Automated Radiographic Assessment of Cervical Spine Alignment, Curvature, and Instability Using Pose Estimation and Deep Learning

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INTRODUCTION: Cervical spine alignment, curvature, and instability are critical in the diagnosis and management of spinal deformities and degenerative conditions. Manual assessment of radiographic parameters—such as Cobb angle, sagittal vertical axis (SVA), and vertebral alignment—is time-consuming and prone to inter-observer variability. Herein, we present a deep learning pipeline that automates the detection of anatomical keypoints on cervical spine radiographs using a YOLOv8 pose estimation model. These keypoints are then used to compute clinically relevant metrics of spinal alignment, sagittal balance, and curvature, enabling standardized and efficient evaluation of any cervical pathology present.

METHODS: An open-access dataset of 4963 lateral cervical spine radiographs—comprising both spondylotic and healthy cases—was utilized. Each image is annotated with 23 anatomical keypoints corresponding to vertebral landmarks. A YOLOv8 pose estimation model was trained on preprocessed images to detect anatomical keypoints across the C2–C7 vertebrae (Figure 1). From the predicted keypoints, clinically relevant metrics—Cobb angles (C2–C7), cervical disc angles (CDA), sagittal vertical axis (SVA), measurements of spondylolisthesis at anterior and posterior vertebral edges, and vertebral body slopes—were computed. All measurements were compared against reference annotations for validation.

RESULTS:

The YOLOv8 model achieved high accuracy in keypoint localization, with an average Euclidean distance error of less than 3.5 pixels across all vertebral landmarks (Table 1). Quantitative measurements derived from predicted keypoints showed strong agreement with reference values from the open source dataset (mean absolute error < 4.0° for angular metrics) (Table 2). The model generalized well across both symptomatic and asymptomatic subgroups.

DISCUSSION AND CONCLUSION:

This study demonstrates the feasibility of using a deep learning-based keypoint detection pipeline to automate the radiographic assessment of cervical spine alignment and instability. By streamlining the measurement of clinically relevant spinal metrics, this approach offers a reproducible and scalable tool for objective evaluation in both research and clinical settings.

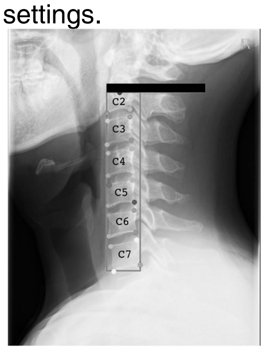

Figure 1. Sample lateral cervical spine radiograph annotated with 23 keypoints corresponding to vertebral landmarks from C2 to C7. For C2, keypoints include the vertebral body centroid (VBC) and inferior anterior vertebral body corner (IAVBC), inferior posterior vertebral body corner (IPVBC). For C3-C7, keypoints include the IAVBC, IPVBC, Superior Anterior Vertebral Body Corner (SAVBC), and Superior Posterior Vertebral Body Corner (SPVBC). These anatomical landmarks are used to compute quantitative metrics for evaluation of cervical spine pathology.

Table 1. Mean Euclidean error (pixels) for predicted keypoints by vertebral level (C2–C7).

Vertebral Level	Mean Euclidean Error (px)
C2	
VBC	3.12
IAVBC	2.80
IPVBC	2.86
C3	
SAVBC	2.84
SPVBC	2.96
IAVBC	2.72
IPVBC	2.76
C4	
SAVBC	2.79
SPVBC	3.05
IAVBC	2.76
IPVBC	2.66
C5	
SAVBC	2.97
SPVBC	2.97
IAVBC	3.04
IPVBC	2.90
C6	
SAVBC	3.02
SPVBC	2.97
IAVBC	3.07
IPVBC	2.88
C7	
SAVBC	2.92
SPVBC	2.94
IAVBC	3.14
IPVBC	3.45

VBC*: Vertebral Body Centroid;* ***SAVBC****: Superior Anterior Vertebral Body Corner;* ***SPVBC****: Superior Posterior Vertebral Body Corner;* ***IAVBC****: Inferior Anterior Vertebral Body Corner;* ***IPVBC****: Inferior Posterior Vertebral Body Corner*

Table 2. Mean absolute error (°) for calculated angular radiographic parameters.

Measure	Mean Error (°)
Alignment	
C2-C6 Cobb	3.47
C2-C7 Cobb	3.67
Vertebral Body Slopes	
C2	2.88
C3	2.49
C4	2.69
C5	2.69
C6	2.46
C7	2.33
Disc Angles	
C2-C3	3.11
C3-C4	3.72
C4-C5	3.42
C5-C6	3.18
C6-C7	3.96
Vertebral Body Angles	
C3	2.93
C4	3.47
C5	3.29
C6	3.25
C7	3.08