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Cobb angle estimation from AP X Ray Images using Region Proposal Neural Networks

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Abstract **—** Accurate determination of cobb angles is crucial for the diagnosis and treatment planning of Scoliosis. Current standard practice is based on manual estimation from X-ray images which is not only time consuming but also highly variable between raters. To alleviate this issue, we propose an AI based technique to automatically detect the Cobb angles from spine anterior-posterior (AP) X-rays. Our technique first detects the vertebral column as an object followed by a centerline detector that estimates the centerline of the vertebral column. The sectioning into each vertebra as well as lumbar and thoracic regions is then achieved. Cobb angles are computed using the slope of each subsequent pair of points. The data from AASCE MICCAI challenge 2019, was employed for training and testing. The results were assessed according to evaluation criteria SMAPE, where our technique could obtain a SMAPE of as low as 22. (Symmetric Mean Absolute Percentage Error)
Keywords *— Scoliosis _ Mask _ Object Detection _ Cobb Angle Ground Truth.*

I. INTRODUCTION

Scoliosis is a 3D deformity of the human spinal column that is caused from the bending of the latter, causing pain, aesthetic, and respiratory problems. This internal deformation is reflected in the outer shape of the human back. The prevalence rate of scoliosis (>10 degrees) was found in 2.52% (172 of 6824 schoolchildren) in a study by Quang et.al [1].
Estimating the angles of curvature –Cobb angles is one of the most important parameters for the evaluation of Scoliosis. It is the gold standard for diagnosis, treatment planning and therapeutic decision making for Scoliosis. According to Lenke criteria of curve classification, the spine is divided into three regions PT (Proximal Thoracic), MT (Main Thoracic) and TL(Thoracic Lumbar). PT has an apex between T3, T4 or T5 whereas MT has an apex between T6 and the T11-T12 disc. Thoracolumbar apex is between T12 and L1, and lumbar apex is between L1-L2 disc and L4(1). PT, MT, and TL are the three Cobb angles computed for treatment planning and its accuracy is crucial for deciding if surgical intervention is required. As the Cobb angle is a 2D measurement of a 3D deformity, it may not be the best indicator of the severity. manifested in external appearance. The 3D representation of the human spinal column that would successfully depict the real nature of scoliosis is still under research [2].

The procedure of calculating cobb angles is time-consuming and observer dependent, leading to high inter-observer variability that could negatively impact assessing prognosis and treatment decisions [3]. Thus, there has been increasing interest in automatic estimation of Cobb angles directly from the X-ray images however the results have not yet prompted direct clinical application, and the problem of accurate detection persists. In this context, our work attempts to develop a novel technique for Cobb angle detection. We use the MICCAI 2019 challenge on Accurate Automated Spinal Curvature Estimation (AASCE) [4] from training/testing dataset containing 609 AP x-rays 4 whose results were assessed on 98 test images. The ground truth (GT) annotations are already provided.

II. LITERATURE REVIEW

To this date mainly two approaches have been undertaken to estimate the Cobb angle. Specifically, these include Segmentation based, and Landmark based techniques The Segmentation based methods first segment all the vertebrae or the end plates of the vertebrae to identify the most tilted vertebrae from which the Cobb angles are estimated [5].

The Landmark based methods treat some part of the vertebral column as an object and then calculate the cobb angles by mathematical modelling.

Unlike traditional machine learning methods, deep neural networks do not require any handcrafted features for training and can be trained end-to-end for object detection and semantic segmentation. As such, a CNN network is a suitable choice for extracting the vertebral regions of a spine. In biomedical image segmentation, recent successes in precise image segmentation were achieved by using a U-Net architecture by Ming et.al [6].

Taking each vertebra as an object increases the number of classes as well as increases the probability of overfitting by virtue of the given dataset. Unlike conventional machine learning methods and deep learning methods which treat each vertebra as an object, we have considered the whole vertebral

[1]https://surgeryreference.aofoundation.org/spine/deformities/adolescent-idiopathic-scoliosis/further-reading/lenke-classification#introduction

column as an object to perform semantic segmentation. Apart from U-net used by Ming et. Al [6], Mask-RCNN is also a prominent architecture used for instance segmentation and object detection.

Mask RCNN overview: Mask R-CNN adopts the same two-stage procedure, with an identical first stage (which is RPN). In the second stage, in parallel to predicting the class and box offset, Mask R-CNN also outputs a binary mask for each RoI (Region of Interest). This contrasts with most recent systems, where classification depends on mask predictions.

This approach follows the spirit of Fast R-CNN [7] that. applies bounding-box classification and regression in parallel. Formally, during training, we define a multi-task loss on each sampled RoI as $L = L_{cls} + L_{box} + L_{mask}$.

In short, Mask RCNN innovatively uses ROI align, to avoid quantization of stride while pooling. It uniquely classifies each pixel with respect to class, object, or instance. Fig 1.1 gives intuition of the architecture.

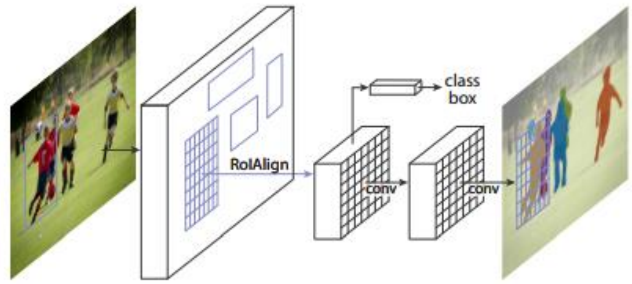


Fig 1.1 Mask RCNN framework

Contribution: We propose a novel approach to treat vertebral columns as a single object, perform computer vision techniques on it and subdivide it into thoracic and lumbar sections mathematically to figure out cobb angle.

III. METHODOLOGY

A. Block diagrams

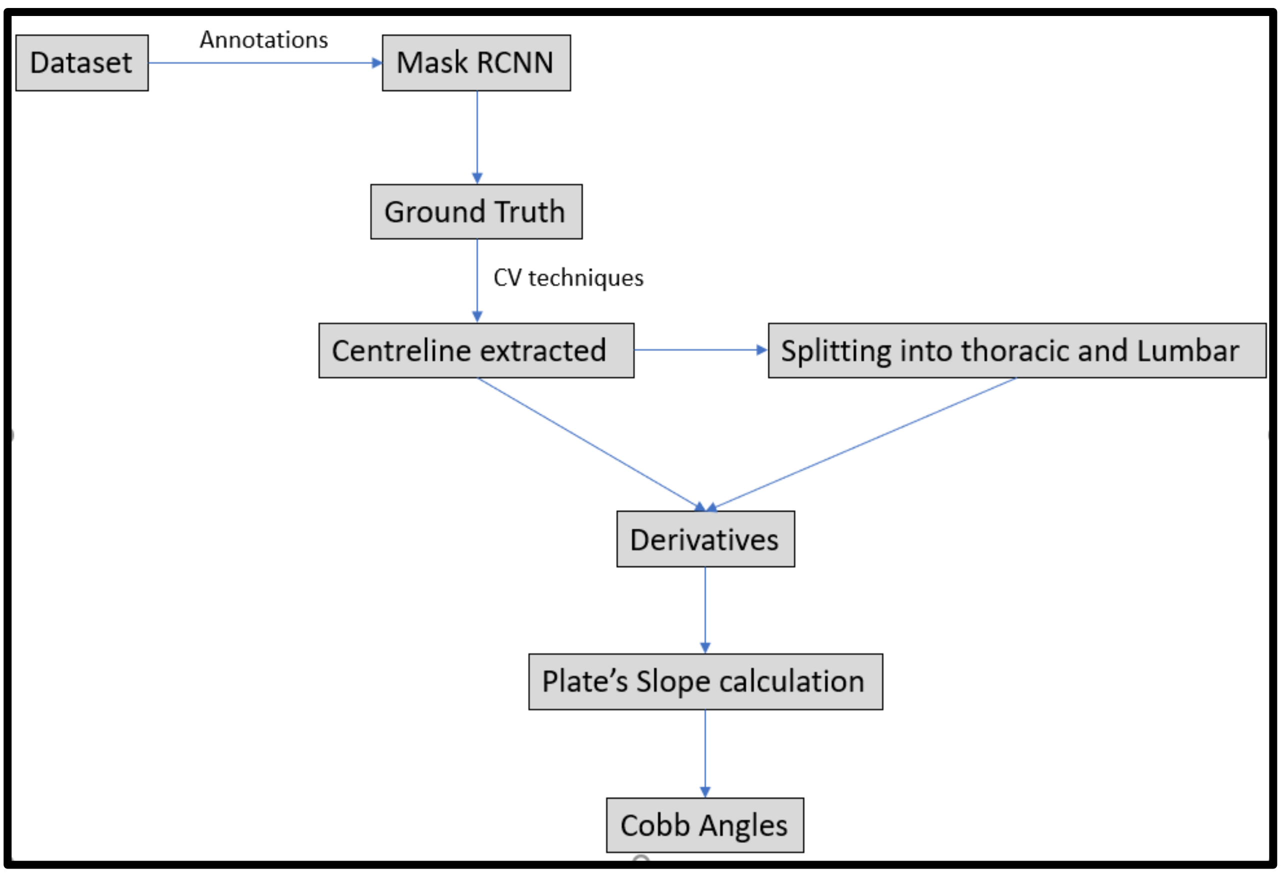


Fig 3.1 Procedural Block diagram

B. Synthesis/Algorithm/Design/Method

1) Modification of dataset

Normalized co-ordinates were given for each corner of each vertebra in the dataset. These coordinates were scaled or denormalized and arranged in a way to make a polygon of 68 corners from them and then used as annotations. The coordinates afterwards, were formatted with VGG19 annotator in the format required for Mask RCNN. A json file was created for training and validation dataset separately.

2) Customizing Mask RCNN:

After modification of the dataset, base code given by Mask RCNN is configured to train the given dataset. Two classes were considered following the decorum of the architecture, one for the vertebral column, and background being the other one. The customized neural network was trained for 3000 steps in 30 epochs keeping the learning rate as 0.001 and learning momentum 0.9. Weight decay regularization was used with decay rate of 0.0001. Batch normalization was frozen due to low batch size of 2.

3) Generation and processing of ground truths:

Mask RCNN generates ground truths of the masks generated for the detected object. Such ground truths were processed using following image processing techniques. Contour detection: It detects the outlines of the mask in the form of contours (set of coordinates).

Centerline extraction: Coordinates with similar ordinates were grouped together and centerline was extracted by calculating the center of each pair of equal-ordinated coordinates.

Smoothening: Extracted centerline was smoothened using savgol filter. Slope at each point was calculated.

4) Subdivision of centerline

Out of all coordinates of centerline,17 prominent points were chosen by skipping intermediate points. First 12 out of 17 were termed as Thoracic and remaining 5 were considered as Lumbar.

5) Calculation of cobb angles

Derivatives were calculated according to centerline, therefore each value was inversed and multiplied by -1 to calculate respective perpendicular slope of end plate. As per the evaluation criteria of challenge, three cobb angles namely Proximal Thoracic (PT), Main Thoracic (MT) and Thoraco-Lumbar (TL) [8] were calculated to figure out the Symmetric Mean Absolute Percentage Error (SMAPE).

$$\text{SMAPE}= \frac{1}{N}\sum_N \frac{\sum_m |a_g - a_p|}{\sum_m (a_g + a_p)}$$

Cobb angles were calculated using inverse trigonometric identity like et al. Horng [6].

$$\phi = \frac{180}{\pi}\left| arctan\left(\frac{T(p_{R,M}) - T(p_{R,m})}{1 + T(p_{R,M}) \cdot T(p_{R,m})}\right)\right|$$

where T(p) is the tangent slope of the centerline at point p, $p_{R;M}$ is the point with the maximum slope in region R, and $p_{R;m}$ is the point with the minimum slope in R.

IV. Overview

Problem of human error while calculating cobb angle can be solved using recent advancements in Neural Networks. We have used Mask RCNN to detect the Anterior-Posterior X ray images. Though the SMAPE can be reduced by minimizing the validation loss for generating the ground truth.

V. Results and Discussions

The validation accuracy of Mask RCNN architecture was according to table 5.1.

Type	Loss	Accuracy
Class	0.0137	98.7%
Bounding box	0.0889	91.1%
Mask	0.2203	78%

Table 5.1 Mask RCNN result overview.

After the mentioned image processing steps, the final calculated SMAPE according to the given formula was 21.69. Best SMAPE till the challenge ended was 21.71 [9].

VI. Helpful Hints

A. *Figures and Tables*

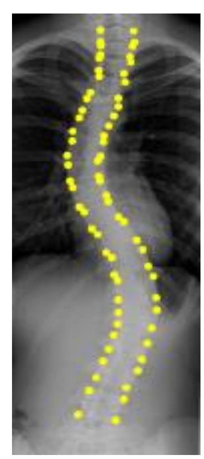
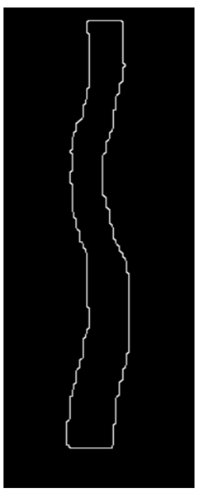



Fig 6.1 Given Landmarks plotted

Fig 6.2 Generated Mask Fig 6.3 Ground Truth



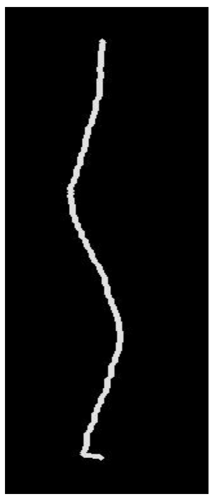
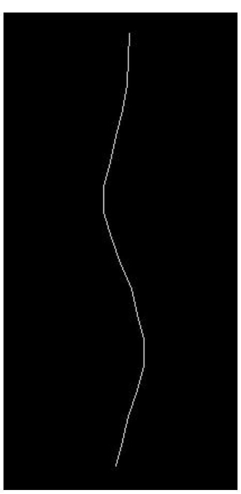


Fig 6.4 Contours detected Fig 6.5 Centerline Extraction



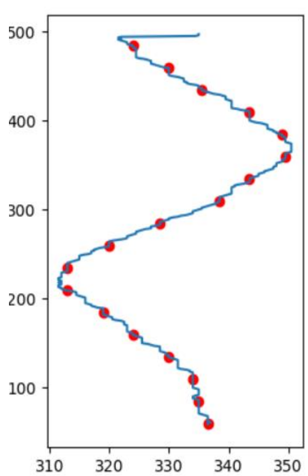


Fig 6.6 Smooth centerline subdivision

Fig 6.7 Points for

VII. Future Scope

This model can be further improved by further modification and fine tuning of Mask R CNN architecture. Speed of processing can also be optimized if suitable research is undertaken.

VIII. Conclusion

We studied and compared the structures and peculiarities of various neural networks. Applied transfer learning on Mask RCNN and generated ground truths of masks. Then centerline, derivatives and Cobb angles were figured out and SMAPE was calculated 21.69.

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