Breakout Session 6: Track B

Application of AI/ML Models for Musculoskeletal Spine Research in Patients with Metastatic Spinal Disease: Successes and Challenges

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Curating musculoskeletal CT data to enable the development of AI/ML approaches for analysis of clinical CT in patients with metastatic spinal disease

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FINANCIAL DISCLOSURE

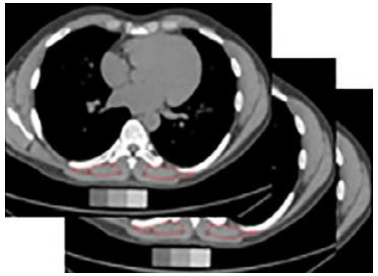
Parent grant: Establishing Vertebral Fracture Risk Models in Cancer Patients (AR075964)

- Our parent grant aims to develop and validate patient-specific, precise prediction of vertebral fracture risk to optimize patient management before catastrophic neurologic deficits occur.

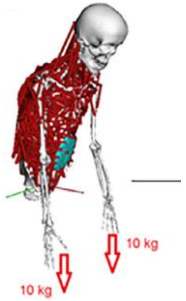
Estimating Vertebral Fracture Risk In Vivo

Simulation of daily tasks

QCT-derived muscle CSA and density.



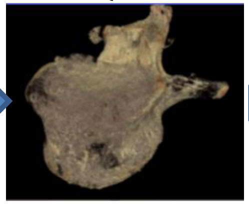
Subject-specific musculoskeletal models



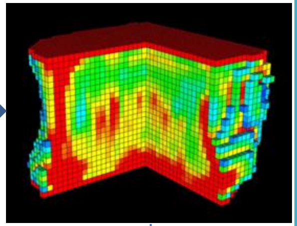
Computing vertebral strength

Clinical Imaging (CT/ MRI)

QCT



CT-based computational analysis



$$\text{Fracture risk } (FVF_{RX}) = \frac{\sum \text{Applied activity based loads}}{\text{Vertebral strength}}$$

Developing Vertebral and Muscle Segmentation Approaches in Cancer Patients is Highly Challenging!

- Segmenting pathologic vertebrae
  - Altered geometry (Shape, Loss of anatomy, Fractures, Instrumentation / Vertebral cement augmentation)
  - Significant degradation of radiographic bone appearance.
  - Lack of annotated databases (Vertebrae, Bone lesions)

Up to 11h/spine/patient.

- Subject-specific musculoskeletal models to compute vertebral loading.
  - Segmenting *=< 10 muscle (L/R) per vertebra (n=17).*
  - *Muscles often exhibit extensive damage.*
  - *Loss of inter-muscle boundaries.*

Up to 9h/spine/patient.

- *Longitudinal assessment (vertebrae, muscle)*
  - *Challenging registration due to degraded Anatomy /Bone appearance/ Fracture/ Treatment effects.*

Administrative supplement
3R01AR075964-03S1

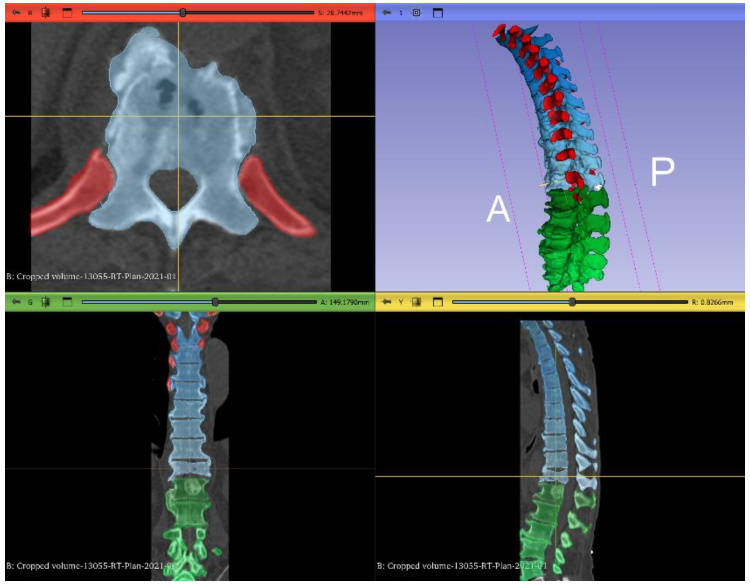
Our Administrative supplement aims were:

1. Develop a Deep Learning (DL) testbed for vertebral and spinal muscle segmentation from clinical CT.

2. Establish a curated CT dataset of metastatic spines based on our patient cohort (AR075964).

3. Disseminate the 4D dataset following best practices: via the Cancer Image Archive (TCIA).

Task 1: DL Spinal Column Segmentation



Data preparation

•147 patients included.

•2499 manually annotated T1-L5 complete vertebral segments.

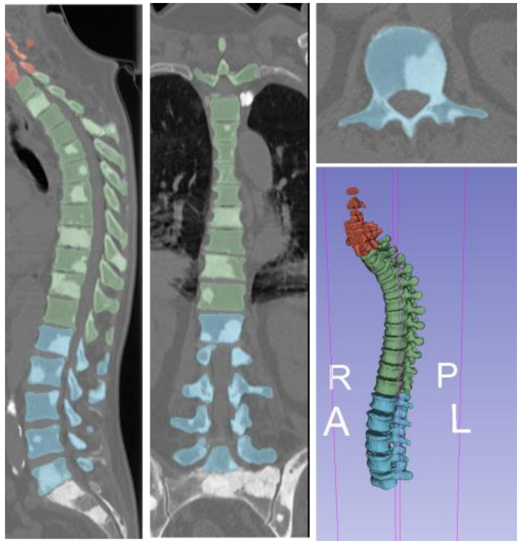
DL-model

nnUNet[1]: a self-configuring method for DL-based 3D image segmentation.

Results

•Average Dice score on test set: **94.34 (± 2.39)%**.

•Inference time of 4 min. vs 9-13 hours manual segmentation.

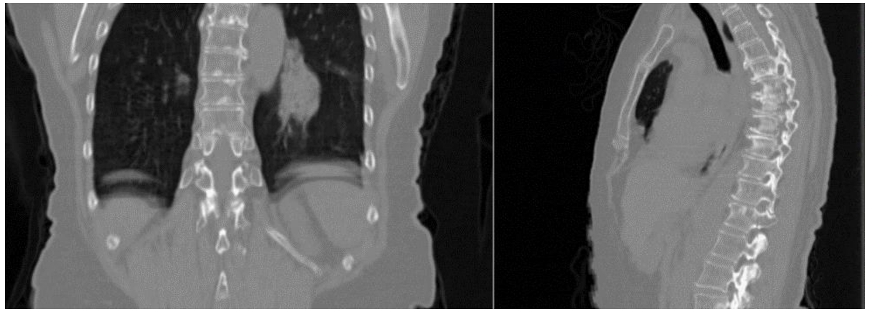


Study Publication: A. Diaz-Pinto. DeepEdit: Deep Editable Learning for Interactive Segmentation of 3D Medical Images. 2023, arXiv:2305.10655.

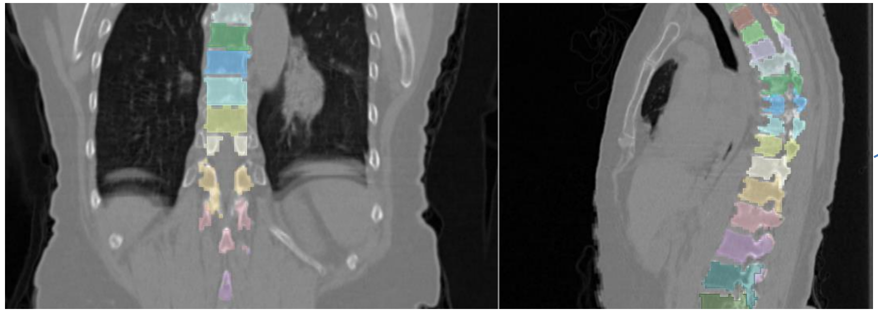
[1]https://arxiv.org/pdf/1809.10486.pdf

DL Segmentation Comparison

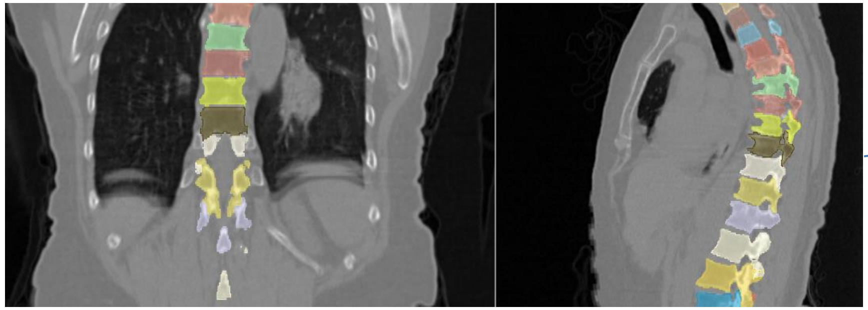
Input CT



TotalSegmentator [2]
1.5mm^3



Our method
0.31mm^2 x 0.65 /1.25mm



[2] https://github.com/wasserth/TotalSegmentator

Task 1: Spine Muscles DL

Data Preparation

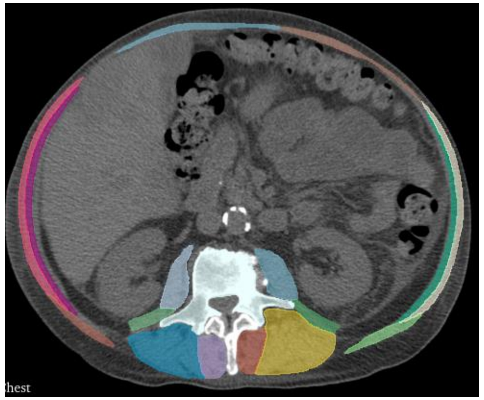
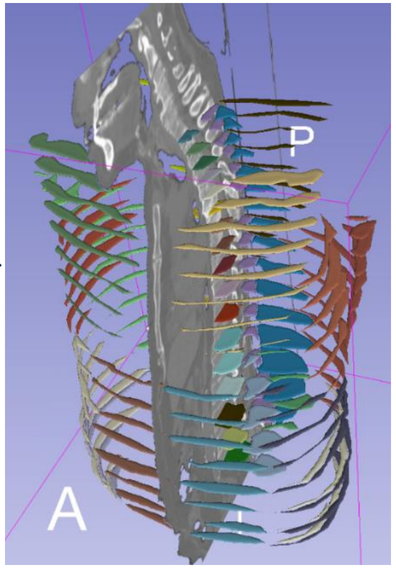
- 149 patients included.
- CT data selected at the center of each T1-L5 level.
- For each CT data, 10 muscle groups (L / R) segmented and labeled
- 1510 annotated CT slices.

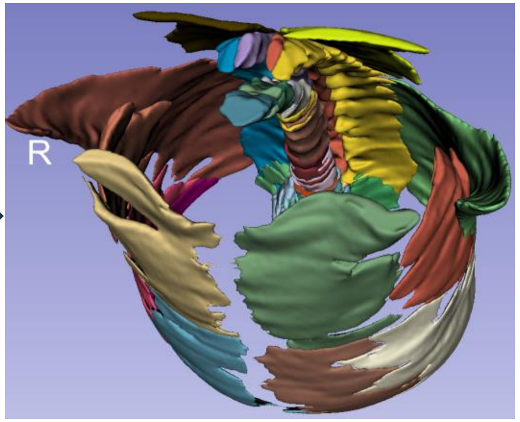
DL Spine Muscle Model

- 5-fold model using the nnU-Net defaults.
- 2D → 3D segmentation.

Results

- **Dice > 0.8**
- Radiologist review could not tell which were the training and DL data

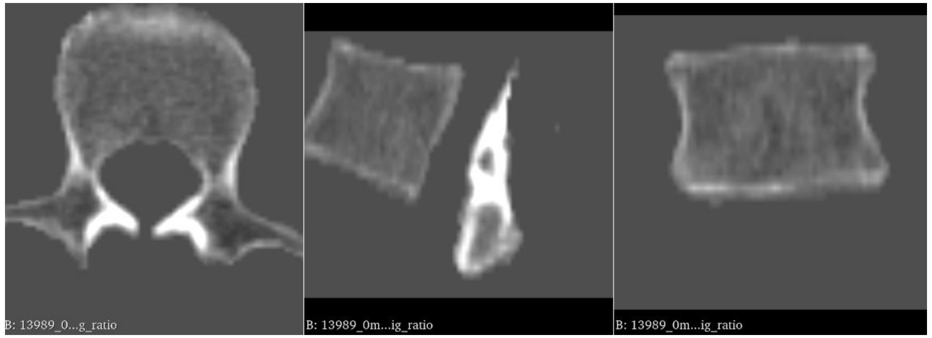





Longitudinal Assessment of Changes in Vertebral Geometry and Strength

- State-of-the-art spine CT registration approaches.
  - Usually assume similar vertebral appearance, bone structure, and intensity in the fixed and moving images.

- These assumptions often do not hold for metastatic spines.
  - Metastatic lesions can cause metastatic vertebrae to undergo significant changes in geometry and bone structure within a short period of time.
  - Fractures
  - Surgical treatments.

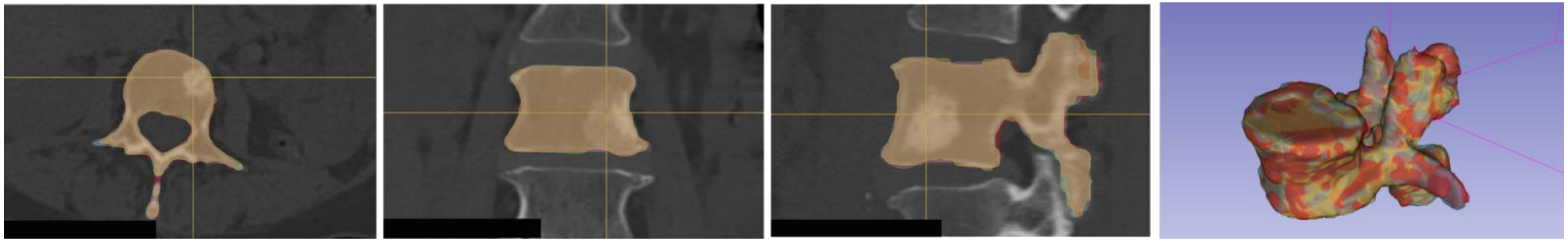


Baseline CT

6-months follow-up CT

Development of DL Registration Approach for Metastatic Spines

- Segmentation-based registration: Vertebrae are automatically segmented using our DL model. The resulting 3D surfaces are used for a longitudinal registration.



- Assessment of the longitudinal-based evolution of changes in lesion radiographic characteristics.

At radiation therapy | 3 Month | 6 Month

<u>Study Publication</u>: Sanhinova M. Registration of longitudinal spine CTs for monitoring lesion growth. SPIE Medical Imaging, Paper 12926-94.

Task 2: Curation of CT Data

- **Target**: 145 metastatic spines at radiotherapy (baseline) and 3, 6 and 12 months post-radiotherapy

- **Current**: Curated dataset of 83 CT scans of patients with metastatic spine disease, T1-L5 at baseline has been completed.
  - Data include raw images, manual segmentations and contours, vertebral lesion-type classifications, and patient demographic details.

- Work remaining:
  - Complete curation of the CT data of 62 patients at baseline. Lesion annotations and demographic data for this cohort are completed.
  - Complete CT image curation and lesion annotations for longitudinal data.

Study publication: Nazim Haouchine, An open annotated dataset and baseline machine learning model for segmentation of vertebrae with metastatic bone lesions from CT, 2024, radiology AI, **In preparation**.

Task 3: Disseminate the 4D Dataset: Cancer Image Archive (TCIA).

- Our data has been accepted by the Cancer Image Archive (TCIA). (TCIA: https://www.cancerimagingarchive.net/).

- Database title: Spine-Mets-CT-SEG
- DOI https://doi.org/10.7937/kh36-ds04

- Initial database includes:
  - 83 patients with CT image data in DICOM format, comprising 1094 vertebrae, 45 cervical (C7 only), 585 thoracic, and 464 lumbar vertebrae.
  - The segmentation label maps are provided in DICOM format with one file, including the entire multi-class labels.
  - All CTs were manually labeled at a voxel level. Vertebral lesion classification and patient demographics are provided in JavaScript Object Notation (JSON) format.

- Future work
  - Complete the submission for baseline (62 patients)
  - Complete data curation and submission for follow-up (3, 6, and 12m) data.

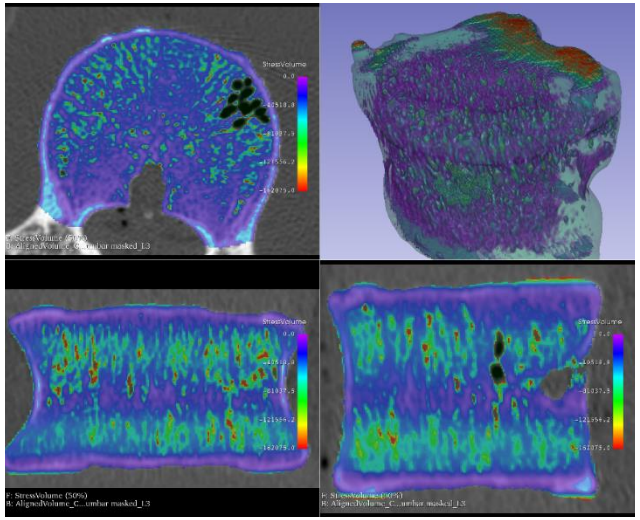
Future Work

Integrate within 3DSlicer image computing platform (www.slicer.org):

1. Our DL models (spine, muscle) in musculoskeletal models for automated assessment of patient-specific vertebral fracture (VF) risk.

2. DL-registration and ML (Radiomics) to evaluate bone lesion characteristics' effect on evolving VF risk & location of failure (CT-Analytics) = fracture risk.

3. Evaluate patient clinical parameters and treatment modalities' contribution to VF risk:
   - Primary.
   - Radiotherapy parameters.
   - Chemo- and Immuno-therapies.



CT-derived vertebral stress/strain

Collaborators

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- BWH/DFCI :Clinical
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  - Nazim Haouchine PhD*
- MIT
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- Nvidia
  - Andres Diaz-Pinto PhD, UK
- EBATINCA LLC
  - Csaba Pinter PhD $ *

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An accurate assessment of patient-specific fracture risk would facilitate the selection of whether, how, and when to intervene before a pathologic vertebral fracture develops.

Such individualized prediction is not available in clinical practice.

Thank you for your attention