An Image Autoencoder for Learning Latent Disc Geometry from Segmented Lumbar Spine MRI

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INTRODUCTION: Low back pain is the world's leading cause of disability, and while the full etiology is not clear, pathology of the lumbar intervertebral discs is frequently considered a driver of pain. Geometric determinants of the intervertebral disc provide insight to its mechanical behavior and pathological state. For example, disc bulging is a classic feature of degenerative disc disease [1]. In this work, we propose a deep learning framework to extract latent features from segmented disc MRI using an image autoencoder, which is a convolutional neural network (CNN) trained to reconstruct 3D disc images from latent features. The model architecture consists of an encoder that abstracts visual information from an image, a bottleneck layer that defines the minimum latent feature set required to reconstruct the image, and a decoder that reconstructs the input image from these latent features. Thus, the bottleneck representation of a segmented disc defines a latent description of disc geometry with potential clinical significance. Here, we develop an interpretation of the latent features and demonstrate that these features provide valuable information for identifying disc pathology.

METHODS: ***Dataset*** For the current study, we examined 195 sagittal T1-weighted MRI sequences from a publicly available multi-institutional dataset comprising lumbar spine MRI scans of 218 patients [2]. Imaging systems and parameters varied by institution (make: Siemens, Philips; field strength: 1.5-3T; TE: 8ms-124ms; TR: 446-5570ms; flip angle: 80-160 deg). For each patient, the dataset included pixel-wise annotations of lumbar intervertebral discs, and metadata included common spine conditions for each lumbar disc, such as disc bulging. We divided the dataset allocating 80% (n=156) for training and 20% for testing (n=39). ***Segmentation model*** A Swin Transformer model **(Figure 1A)** was trained for 200 epochs with batch size=4 to segment the discs and a custom loss function that includes terms for binary cross-entropy and dice similarity coefficient (DSC) was implemented for training. Then, a custom Python script was implemented to orient each disc along anatomical planes and compute standard measures of disc geometry (disc height, anteroposterior width, and lateral width). ***Latent feature extraction*** The proposed pipeline to extract latent features from segmented MRI involves two steps. At first, disc masks were used to train a CNN-autoencoder for unsupervised latent feature extraction **(Figure 1B)**. Individual discs were isolated from each spine to ensure their representation by distinct latent vectors: this approach resulted in a total of 193 observations used to train the autoencoder. The CNN-autoencoder architecture comprises 3D convolutional and deconvolutional layers within the encoder and decoder, and batch normalization layers to promote training stability. The model was considered to have converged when the overall mean IoU between input and output masks exceeded 0.995, indicating that the input mask was almost perfectly reconstructed. Binary cross-entropy was used as loss function. The autoencoder bottleneck layer, which is a crucial hyperparameter that defines the number of latent features extracted from the segmented volume, was tested with different dimensions (64x1, 8x1, 4x1, and 3x1). No skip connections were included to guarantee that all the information of the segmented volume is mapped into the latent space. The second step entailed training a gradient boosting classifier on the combined dataset of latent and standard geometric disc features, as well as on each dataset separately, to predict disc bulging **(Figure 1C)**. ***Latent feature interpretability*** To interpret the physical meaning of latent features, we developed the following experiment. Three of the four features are held fixed at their respective mean, while the fourth was systematically varied from its minimum to maximum value. For the feature that varies, we inspected the minimum value, values at 1/3 and 2/3 of the range, and the maximum value. We generated segmentation volumes from the decoder based on these latent feature vectors **(Figure 2).**

RESULTS: For segmentation via the Swin Transformer, we obtained an intersection over union (IoU) of 0.74 (95% CI, 0.71-0.78) and dice similarity coefficient of 0.85 (95% CI, 0.83-0.87), which aligns with previous analysis of this dataset [2]. The autoencoder converged at dimension 64x1, 8x1, and 4x1, so consequently we chose the minimum bottleneck size (n=4). Incorporating latent features into a gradient boosting classifier improved the prediction of disc bulging over the use of geometric features alone, achieving results comparable to those reported in studies that combine geometric and anthropometric data [3]. In terms of features interpretability, we found that latent features encode information specific to spinal level. Specifically, feature 2 captured variabilities in the upper lumbar levels, features 1 and 3 in the middle levels, and feature 0 in the lower levels **(Figure 2)**. **Figure 3** displays the results from extracting latent and geometric features respectively from real and predicted masks.

DISCUSSION: This feature learning method effectively but marginally improves disc bulging predictions when combined with typical geometric determinants of disc shape. When projecting segmented masks into a space defined by just four dimensions, the model aims to maximize orthogonality between dimensions and it appears that leveraging the inherent differences across spinal levels effectively aligns with this objective. Given only four dimensions are required to reconstruct discs demonstrates there is an unexpected simplicity in disc shape across spinal levels, individuals, and disease states.

SIGNIFICANCE: We developed an image autoencoder to extract latent features from segmented disc MRI. These latent features improve predictions of disc bulging and offer interpretable insights, evidenced by their correlation with superior versus inferior spinal levels.

REFERENCES: [1]Battiè, *JBJS* 2006. [2]Van der Graaf, *Nature* 2024. [3]Hung, *IJERPH,* 2021

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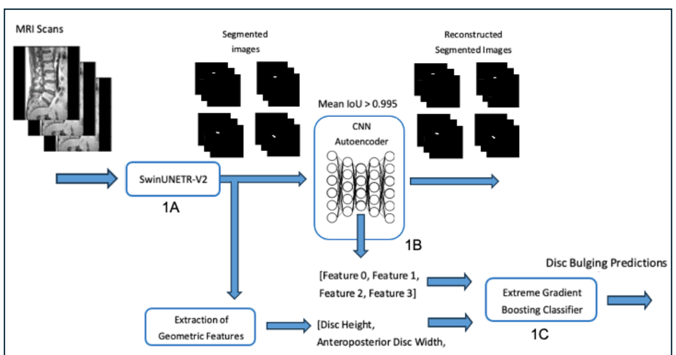

Figure 1: Pipeline followed in the current study

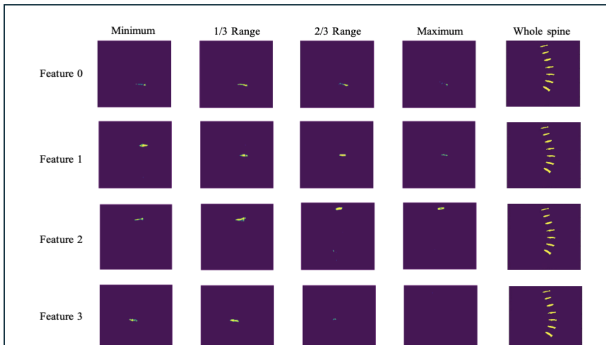

Figure 2: Visual representation of latent features

A

Features	F1-score (95% CI)	AUC-ROC (95% CI)
Latent features	0.65 (0.63-0.66)	0.71 (0.69-0.72)
Geometric features	0.71 (0.70-0.72)	0.77 (0.76-0.77)
Geometric and latent features	0.74 (0.73-0.74)	0.80 (0.79-0.81)

B

Features	F1-score (95% CI)	AUC-ROC (95% CI)
Latent features	0.67 (0.66-0.69)	0.71 (0.69-0.73)
Geometric features	0.64 (0.61-0.63)	0.69 (0.66-0.68)
Geometric and latent features	0.70 (0.70-0.71)	0.73 (0.73-0.74)

Figure 3: Predictions of disc bulging using latent and geometric features from (A) ground truth masks and (B) predicted masks