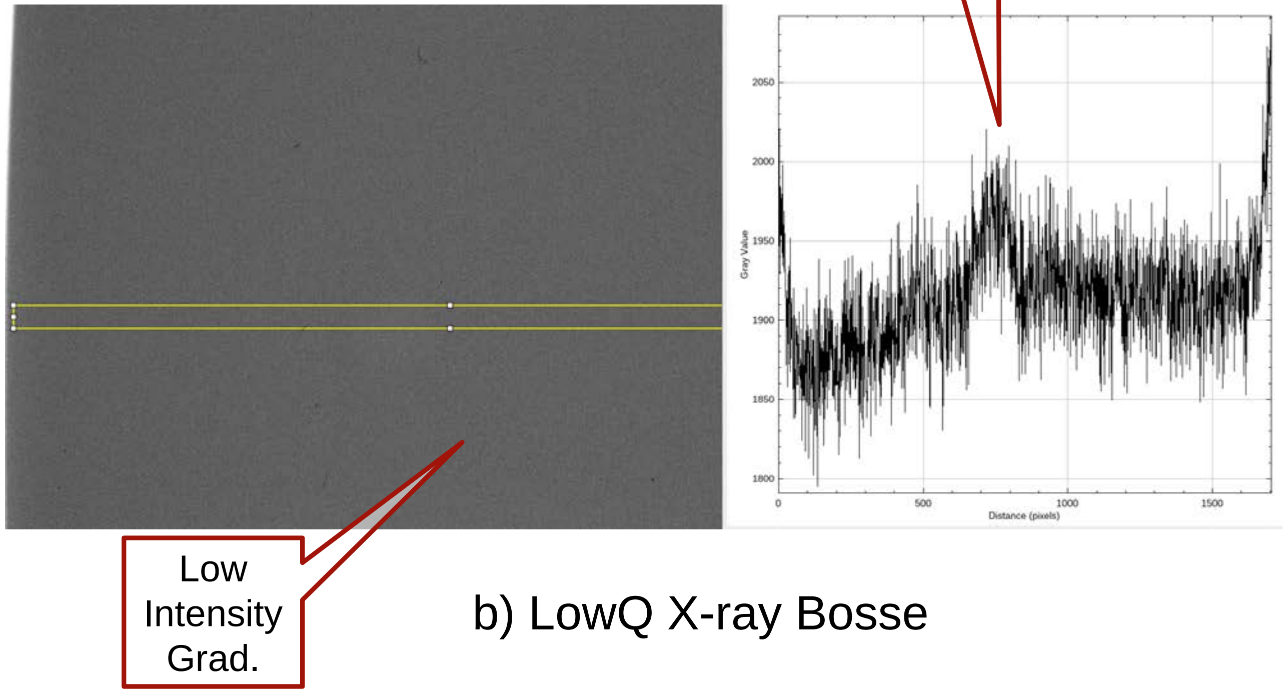
ANOMALY AND ROI DETECTION IN SINGLE PROJECTION

HighQ <u>single projection</u> image data from µCT measuring devices are not always better than image data from LowQ devices for ROI and anomaly detection!



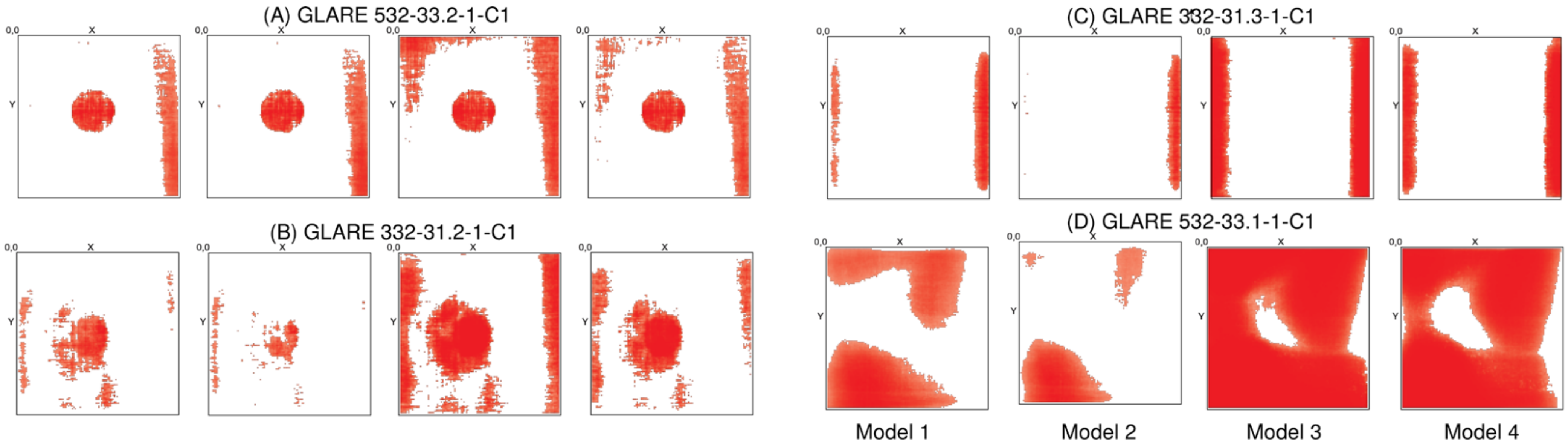


a) HighQ µCT Zeiss Xradia



b) LowQ X-ray Bosse

ANOMALY DETECTION IN FML CT DATA (POSITIVE TRAIN.)



- A **CNN** is used to detect anomalies in a CT volume (feature marking of damage candidates) // Data from **HighQ** device
- Specimen: FML plate with different damages: A: foil pseudo defect,, B: Resin washout B, C: Baseline, D: Layer delamination:

1 Chirag Shah, Stefan Bosse, and Axel von Hehl. Taxonomy of Damage Patterns in Composite Materials, Measuring Signals, and Methods for Automated Damage Diagnostics, Materials 15 (MDPI), no. 13 (2022): 4645 ....

METHODS AND ALGORITHMS

- 3D CAD modelling using automated model code generators, Monte Carlo simulation, and openSCAD
- X-ray simulation using own simulation software based on prooven and accurate gvxr/gVirtualXray library
- 3D CT reconstruction with Filtered Back Projection (using sine filters)
- Convolutional Neural Networks in different flavors
- Anomaly detectors applied to images and CT volume data

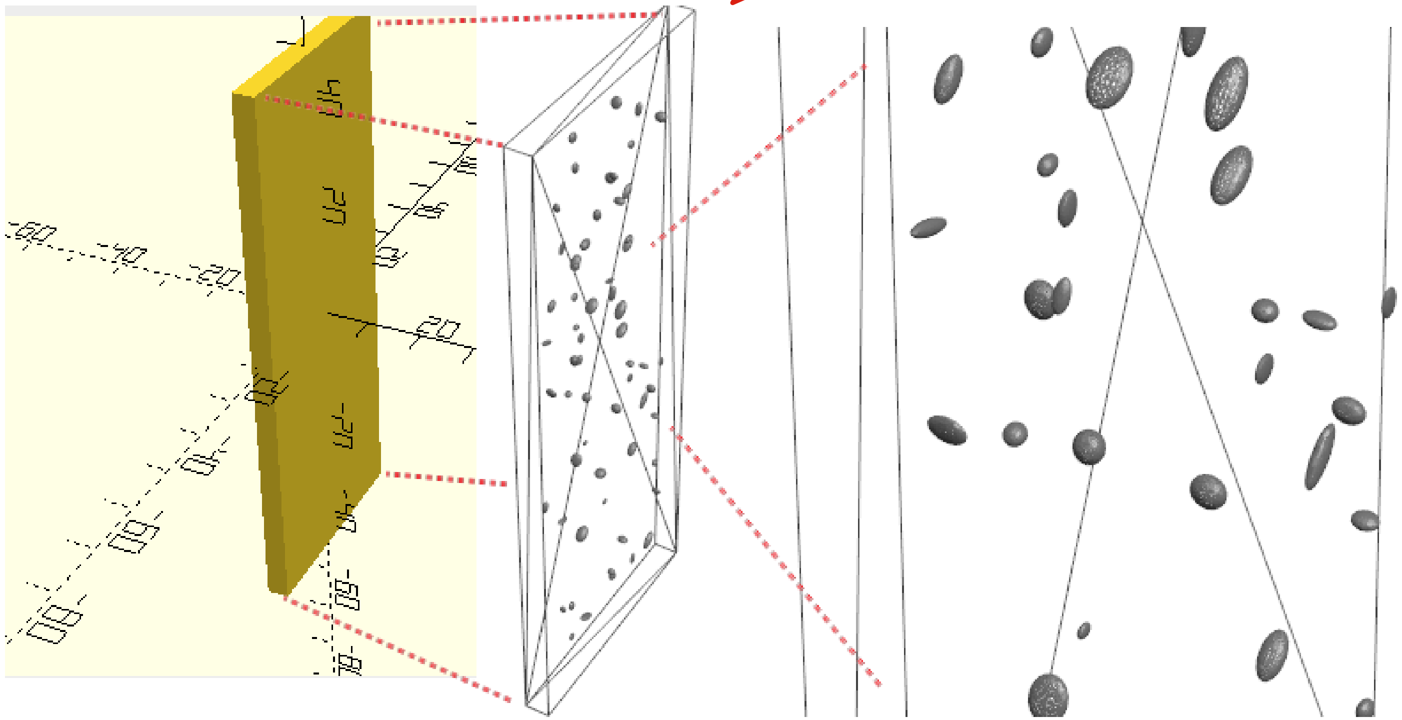
X-RAY SIMULATION

- **Input**: Polygon mesh grid (STL, Stereolithography file format) model
  - An STL file describes a raw, unstructured triangulated surface
  - Decomposition of multi-material structures in single density parts (finally merged in simulator)
  - 3D Model design: Constructive Solid Geometry (CSG)
- **Output**: X-ray intensity image with a specific detector resolution (number of pixels) and pixel size, floating point or integer data format (at least 16 Bits)
- Spatial source, object, and detector geometries can be fully parametrized including rotatated planes
- **Core software library**: gvxr / gVirtualXray using GPU computations and the OpenGL Shading Language (faster than 1ms / image)
  - https://gvirtualxray.fpvidal.net/
  - Based on the **Beer-Lambert law to compute the absorption of light** (i.e. photons) by 3D objects (here polygon meshes).

X-RAY SIMULATION: CAD MODEL

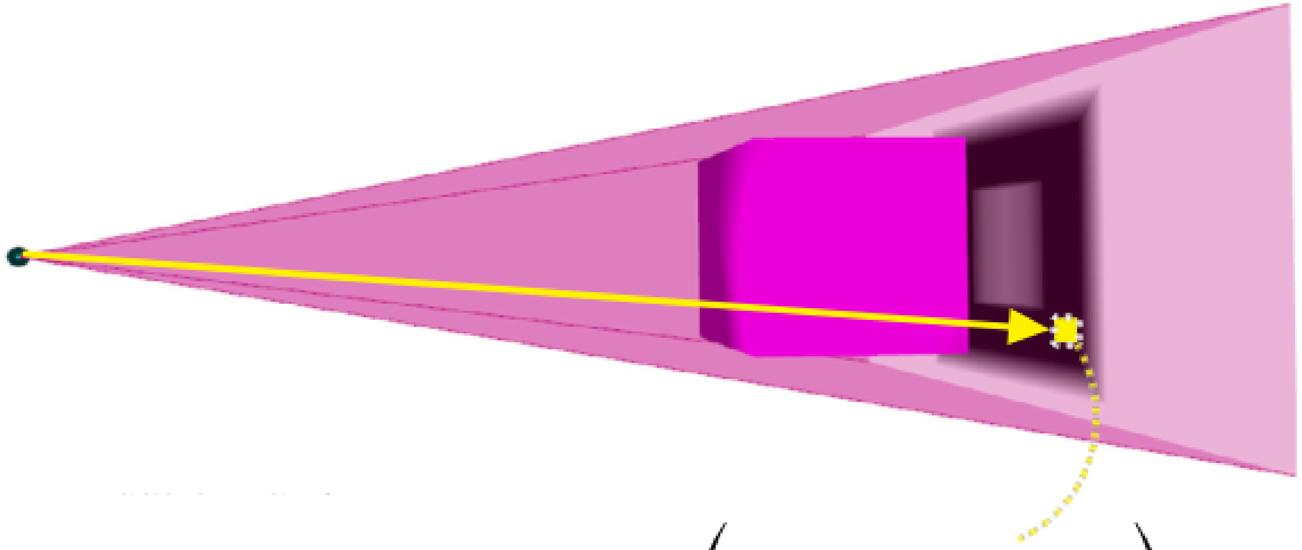
```
rotate ([90,90,90])
difference () {
  rotate ([90,0,0]) cube([100,4,40],true);
  union () {
    translate([3.17,6.14,0.67])
      rotate ([0,0,-1.43])
      scale([1.15,1.12,0.31])
      sphere(r=0.5,$fn=20);
    translate([-16.66,-4.05,0.39])
       rotate ([0,0,40.14])
       scale([0.89,2.21,1.46])
       sphere(r=0.5,$fn=20);
…
  }
}
```

Constructive Solid Geometry Model



X-RAY SIMULATION

- C++ simulation library gvxr/gVirtualXray[1]
- Integrated in own simulator program XraySim: https://github.com/bslab/xraysim
- GPU/OpenGL Ray tracing using Beer-Lambert law
- Attentuation along direct transmission path from source to detector – no scattering and reflection

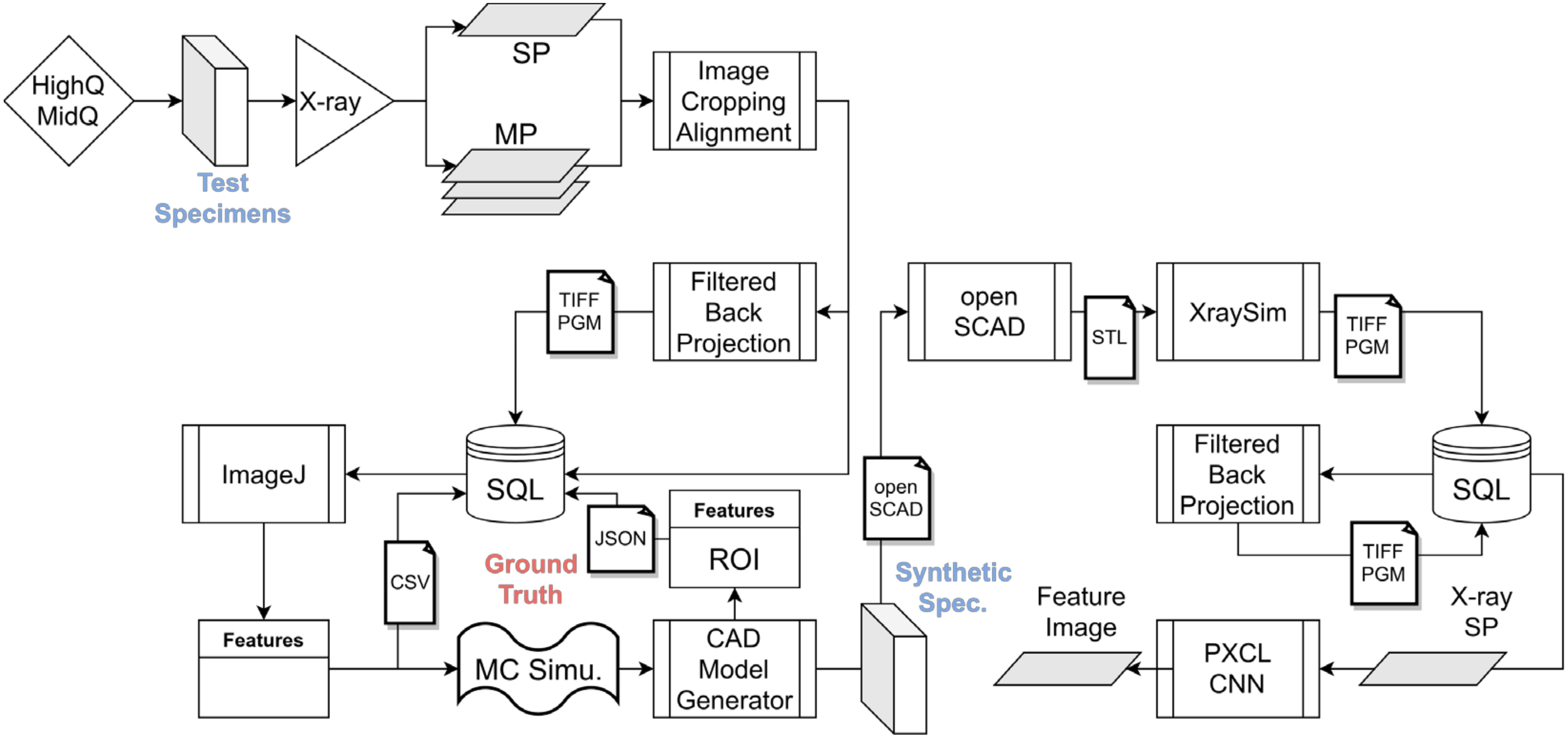


$$\mathbf{I}(x,y) = \sum_i \mathbf{R}(E_i)\,\mathbf{D}(E_i)\ \exp\left(-\sum_j \mu_j(E_i)\,\mathbf{d}_j(x,y)\right)$$

> “I(x,y) is the integrated energy in eV received by pixel (x,y). In the polychromatic case, the beam spectrum is discretised in several energy channels. E_i corresponds to the energy in eV of the i-th energy channel. $D(E_i)$ is the number of photons emitted by the source at that energy E_i. The detector response $R(E_i)$ mimics the use of a scintillator by replacing the incident energy E_i with a smaller value, i.e. $R(E_i) < E_I$. $\mu_j(E_i)$ is the linear attenuation coefficient of the j-th material at energy E_i. $d_j(x,y)$ is the path length.”

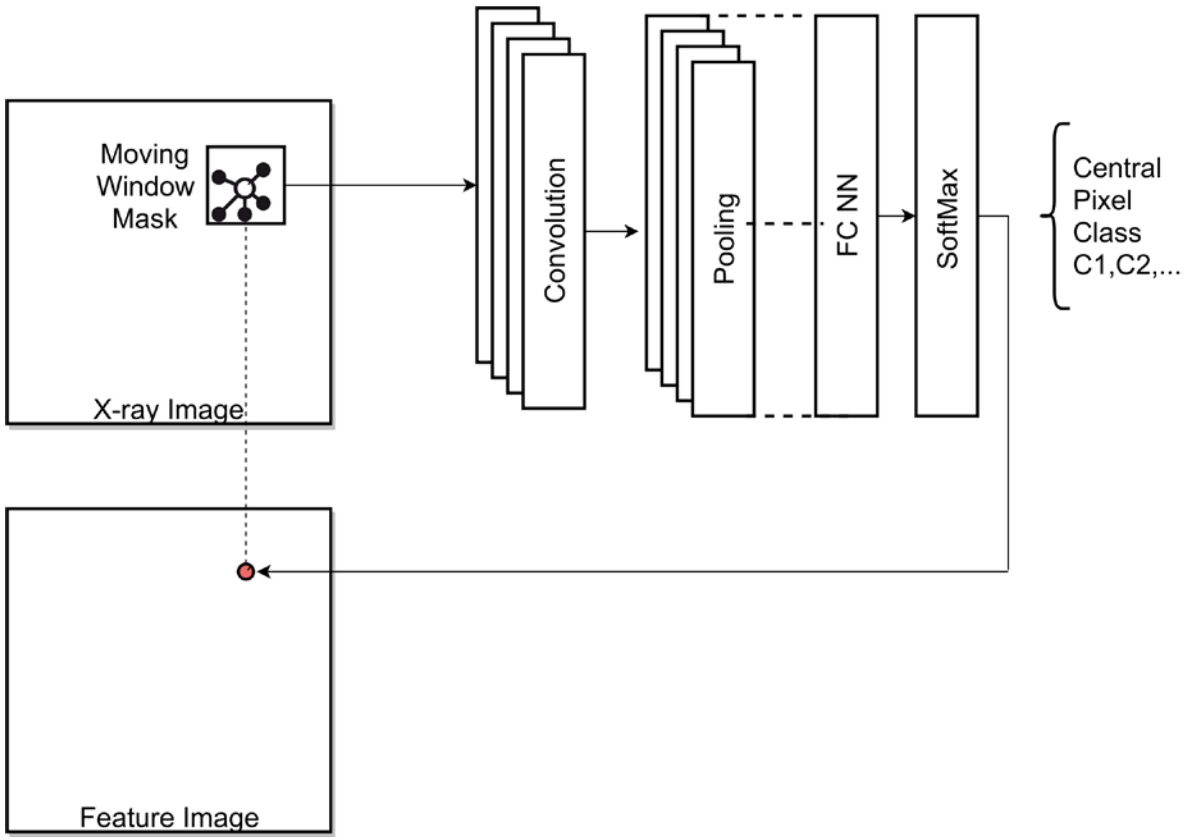
[1] Simulation of X-ray projections on GPU: Benchmarking gVirtualXray with clinically realistic phantoms, Jamie Lea Pointon, Tianci Wen, Jenna Tugwell-Allsup, Aaron Sújar, Jean Michel Létang, and Franck Patrick Vidal Computer Methods and Programs in Biomedicine, 2023.….

WORKFLOW


HighQ
MidQ
Test
Specimens
X-ray
SP
MP
Image
Cropping
Alignment
TIFF
PGM
Filtered
Back
Projection
open
SCAD
STL
XraySim
TIFF
PGM
ImageJ
SQL
CSV
JSON
Features
ROI
Ground
Truth
Features
MC Simu.
CAD
Model
Generator
open
SCAD
Synthetic
Spec.
Filtered
Back
Projection
SQL
TIFF
PGM
Feature
Image
PXCL
CNN
X-ray
SP

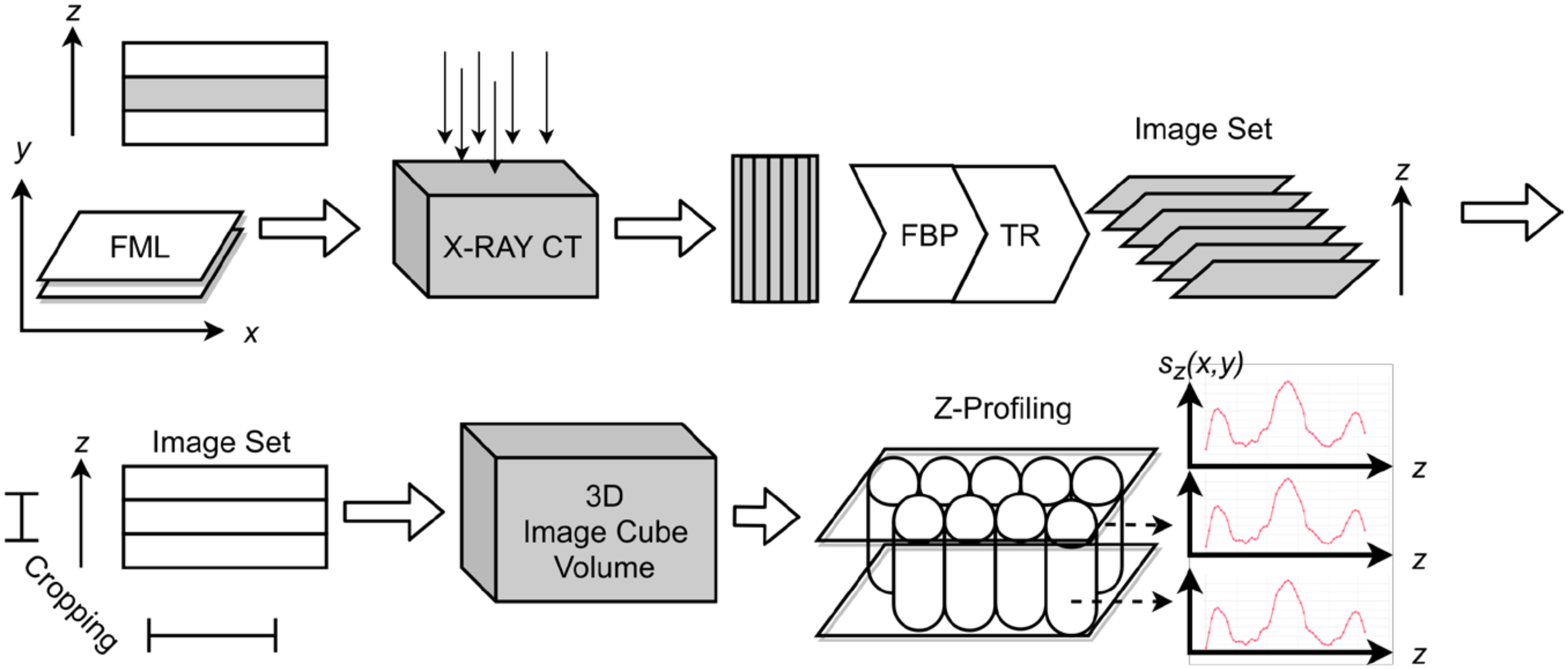
SEMANTIC CNN PIXEL CLASSIFIER

- **Input**: A sub-window of an X-ray image
- **Output**: The object class to which the central pixel of the window belongs
- The CNN classifier is applied to all pixels of an input images and produces an equally sized feature marking output image
- Point clustering (e.g., using DBSCAN) can be used to extract list of geometric objects (pores, damages, …)
- Supervised positive training (classification of known features classes)



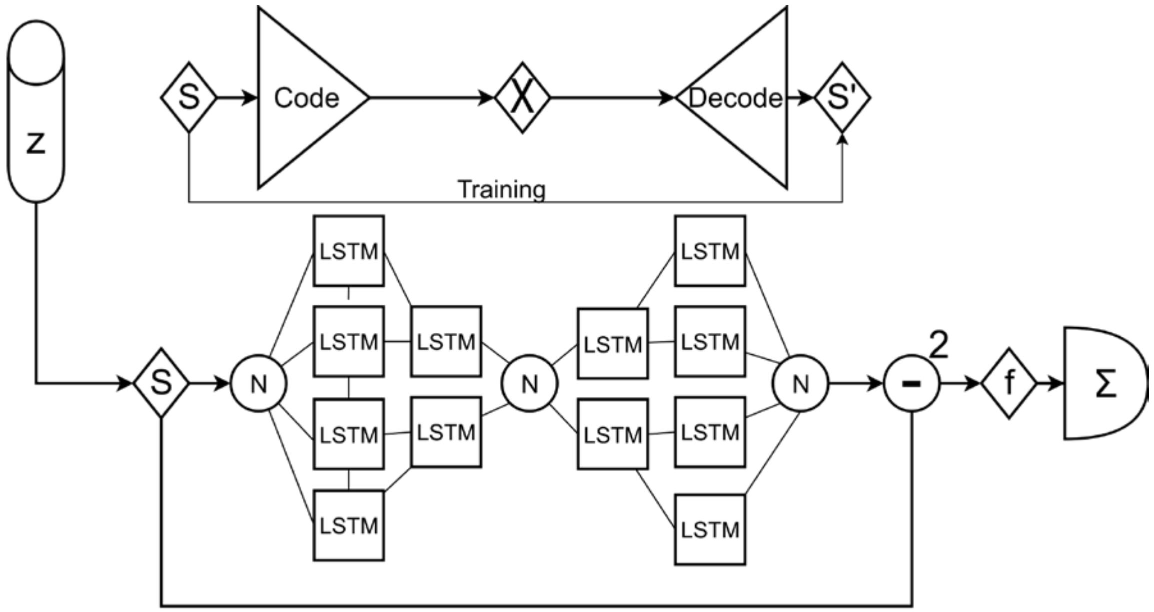
ANOMALY DETECTION IN FML CT DATA

- Goal: Find (mark) damages (deformation, cracks, delaminations) in 3D CT volumes
- Method: Z-Slicing of 3D CT volumes and application of an anomaly detector to z-profiled slices



ANOMALY DETECTION IN FML CT DATA: NEGATIVE TRAIN.

- An anomaly detector is build with a Autoencoder, either using a CNN or a LSTM-ANN
- The AE is trained with z-profile slices without defects or damages (base-line, ground truth data)
- The AE „learns“ the z-profile structure of the FML plates and outputs a simplified representation (neg. Train.)
- If there is a damage/defect, the AE is not able to reconstruct the base-line structure, and an error occurs



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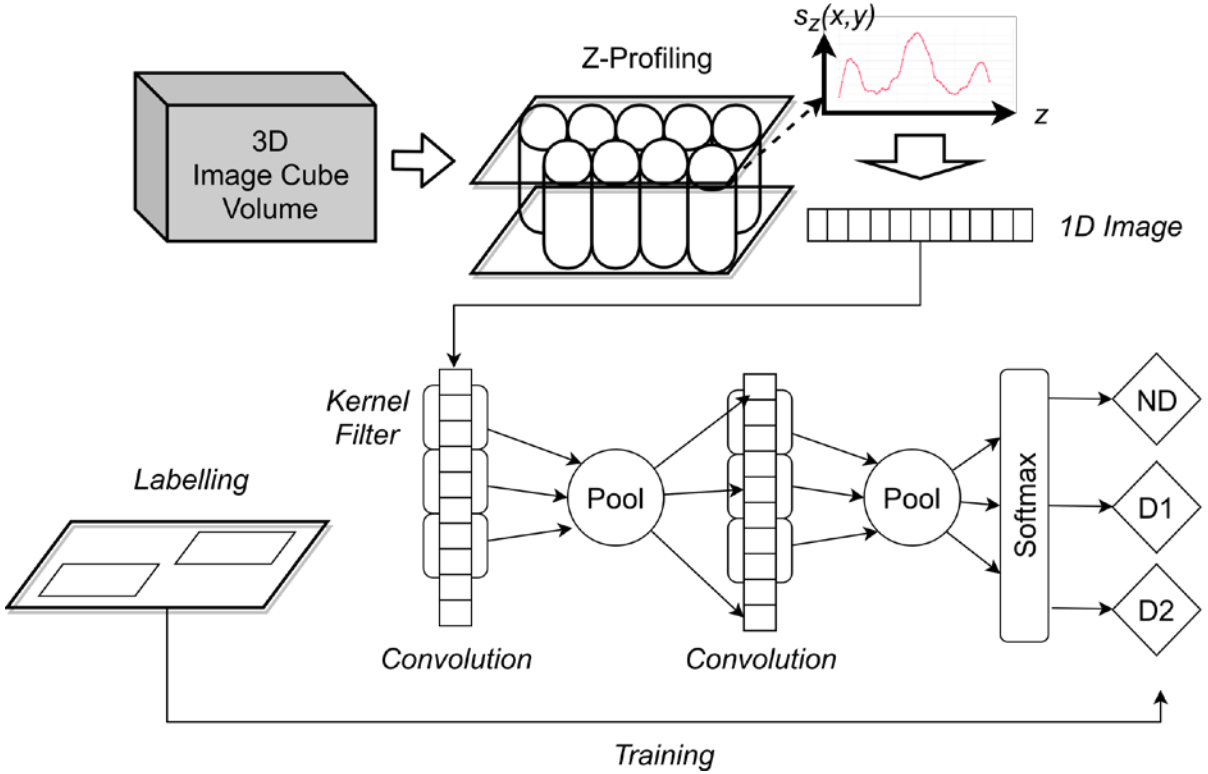
ANOMALY DETECTION IN FML CT DATA: NEGATIVE TRAIN.

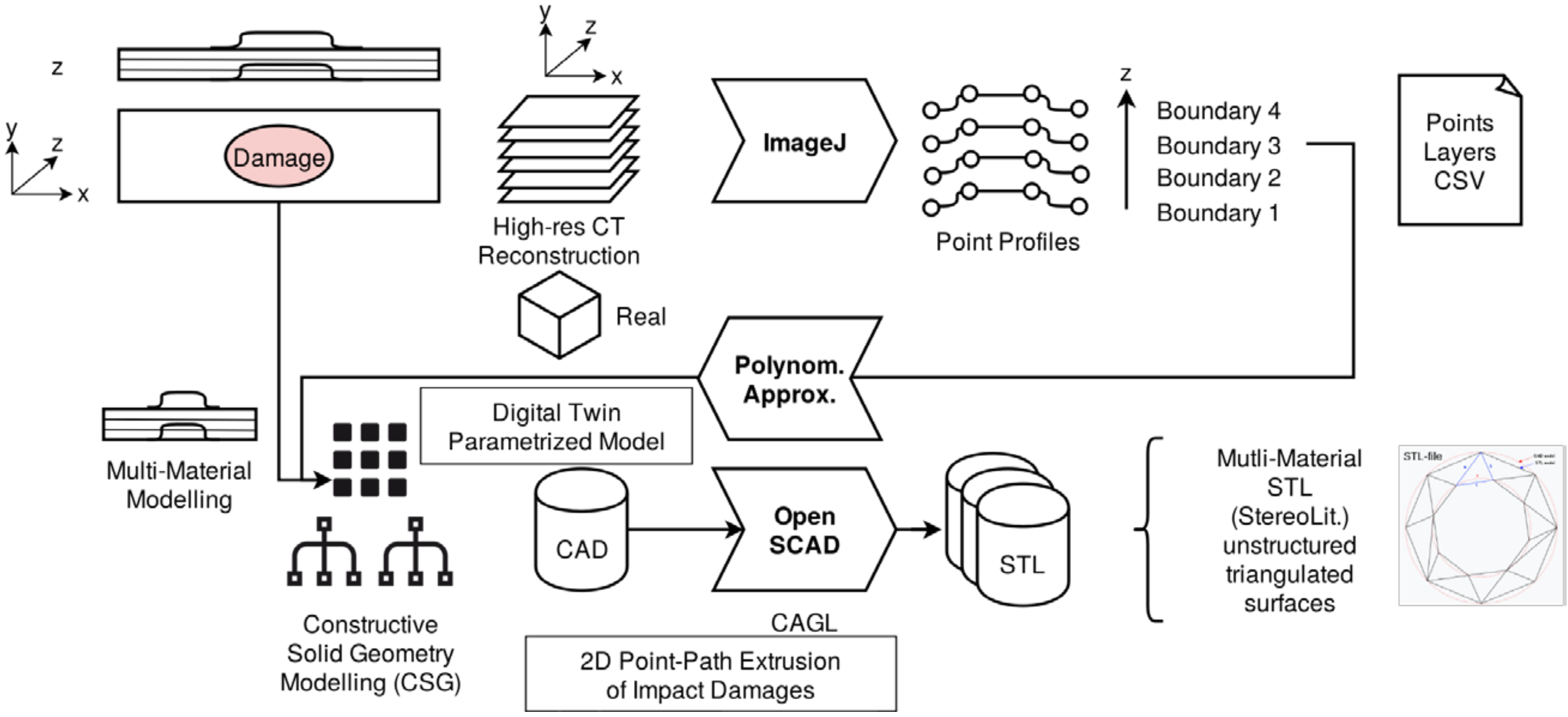
- A CNN is trained with damaged z-profiles to classify damaged versa undamged z-profile slices

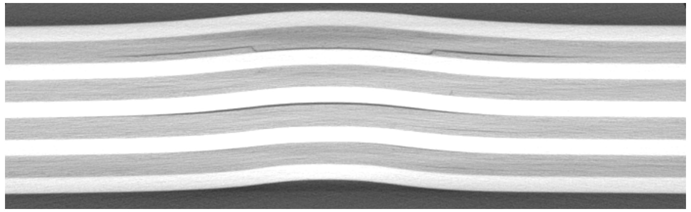


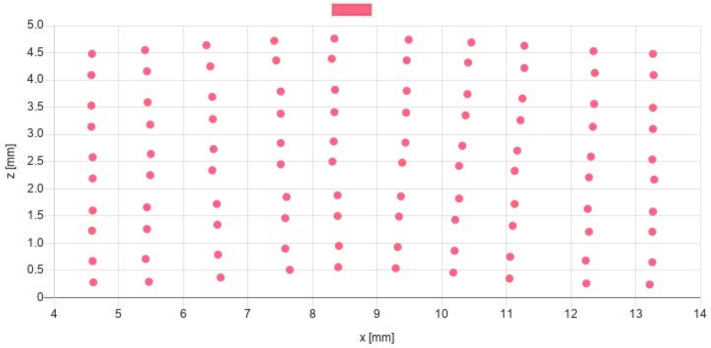
ANOMALY DETECTION IN FML CT DATA: SIMULATION

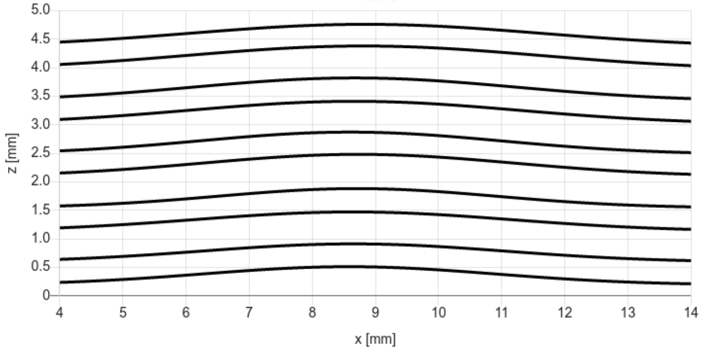
- A typical sample set contains less than 10 different specimens, each with a distint and unique impact damage (and base-line = no damge)
- **Data augmentation by simulation is required to increase feature and data variance!**
- But in contrast to mechanical pore modelling in homogeneous materials, modelling of impact damages in FML is much more complicated reaching high accuracy (wrt. real structures and images)
- Hand-made layer boundary point-marking using image tools
- Functional approximation $\rightarrow$ 3D CAD model $\rightarrow$ X-ray simulation

ANOMALY DETECTION IN FML CT DATA: SIMULATION









Don’t trust data-driven modells!

CONCLUSIONS

Data

- **Single- and Multi-Proj. X-ray Images**
- **Data and feature variance is always limited**!
  - CT scans require high measuring time and produce big data volumes
  - Noise (LowQ)
- Supervised Learning: Hand-made **labelling is a challenge** and inaccurate
  - Relation between image and target features can be very low (contrast)
- CT data can not be used directly for **labelling** due to geometrical distortions (wrt. single projection input data)

Methods

- 3D CT reconstruction using **Filtered Back Projection** (sine wave filters)
- **Convolutional Neural Networks** for pore and damage feature marling (data-driven negative training) and **LSTM** anomaly detectors (positive training)
- **X-ray simulation** based on Beer-Lambert law and multi-material polygon mesh models
- **Monte Carlo simulation** of materials with defects and damages (openSCAD, **Constructive Solid Geometry**)
- **Measuring devices**: LowQ, MidQ, HighQ

Results

- **A pure data-driven feature marking model (semantic image pixel classifier) trained with synthetic images only can be applied to real images**
- **The semantic pixel feature marling model is capable to highlight low-contrast features (e.g., hidden pores)**
- **X-ray noise has significant impact on feature prediction results**
- **Accurate and representative training examples (labelling, simulation models) are a pre-requisite for robust data-driven models and a challenge!**

THANK YOU

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