Scoliosis Subteam Midterm Presentation

Eric Chen, Nathan Zhong, Lucas Yim, Austin Peng,
Brian Zhang, Nikil Vangala, Patrick Weng

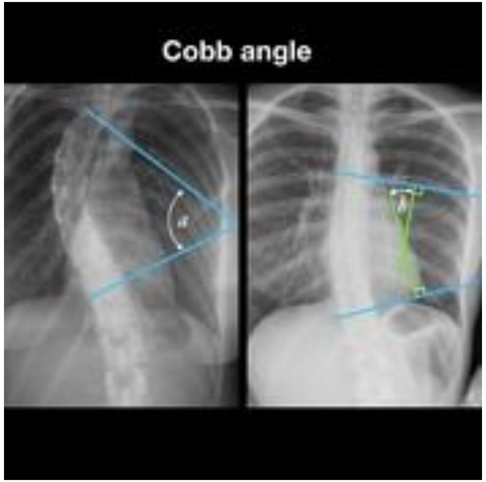
Overview

- Introduction/Problem Definition
- Techniques/Tools/Approaches
- Datasets
- EMADE progress
- Future Work

What is Scoliosis Detection?

Definitions

- Adolescent Idiopathic Scoliosis (AIS) - Most common type of scoliosis; affects children ages 10-18.
- Cobb Angle - The maximum possible angle calculated from a pair of vertebra in the spine.
    - An angle of at least 10 degrees is defined as scoliosis.
    - Angles between 10 and 20 degrees require close monitoring from a doctor
    - Angles between 20 and 40 degrees, can necessitate back braces.
    - Beyond 40 degrees, surgery is generally required.
    - Between professionals, recorded angles can vary from 2-10 degrees. This inconsistency is exacerbated by patient positioning.



Problem

Given a set of x-ray spinal images, we would like to determine the cobb angle quickly and accurately.

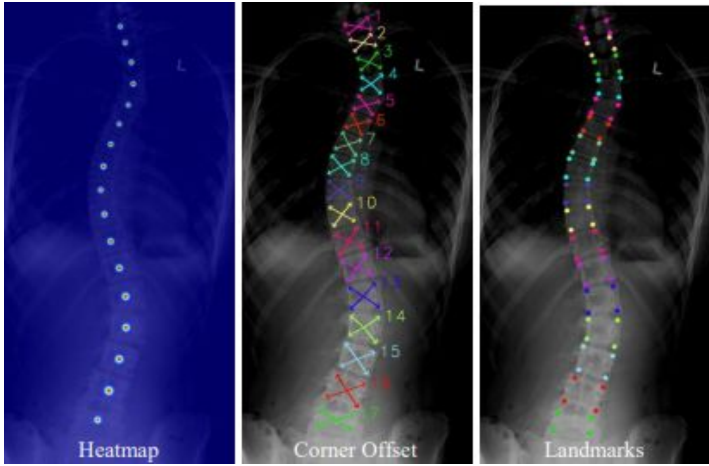
Several vertebra detection and cobb angle detection challenges exist; we considered several challenge winners and research papers on challenge datasets.

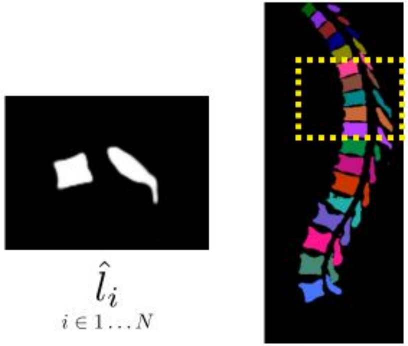
Initially considered VerSe, a 3D vertebra segmentation model last semester. Discarded because it wasn't suited to the problem.

Approches & Techniques

Landmark Detection vs. Segmentation

- Following vertebrae localization, AASCE paper uses landmark detection but most models use segmentation
  - Landmark Detection:
    - Vectors drawn to the the corners
    - Landmarks are the corners of vertebrae and Cobb angle calculated from there
  - Segmentation:
    - Deep convolutional network trained to segment objects and label
    - Final semantic label identified with localization label
- Why landmark detection?
  - Segmentation sensitive to image quality
  - Segmentation has difficulty separating attached vertebrae



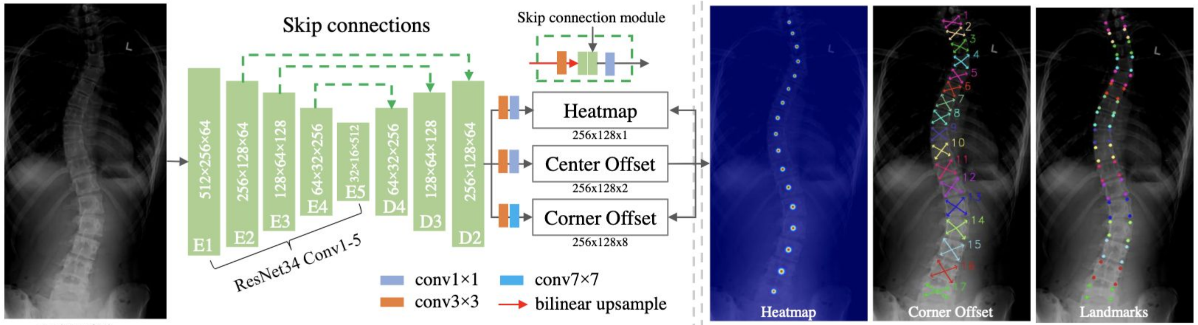


$\hat{l}_i$
$i \in 1 \ldots N$

$\hat{l}_{\text{final}}$

AASCE Paper

- Proposed a method predicting cobb angles based on identifying centerpoints of vertebrae, then finding corresponding corner points, and finally calculating cobb angle.



(a) Vertebra-Focused Landmark Detection Network (b) Landmark Decoding

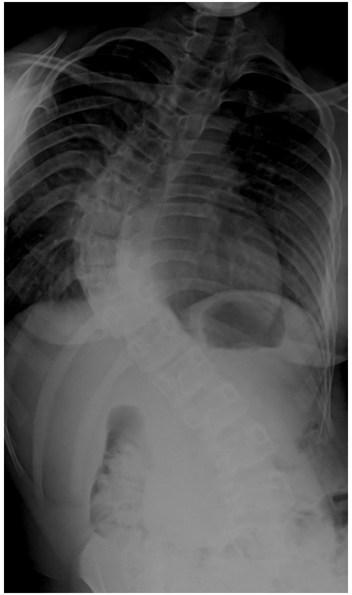
Datasets

Accurate Automated Spinal Curvature Estimation (AASCE)

Contains 580 x-ray images

- Each image is associated with three cobb angles that were used as the training/evaluation metric
- Landmarks for 17 vertebrae are given (68 points) for calculating cobb angle
- Self derived single cobb angle from ground truth landmarks
- Challenge participants were judged on their SMAPE values
  - Challenge winner: 21.375
  - Paper Model: 10.31

Examples



Shriner's Dataset

- X-ray images sent to us from the Shriner's Children Hospital
- Original sent .nii files (which contains metadata about the patient) which we unpacked into pngs
- Images tend to be less uniform and have more variation than the AASCE dataset
    - Some of them are so different that it turn, the AASCE model tends to perform very poorly on predicting vertebrae
- In turn, running the AASCE model on the Shriner's data initially with no preprocessing resulted in very bad predictions
- Overlay images include inconsistent information for truth data

Goal: Run EMADE using the AASCE dataset (since we have truth data for that) and then pull the generated model out and run Shriner's dataset on that to get Cobb Angle predictions.

1) Cropping
2) Edge Sharpening

Initial Cropping

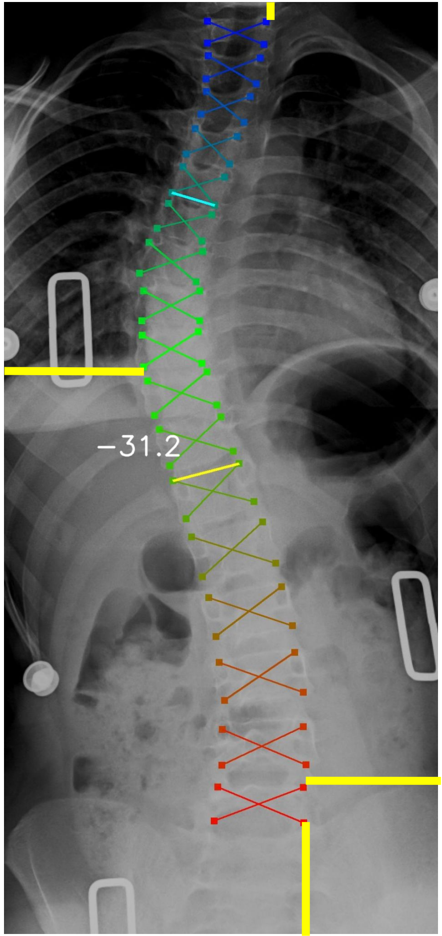
- Initially, picked out a couple images and manually altered the numbers to find a cropping scheme that worked somewhat well
- Decided to take off 500 pixels from both sides of the image, and include a 100 pixel buffer room
- Also took off 2300 pixels from top and bottom, split with 1:2 ratio, with 300 buffer room on top and 200 buffer room on the bottom
- Formula:

  Sides: $(\text{img.width} - 1000) / 2 - 100$
  Top: $(\text{img.height} - 2300) / 3 - 300$
  Bottom: $(\text{img.height} - 2300) * 2 / 3 - 200$

- Evaluation improved but still facing issues with 1) model localizing the mouth and pelvic bone and 2) color contrast

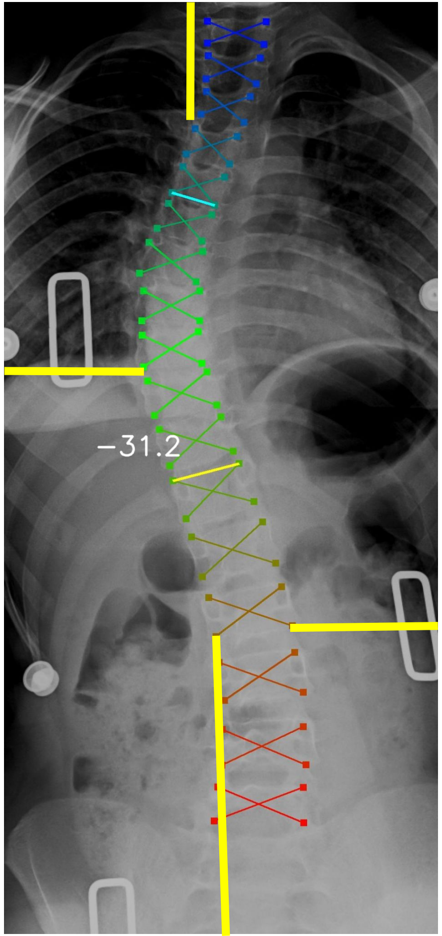
Improved Cropping

- Wanted to do a better job with localizing the spine and making the cropping more unique to each image
- Found the average distance between the edge of the image and the top/bottom/left/right most points for the AASCE images
- For each Shriner's image, found the top/bottom/left/right most points from the initial cropping predictions, found the distance between those points and the edge of the ORIGINAL picture, and cropped the image so that the distances match the averages from AASCE
- Evaluation improved greatly; still facing some issues with crosses in the mouth but doesn't affect Cobb Angle calculations for the most part; Still facing issue with distorted image contrast



Improved Cropping Part 2

- One thing I noticed was if the initial cropping predictions were faulty (i.e. one cross was in the mouth), the second round of cropping would be cropping based on a faulty prediction
- Instead chose to exclude the top three and bottom three vertebrae and follow the same technique as the previous slide
- Again, improved slightly in evaluation; probably due to the fact that if the top vertebra localization was wrong, it would shift all the vertebra up by one so the cropping would've ended up pretty similar
- But Cobb Angle measurement is improving and getting closer to doctor's "truth value" (55.4)



Edge Sharpening

- As the Shriner's images had much less defined spine and vertebrae when compared to AASCE, edge sharpening techniques were explored to see if it improves.
- Three image enhancement algorithms were explored on the National Library of Medicine MedPix Dataset:
  - Contrast Limited Adaptive Histogram Equalization (CLAHE)
    - Histogram-based method used to improve contrast in images
  - Unsharp Masking
    - Linear filter that is capable of amplify high-frequencies of an image.
  - High-Frequency Emphasis Filtering (HEF)
    - Gaussian High Pass Filter to emphasis and accentuate the edges.

Edge Sharpening Part 2

- Contrast Limited Adaptive Histogram Equalization:
  - Computes the histogram for the region around each pixel in the image, improving the local contrast and enhancing the edges in each region.
- Unsharp Masking:
  - Sharpened image = original image + intensity of the edges * (original image - gaussian blurred image edges)
- High-Frequency Emphasis Filtering
  - Sharpened image = (original image + (Gaussian High Pass Filter)) * (Histogram Equalization)

Original

HEF

UM

CLAHE

EMADE

Packaging Data - AASCE Dataset

- Original data was provided in mat format and jpg format
- Given 3 sets of data: train, test, validation
  - test and validation sets had truth data for Cobb angle and landmarks
  - each instance has 136 corresponding landmarks (values between 0~1)
  - need to extract actual landmark truth data from mat format
- Packaged data to have image data and the maximum Cobb angle measurement

Packaging Data - Shriner's Dataset

- Used existing png format Shriner's x-rays
- Does not contain professionally marked vertebrae landmarks
    - Will likely need to use segmentation rather than landmark detection
- Cobb angle truth data was collected by hand and stored into a csv format
    - Most x-rays had at least 1 Cobb angle measurement
    - Some did not have any measurements
- Packaged image data with the Cobb angle measurement from the 'Thoracic' portion of the spine

Evaluation Functions - SMAPE

- Symmetric Mean Absolute Percentage Error (SMAPE)
- Preferred over MAPE for scoliosis measurements on Cobb Angles
- Symmetry addresses the boundlessness of MAPE

$$SMAPE = \frac{100}{n} \times \sum_{i=1}^{n} \frac{\left|Y_i - \widehat{Y}_i\right|}{\left(|Y_i| + |\widehat{Y}_i|\right)/2}$$

Evaluation Functions - MSE

- Mean Squared Error
- Measures amount of error in statistical model by averaging the squares of the error
- Standard Evaluation function

$$\text{MSE} = \frac{1}{n} \sum_{i=1}^{n} (y_i - \tilde{y}_i)^2$$

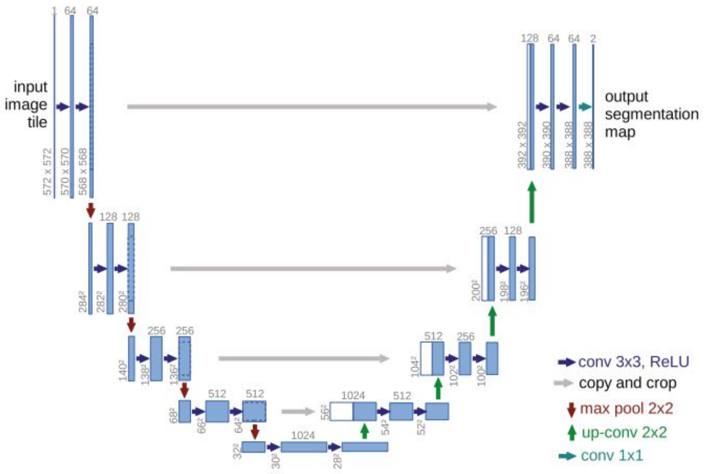
Azure

- Using Azure Compute to perform our preprocessing
- Created an Azure SQL Database under the advice of our contact at Shriners
  - Based on Microsoft SQL instead of MySQL and MariaDB which EMADE is known to run on
  - Future work includes verifying the functionality of Microsoft SQL and determining if Microsoft SQL is viable to run EMADE with small tweaks
- Planning on running our EMADE experiments through Azure Compute

Models

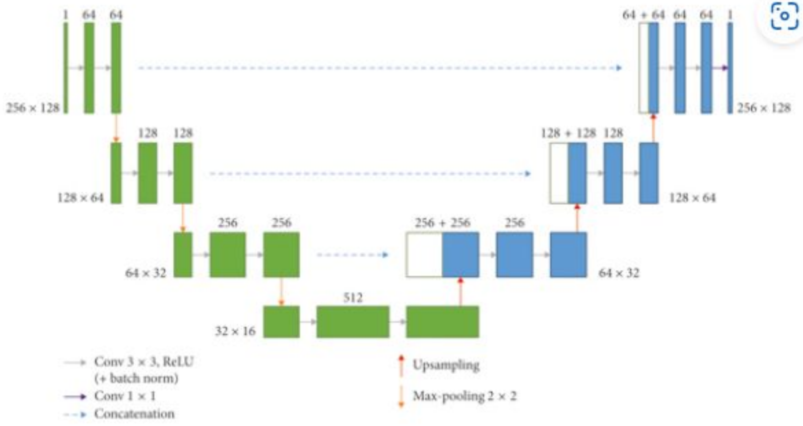
U-Net

- Popular deep convolutional network created by Ronneberger, Fischer, and Brox from University of Freiburg
- Builds off architecture of fully convolutional networks
  - Supplemented contracting network with successive layers
  - Pooling layers replaced by upsampling, increasing resolution of features which are combined with upsampled output
  - Upsampling lets network propagate context info to higher layers
  - Creates an expansive path that mirrors contracting path with overall U-shape



U-Net

- Application towards scoliosis
  - Initially made for cell segmentation which was adapted for vertebrae segmentation
  - Employs technique to segment objects of same class via their border
    - Weighted loss for border pixels, forcing network to learn them
    - Can help with vertebrae touching each other
  - Alter the crop and copy operation in original U-Net
    - Cropping central area of feature map would lose important information of vertebrae
    - Replace the operation with only concatenation of feature maps

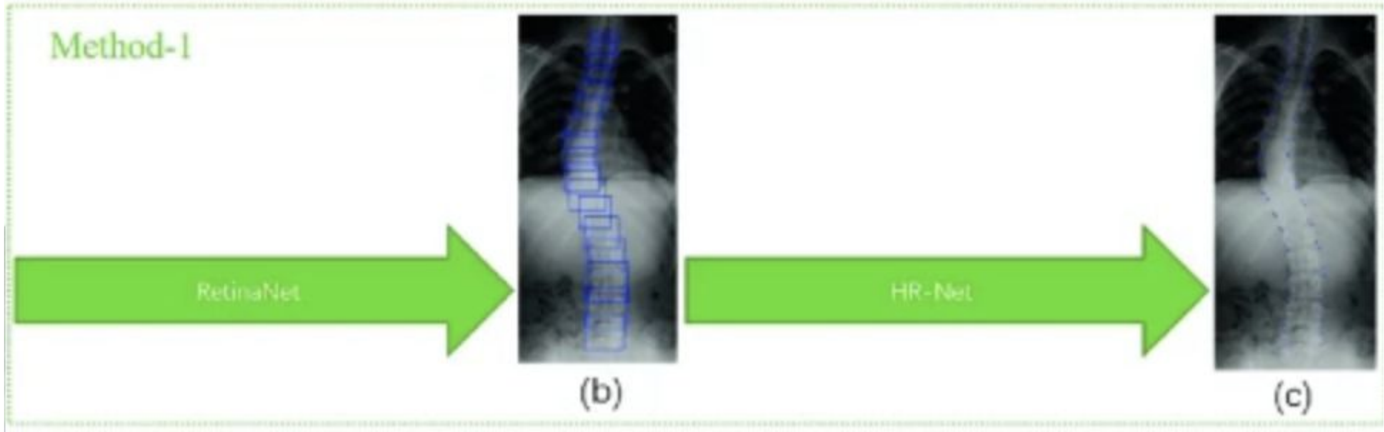


Seg4Reg

- Performs vertebrae segmentation followed by Cobb Angle regression
- Preprocessed images with random rescale, rotation, and Gaussian noise
- Used a neural network to generate segmentation masks on the vertebrae
- Used another neural network to predict Cobb Angles off of segmentation masks

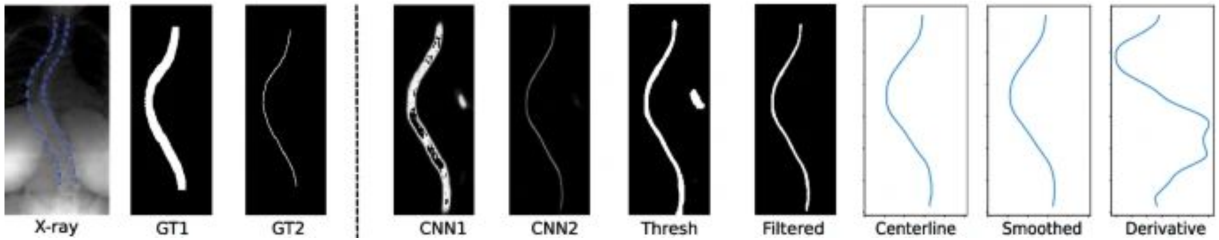
RetinaNet + HR-Net

- RetinaNet detects vertebra and creates a bounding box around each one
- HR-Net uses the bounding boxes to identify 4 key points around each vertebra
- Mathematically calculate cobb angle from the key points



Centerline Extraction from Cascaded Neural Networks

- Cascaded Neural Nets derive a centerline from the image.
- Postprocessing steps handle guaranteeing continuity of the curve, detecting the sides of the centerline, and finally selecting points between the sides as the final centerline curve.
- Partitioned the dataset in to 10 subsets and optimized an ensemble of models on combinations of 9 of the subsets, leaving 1 remaining as the testing set.
- The cascaded nature of the neural nets allowed the model to better handle contrast



Future Work

Adding Primitives to EMADE

- Main Idea: Use EMADE to find best combination of image processing primitives with the best model primitive, optimizing for Cobb Angle as objective
- Image Processing Primitives:
  - Current ones in EMADE fall into signal methods and spatial methods
    - Function from sci-kit image or OpenCV
    - Have to wrap using RegistryWrapper for it to enter the primitive registry
  - Adding new ones seem to follow similar format or custom functions can be coded into helper functions and then wrapped
- Model Primitives:
  - Progress starts with understanding the code behind the models we want to add
  - Then implementing that code into EMADE with alterations for scoliosis detection
  - Then create RegistryWrapper with correct parameters

Additional Metrics

Shriners also wants (currently unspecified) metrics from their x-rays including potentially:

- Apical Vertebral Translation - Offset of C7 (middle) vertebrae from spine base
- Regional Cobb Angle measurements - Thoracic, Proximal, Lumbar
- Coronal Balance/Decompression - Essentially offset of shoulder vertebra from hip vertebra

Shriners is also preparing to send over ~700 more x-ray images

Sub Team Meeting:
10AM Friday

References

Papers

- Yi, Wu, Huang, Qu, Metaxas, “Vertebrae-Focused Landmark Detection For Scoliosis Assessment”
- Ronneberger, Fischer, Brox, “U-Net: Convolutional Networks for Biomedical Image Segmentation”
- Horng, Kuok, Fu, Lin, Sun, “Cobb Angle Measurement of Spine from X-Ray images using Convolutional Neural Network”
- VFL Repo: https://github.com/yijingru/Vertebra-Landmark-Detection
- Chen, K., Peng, C., Li, Y., Cheng, D., Wei, S. (2020). Accurate Automated Keypoint Detections for Spinal Curvature Estimation. In: Cai, Y., Wang, L., Audette, M., Zheng, G., Li, S. (eds) Computational Methods and Clinical Applications for Spine Imaging. CSI 2019. Lecture Notes in Computer Science(), vol 11963. Springer, Cham. https://doi.org/10.1007/978-3-030-39752-4_6