**­­­MONAI for Assisting in Diagnosis of Lumbar Disc Herniation**

**Applying MONAI to Assist in the Diagnosis of Lumbar Disc Herniation**

**Key Investigators**

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**Objective**

The primary object of this project is to enhance the diagnostic accuracy and quantification of lumbar disc herniation (LDH) by leveraging a state-of-the-art medical AI tool, MONAI, for the analysis of MRI images. Our aim is to achieve a heightened level of precision in automatically identifying and segmenting crucial disc herniations through the integration of human labeling. We will particularly focus on two pivotal anatomical planes: the sagittal and transverse views. Furthermore, in close collaboration with medical specialists, our objective is to develop a robust model for quantifying the extent of LDH. Subsequently, we plan to explore the correlation between the identified extent and the level of pain experienced by the patient. We anticipate that this interdisciplinary approach will not only refine diagnostic processes but also contribute valuable insights into the relationship between the anatomical manifestation of LDH and its associated clinical symptoms.

This project is structured in two distinct stages. Initially, we employ the robust capabilities of MONAI Label to effectively segment lumbar disc (LD) MRI images. Subsequently, our focus shifts to the development of a statistical model designed to quantify the extent of LDH. This sequential approach ensures a comprehensive analysis, encompassing both accurate segmentation and a quantitative understanding of the severity of LDH.

**Models Overview**

Adapted from a SegResNet-based model, *MONAI Label's segmentation\_vertebra.py pipeline* [1], our Unet-based models (pipelines) (**Fig. 1**) were used to train MRI images for segmenting spine structure. Since we had to deal with either herniated or healthy LD, each being presented both in sagittal and transverse planes, 4-versions of models were developed.

Derived from the segmentation\_vertebra.py pipeline of a SegResNet-based model within MONAI Label [1], our Unet-based models (depicted in Fig. 1) were adapted for training MRI images to accurately segment the spine structure. Given the necessity to address both herniated and healthy lumbar discs (LD) presented in both sagittal and transverse planes, we developed four distinct versions of our models.

A diagram of a project

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Figure 1. The structure of UNet

**Data**

146 LDH patients with chronic pain that persisted for at least 12 weeks were recruited, and LDH was diagnosed by medical history, physical examination, and consistent MRI assessment confirmed independently by two radiologists. Subjects were scanned twice (pre and post-surgery) on a 3 Tesla GE-Discovery 750 scanner.

**Scanner Specifications**



**Preprocessing**

1. Converted image format from DICOM to NIFTI by using bash scripts.
2. Categorized 146 images into herniated or healthy group in both sagittal and transverse planes, among which 34 were randomly selected as our primary dataset for training models.

**Training Configurations**

**Environments**

1. GPU: RTX 4090 24GB | RTX 3070 8GB
2. OS: Windows 11
3. Others: CUDA, Pytorch-GPU, Anaconda

**Input**

One channel - MRI image

**Output**

Sagittal Plane:

1. Herniated: Four channels - Label 1: Intervertebral Disk - Label 2: Vertebrae - Label 3: Cerebrospinal fluid 4: Herniated area
2. Healthy: Three channels - Label 1: Intervertebral Disk - Label 2: Vertebrae - Label 3: Cerebrospinal fluid

Transverse Plane:

1. Herniated: Three channels - Label 1: Vertebrae - Label 2: Cerebrospinal fluid - Label 3: Herniated area
2. Healthy: Two channels - Label 1: Vertebrae - Label 2: Cerebrospinal fluid

**Model Diagram**

A diagram of a process

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Figure 2. The training process of a model

**Stage 1: Data Conversion and Preparation**

The data format was converted from DICOM to NIfTI for compatibility with 3D-Slicer's loading requirement.

**Stage 2: Annotation and Models Training**

1. Compiled the Unet-based pipeline and deployed MONAI Label server for performing training network.
2. Annotation was performed through human labeling with the settings and the labels specified in the Unet-based pipeline. In addition, the annotation was adjusted based on the input LD plane (sagittal or transverse).
3. Set the parameters (epoch and split-value) and trained the network.

**Stage 3: Model Development and Refinement**

After we ran automatic inference to get intervertebral disk, vertebrae, cerebrospinal fluid, and herniated area with the trained UNet network, the model was iteratively improved until the accuracy evaluation was satisfied, including re-submission of refined annotation and/or increase of the training datasets to fine-tune the model.

**Results**

Four models were developed corresponding to herniated or healthy group in both sagittal and transverse planes since we discovered that the accuracy derived from 4 individual models was greater than a single model that dealt with all 4 scenarios.

**Sagittal plane**

Figure 3 demonstrated the segmentation results with an accuracy of 84% using 34 subjects after 50 epochs.

**An x-ray of a knee and knee joint

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**Figure 3**

**Transverse plane**

Figures 4 showed the segmentation and localization of intervertebral discs and cerebrospinal fluid on a healthy LD.

An arrow pointing to a chest x-ray

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**Figure 4**

Similarly, as depicted in Figure 5, the model, being applied to the transverse plane of herniated LD, was capable of segmenting its intervertebral discs, cerebrospinal fluid and herniated area.

**An arrow pointing to an x-ray

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**Figure 5**

In a summary, by customizing and adjusting parameters, combined with expertise of human labeling, our models have acquired the capability of effective­­­ly and accurately performing auto-segmentation and identifying herniated LD.

**References**

[1] Project-MONAI. (n.d.). Project-Monai/Monailabel: Monai label is an intelligent open source image labeling and learning tool. GitHub. https://github.com/Project-MONAI/MONAILabel/

[2] Ronneberger, O. (2015, May 18). U-NET: Convolutional Networks for Biomedical Image Segmentation. arXiv.org. https://arxiv.org/abs/1505.04597