

Deep Learning to Automate Identification and Characterization of Rib Fractures on Chest Computed Tomography Scans



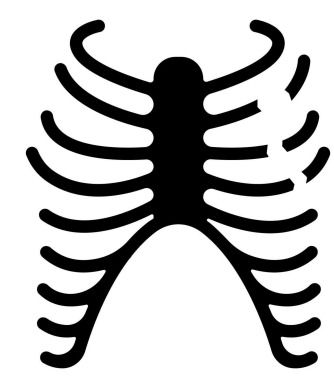
Stanford
MEDICINE
Surgery

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Introduction

Rib fractures:

- common injuries
- knowing specific injury pattern (e.g. degree of displacement) important for clinical decisions



Problem: characterizing rib fractures in-depth is time-consuming

Study aim: automate rib fracture identification + characterization on CT scans using deep learning

Methods

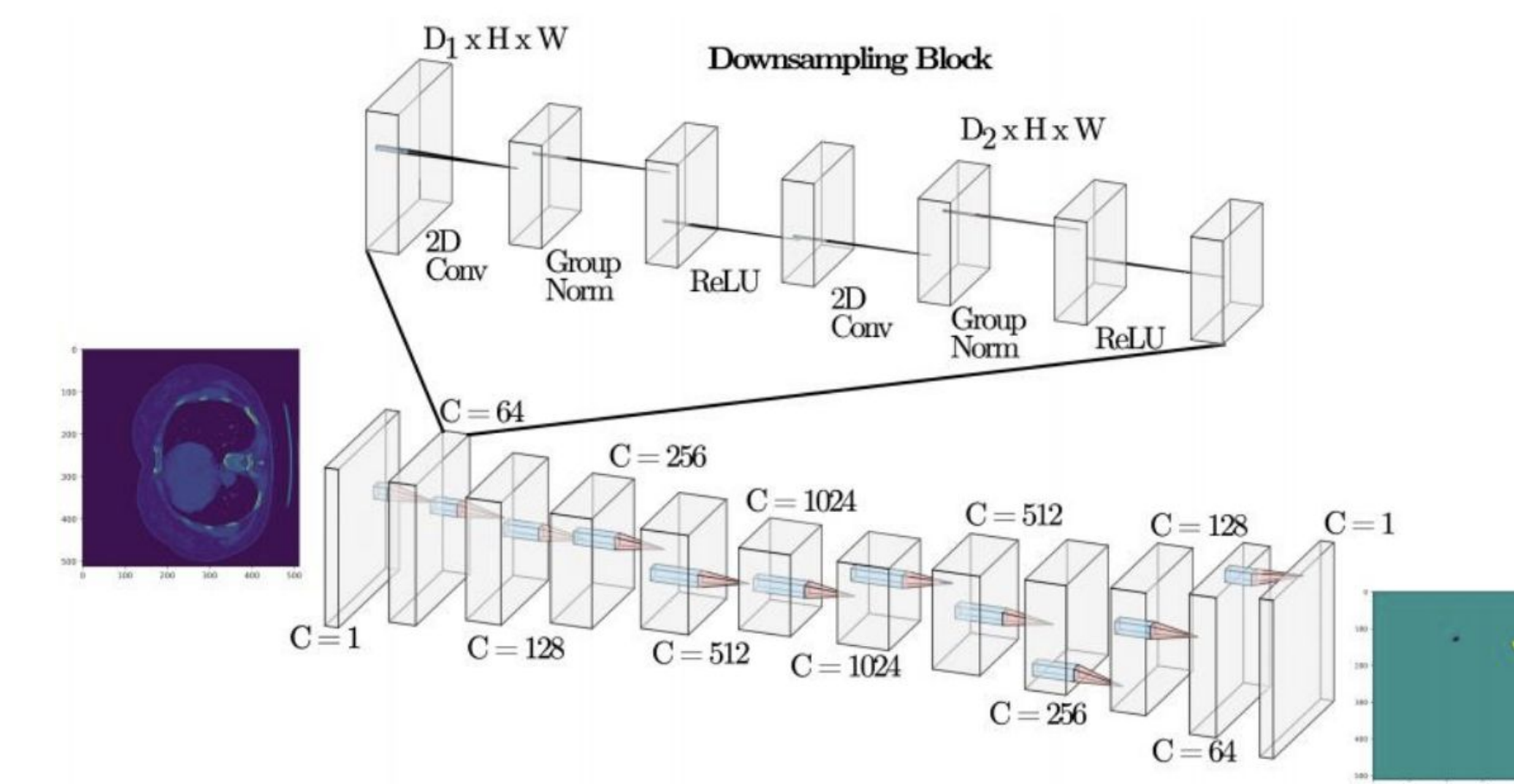
Data Source: RibFrac dataset

5k annotated rib fractures
660 chest CT
(420:80:160 train:val:test)

label code	description
-1	fracture of unknown type (ignored)
0	background
1	displaced fracture
2	non-displaced fracture
3	buckle fracture
4	segmental fracture

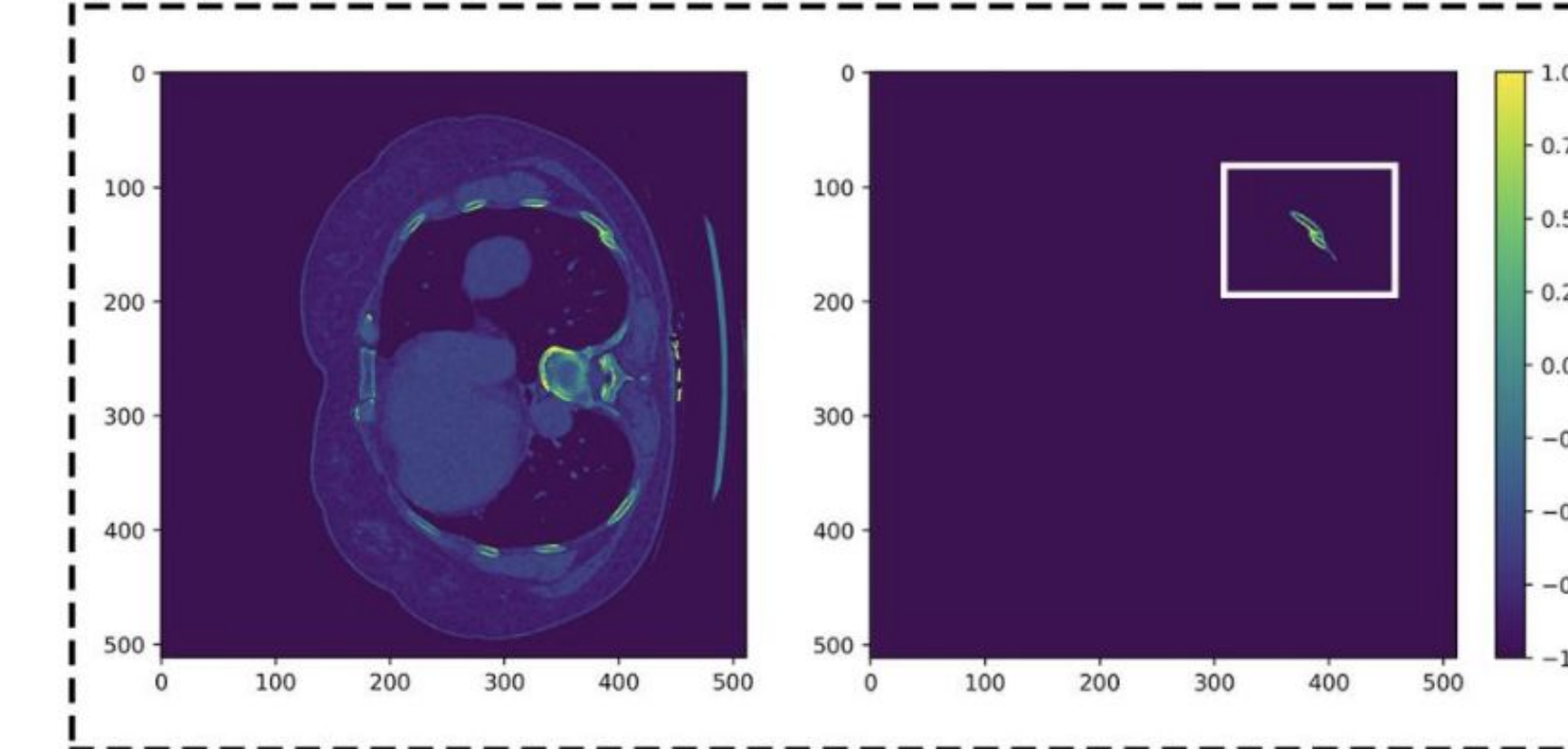
Per-pixel label codes, RibFrac dataset

Fracture identification

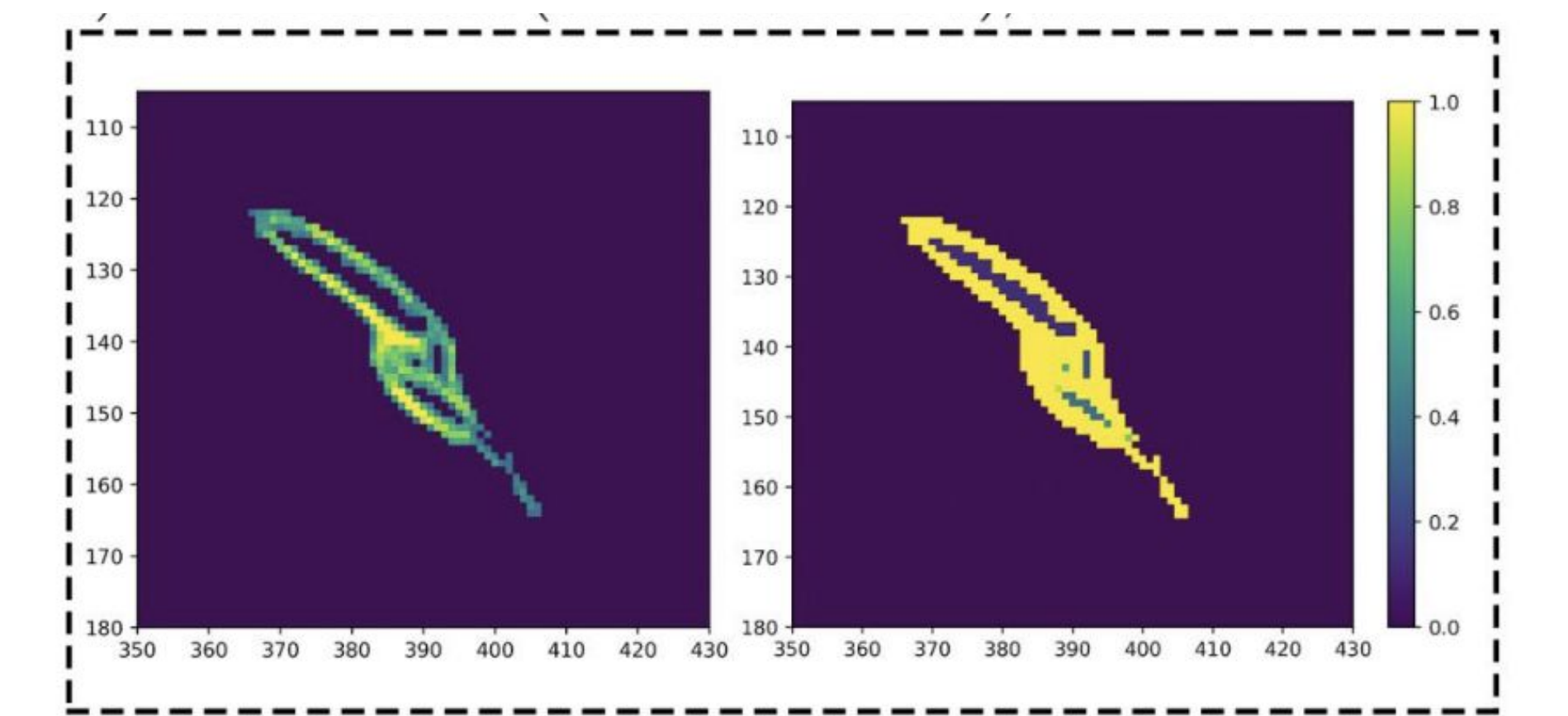


Fracture % displacement calculation

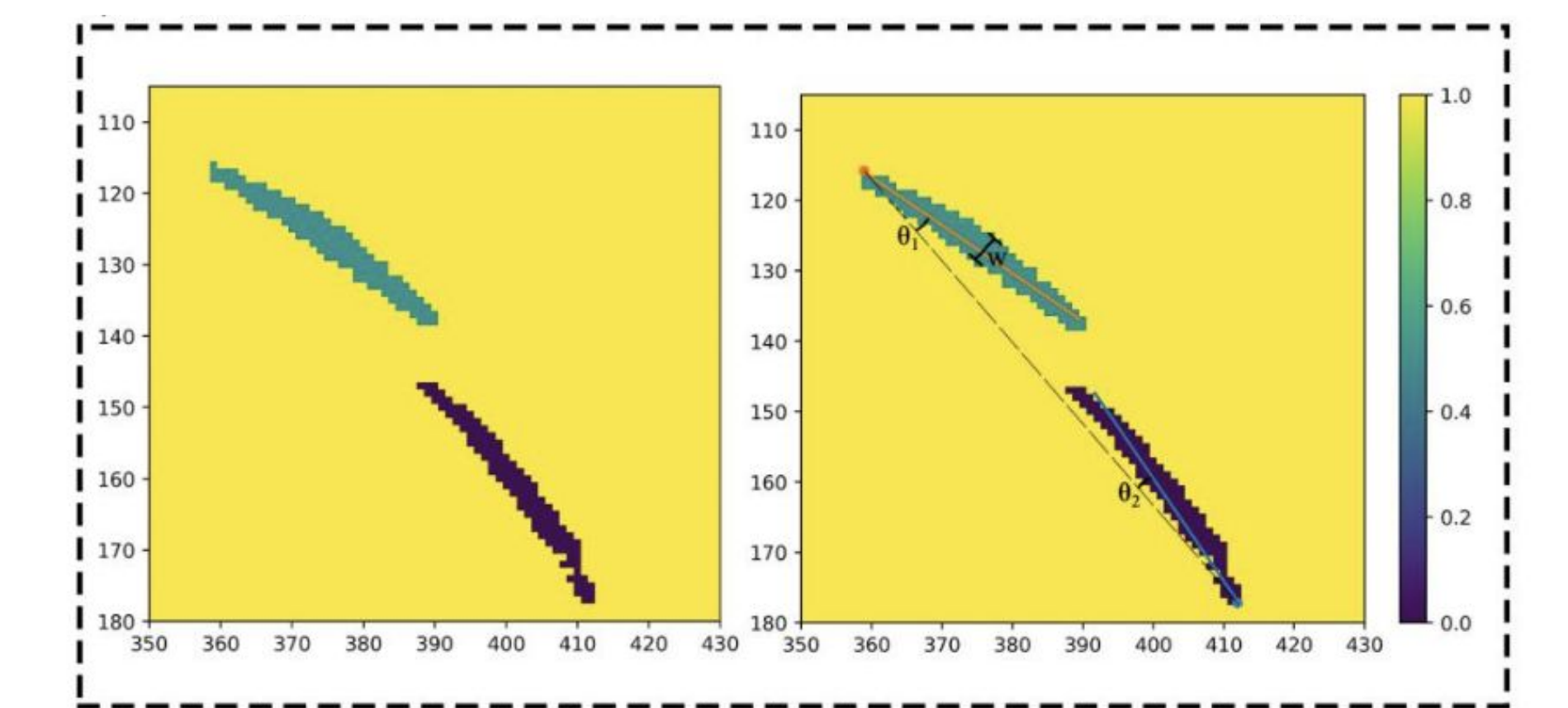
1. Masking



2. Bone Detection (Randomized BFS)



3. Slice aggregation, orientation fitting



Results

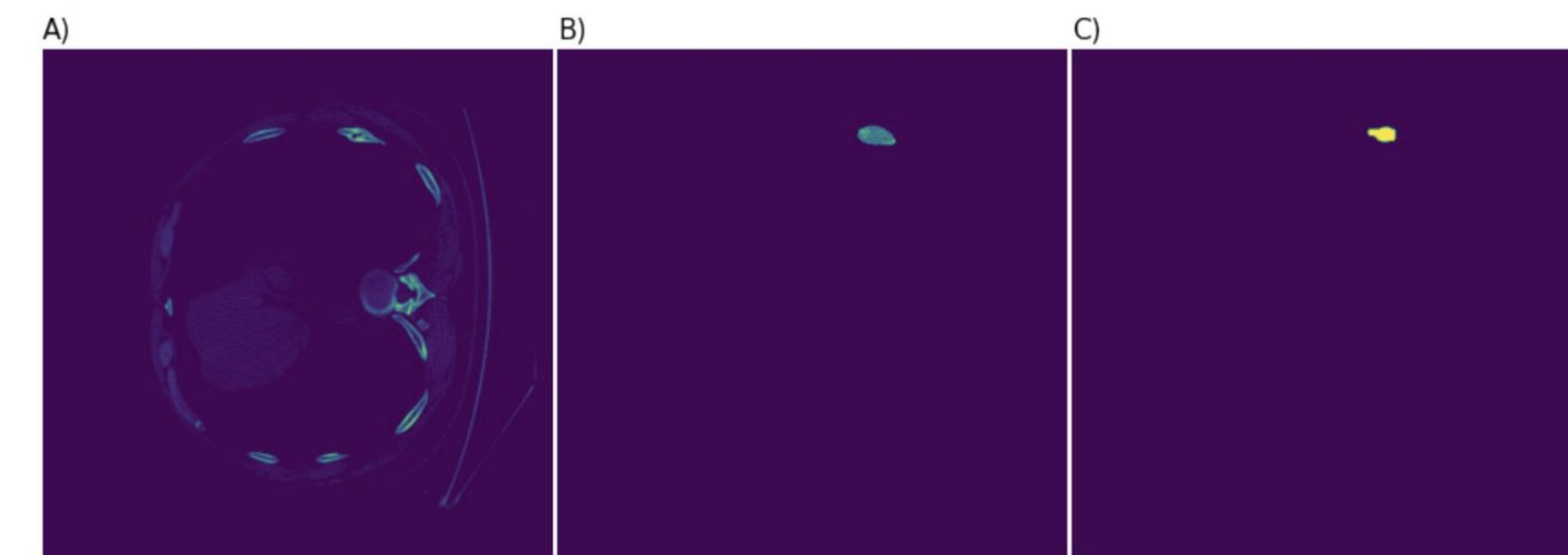


Figure 1. A qualitative example of the model prediction outputs. A) A single CT scan slice from the validation set. B) The 2D UNet model prediction. C) The ground truth label.

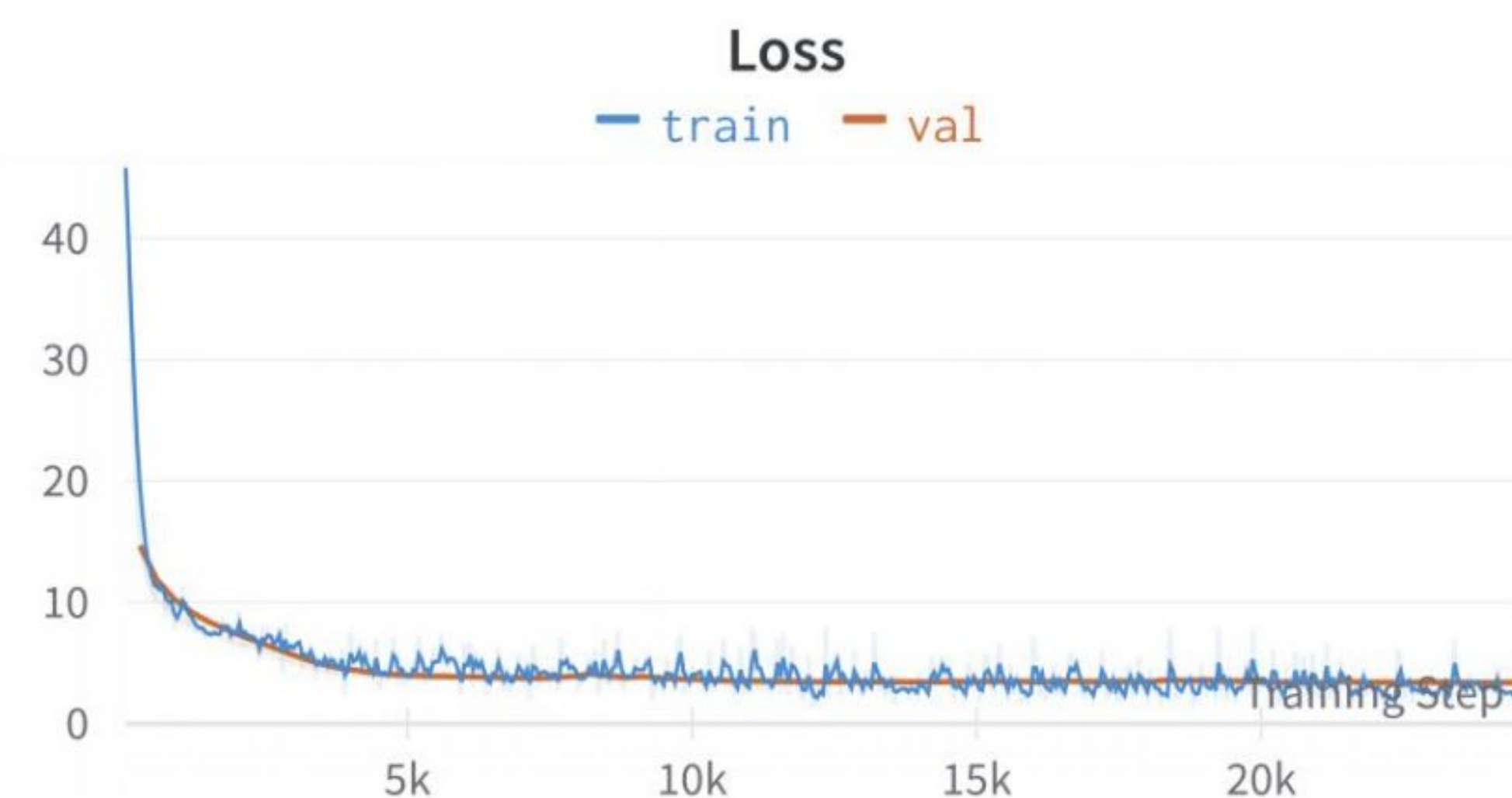


Figure 4. Training and validation loss curves over 5 epochs for the CE+BD+MC+RW-0.5 loss function.

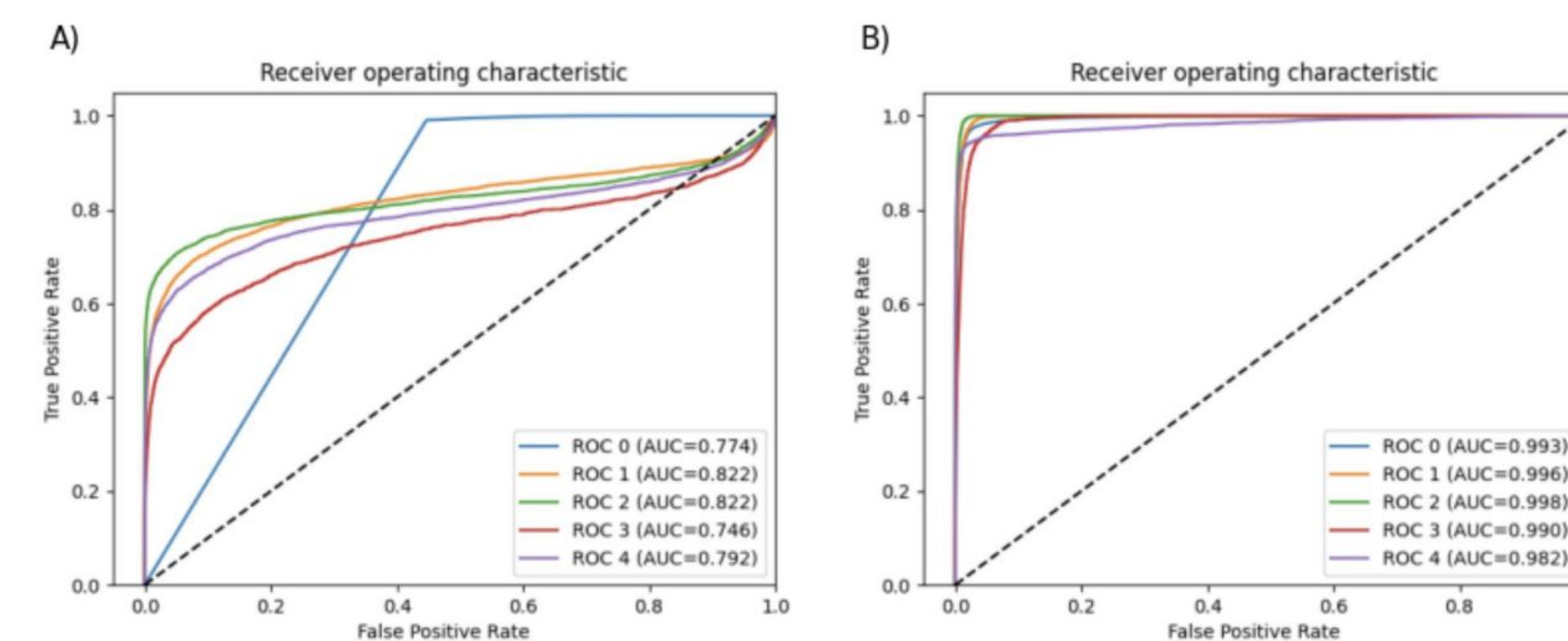


Figure 3. A) ROC curves computed for the CE+BD+MD model without class re-weighting. B) ROC curves for same model except with class re-weighting ($\beta = 0.5$). These ROC curves were computed based on a random sample of 500 slices from the validation set.

loss function	β (class re-weighting)	binary DICE	macro F1	epochs	learning rate
CE	0	0.0780	0.2396	5	1e-6
CE	0.5	0.0284	0.2248	5	1e-6
CE + MD	0.5	0.0251	0.2307	5	1e-6
CE + BD + MD	0	0.8817	0.2084	5	1e-6
CE + BD + MD	0.5	0.6572	0.2506	5	1e-6
CE + BD + MD	1	0.3900	0.2649	5	1e-6

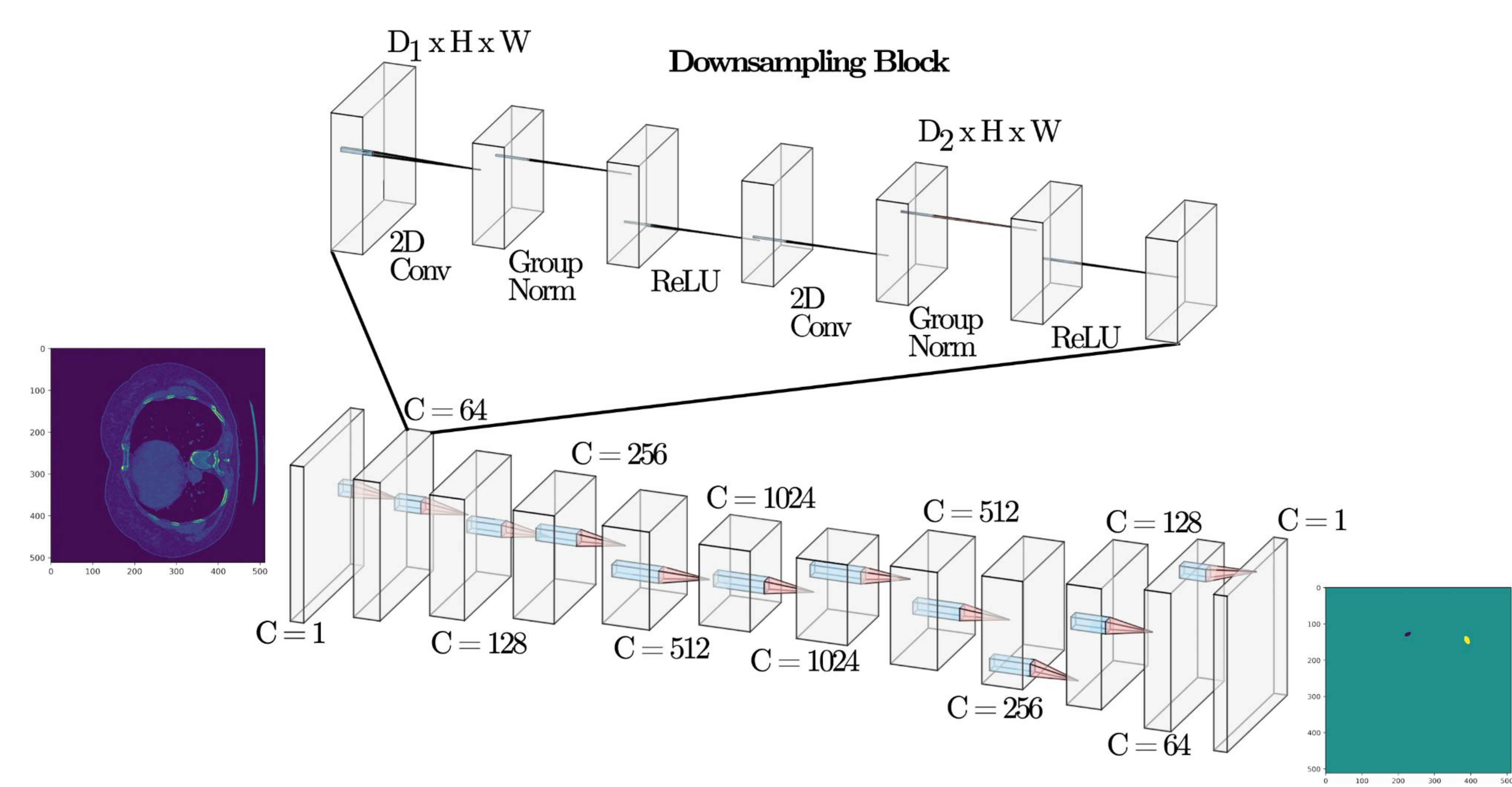
Conclusions

Accomplishments:

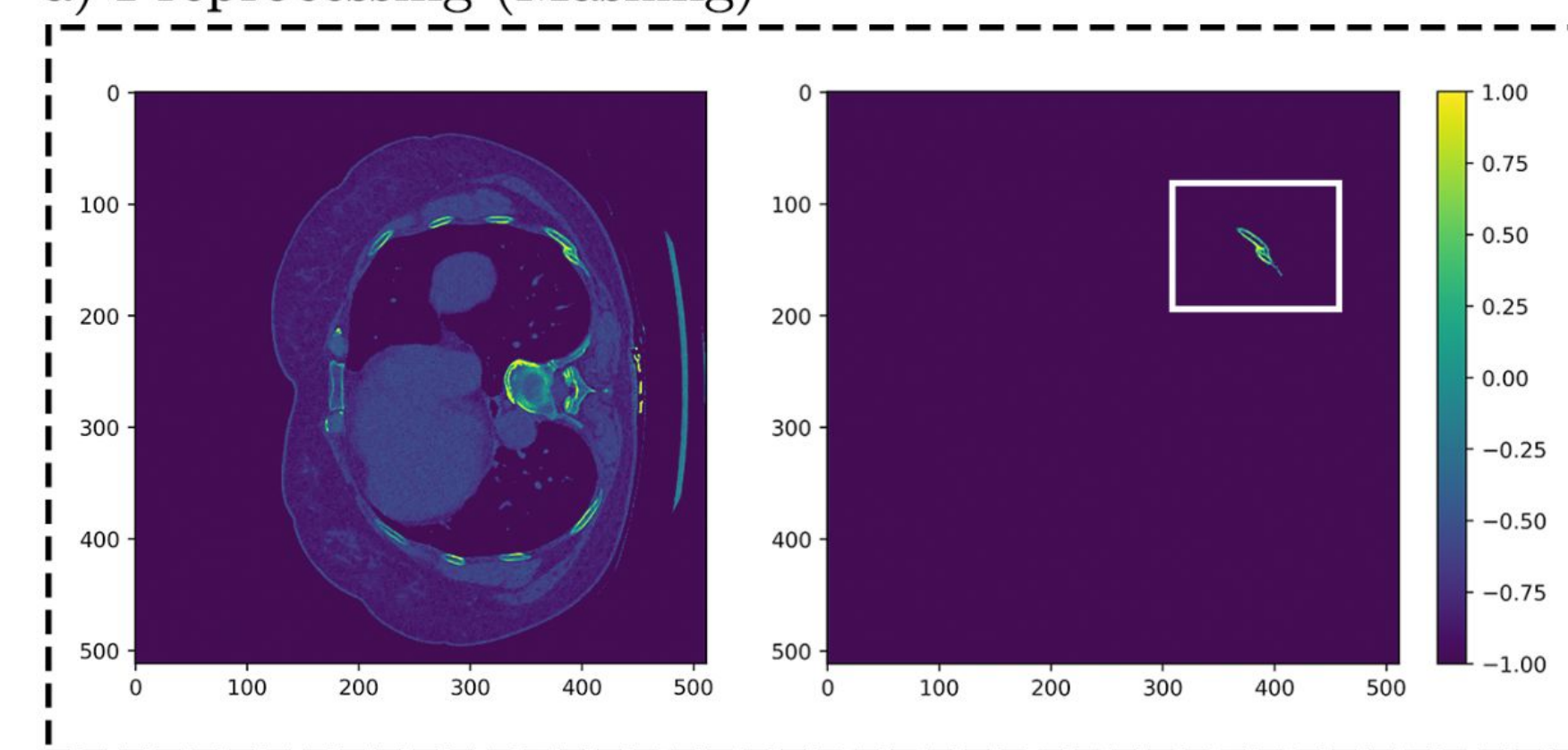
- 2D U-Net CNN capable of accurately detecting and characterizing rib fractures in chest CT scans
- Finely tuned batch size, negative sampling degree, class re-weighting parameter, and loss function weights
- Novel post-processing fracture displacement percentage calculation
- **Offers significant improvement in clinical utility of CT fracture detection pipelines**

Future Work:

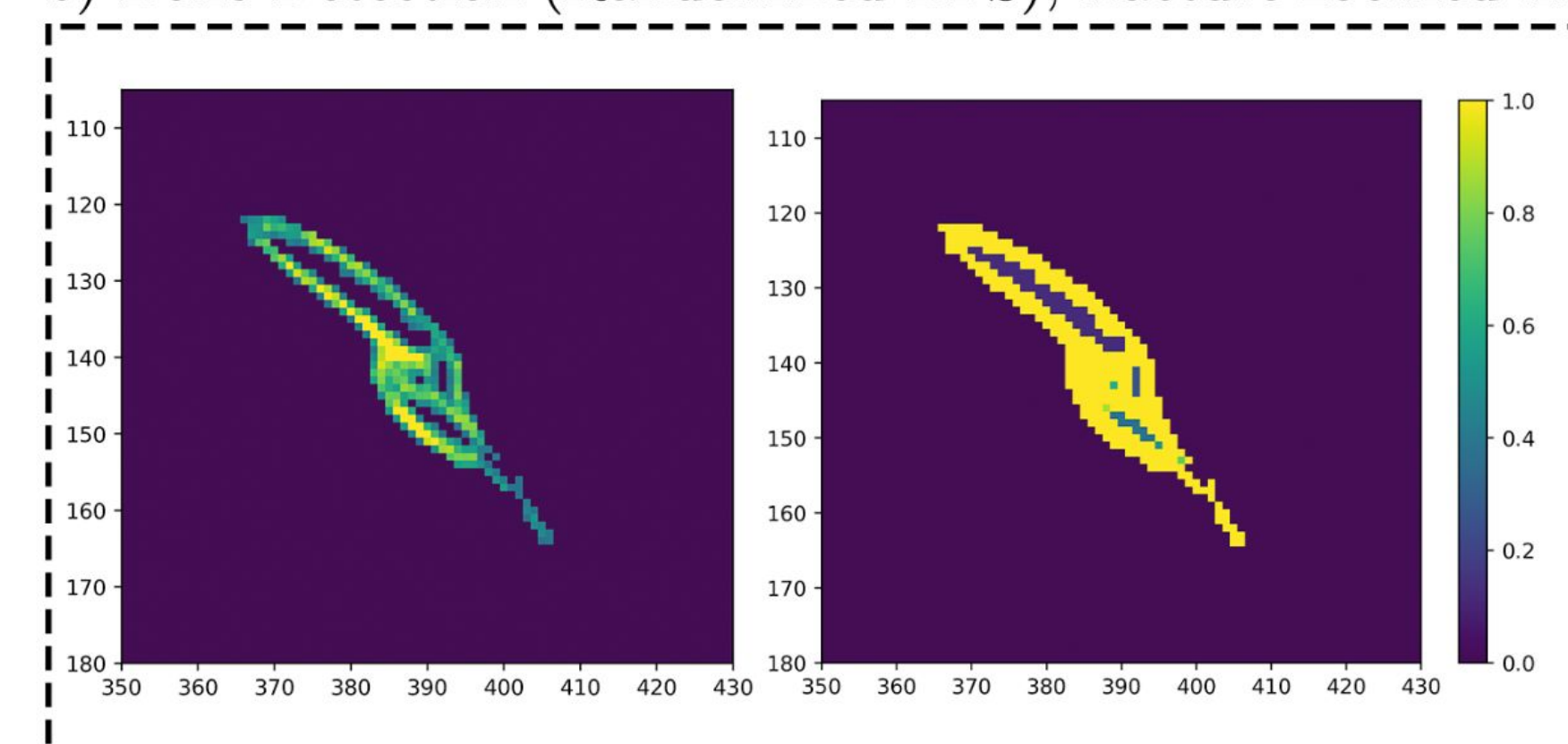
- Extending CNN to 3D and processing multiple chest CT scan slices at once
- Alternative post-processing class reweighting procedures, including blob detection and linear SVM fitting



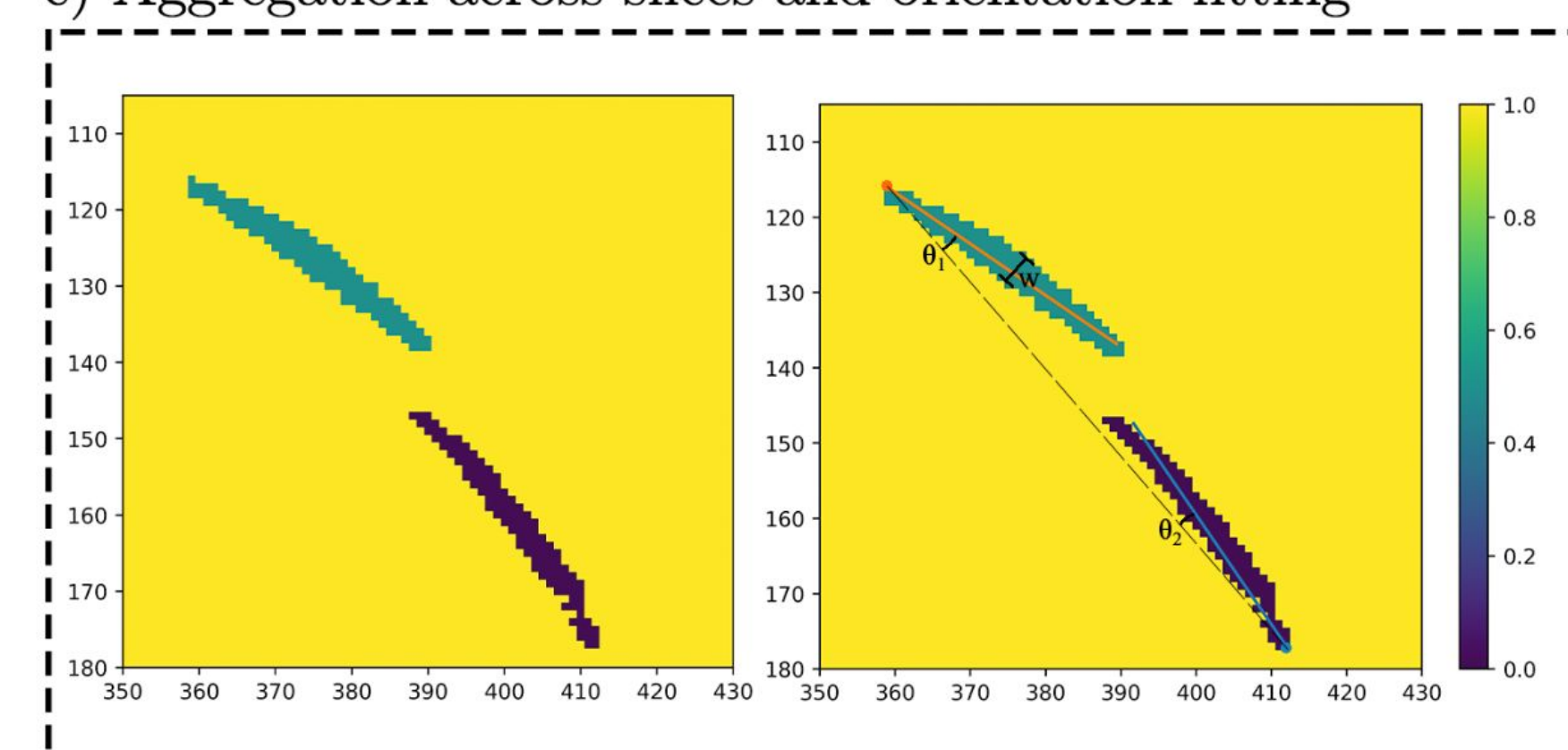
a) Preprocessing (Masking)



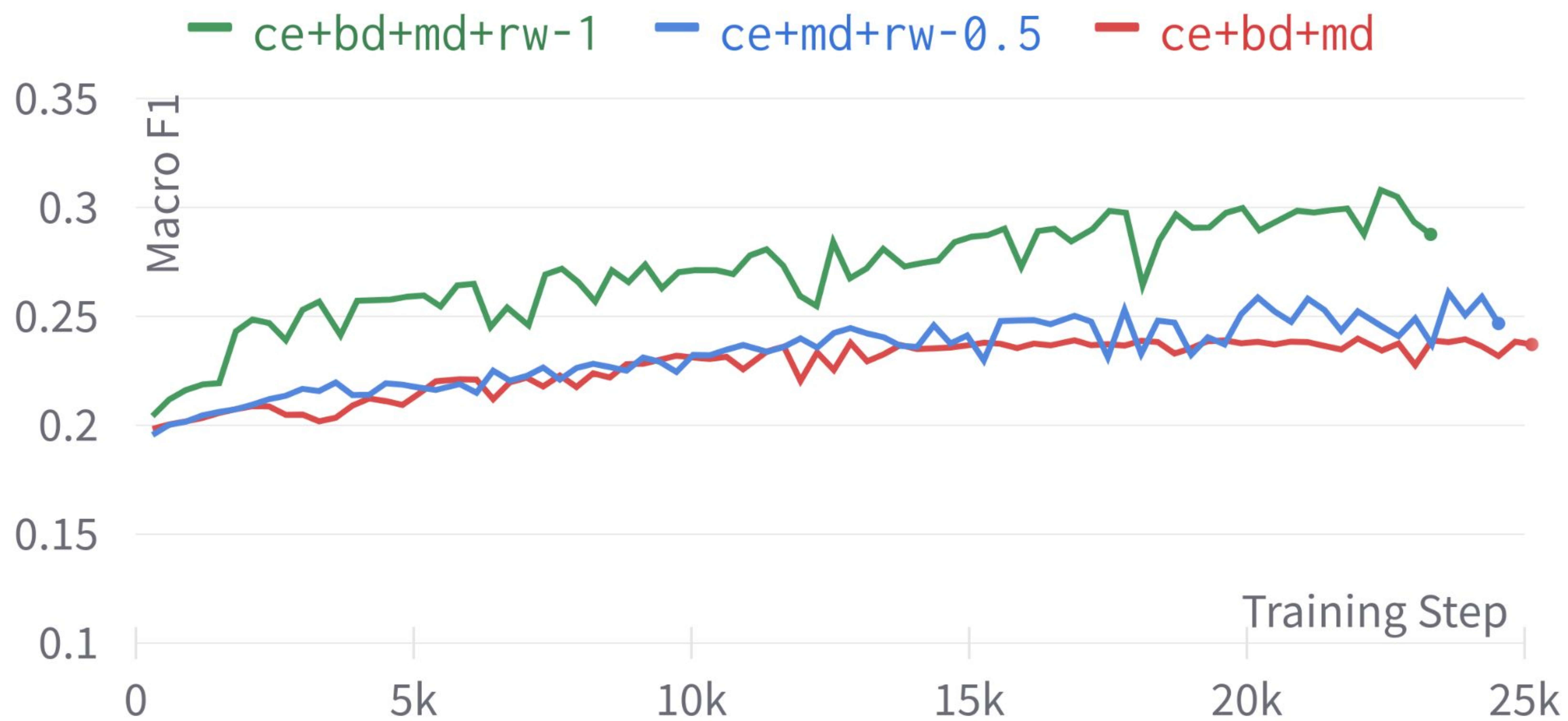
b) Bone Detection (Randomized BFS), fracture zoomed in



c) Aggregation across slices and orientation fitting



Macro F1



Loss

train val

