Kaggle Competition: Spinal Fracture Detection

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Overview

1. Clinical Background
2. Competition Background
3. Clinical Dataset
4. Model Development
5. Conclusion

Clinical Background

Spinal Fractures

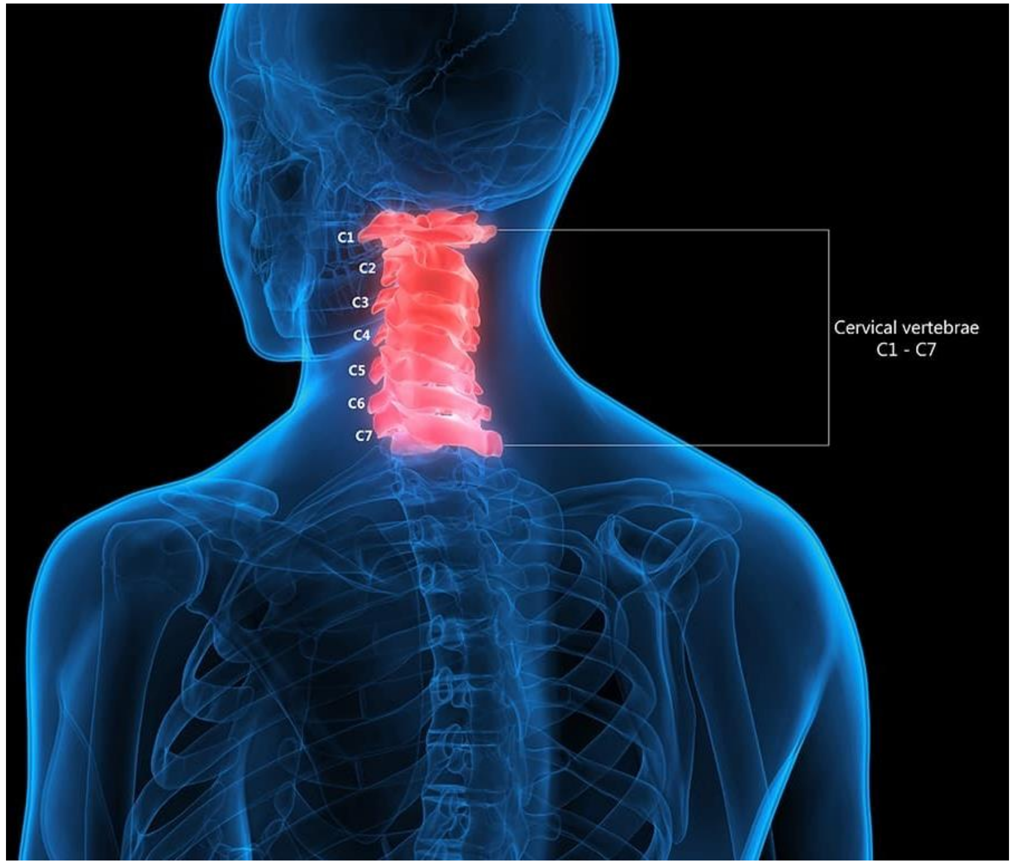
Clinical Background

- 1.5 million annual spinal fractures in U.S. result in 17k spinal cord injuries
- Most common site of vertebrae fracture is cervical spine (neck)
- Increased rate of spinal fractures in older populations

Spinal Fractures

Diagnosis

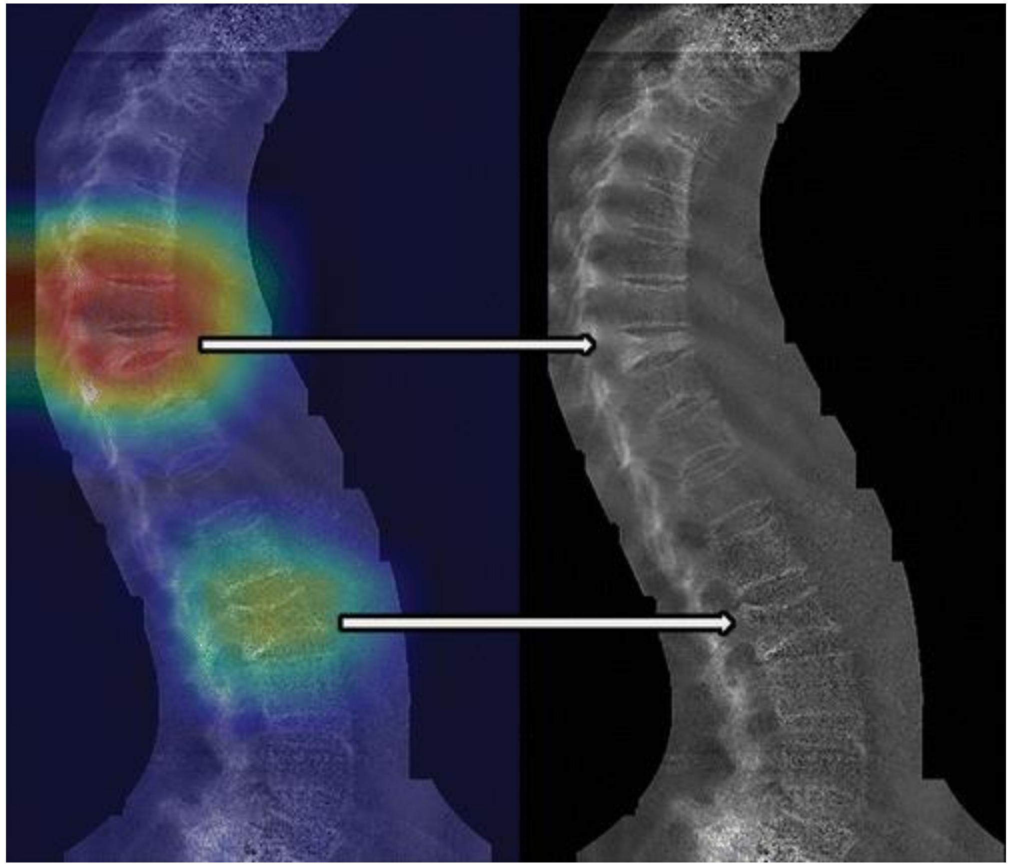
- Diagnosis of adult spinal fractures is performed with computed tomography (CT) scan capture
- In elderly patients, spinal fractures can be **difficult to detect on imaging**
  - Due to superimposed degenerative disease and osteoporosis
- **Critical** to quickly detect and determine location of vertebral fractures
  - Prevent neurologic deterioration & trauma



Competition Background

Kaggle Competition

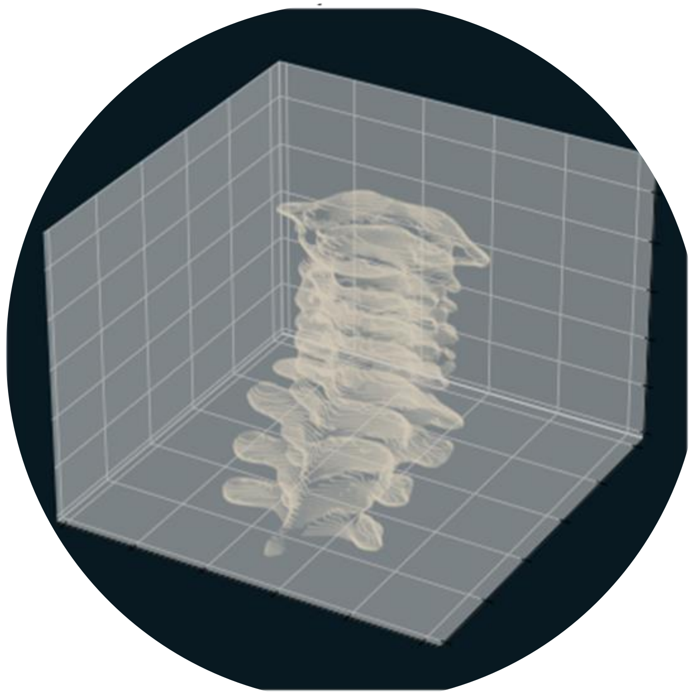
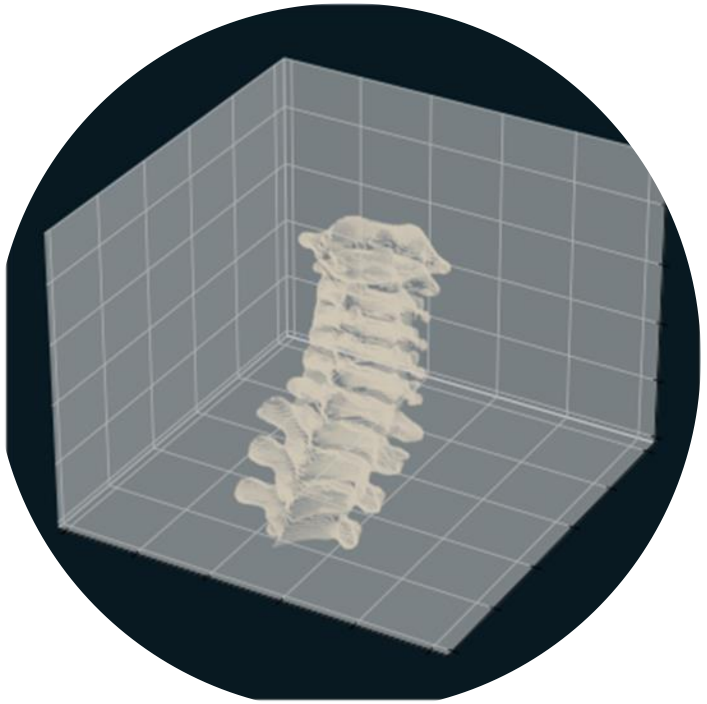
- AI models can detect and localize spinal fractures, which may improve clinical outcomes
- Deep learning classification models require well-labeled image data for development, but **datasets are not widely available** for spinal fracture CT images
- Kaggle competition dataset was released for the development of **deep learning models for spinal fracture detection and localization**
- Kaggle competition consisted of 880+ teams and $30k in prize money



Clinical Dataset

Clinical Dataset

Background

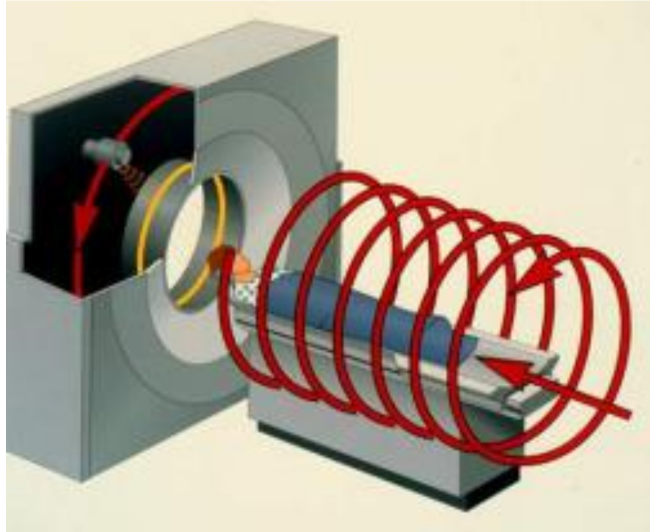



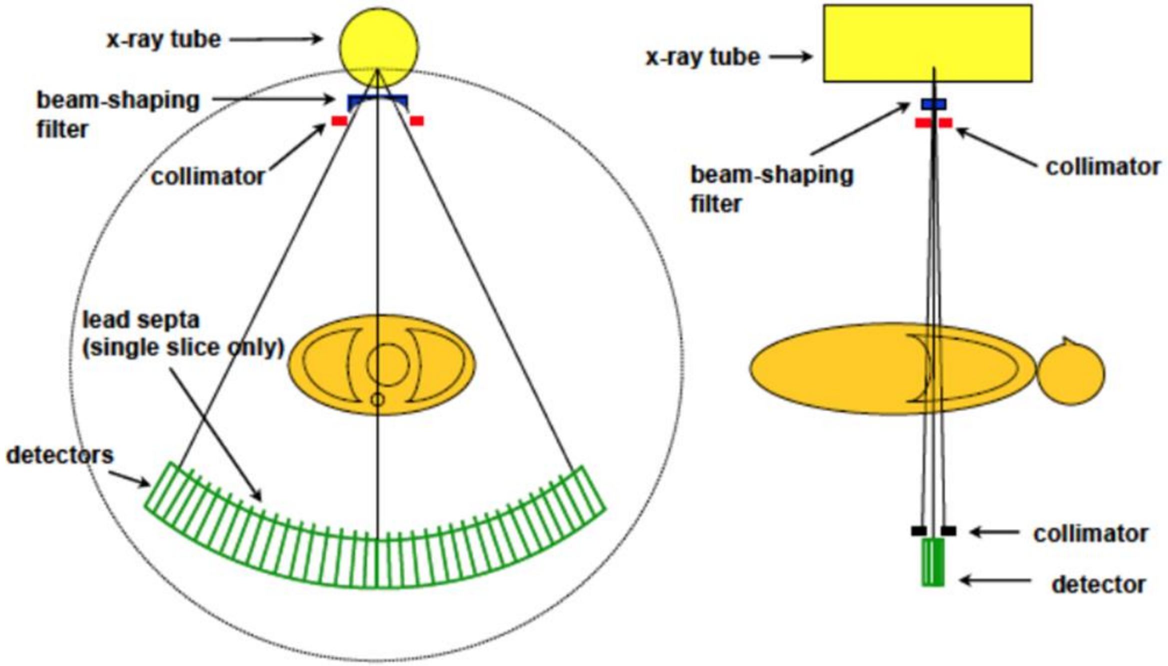
- Dataset organized by Radiological Society of North America, American Society of Neuroradiology and American Society of Spine Radiology
  - 12 research institutions from 9 countries contributed to dataset
- Dataset focused on fractures in cervical vertebrae C1-C7
  - Images annotated by medical experts
- Dataset
  - Public dataset contains n=2,019 CT scans
  - Hidden test contains n=1,500 CT scans

CT Scan

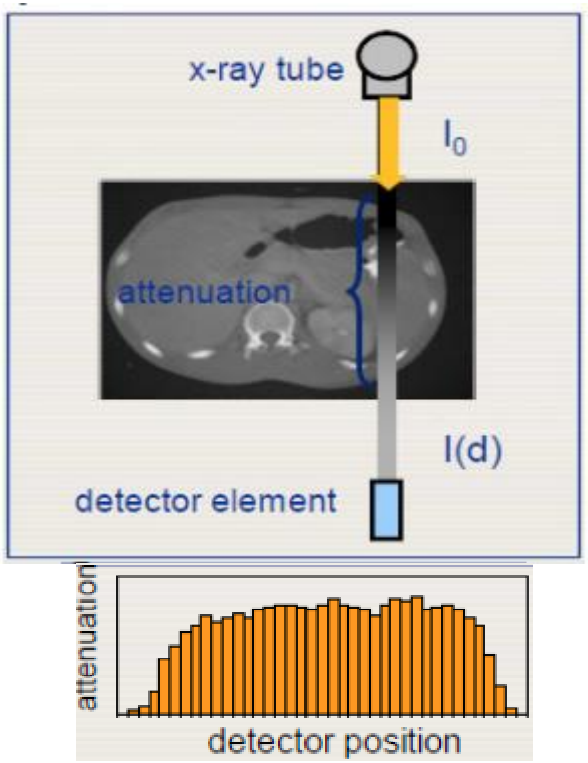
Image Capture

- Rotating x-ray tube and detectors measure x-ray attenuations from different projection angles
- Multiple attenuations are processed using tomographic reconstruction to create cross-sectional slices of patients, which can be viewed as a 3D surface rendering
- CT scanners have many hardware components that affect image capture and quality, such as the x-ray tube, beam filter, detector array and data acquisition system





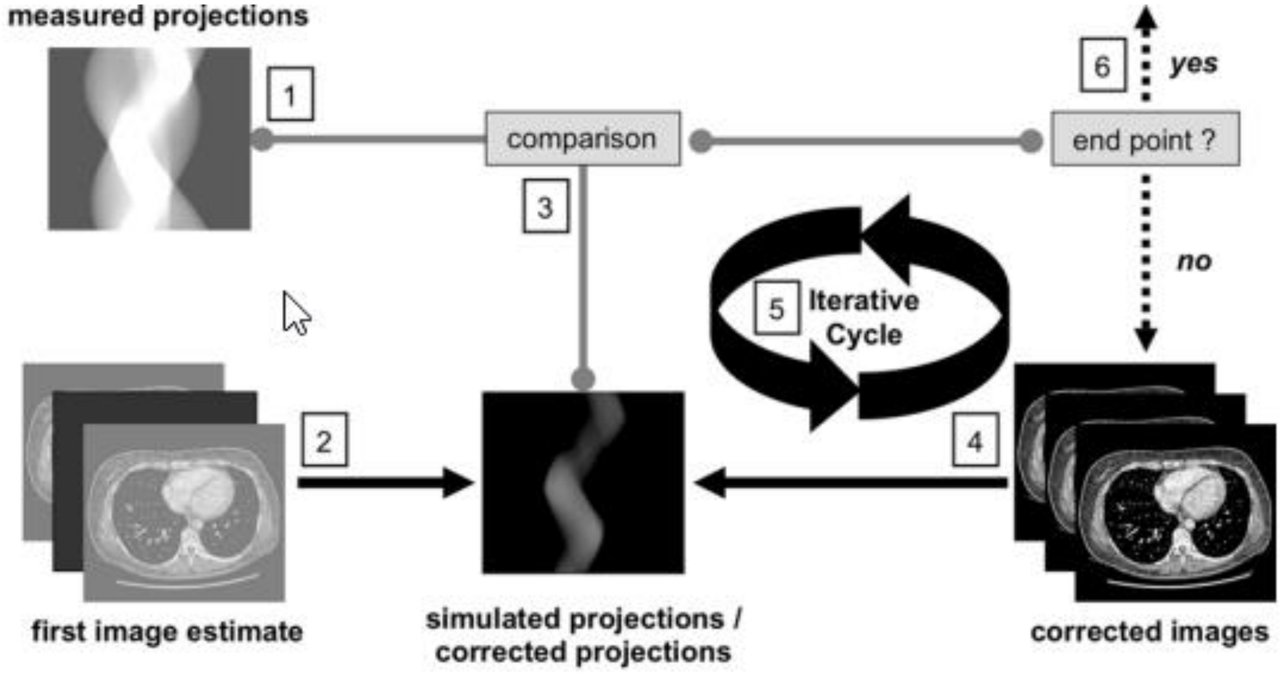
Helical CT scan capture



CT Scan

Image Reconstruction

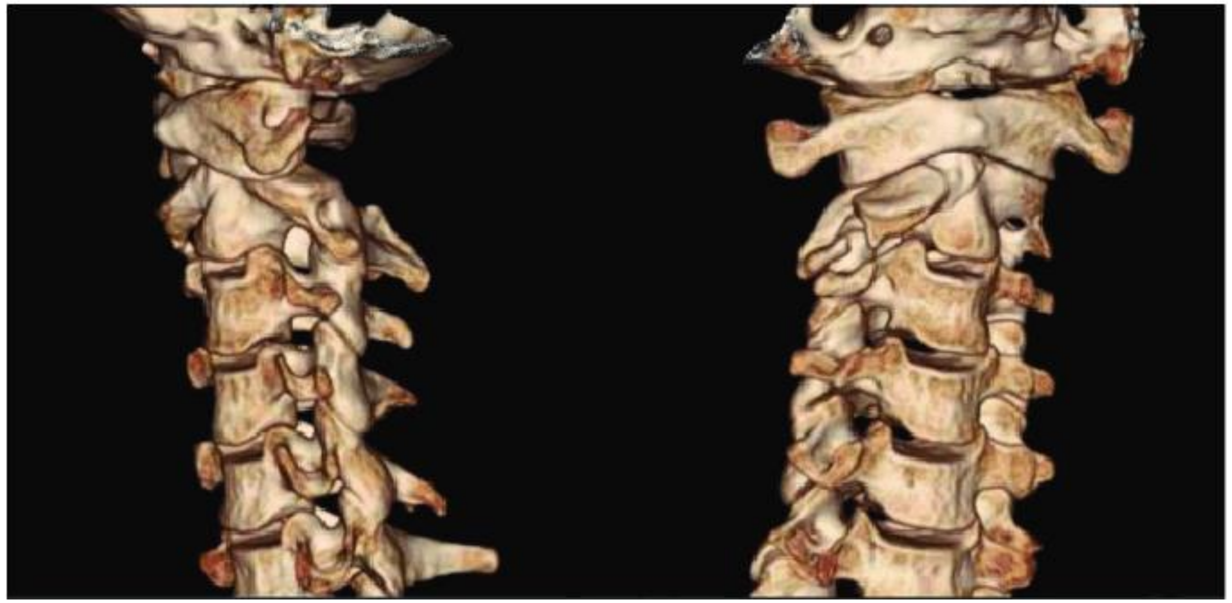
- Scan projection radiograph is a low exposure image that is first performed to help plan scan: determine scan range, field of view and gantry angle
- Reconstruction completed using filtered back projection (FBP) or iterative reconstruction
  - While reconstruction can be completed via open-source packages (i.e.: SIRT algorithm in ASTRA Python toolbox), reconstruction is typically completed shortly after scan using vendor-specific algorithm
- CT scans in Kaggle dataset were reconstructed by competition organizers
  - FBP reconstruction used with “bone kernel”
  - Bone kernel: higher resolution, but more noise



Iterative reconstruction

CT Scan

Image Quality



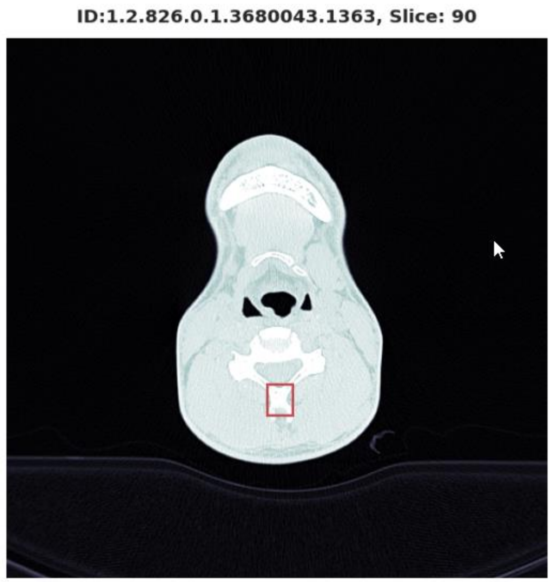
- Image quality dependent on contrast, resolution and noise
- Primary acquisition parameters:
  - Tube voltage, tube current, rotation time
- Secondary acquisition parameters:
  - Detector configuration and beam collimation
  - Pitch
  - Type of reconstruction
  - Reconstruction filter
  - Slice thickness
- Due to different scanners and acquisition parameters, CT scans in Kaggle dataset vary in image quality

Clinical Dataset

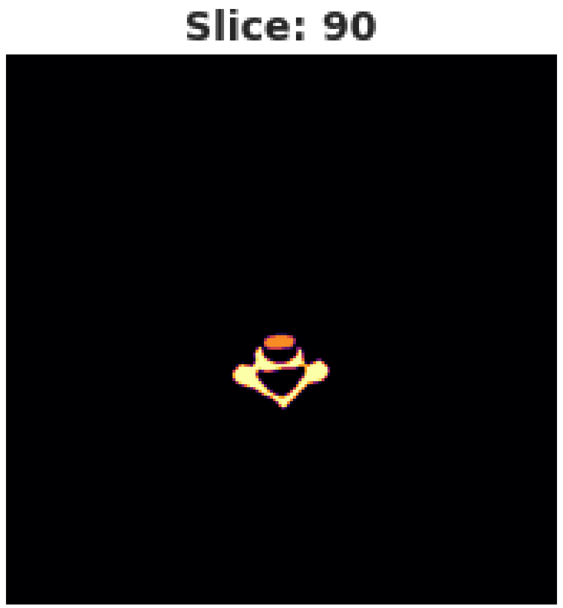
Background

- N=2019 patients have **scan-level** fracture information for vertebrae C1-C7
  - Large dataset: **700k+ image slices**
- CT scans: 0.5 to 1mm slice thickness, axial orientation
- Image slice size: 512 x 512 pixels
- DICOM format

StudyInstanceUID	patient_overall	C1	C2	C3	C4	C5	C6	C7
1.2.826.0.1.3680043.25891	1	0	0	0	0	1	1	0
1.2.826.0.1.3680043.17325	1	0	0	0	1	1	0	0
1.2.826.0.1.3680043.30177	1	0	0	1	0	0	1	1
1.2.826.0.1.3680043.23052	0	0	0	0	0	0	0	0
1.2.826.0.1.3680043.27299	1	0	0	0	0	0	0	1



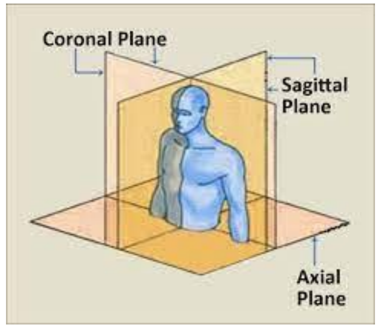
- N=235 scans with fractures have **slice-level** bounding boxes that show fracture location
- Bounding boxes are in .csv format in axial orientation

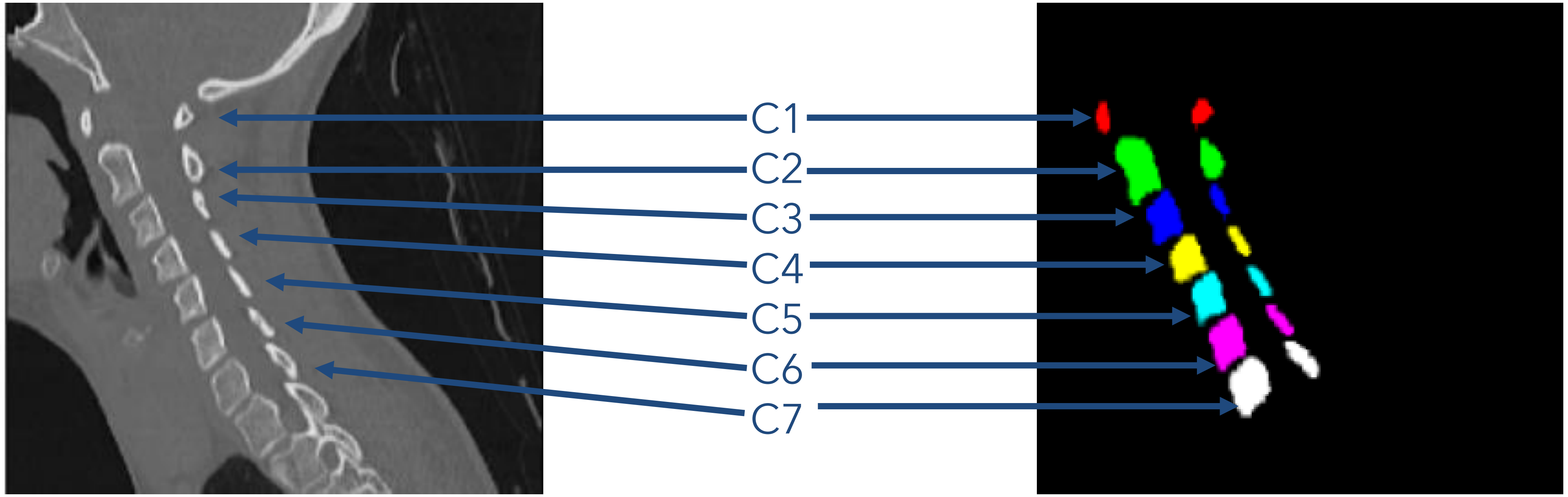


- N=87 scans have **slice-level** segmentations for vertebrae
- Semantic segmentation: label each pixel with its class
- Segmentations are in NIFTI format in sagittal orientation

Clinical Dataset

Segmentations in Sagittal Orientation

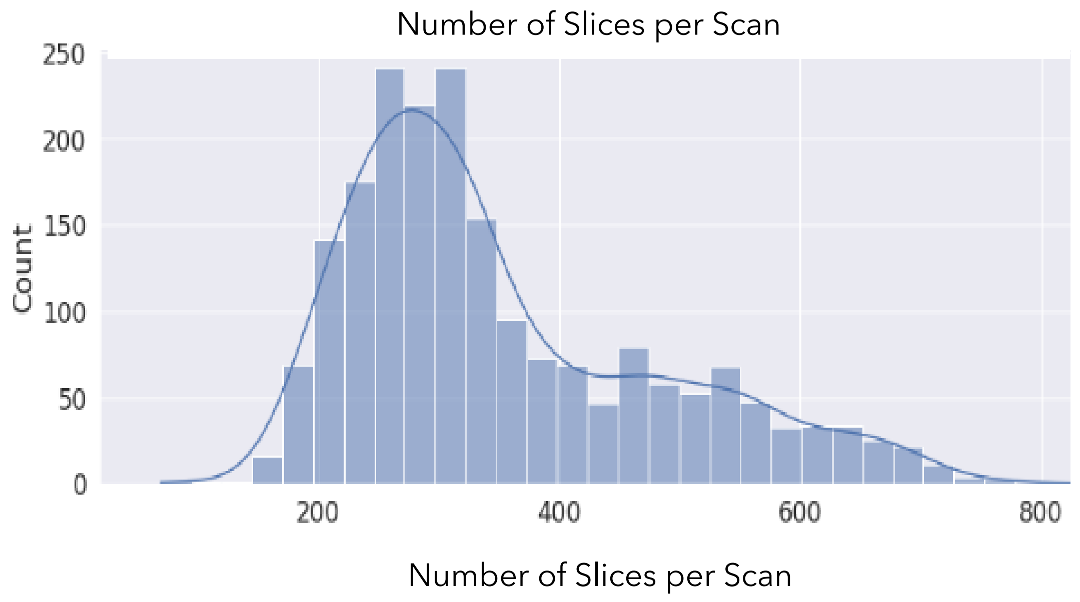


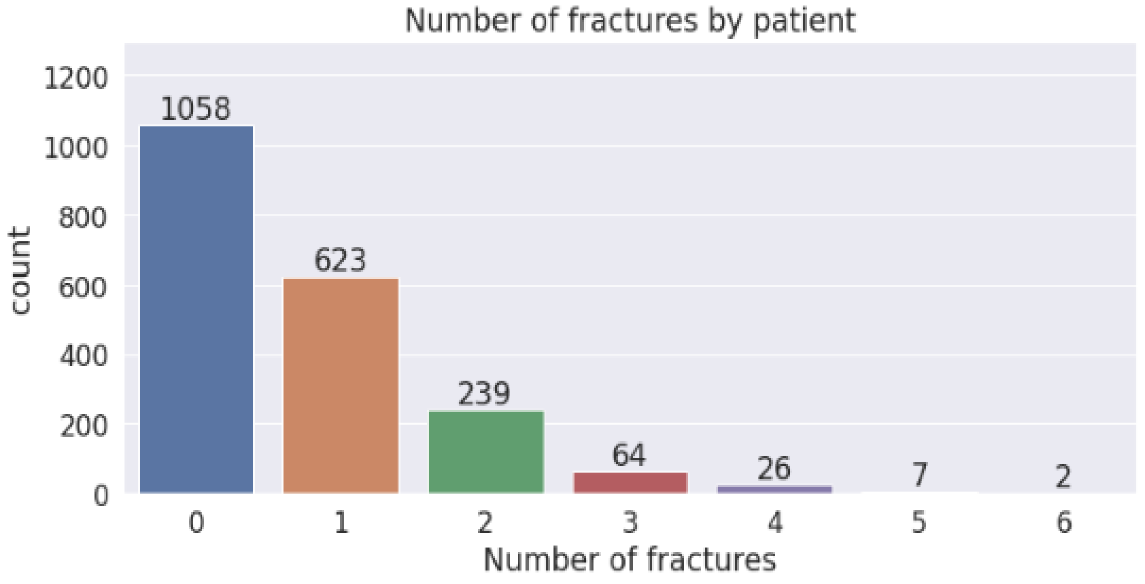


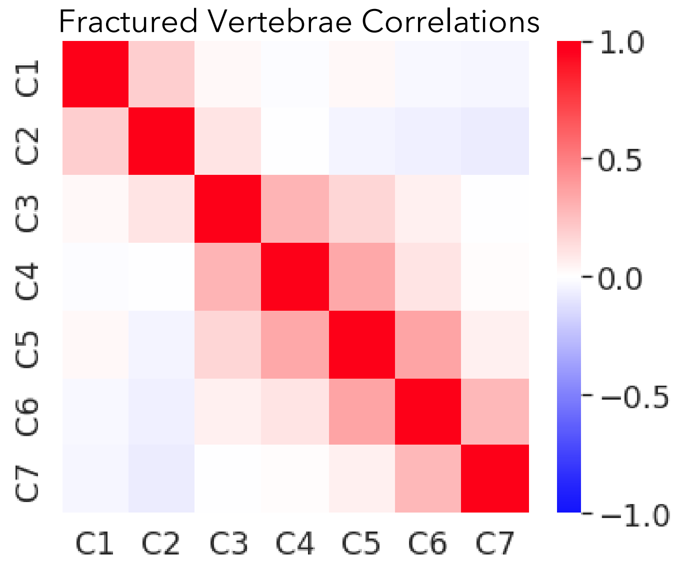
Clinical Dataset

Exploratory Analysis

- N=7 different cervical vertebrae shown in images, as well as other anatomical structures, such as thoracic spine, neck and skull
- Similar number of CT scans for fractured and non-fractured patients
- Similar number of fractures across different vertebrae
- CT scans most frequently have ~300 image slices, although certain patients have 800+ slices
- Most fractured patients have a fracture in only a single vertebra
- Scans with multiple fractures indicate that adjacent vertebrae are more likely to both be fractured



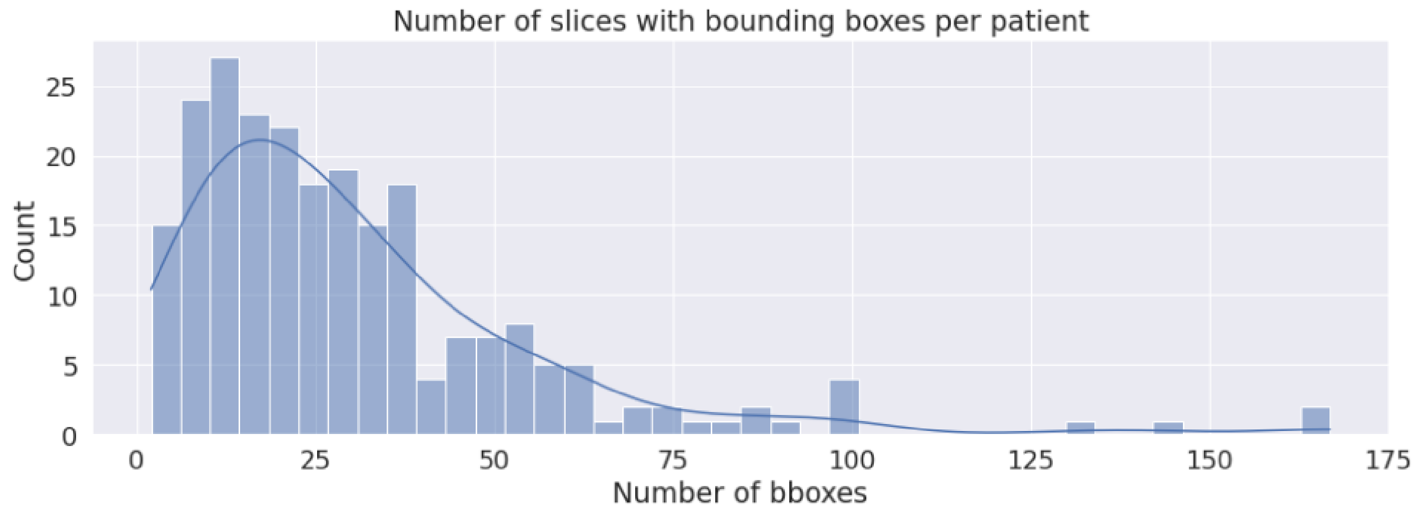


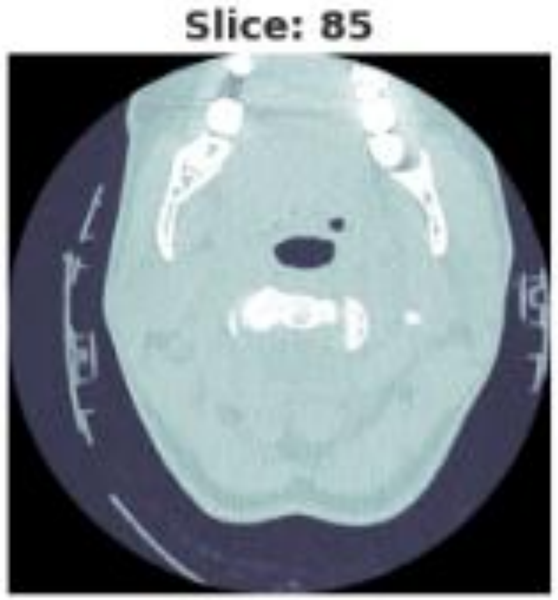


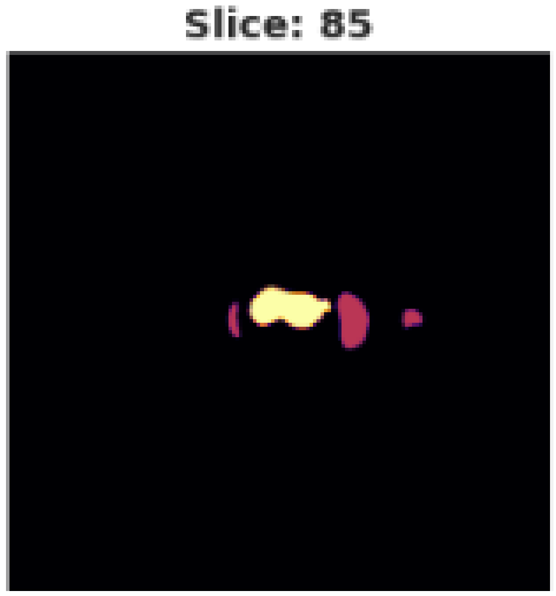
Clinical Dataset

Technical Challenges

- Differences in patient position and size, as well as image quality and field of view, across scans
- Class imbalance
  - Based on fractured patients with bounding boxes, fractures show up in only ~25 slices out of ~300 total slices per scan
- Lack of annotated data: ground truth data gives scan-level fracture information, but **slice-level ground truth data is limited**
  - Slice-level segmentations available for 4% of patients
  - Slice-level fracture bounding boxes available for 24% of patients with fractures
- Segmentation data: Certain classes consist of small numbers of pixels







Model Development

Model Development Steps

1. Development Approach
2. Data Loading
3. Training
4. Pseudo-Labeling
5. Semi-Supervised Learning

Model Development Approach

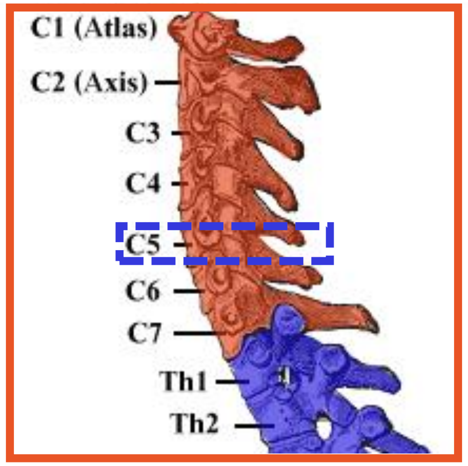
- **Problem: Scan-level** fracture annotations are available, but **slice-level** fracture annotations are not readily available
  - Training scan-level fracture detection model would most likely not be successful due to minimal annotated data
- **Solution:** Leverage bounding box data (n=235 patients) to train slice-level fracture detection model
  - For patients with bounding box annotations, make an educated **assumption** that all **slices without bounding boxes do not contain fractured vertebrae**
  - Use bounding box information to provide slice-level (axial) localization to model

Scan-level annotation

StudyInstanceUID	patient_overall	C1	C2	C3	C4	C5	C6	C7
1.2.826.0.1.3680043.1363	1	0	0	0	0	1	0	0

Slice-level annotation

StudyInstanceUID	Slice	C1	C2	C3	C4	C5	C6	C7
1.2.826.0.1.3680043.1363	90	0	0	0	0	1	0	0



Orange indicates scan-level annotations available for entire dataset and corresponding ROI for model. Blue indicates slice-level annotations and corresponding ROI for model. Bounding box information was leveraged to provide axial localization, rather than in sagittal and coronal directions.

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Data Loading Pipeline

Data storage

- Save images in online directory
- Change orientation of segmentations from sagittal to axial
- Create CSV with image filenames and ground truth metadata targets
- Data split: 80% training, 10% validation, 10% test
- Validation and test set patient scans not included in training

Dataset class

- Iterate through CSV and load individual images and ground truth targets
- Apply transformation & normalization to image

Sampling

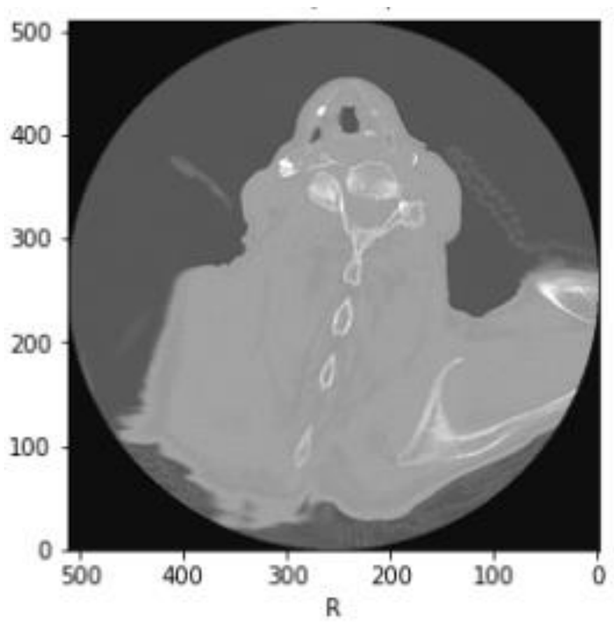
- Determine order of data that is loaded into model
- Training data randomly shuffled each epoch
- Validation data loaded in identical order each epoch using manual seed
- Custom Sampler allows for oversampling

Dataloaders

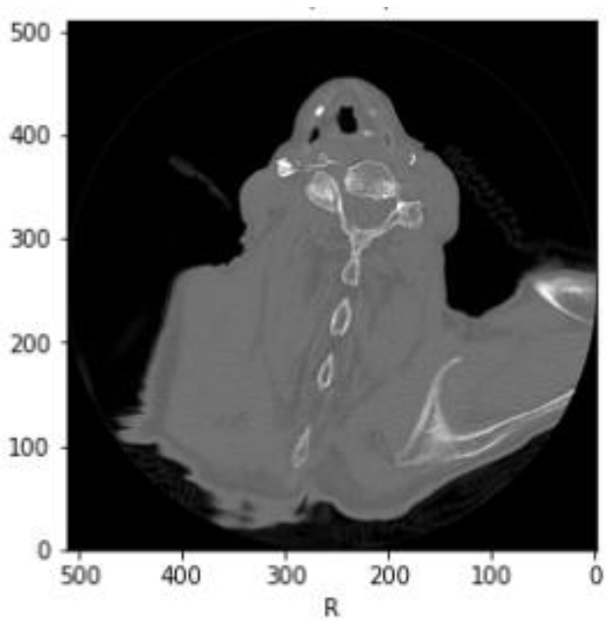
- Parallelize data loading process to increase speed and memory
- Individual dataloaders for training, validation and test
- Different transformations for training, validation and test

Data Pre-Processing

- Goal: allow network to see inputs with uniform intensities across dataset
- Intensity pre-processing
  - Transformation: truncate outlier Hounsfield intensity values that are not within expected range (i.e.: artifacts) using Clamp transform
  - Normalization: transform Hounsfield scale to intensity values in range [0, 1]



Original Image Slice



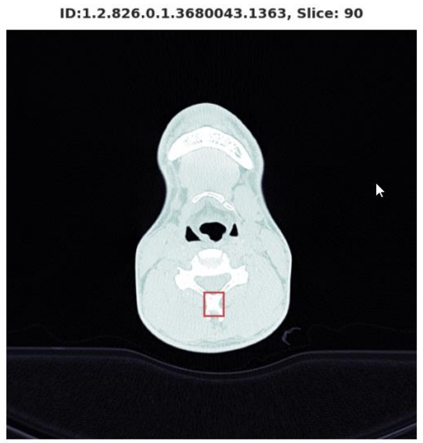
Transformed & normalized image slice

Data Loading

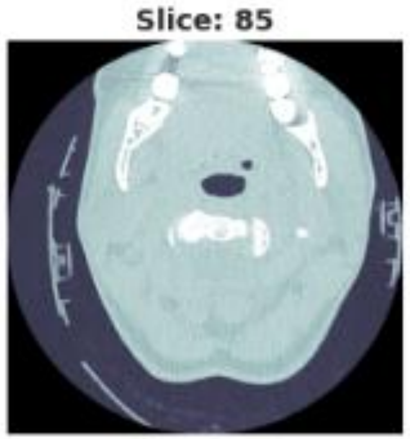
- Extract metadata (which vertebrae are fractured in each slice) from bounding box data to use as ground truth targets for fracture detection model
- Train fracture detection model using n=235 fractured patients with bounding boxes and n=235 non-fractured patients
  - Use all image slices (110k+ images) from this patient cohort to train model

Input Images

C5 Fracture



No Fracture



Targets

StudyInstanceUID	Slice	C1	C2	C3	C4	C5	C6	C7
1.2.826.0.1.3680043.1363	90	0	0	0	0	1	0	0

StudyInstanceUID	Slice	C1	C2	C3	C4	C5	C6	C7
1.2.826.0.1.3680043.10051	85	0	0	0	0	0	0	0

Model Development Steps

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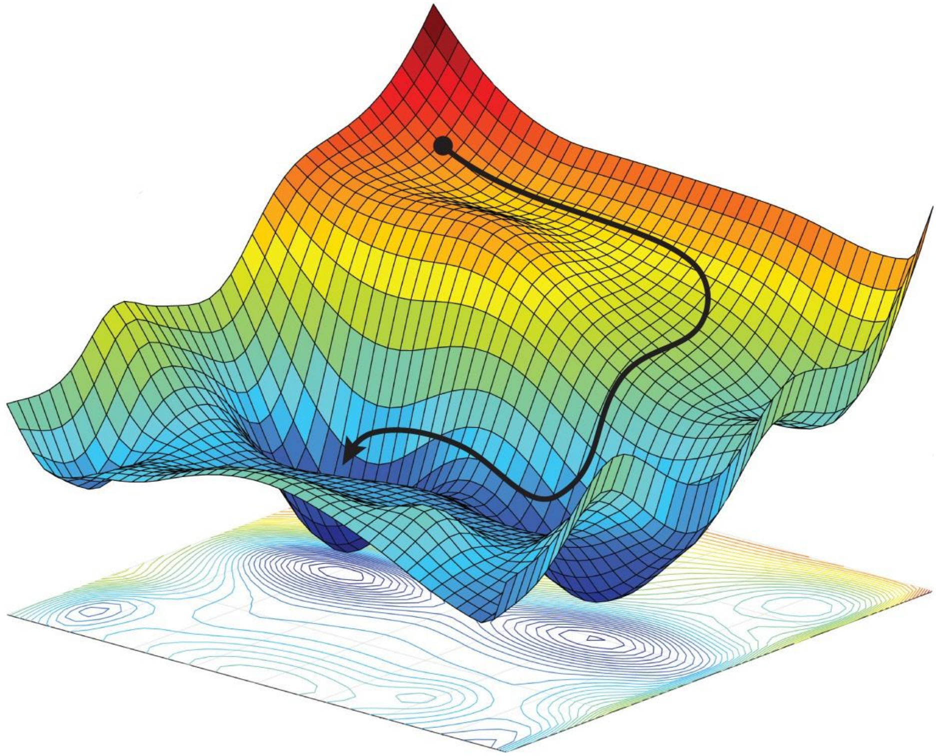
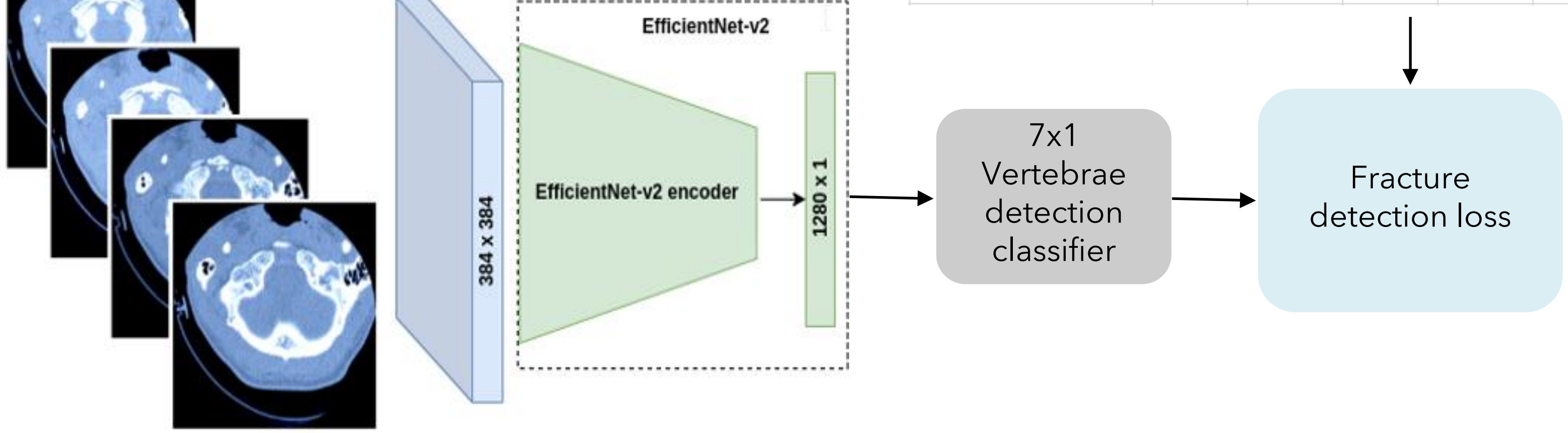
2D Model Training

Fracture Detection

- **2D Baseline:** Use pre-trained EfficientNetV2 (21.5M parameters) as feature extractor to create fracture detection model
  - EfficientNetV2 has improved parameter efficiency and accuracy
  - Finetune final layer using challenge dataset



StudyInstanceUID	Slice	C1	C2	C3	C4	C5	C6	C7
1.2.826.0.1.3680043.1363	90	0	0	0	0	1	0	0



2D Model Training

Fracture Detection

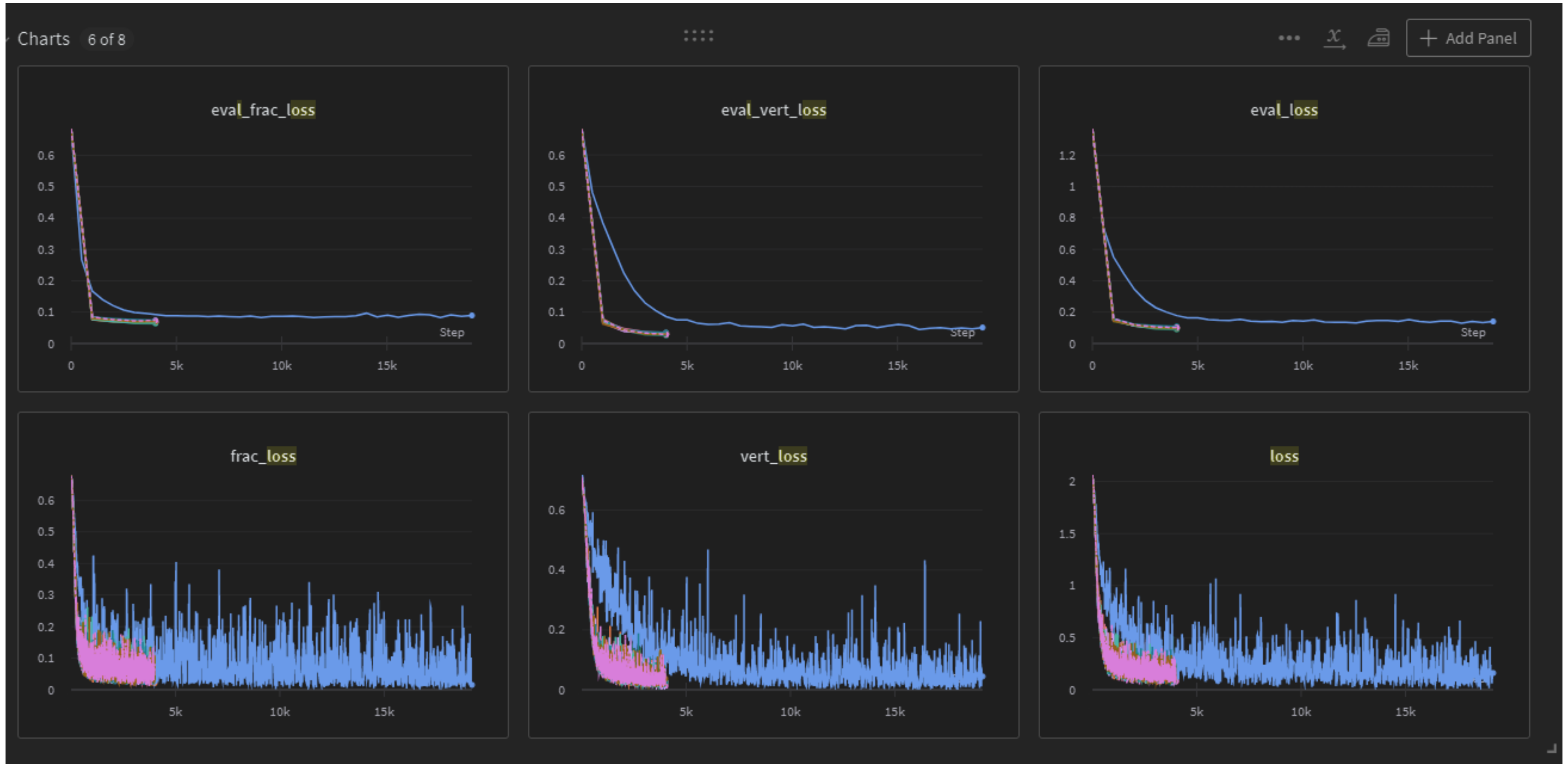
- Training conducted with Nvidia P100 GPU in Kaggle environment
- Computational constraints: 16GB memory
  - Increased batch size to maximum possible number of images
- Loss and metrics recorded with Weights & Biases

PyTorch

scikit-image
image processing in python

W&B

TorchIO



2D Model Training

- Augmentations: dataset is not very large, so very heavy augmentations were not applied
  - N=6 augmentations were applied, most with 30% probability: random resized crop, vertical and horizontal flips, rotations, RGB shift, CLAHE (sharpens contrast to identify small fractures)
  - Metric: Per competition rules, weighted binary cross entropy (BCE) used to evaluate submissions
  - Metric favors a more conservative model: sensitivity more important than specificity

$$L_{ij} = -w_j * [y_{ij} * log(p_{ij}) + (1 - y_{ij}) * log(1 - p_{ij})]$$

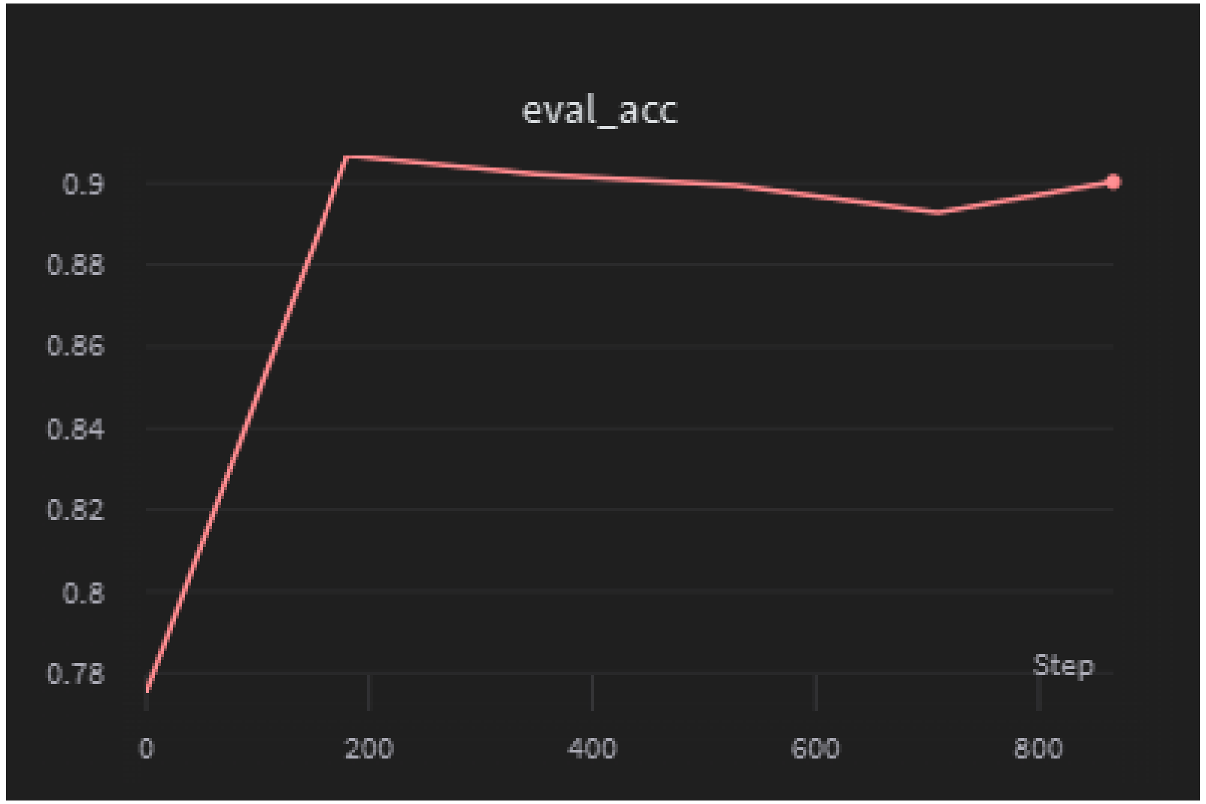
$$w_j = \begin{cases} 1, & \text{if vertebrae negative} \\ 2, & \text{if vertebrae positive} \\ 7, & \text{if patient negative} \\ 14, & \text{if patient positive} \end{cases}$$

- Loss: Weighted binary cross-entropy, identical to metric
- Additional metric :
  - Fracture accuracy: correctly classified vertebrae/total vertebrae

2D Model Training & Evaluation

Fracture Detection

Results: 90% accuracy for fracture detection

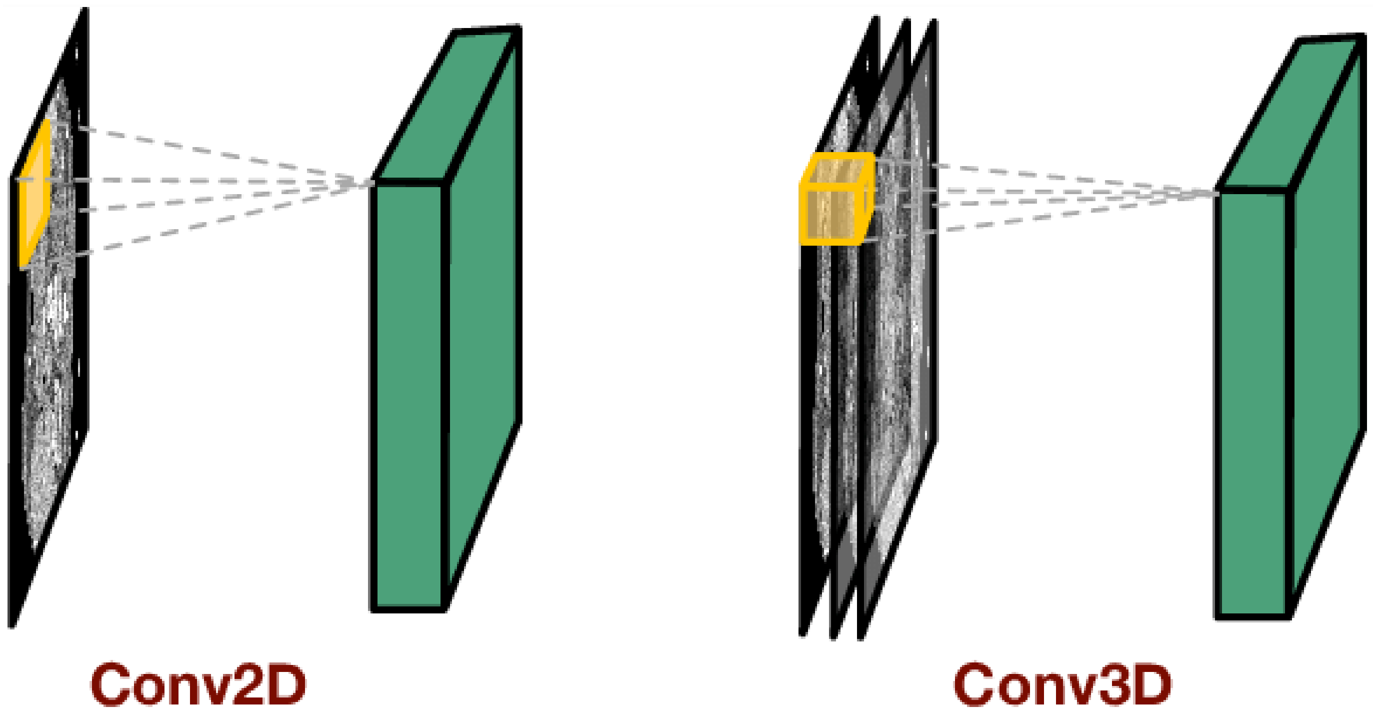


Hyperparameter optimization

- Model: EfficientNetV2
- Optimizer: Adam
- Learning rate: 1E-3
- Loss: weighted BCE
- Regularization: 20% dropout

2D vs 3D Modeling

- With baseline created using **2D model**, next step was to attempt to improve results using **3D model**
- 3D model architectures include significantly more contextual information from adjacent slices, which can improve results
- Input is 3D volumetric patches rather than 2D slices

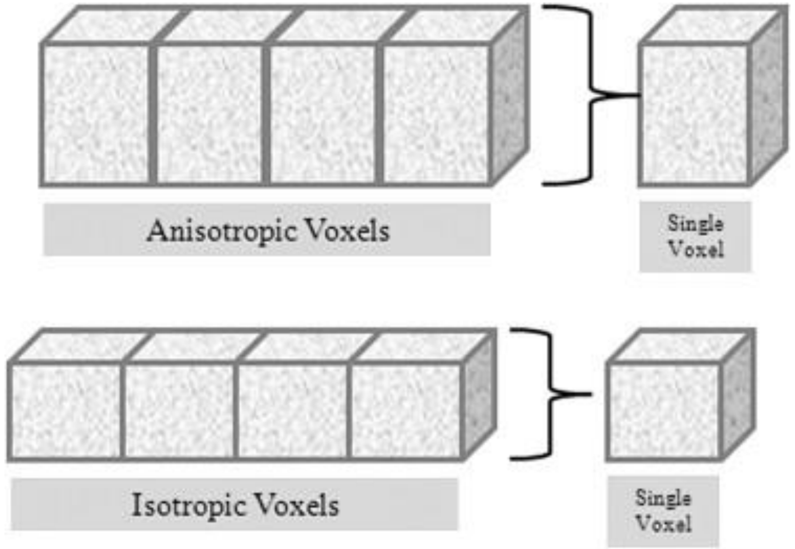


- Use pre-trained 3D ResNet-18 model (Med3D Net, 33M parameters) as feature extractor to create fracture detection model
  - Med3D model was pre-trained on medical images, rather than ImageNet, which can decrease convergence time for new medical imaging tasks
  - Finetune final layer using challenge dataset

Med3D: Transfer Learning for 3D Medical Image Analysis

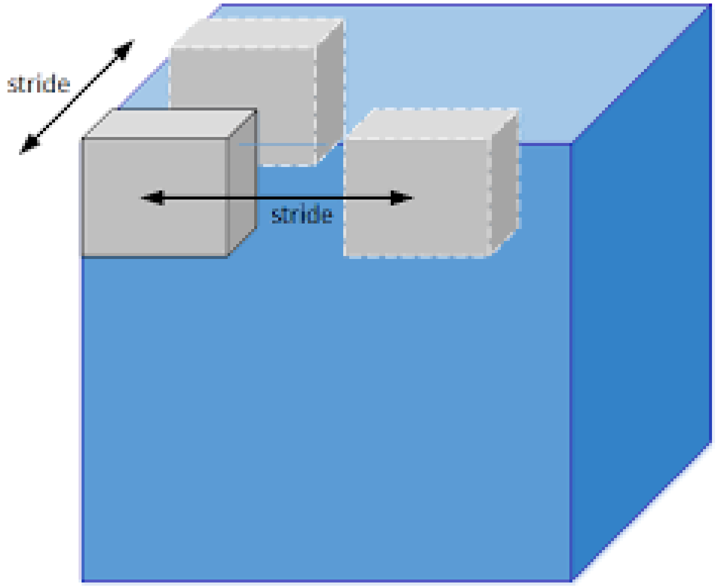
3D Data Pre-Processing

- Intensity pre-processing was previously completed in 2D modeling
- Spatial pre-processing allows network to see inputs with uniform sizes across dataset
  - Resampling: standardize physical resolution by downsampling to 1mm isotropic voxel sizing, which was lowest resolution in dataset
  - Voxel size hyperparameter: tradeoff between more anatomical data in receptive field versus improved resolution
  - Downsampling allows for faster computations



3D Data Loading

- 2D data loading pipeline is maintained, with additional features added
  - Due to GPU memory limitations, patch-based pipeline was implemented
- Images are divided into patches of 56x56x56 pixels
  - This spans length of approximately two cervical vertebrae so that contextual information is included
- Patch LabelSampler: randomly extract patches from volume based on class probabilities
  - Probabilities
    - No fracture: 0.7
    - Fracture: 0.3
  - This effectively implements oversampling of fracture data
  - Sample n=8 patches per volume per epoch
- TorchIO queue to improve data parallelism
- PyTorch DataLoader is based on TorchIO queue



3D patches sampled from 3D volume

3D Model Training & Evaluation

Fracture Detection

Training

- Augmentations N=6 augmentations were applied, most with 30% probability
  - Random patch scaling, vertical and horizontal flips, rotations, RGB shift, CLAHE
- Hyperparameter optimization
  - Model: 3D ResNet-18
  - Optimizer: Adam
  - Learning rate: 1E-3
  - Loss: weighted BCE
  - Regularization: 20% dropout

Results

- 88% accuracy for fracture detection, which was lower than 90% accuracy for 2D EfficientNetV2 model
  - This was surprising, as 3D models have more contextual information, which is almost always helpful
  - Post-competition, other competitors also reported slightly worse results for 3D models on this dataset
- Slice-based strategy using 2D EfficientNetV2 was selected as approach

Model Development Steps

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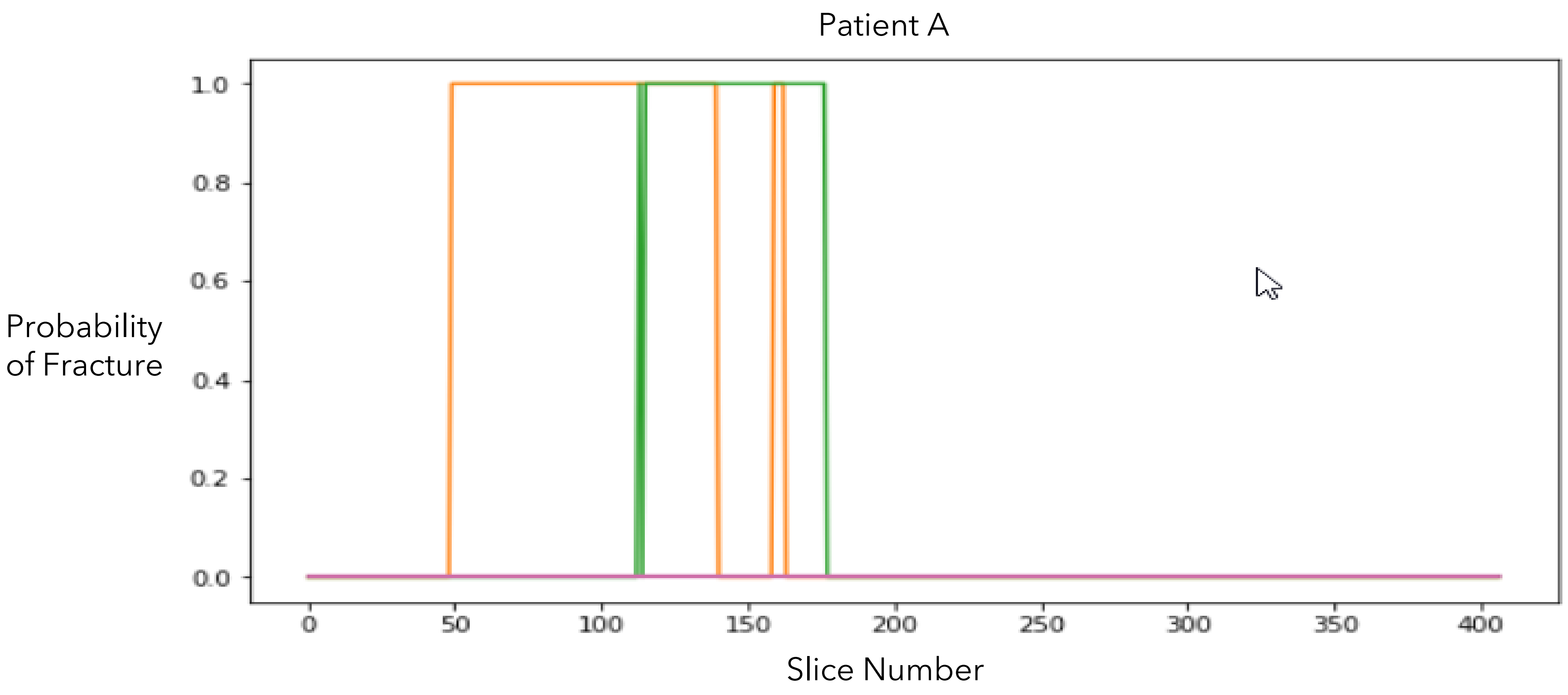
5. Semi-Supervised Learning

Model Inference

Fracture Detection

- Fracture detection model inference performed on rest of fractured dataset (n=734 patients without bounding boxes) to generate slice-level predictions of vertebrae fracture
  - Not necessary to perform slice-level inference on non-fractured patients, as no slices contain fractures
- Generated pseudo-labels for all image slices in dataset that predict probability of fractured vertebrae
  - Probabilities were binarized in post-processing
  - Colors below correspond to binarized probability of fracture for 7 different vertebrae in all image slices for a particular patient



Model Development Steps

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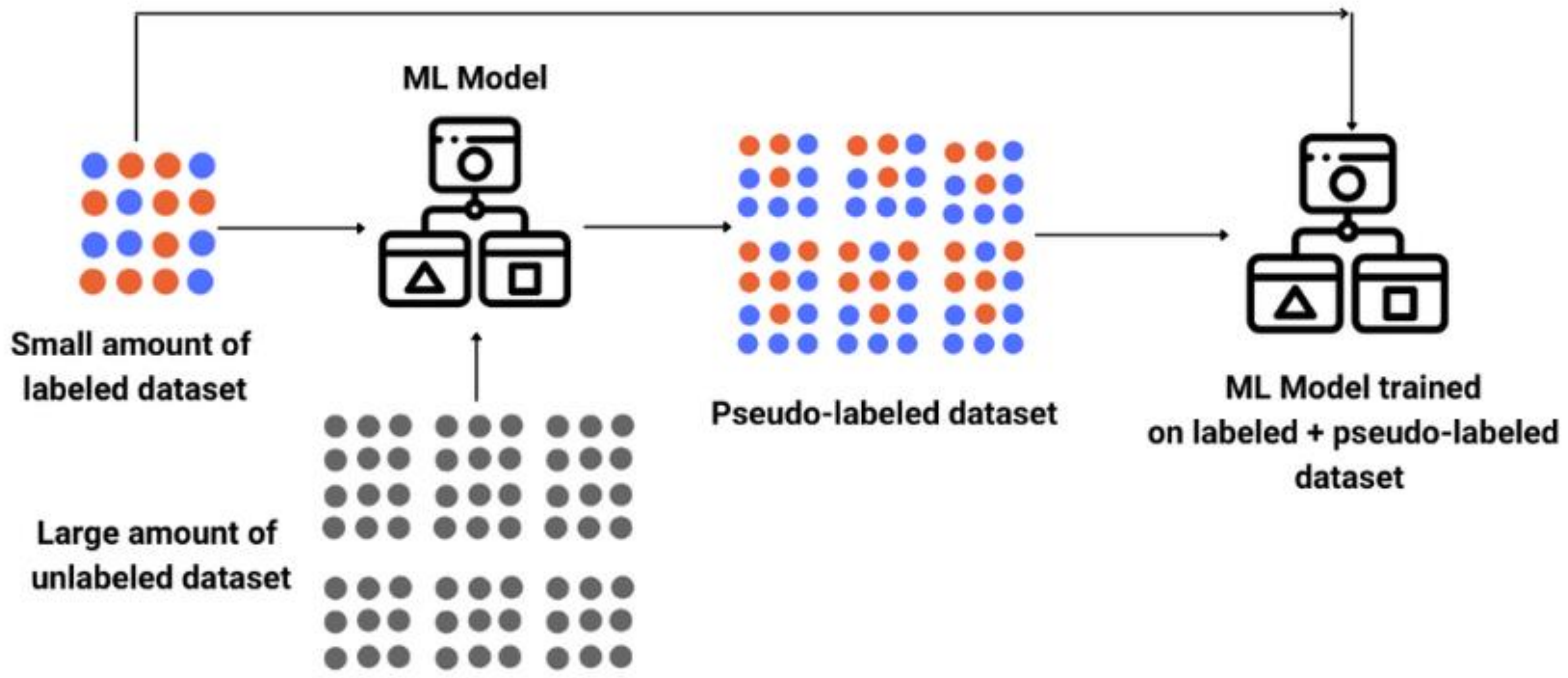
Model Re-trained with Entire Dataset

Semi-supervised Learning

- With labels and pseudo-labels generated for all slices in dataset, EfficientNetV2 network was **re-trained**
  - **Semi-supervised** learning: combination of supervised and unsupervised learning



- Network re-trained using n=2019 patients with all 700k+ image slices and slice-level labels/pseudo-labels
- Data split: 90% training, 10% validation, hidden public test set from Kaggle (n=420 patients)

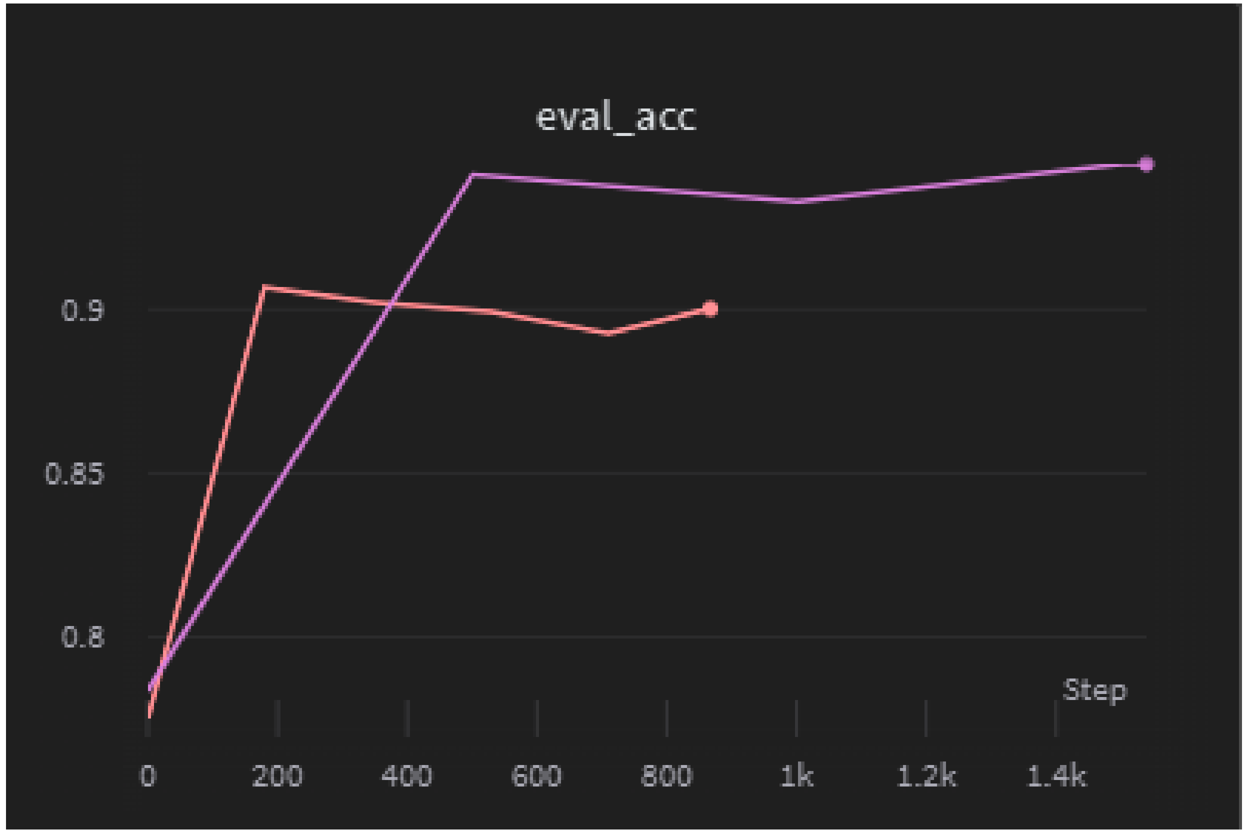
Model Re-trained & Evaluation

Fracture Detection

- Augmentations: dataset is large, so heavier augmentations were applied
  - N=6 augmentations were applied, most with 40% probability: random resized crop, vertical and horizontal flips, rotations, RGB shift, CLAHE
- Loss & metric: Weighted binary cross-entropy
- Additional metric: fracture accuracy
- Hyperparameters from earlier training worked well
  - Model: EfficientNetV2
  - Optimizer: Adam
  - Learning rate: 1E-3
  - Loss: weighted BCE
  - Regularization: 20% dropout
- **Final score:** 0.45 public and 0.50 private
  - Top 7% submission

Results: 94% evaluation accuracy for fracture detection

+4% increase with semi-supervised learning



Model Development Steps

1. Development Approach
2. Data Loading
3. Training
4. Pseudo-Labeling
5. Model Tuning

Conclusion

Summary

- Results were quite predictive, with 94% evaluation accuracy and 0.50 weighted BCE for hidden test set
- Potential Improvements
  - Calculate sensitivity and specificity, as well as accuracy, to aid in error analysis
  - Model more robust at predicting non-fractures than at predicting fractures
    - Improved use of oversampling, or implementing focal loss, may help mitigate accuracy differences between classes, which would be key for a clinical product
  - Ensemble modeling
- Constraints:
  - Time: started three month-long competition with one month left
  - Limited computational power prevented pursuing additional hyperparameter tuning
  - Kaggle weekly GPU quota led to highest scoring model submission coming in slightly after competition deadline

Discussion & Conclusion

- During competition, Kaggle discussion topics and notebooks were helpful for initial data exploration and model development
- Post-competition, notebooks of highest scoring submissions were helpful for lessons learned
- Highest scoring notebooks used various approaches:
  - Semantic segmentation: train model based on limited segmentation data and leverage localization information
    - 2D: with 2D masks generated, train object detector to determine bounding boxes for all vertebrae
    - 3D: train 3D U-Net to create masks & bounding boxes for all vertebrae
  - Utilize contextual information
    - Similar to my experience, most 3D CNN classification models were not very successful
    - 2.5D approach was helpful: each 2D input slice to model also had information from adjacent slices
  - Sequential models (RNN, LSTM, transformer) were used to learn features of entire vertebrae
  - Heavy augmentations: Mixup, random brightness were particularly helpful
- Results suggest that deep learning fracture detection models have the potential to be used as powerful tools to aid clinicians in rapidly diagnosing the location of cervical spinal fractures
- In the future, models may be helpful in prioritizing positive CT scans for reviews in high volume hospitals and in underserviced areas