Automatic Damage Detection, Segmentation and Characterization using Deep Learning

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Introduction

Detection - Finding if damage exists

Segmentation (localization) - Precisely outlining damaged areas

Characterization - Analyzing damage type and severity (quantification)

Deep Learning - Used for automating the process

Introduction

Developing an automated and accurate process for **detecting, segmenting, and characterizing** impact damages in **Fiber Metal Laminate (FML)** materials.

Application**: aerospace and automotive industries** due to their superior mechanical properties like high fatigue and corrosion resistance, light weight etc.

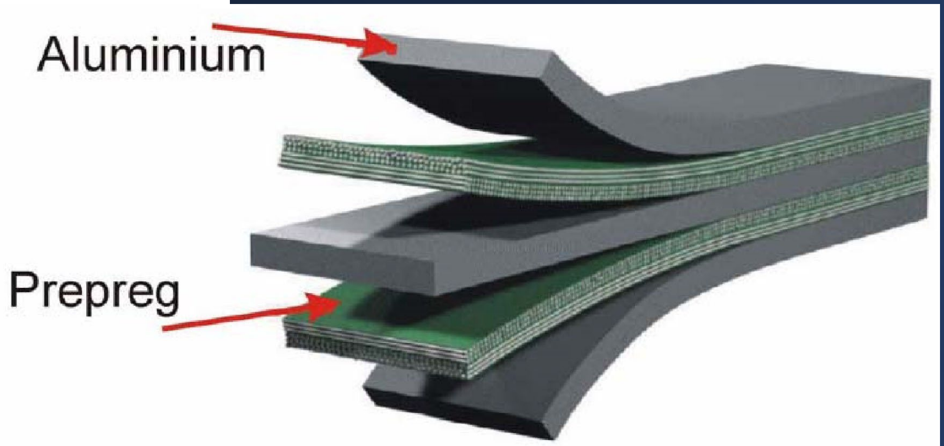
GLARE (Glass Laminate Aluminum Reinforced Epoxy) 5-5/4 with 54% Metal Volume Fraction, specimen thickness 4mm and size 150 × 500 mm.

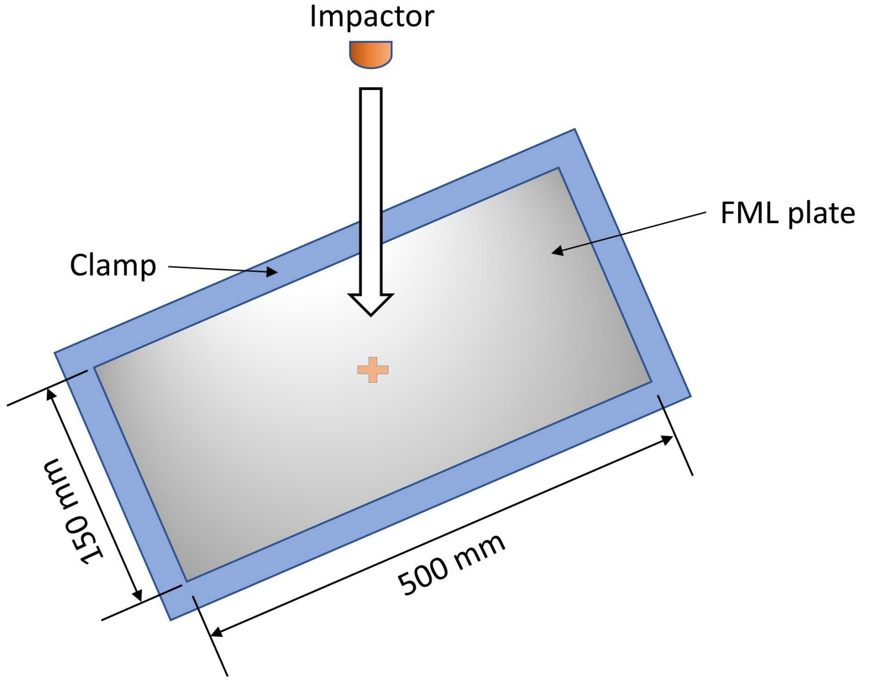
Introduction

The impacts were made at varying energy levels of **5J, 7.5J, 10J, and 12.5**J by shooting a projectile from the impact gun.

The plates were reduced to a size of 50 mm around the impact location via water jet cutting.

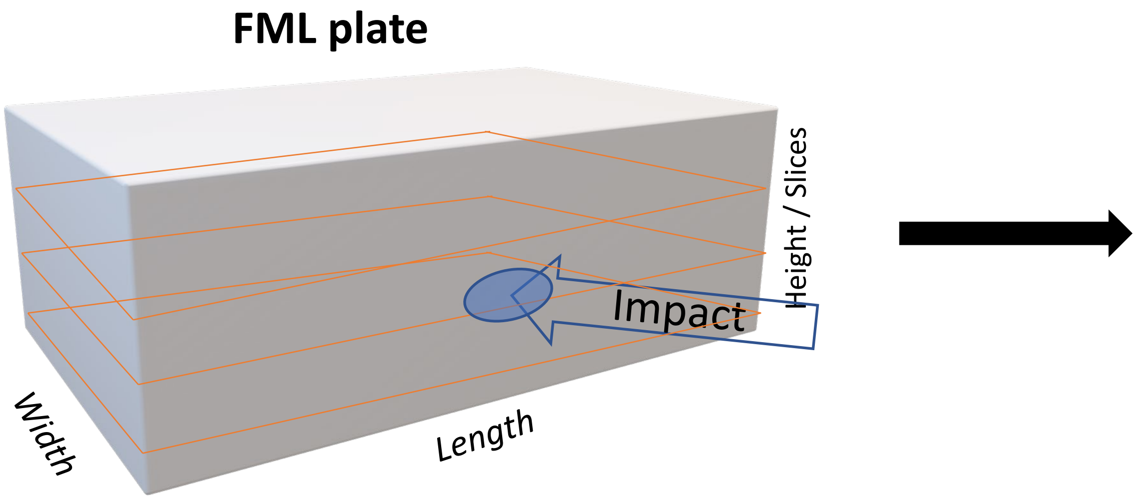
The smaller specimen were then investigated with the X-ray computed tomography (CT) to capture the cross-sectional slices of the damaged plate.

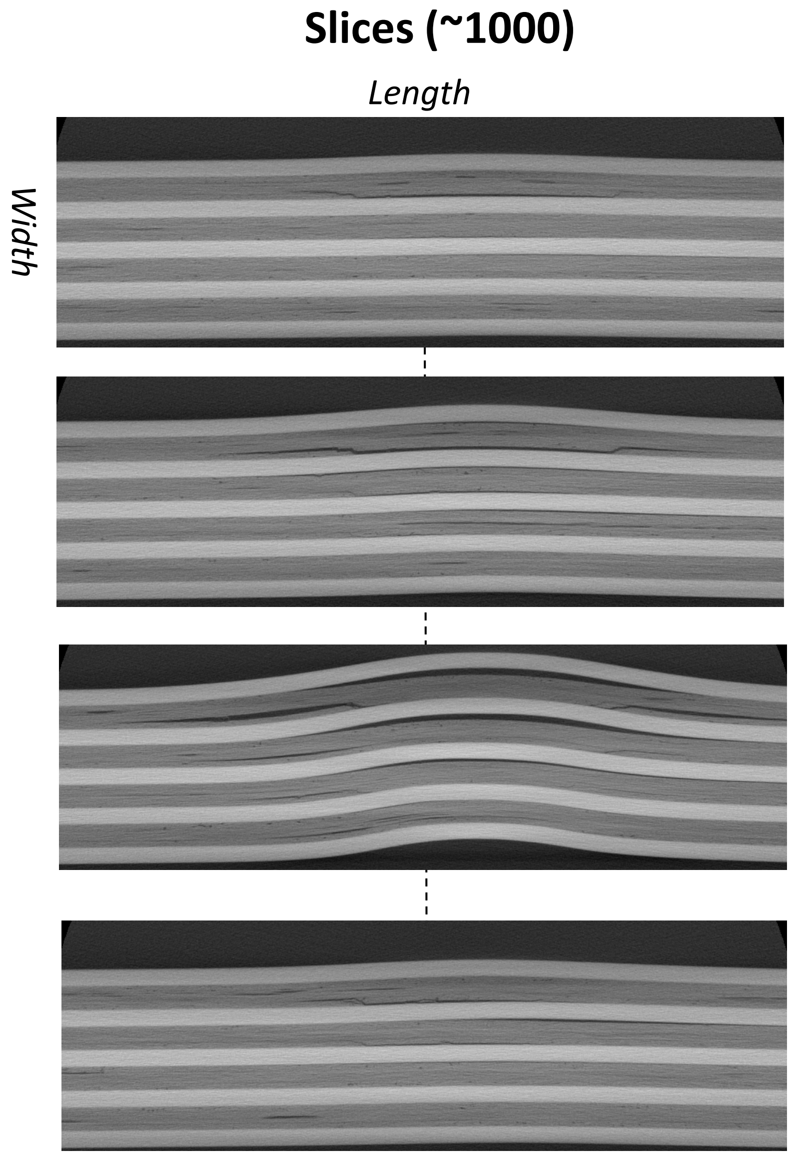




Introduction

- Example CT slices:

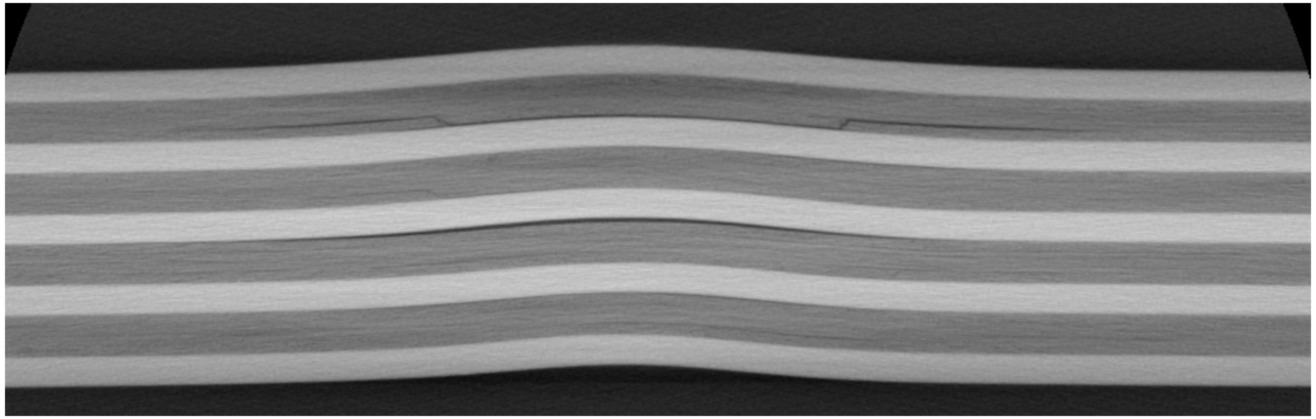




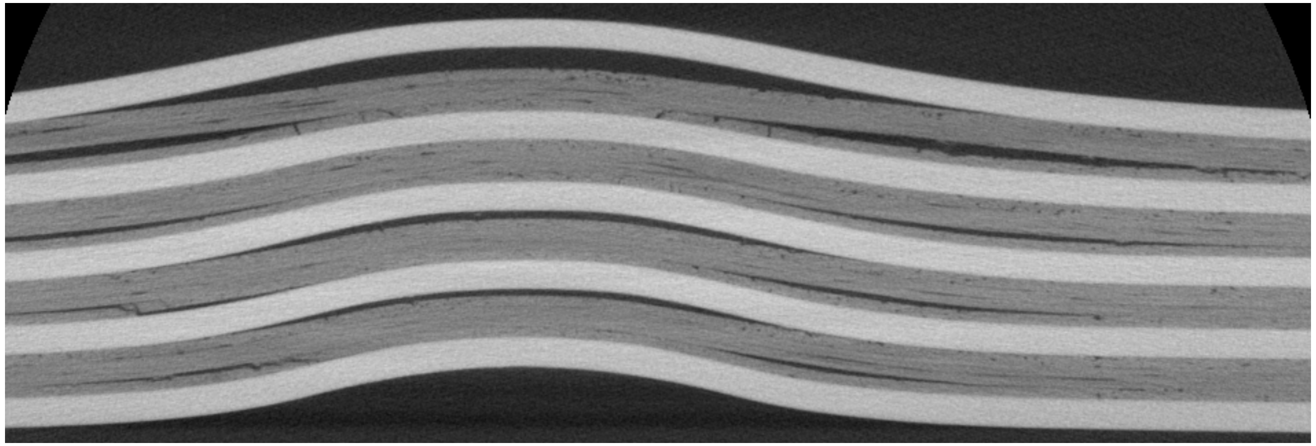
Introduction

- Example CT slice (5 J vs. 12.5 J)

5 Joules



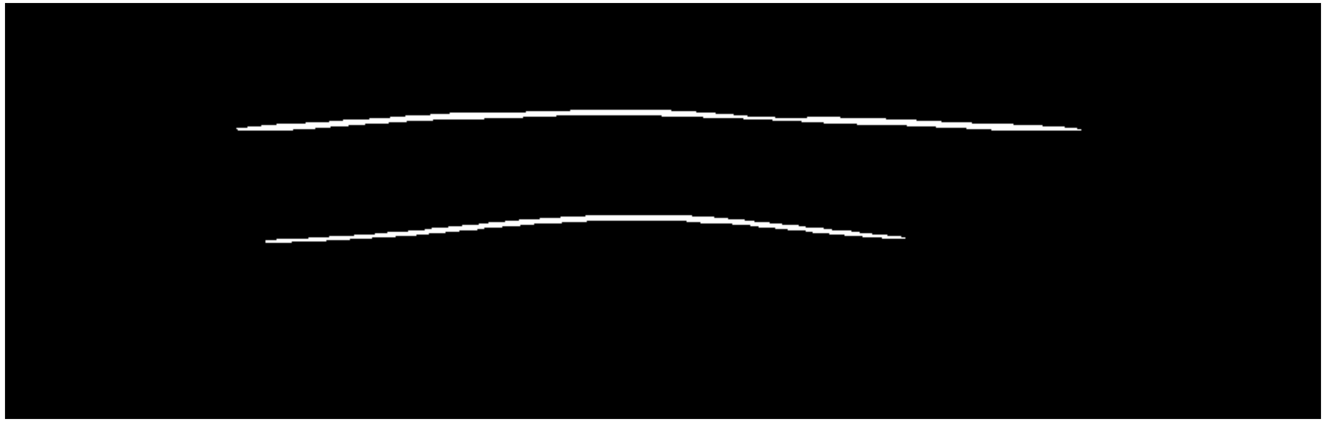
12.5 Joules



Introduction

- Example Masks (5 J vs. 12.5 J)

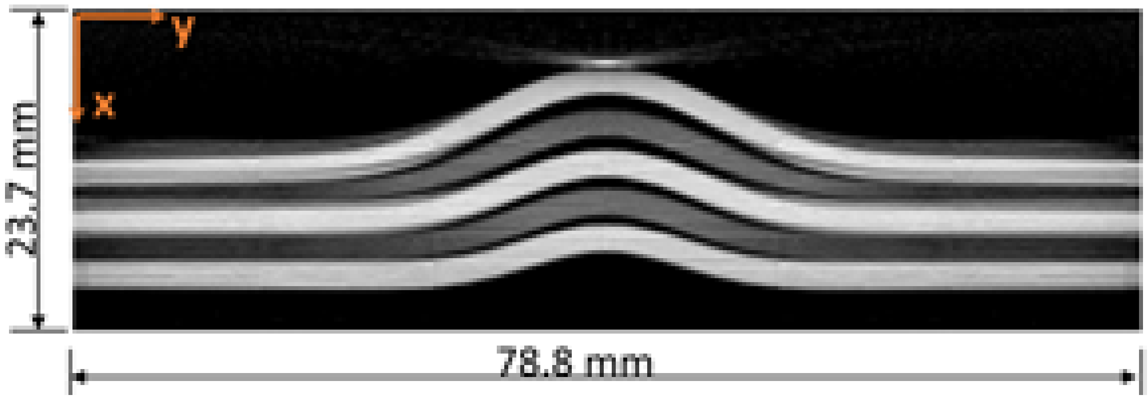
5 Joules

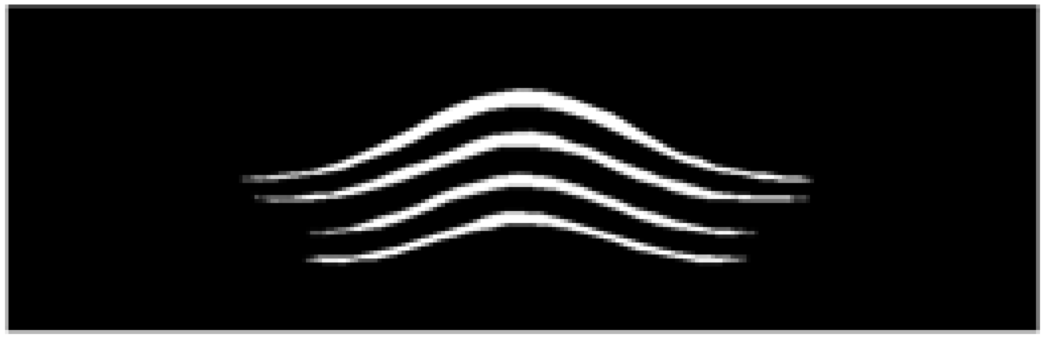


12.5 Joules

Synthetic Dataset

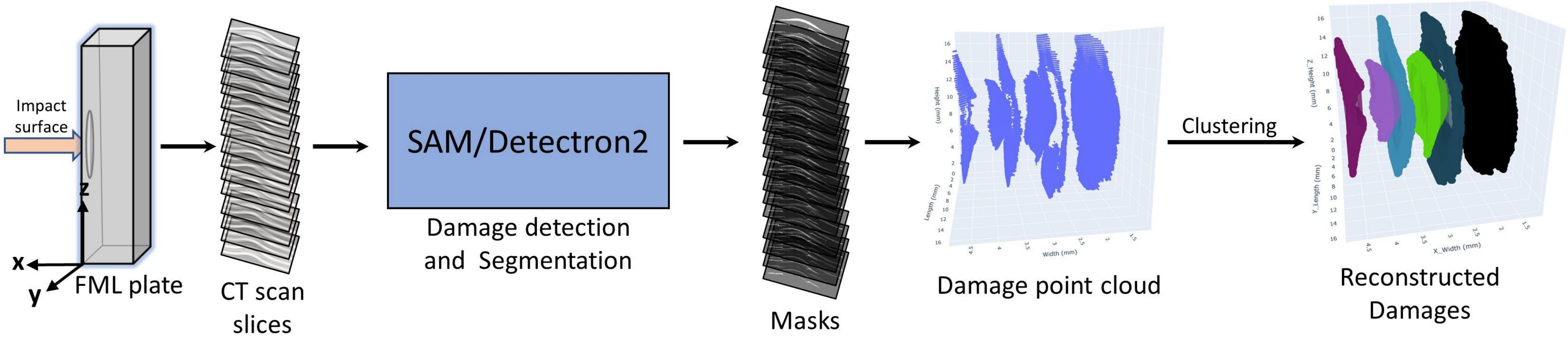
- No absolute ground truth damages
- Lot of artefacts and noise due to CT reconstruction
- Synthetic data created for reliability using CAD model (OpenSCAD) and XraySim (gVirtualXray)





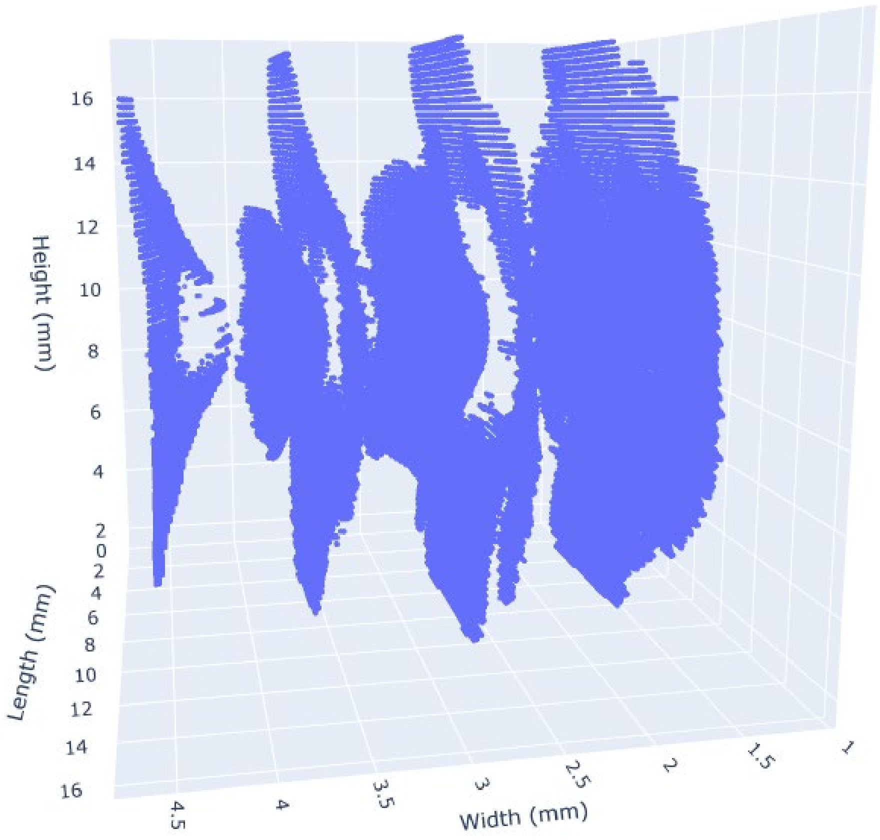
Introduction

- Complete process pipeline.

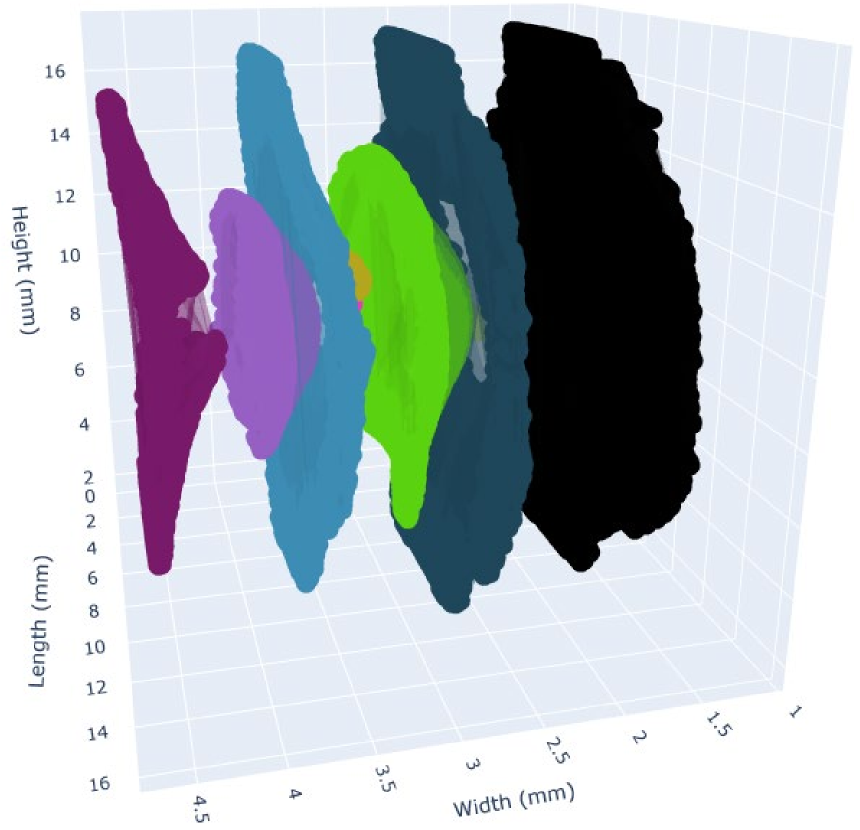


Damage point cloud

- Example (7.5 Joules impact)

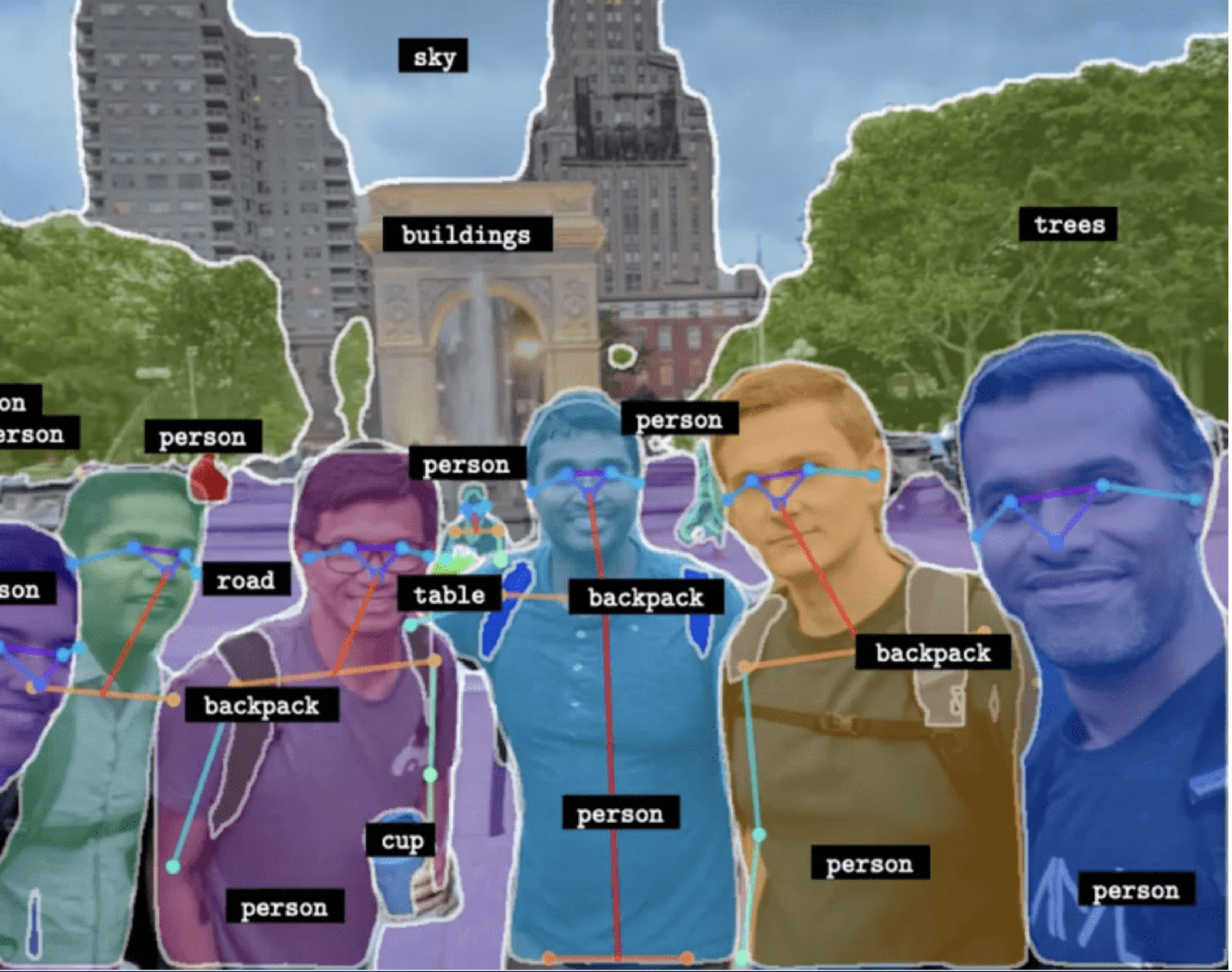


Clustering and hull fitting



Detectron2

- A powerful, modular computer vision library developed by Facebook AI Research (FAIR) for object detection and segmentation tasks.
- Built on PyTorch framework for deep learning research and applications.
- Key development Features:
  - **Modular Design**: Easy to add new models and tasks
  - **Fast Training**: Supports both single and multi-GPU training
  - **Model Zoo**: Contains pre-trained models for quick deployment
  - **Extensible**: Supports custom datasets and model architectures
- https://github.com/facebookresearch/detectron2



Detectron2

- Supported Vision Tasks:
  - Object Detection
  - Instance Segmentation
  - Semantic Segmentation
  - Key-point Detection
  - Panoptic Segmentation

Mask R-CNN

Mask Region-Based Convolutional Neural Network.

An extension of Faster R-CNN that **combines object detection and semantic segmentation**.

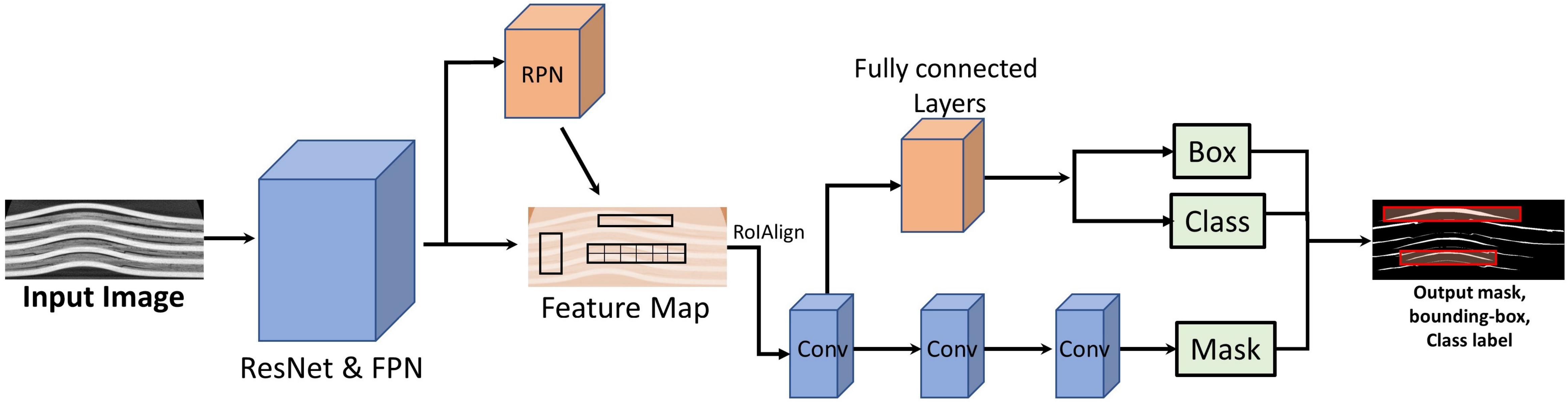
Produces both bounding boxes around objects and pixel-level segmentation masks.

Key innovation: Adds a parallel mask prediction branch to the existing classification and bounding box regression branches.

Uses RoIAlign instead of RoIPool for more precise spatial feature extraction.

Predicts binary masks independently for each class, decoupling classification and segmentation tasks

Mask R-CNN



Input Image
ResNet & FPN
RPN
Feature Map
RoIAlign
Fully connected Layers
Conv
Conv
Conv
Box
Class
Mask
Output mask, bounding-box, Class label

Architecture Components

Backbone Network

- ResNet-50 with Feature Pyramid Network (FPN)
- Processes input image to generate convolutional feature maps
- FPN creates multi-scale feature pyramid for handling various object sizes

Region Proposal Network (RPN)

- Generates candidate object proposals
- Predicts objectness scores and bounding box coordinates
- Fully convolutional network design

RoIAlign Layer

- Improves upon RoIPool with precise spatial sampling
- Uses bilinear interpolation to avoid quantization errors
- Preserves spatial coherence for accurate mask generation

Dual-Branch Head

- Bounding Box Head: Predicts object class and refines box coordinates
- Mask Head: Generates binary segmentation mask for each RoI

Residual Network (ResNet)

Challenge:

- Deep networks suffer from vanishing/exploding gradients
- Gradients become extremely small as they propagate backwards
- Training becomes ineffective in very deep networks
- Accuracy degrades despite increased network depth

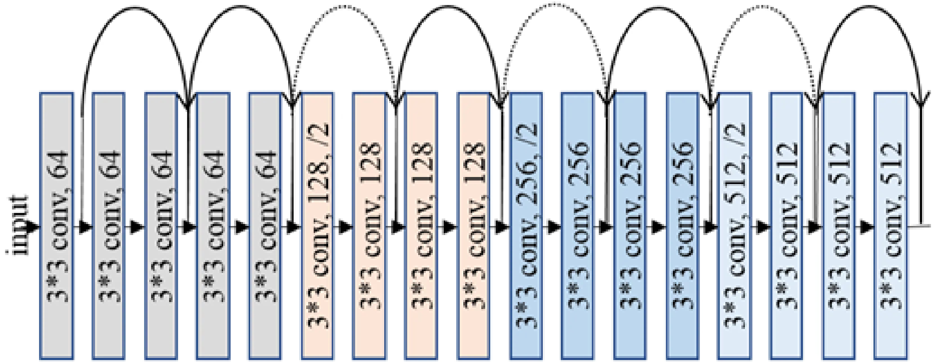
Traditional Solutions

- Normalized initialization
- Intermediate normalization layers
- These help but don't fully solve the problem
- Limited network depth still persists

Residual Network (ResNet)

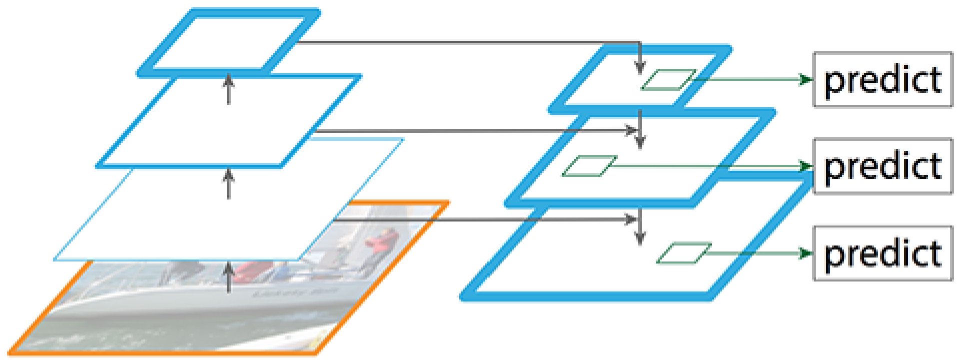
ResNet Solution

- **Skip Connections** (Identity Mappings)
    - Create shortcuts between layers
    - Allow direct flow of gradients
    - Enable better information propagation
- **Advantages**
    - Easier optimization
    - No extra parameters or computation
    - Can train very deep networks (50+ layers)
    - Better gradient flow throughout network



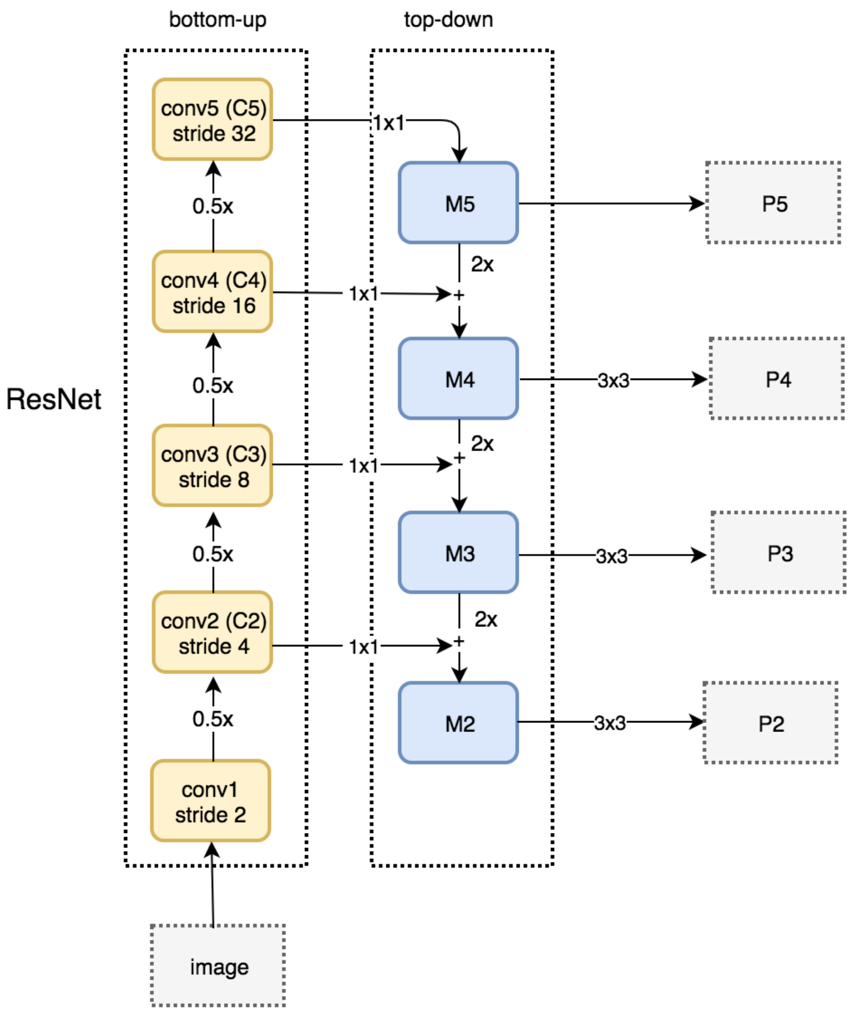
Feature Pyramid Network (FPN)

- Multi-scale feature extractor for object detection and segmentation.
- **Bottom-up Pathway**
  - Traditional convolutional network (e.g., ResNet)
  - Features hierarchically divided into levels
  - Each level has progressively:
    - Larger receptive field
    - Stronger semantic information
    - Lower spatial resolution
- **Top-down Pathway**
  - Upsampling of higher level features
  - 1x1 convolutions for dimension reduction
  - Lateral connections from bottom-up pathway
  - Element-wise addition of features



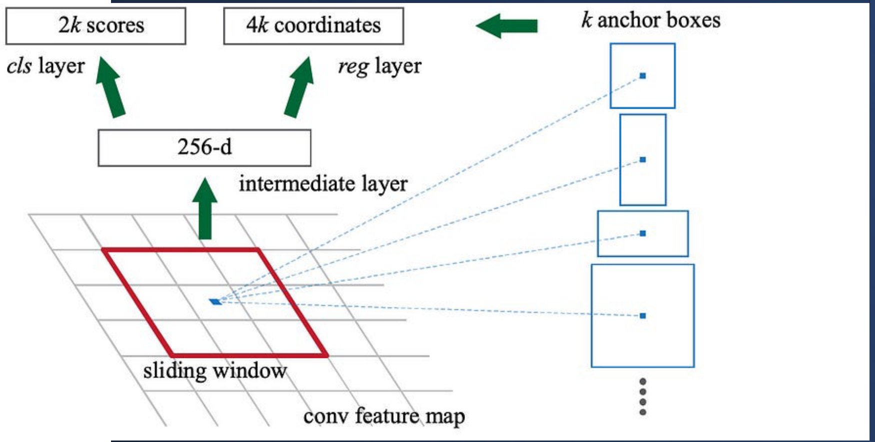
Feature Pyramid Network (FPN)

- 1×1 convolution filter to reduce C5 channel depth to 256-d to create M5.
- In top-down path, upsample by 2 using nearest neighbors upsampling.
- apply a 1×1 convolution to the corresponding feature maps in the bottom-up pathway. Add them element-wise. Apply a 3×3 convolution to all merged layers.
- Reduces the aliasing effect when merged with the upsampled layer.



Region Proposal Network (RPN)

- FPN extracts feature maps then feeds into a detector (RPN).
- A sliding window over the feature maps is applied.
- Predictions on the objectness (has an object or not) and the object boundary box.



Loss Function Components

Total Loss Function:

$$L = L_{\text{cls}} + L_{\text{box}} + L_{\text{mask}}$$

$$\boxed{L_{\text{cls}} = -\log(p_t)}$$

$$\boxed{L_{\text{box}} = \text{smooth}_{L1}(v - \hat{v}) \qquad \text{smooth}_{L1}(x) = \begin{cases} 0.5x^2 & \text{if } |x| < 1 \\ |x| - 0.5 & \text{otherwise} \end{cases}}$$

$$\boxed{L_{\text{mask}} = -\sum_{p,q} \left[m_{pq} \log(\hat{m}_{pq}) + (1 - m_{pq}) \log(1 - \hat{m}_{pq}) \right]}$$

1. Classification Loss:

- Standard cross-entropy loss (log loss).
- Measure the error between the predicted and true class.

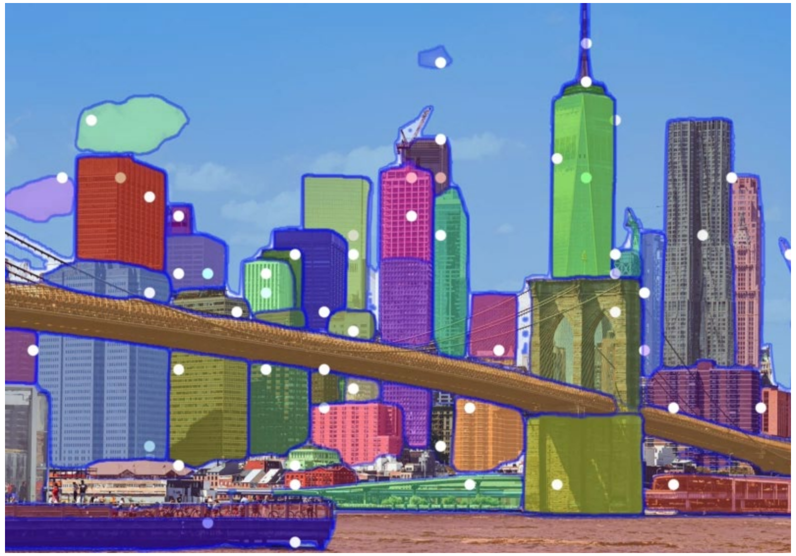
2. Bounding Box Loss:

- Refines bounding box predictions.
- measure the difference between the predicted and true bounding box coordinates.
- v is the true bounding box coordinates and v cap is the predicted coordinates.

3. Mask Loss

1. Pixel-wise binary cross-entropy
2. Applied only to ground-truth class masks
3. Computed per-pixel for accurate segmentation
4. m is the true binary mask and m cap is the predicted mask, p and q index the pixels in the mask.

Segment Anything Model (SAM)



- A foundation model for image segmentation developed by Meta AI
- First universal image segmentation model that works with any segmentation task
- Trained on over 11 million images and 1.1 billion masks
- Open-source model designed for broad accessibility and application

Segment Anything Model (SAM)

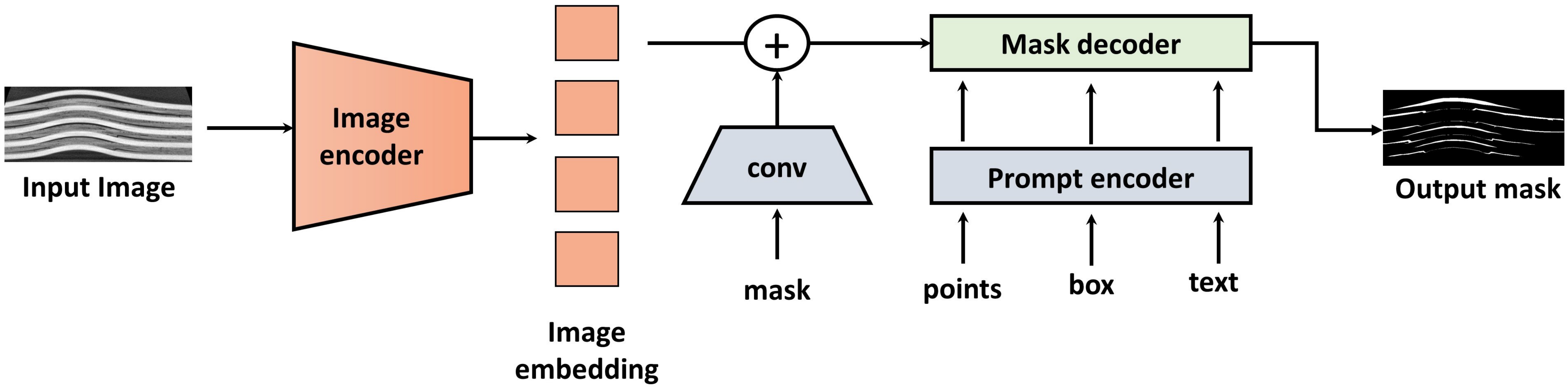
Promptable Segmentation

- Accepts various input prompts: points, boxes, text, and masks
- Generates high-quality segmentation masks in real-time
- Flexible interaction modes for different use cases

Zero-Shot Performance

- Works effectively on unseen objects and scenarios
- Requires minimal prompt engineering
- Generalizes well across different domains

SAM Architecture



SAM Architecture

Image Encoder

- Vision Transformer (ViT) backbone
- Processes input images into dense visual features
- Available variants: ViT-H, ViT-L, and ViT-B
- Creates rich image embeddings with spatial and contextual information

Prompt Encoder

- Handles points, boxes, and text inputs
- Uses positional encodings
- Combines with learned embeddings per prompt type

Mask Decoder

- Transforms embeddings into segmentation masks
- Dynamic mask prediction head
- Processes multiple prompts in parallel
- Outputs high-resolution binary masks

Loss Function and Training

$$\mathcal{L} = \alpha\mathcal{L}_{\text{Dice}} + \beta\mathcal{L}_{\text{CE}}$$

$$\mathcal{L}_{\text{Dice}} = 1 - \frac{2\sum_i p_i g_i}{\sum_i p_i^2 + \sum_i g_i^2}$$

$$\mathcal{L}_{\text{CE}} = -\frac{1}{N}\sum_i [g_i \log(p_i) + (1-g_i)\log(1-p_i)]$$

1.Dice Loss

1. Focuses on overlap between predicted and ground truth masks
2. Effective for small structure prediction
3. P_i are the predicted probability and g_i are the ground truth binary label for each pixel i.

2.Cross-Entropy Loss

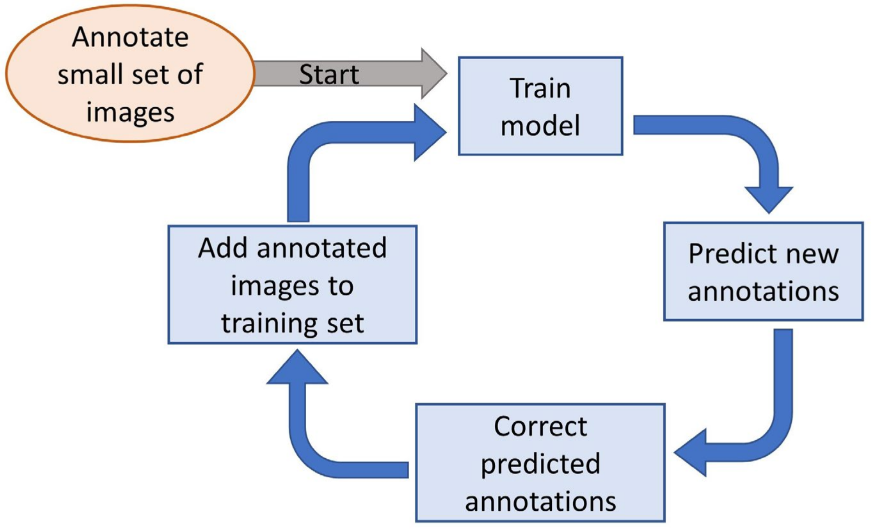
1. Handles class balance
2. Pixel-wise binary classification

3.Balanced Advantages

1. CE: Maintains overall class proportions
2. Dice: Better prediction of small structures
3. Combined approach handles various segmentation challenges

Training

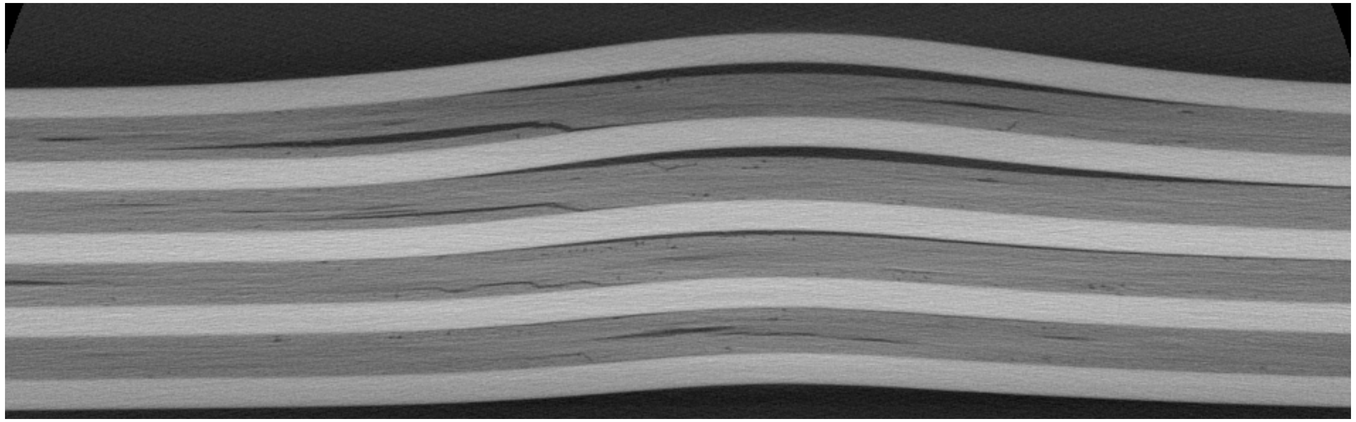
- Trained using 28 images (950x300 , 121 features)
- Evaluated using 8 images (950x300 pixels, 35 features)
- Image pre-processing:
  - Normalisation
  - Gaussian noise removal
  - CLAHE (Contrast Limited Adaptive Histogram Equalization)
- Image annotations:
  - Hand annotate 15-20 images (more the better)
  - Or take help from partially trained model.



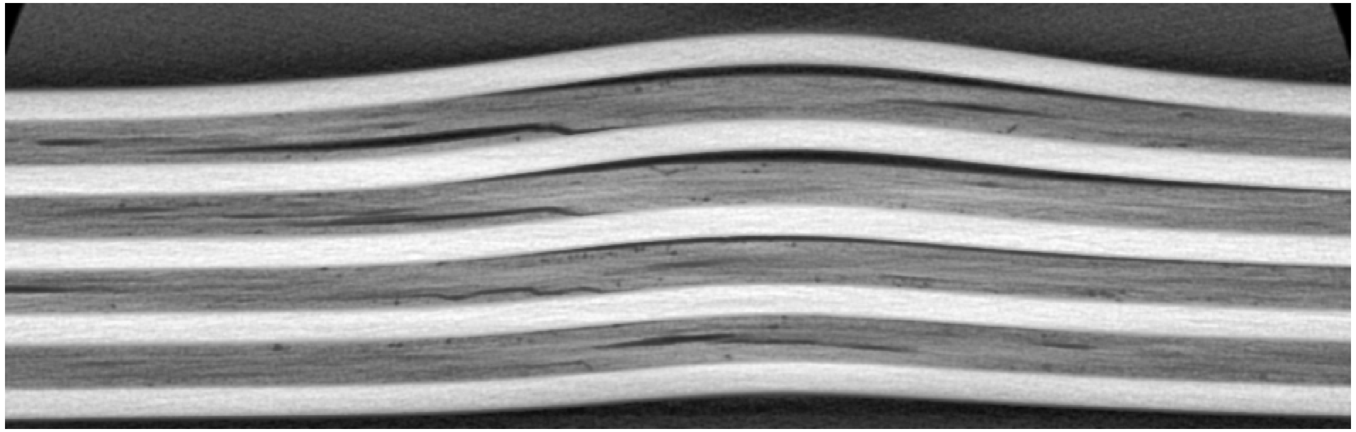
Training

- Example preprocessed training input:

Raw input image



Preprocessed input image

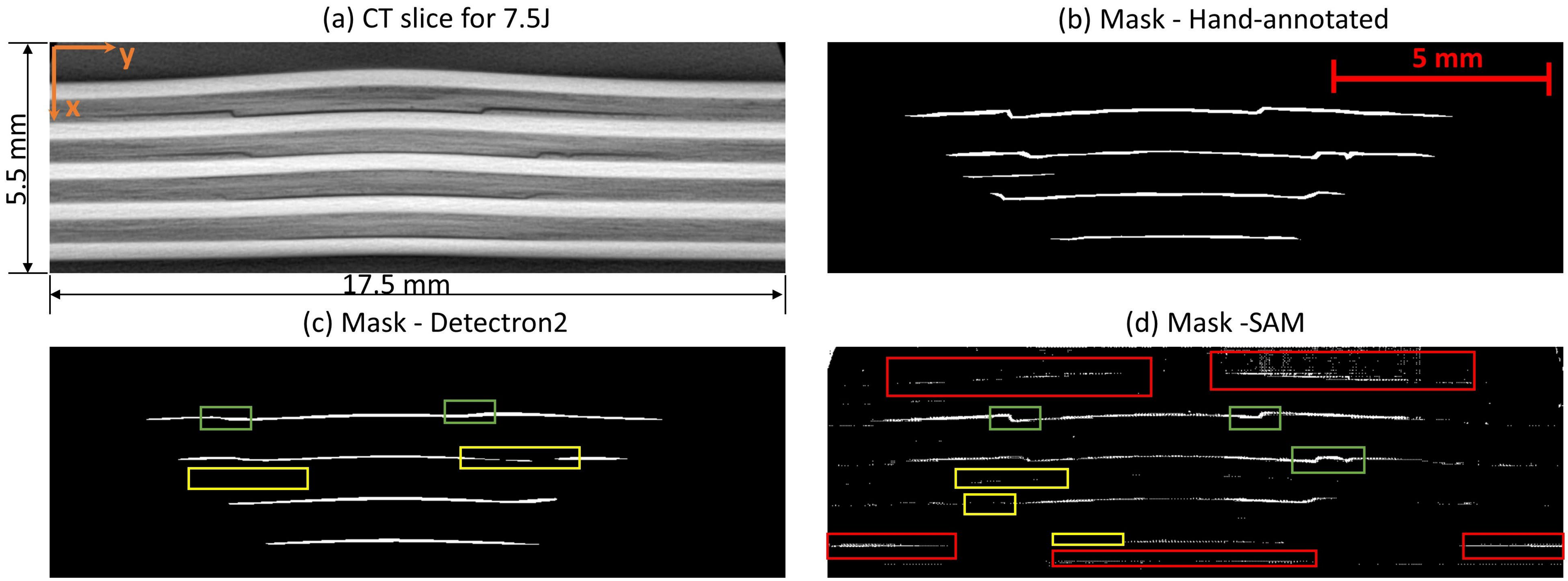


Training

SAM Hyperparameters	**Detectron2 Hyperparameters**
Optimizer: Adam (lr $= 1 \times 10^{-5}$, weight decay $= 0$)	Optimizer: SGD with momentum (lr $= 2.5 \times 10^{-4}$, momentum $= 0.9$)
Batch size: 2, Epochs: 500	Batch size: 2 (ROI batch size per image: 256)
Patch size: 256 pixels, Step size: 256 pixels	Number of workers: 2
Inference threshold: 0.95	Inference threshold: 0.60

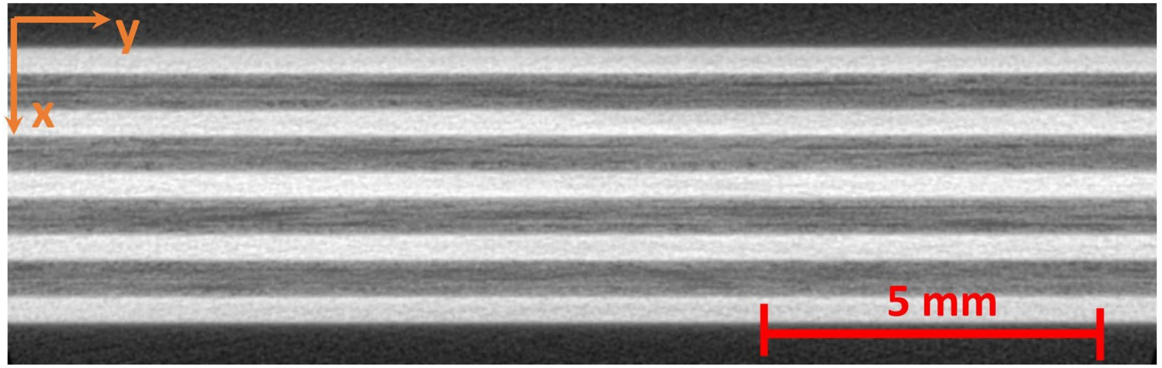
Table II: Key hyperparameters for SAM and Detectron2 training and inference.

Detectron2 vs. SAM



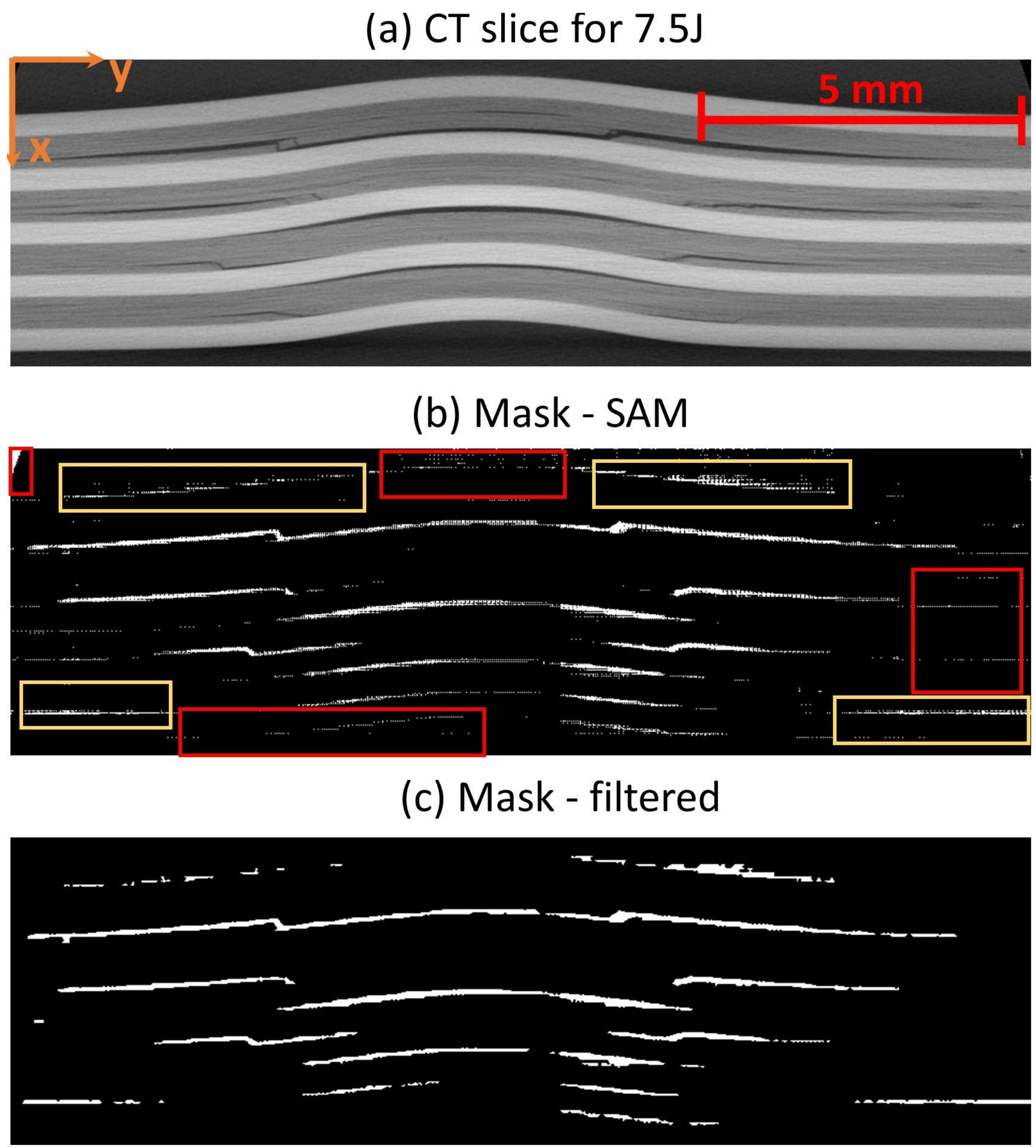
Detectron2 vs. SAM

(a) CT slice for Undamaged plate



(b) Mask -SAM

Detectron2 vs. SAM



Detectron2 vs. SAM

- Detectron2 provides more accurate (approx. 2.12 times better F1-score and 2.65 times better IoU score)
- Approx. 8 times faster training and 80 times faster inference as compared to the SAM.

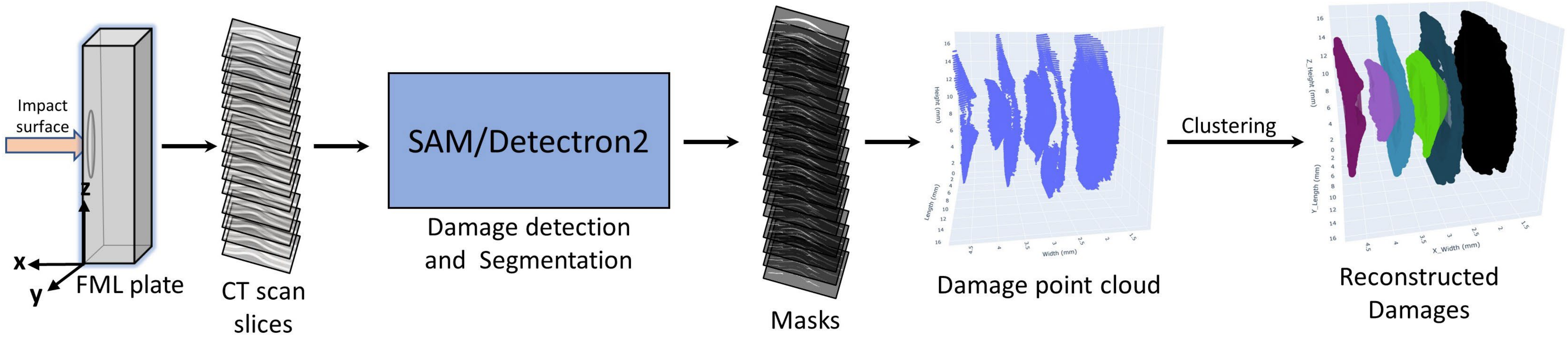
Metric	Detectron2	SAM	SAM (with filter)
IoU	0.53 (± 0.02)	0.19 (± 0.01)	0.25 (± 0.03)
Precision	0.77 (± 0.02)	0.31 (± 0.07)	0.39 (± 0.14)
Recall	0.64 (± 0.02)	0.40 (± 0.11)	0.55 (± 0.12)
F1	0.70 (± 0.03)	0.35 (± 0.17)	0.46 (± 0.20)

Customized Mask Filter

Algorithm 1: High-level mask filtering algorithm applied on the masks generated by SAM.

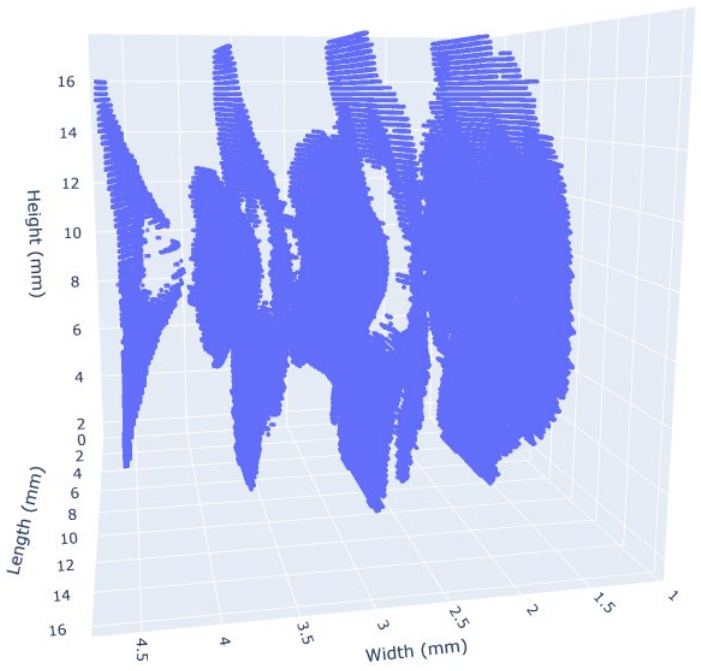
```
Input: Mask image
Output: Filtered mask image
Identify regions of interest in the mask image;
Apply clustering algorithm (DBSCAN):
    • Group dense regions into clusters

    • Identify sparse pixels as noise

Remove noise (sparse pixels) from further consideration;
foreach cluster do
    Compute the shape of the cluster (fit a concave hull);
    Calculate the area of the cluster;
end
Select top N clusters based on area;
foreach cluster do
    if cluster is in top N then
        if cluster shape meets aspect ratio criteria then
            Mark cluster as accepted;
        else
            Mark cluster as potential false positive;
        end
    else
        Mark cluster as rejected;
    end
end
Generate final filtered mask:

    • Retain accepted clusters
```

Complete process pipeline

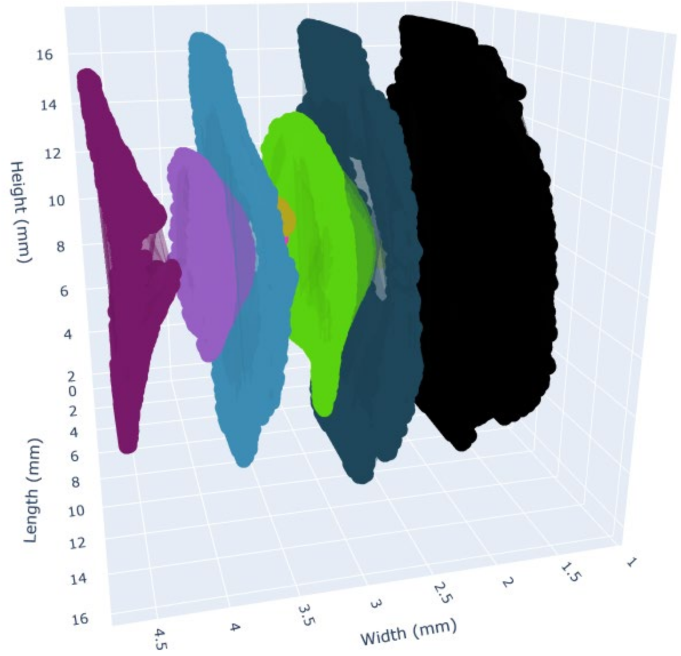


Clustering

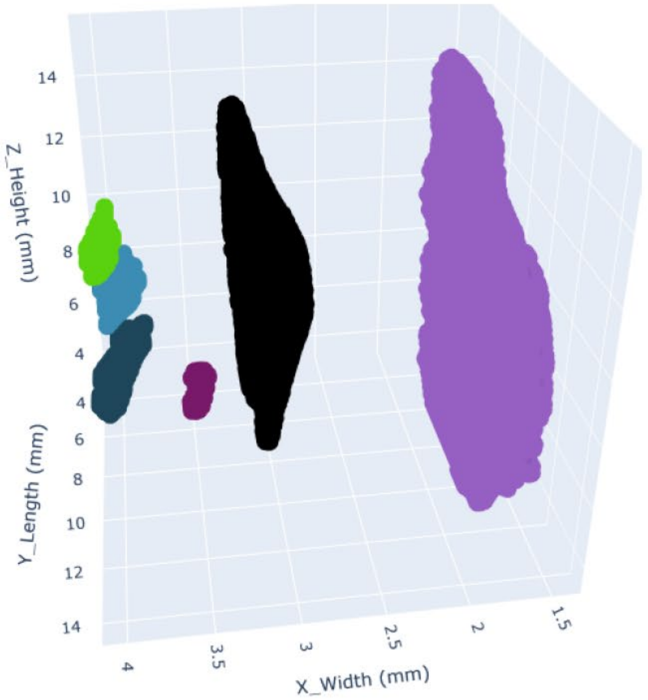
- Clustering of the damage point clouds using DBSCAN (Density-Based Spatial Clustering of Applications with Noise).
- Concave hull fitting.



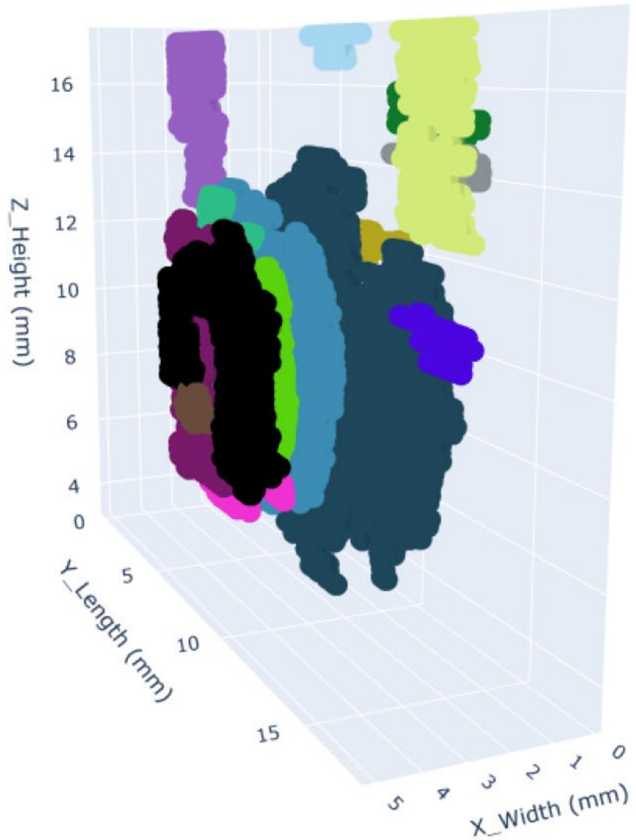
Clustering
and hull
fitting



Detectron2 vs. SAM

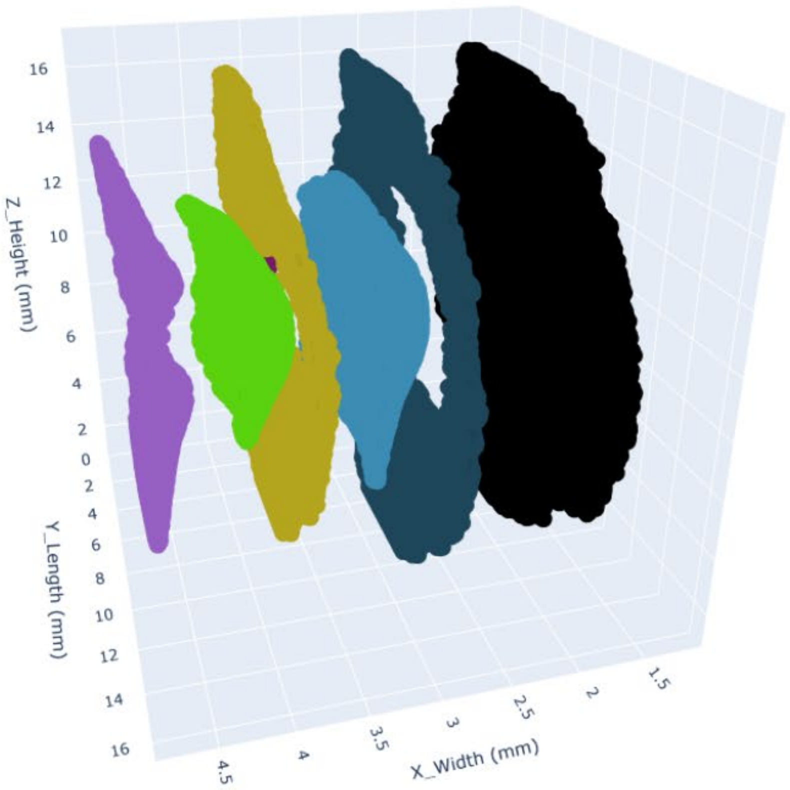


(a) Detectron2 - 5J

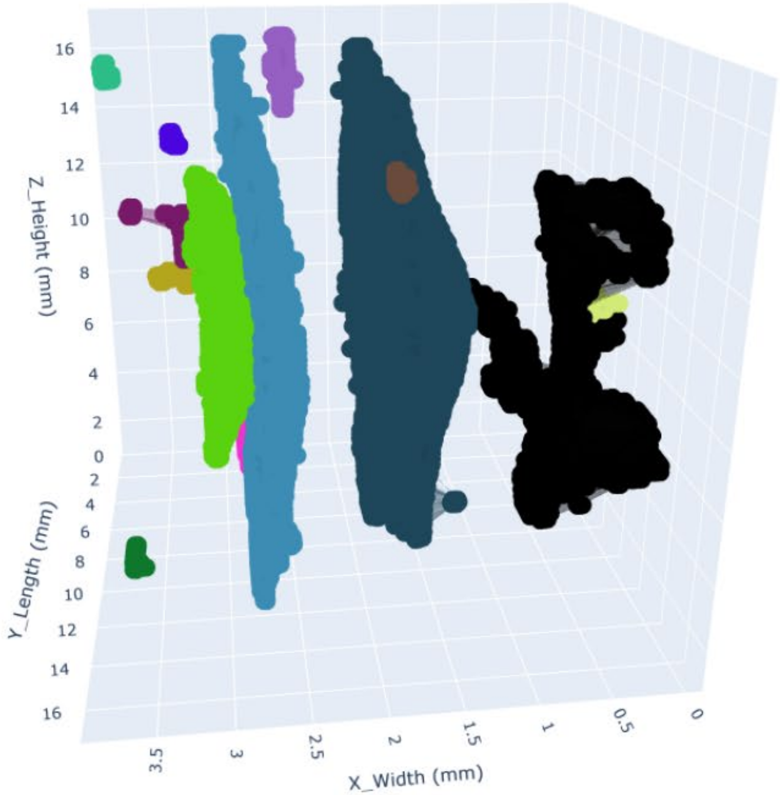


(b) SAM - 5J

Detectron2 vs. SAM

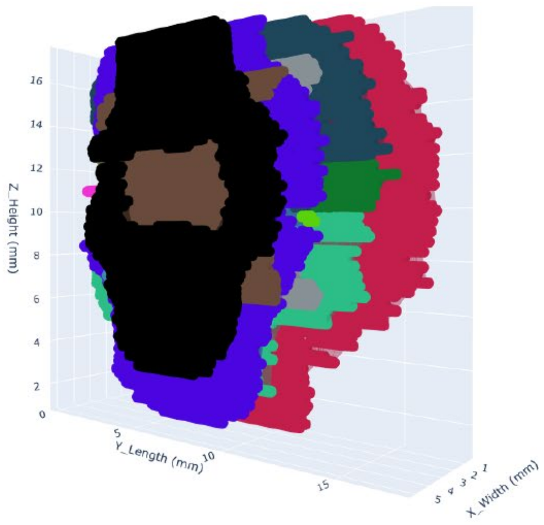


(c) Detectron2 - 7.5J

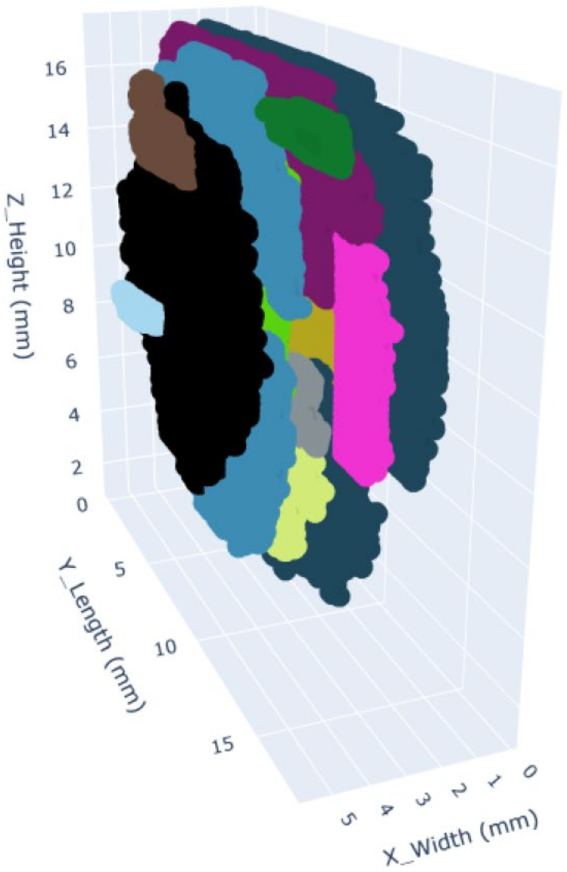


(d) SAM - 7.5J

Detectron2 vs. SAM

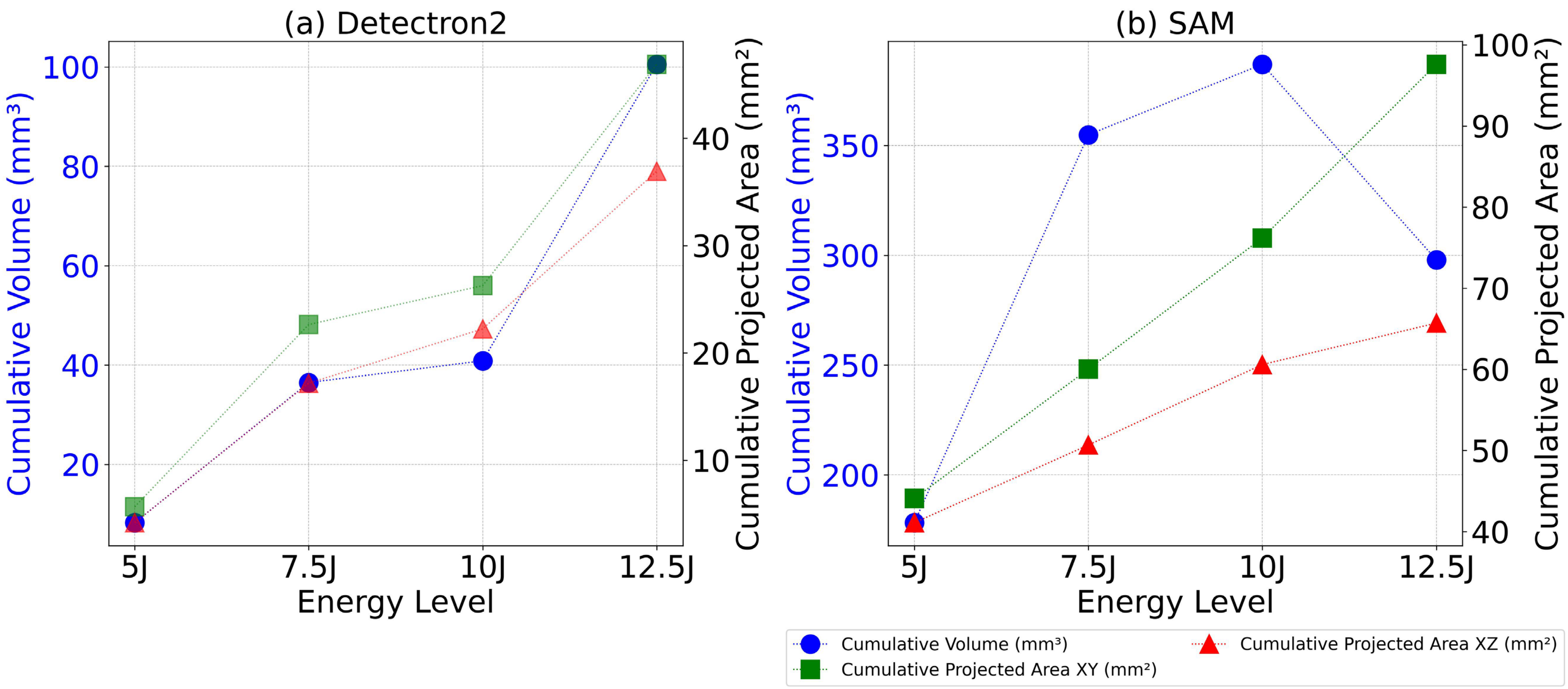


(c) Detectron2 - 12.5J

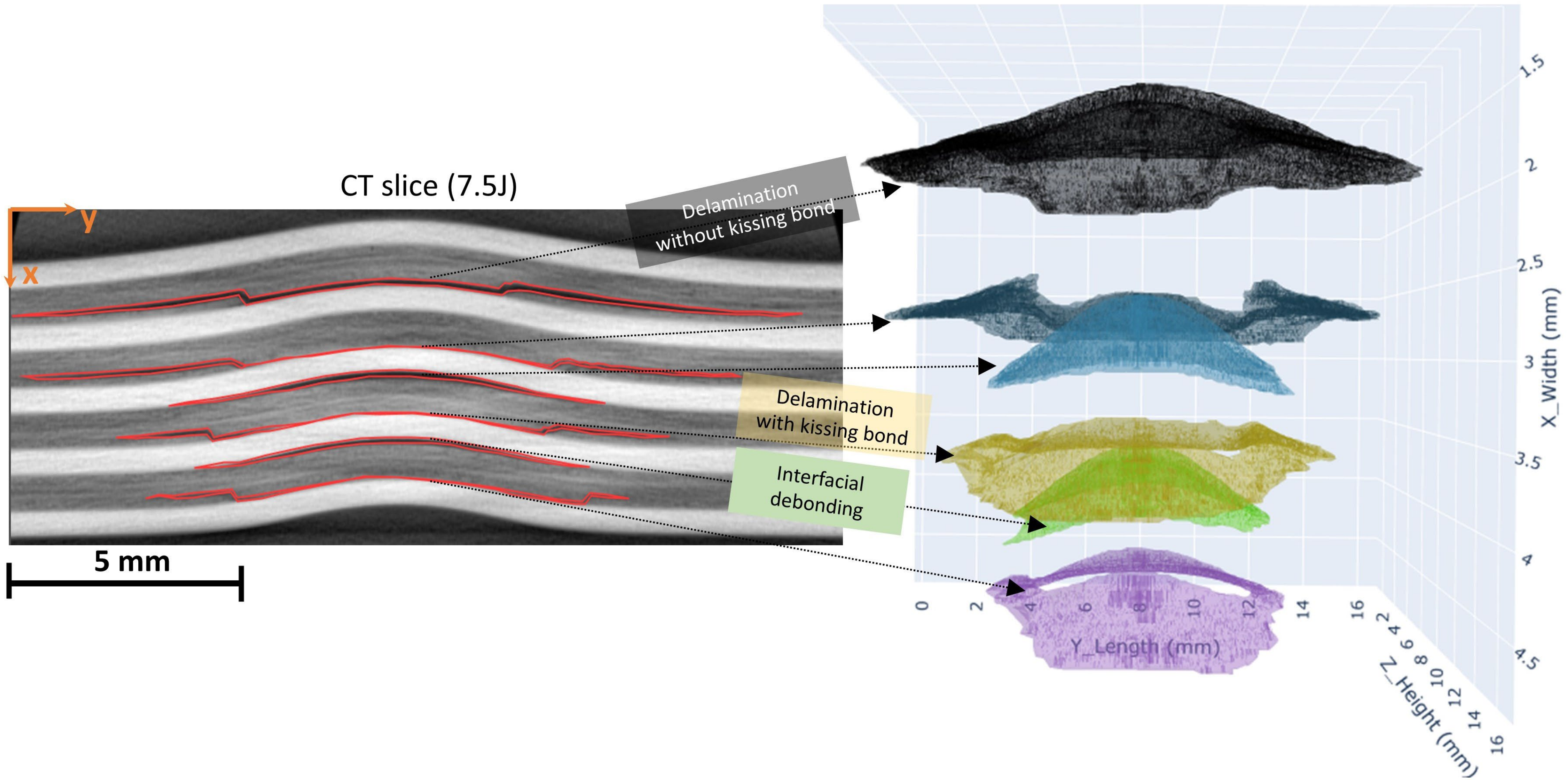


(d) SAM - 12.5J

Detectron2 vs. SAM



Damage types



Residual Attention U-Net

Core Architecture: Ronneberger et. al. (2015)

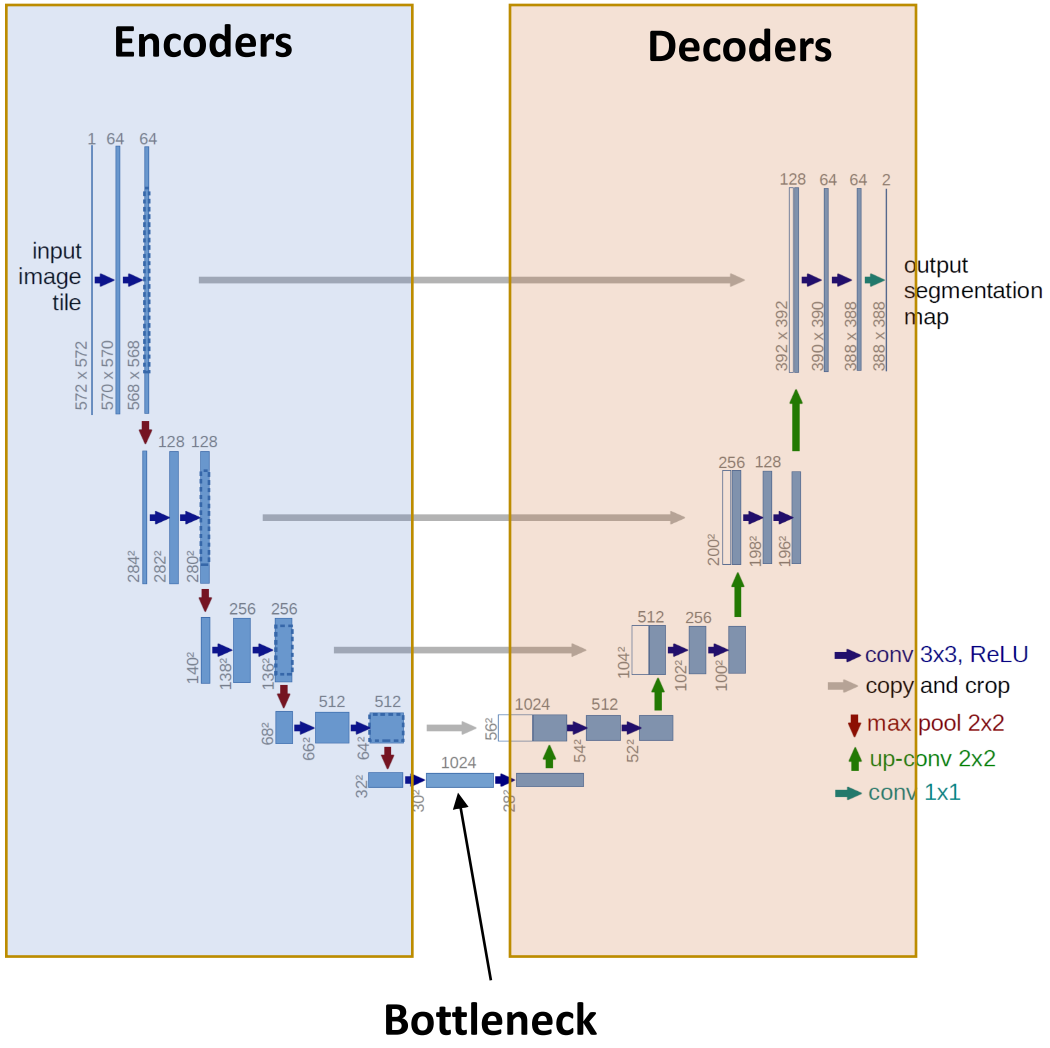
- **Encoder-Decoder Structure**: Contracting path captures context through down-sampling, expanding path enables precise localization through up-sampling
- **Skip Connections**: Preserves fine-grained spatial information lost during down-sampling

(helps to learn both low-level and high-level)

- **Symmetric Design**: Maintains spatial resolution recovery

Key Strengths for Damage Segmentation:

- Excellent performance with limited training data
- Preserves both global context and local detail through multi-scale feature fusion



Segmentation Results

- Better feature prediction for synthetic data plus more reliability
- Relatively simple features as compared to real images
- Precision and recall balanced in both

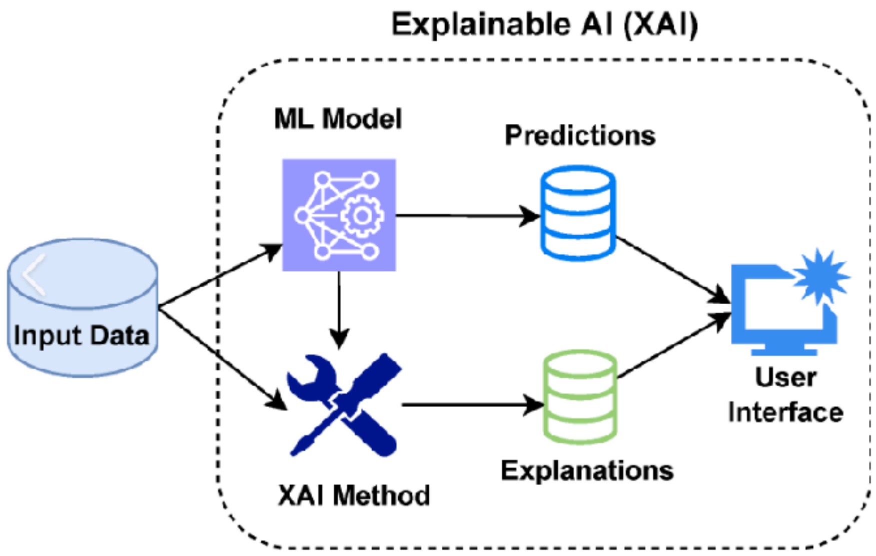
Table I: Validation data predictions from RAUNet (in percentages).

Metric	Real Data (%)	Synthetic Data (%)
IoU	**67.23**	**76.49**
Precision	83.68	84.92
Recall	77.59	88.59
F1 Score	**80.35**	**86.38**

Explainable AI

The Black Box Problem:

- **Complex Decision Making**: Millions of parameters and non-linear transformations
- **Lack of Transparency**: Difficulty in understanding which features influence model decisions
- **Trust and Validation**: Critical need for interpretability in high-stakes applications (medical diagnosis, structural health monitoring)



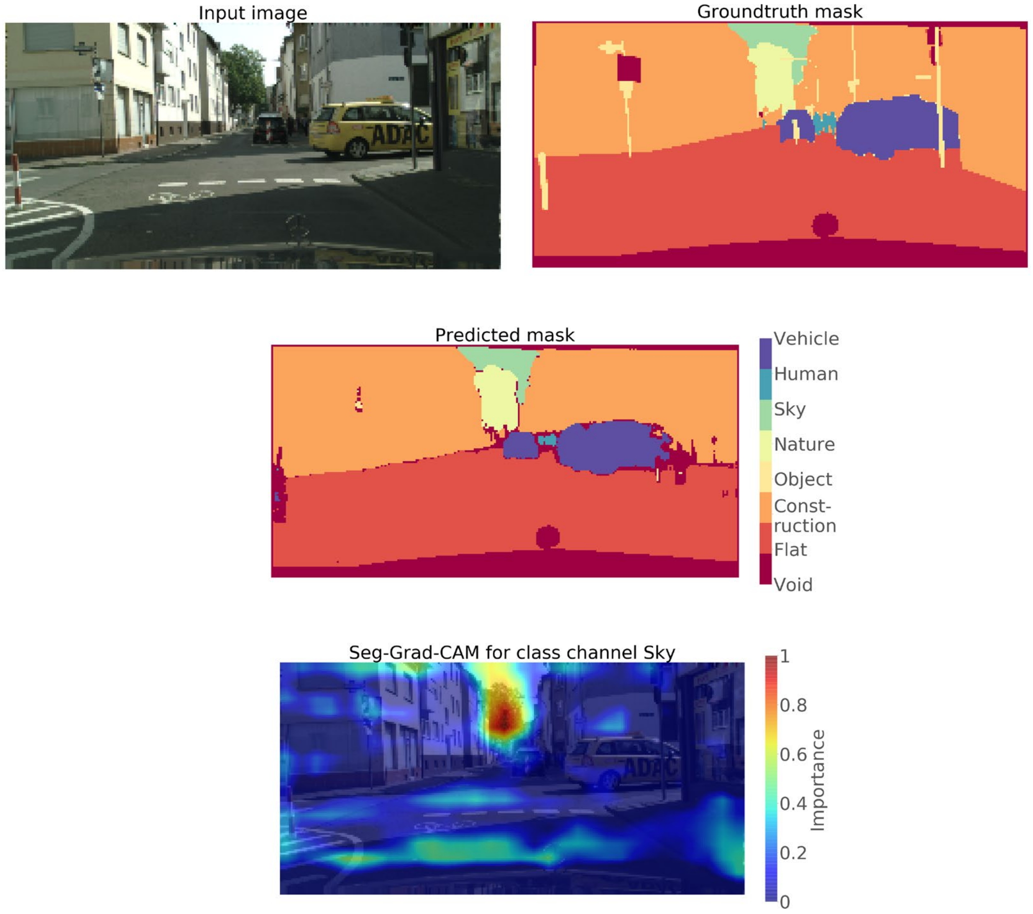
Why Explainable AI Matters for Damage Detection:

- **Clinical/Engineering Validation**: Experts need to understand model reasoning to **trust** automated damage assessment
- **Error Analysis**: Identifying when and why models fail helps improve system reliability
- **Regulatory Compliance**: Many applications require interpretable AI for safety-critical decisions
- **Knowledge Discovery**: XAI can reveal new insights about damage patterns and failure mechanisms

Segmentation Gradient-weighted Class Activation Mapping (Seg-Grad-CAM)

Evolution from Grad-CAM: Vinogradova et. al. (2020)

- **Original Grad-CAM**: Designed for image classification - highlights important regions for class predictions
- **Seg-Grad-CAM Extension**: Adapted for pixel-level segmentation tasks - explains each segmentation decision spatially



Seg-Grad-CAM

Technical Implementation:

- **Gradient Computation**: Calculate gradients of segmentation output with respect to feature maps in target layer. $\alpha^k{}_c$: Weight for the *k-th* feature map and class *c*, calculated based on gradients. y^c:segmentation logits, A^k: *k-th* feature map from the model.

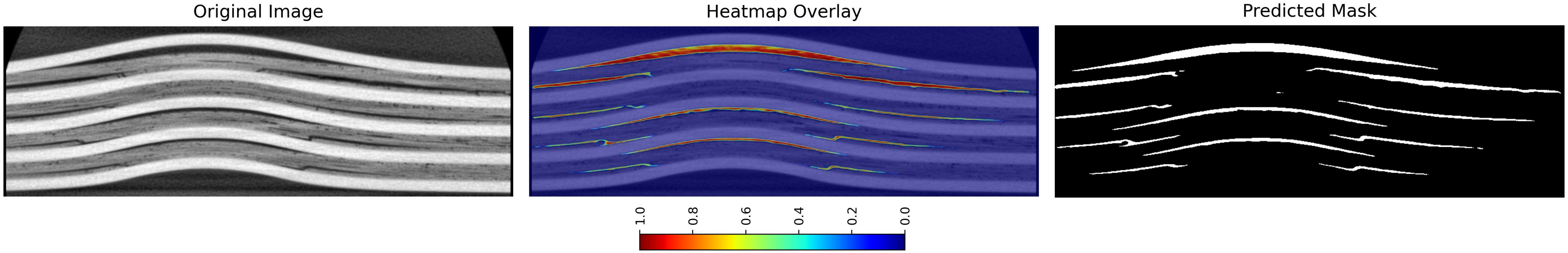
$$L^c = \mathrm{ReLU}\left(\sum_k \alpha_c^k A^k\right) \quad \text{with} \quad \alpha_c^k = \frac{1}{N}\sum_{u,v}\frac{\partial y^c}{\partial A_{uv}^k}$$

Key Advantages for Damage Segmentation:

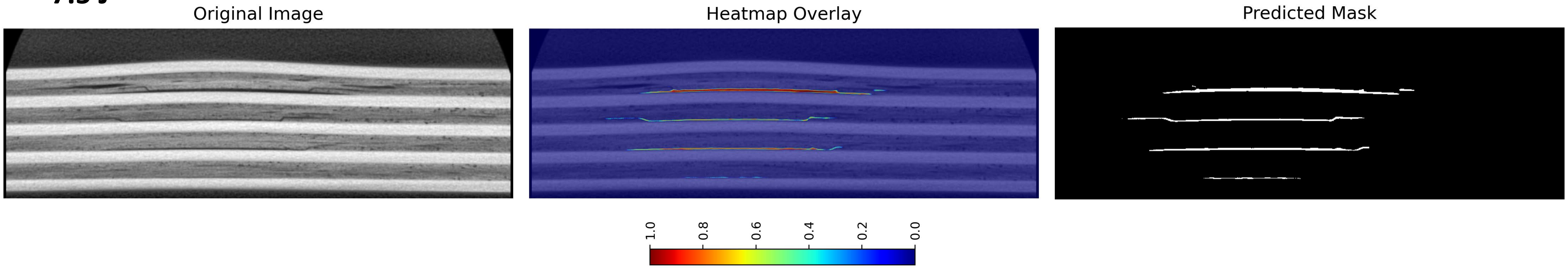
- **Pixel-Level Explanations**: Shows exactly which image regions contribute to each segmentation pixel
- **Multi-Class Support**: Can explain different damage types (delamination, cracks, voids) simultaneously
- **Layer-Specific Analysis**: Examine explanations from different network depths to understand hierarchical feature learning
- Identify biases in training data or model architecture limitations

Saliency Maps

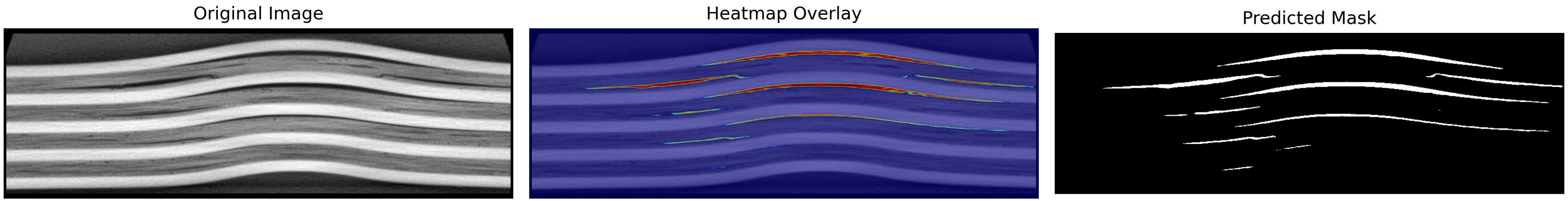
- **12.5 J**



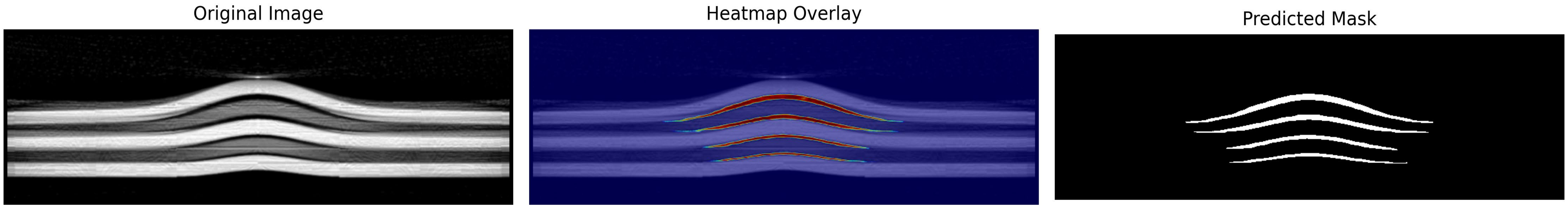
- **7.5 J**



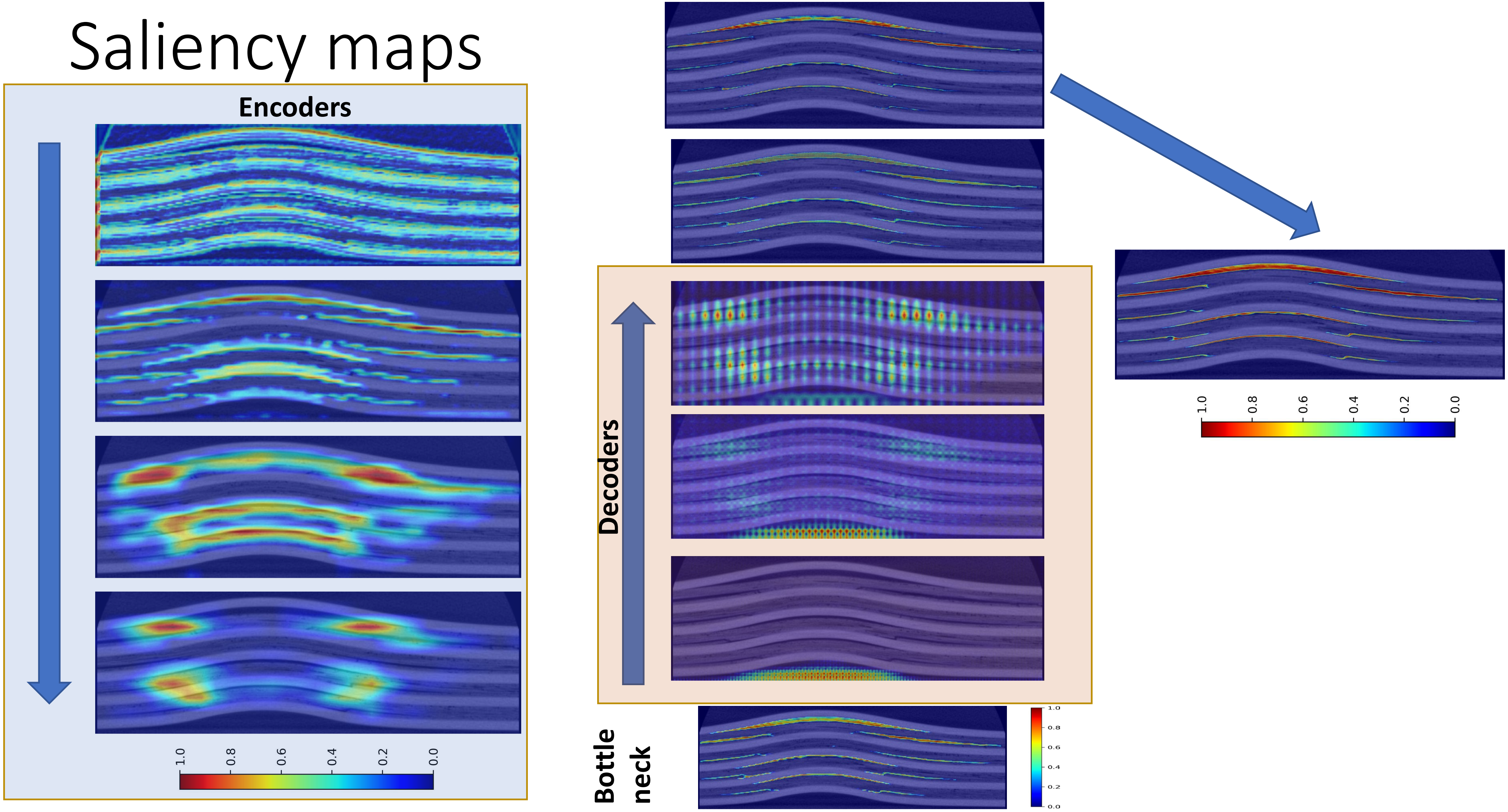
- **10 J**



- **Synthetic**



Saliency maps



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